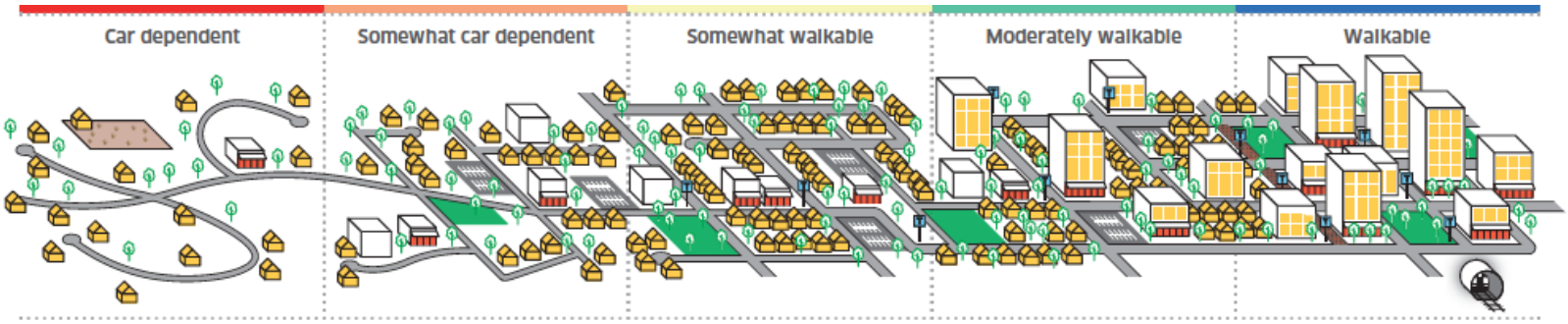


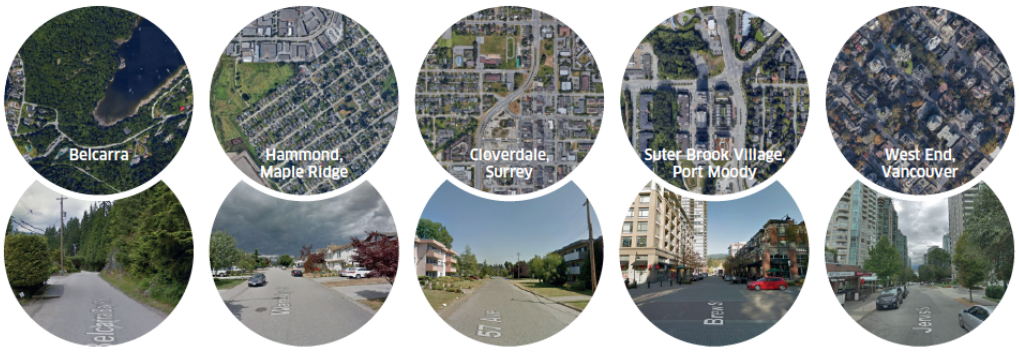
Where Matters II – Final Report
Walkability and Greenspace Relationships with Health and Climate Change

Prepared For:

TRANSLINK
metrovancouver
SERVICES AND SOLUTIONS FOR A LIVABLE REGION
THE UNIVERSITY OF BRITISH COLUMBIA
School of Population and Public Health
Faculty of Medicine
BRITISH COLUMBIA
Ministry of Transportation
real estate foundation
BRITISH COLUMBIA
city of north vancouver
UBC
Health and Community Design Lab

Prepared By:

Dr. Lawrence D. Frank, UC San Diego, Lead | Dr. Alex Bigazzi, UBC, Co-Lead | Dr. Trevor Dummer, UBC, Co-Lead | Ms. Katherine White, UBC | Dr. Katie Crist, UC San Diego | Dr. Atul Aravindakshan, UBC | Ms. Adriana Berjisian, UBC |Mr. Connor Wolff, UBC | Ms. Nasim Niknej, UBC | Mr. Eric Fox, Urban Design 4 Health, Ltd | Ms. Maureen Prentice & Mr. Victor Ngo, Consultants



February 29, 2024

Suggested Citation

Frank, LD, Bigazzi, A., Dummer, T., White, K., Crist, K., Aravindakshan, A., Berjisian, Wolff, C., Niknej, N., Fox, EH. & Prentice, M. (2024). Final Report – Where Matters II: Walkability and Greenspace Relationships with Health and Climate Change. Prepared by the Health & Community Design Lab, School of Population & Public Health, University of British Columbia. Support provided by the Real Estate Foundation of British Columbia, the British Columbia Ministry of Transportation & Infrastructure, Metro Vancouver, TransLink, and the City of North Vancouver.

Acknowledgments

We would like to thank our clients who provided financial support and important input and feedback at several stages of the project:

- Real Estate Foundation of British Columbia
  - Jennifer McCaffrey, Grants Program Manager

- Ministry of Transportation & Infrastructure, Province of British Columbia
  - Kate Berniaz, Director – Clean and Active Transportation
  - Katia Gauvin, Clean Transportation & Programs Branch
  - Keith Elwood, Clean Transportation & Programs Branch

- Metro Vancouver
  - James Stiver, Division Manager, Regional Land Use Policy
  - Erin Rennie, Senior Regional Planner
  - Heidi Lam, Sr. Policy & Planning Analyst
  - Sinisa Vukicevic, Program Manager of Planning Analytics
  - Derek Jennejohn, Lead Senior Engineer

- TransLink
  - Eve Hou, Senior Manager of Policy Development & Decision Analysis
  - Ilan Elgar, Director of Research & Analytics
  - Nicole Geitebruegge, Senior Planner, Transportation Analytics
  - Ryan So, Senior Transportation Planner
  - Victor Gasper, Manager, Customer Research & Insights

- City of North Vancouver
  - Michael Epp, Director of Planning
  - Andrew Devlin, Manager Transportation Planning

WHERE MATTERS...



WHEREVER

YOU

GO...

THERE

YOU

ARE

Executive Summary

Where Matters II documents public health and climate change win – win "co-benefits" from creating walkable communities with access to greenspace. Where Matters II investigated relationships between the built and natural environment where people live and the prevalence of physical and mental chronic diseases and sense of community. The physical environment where we live, work, and play shapes our activity and travel patterns which in turn impacts our wellness and vehicle emissions. Health and climate change are both impacted by the location and design of transportation and land use decisions. Demand for evidence linking built and natural environment features with our individual health and the health of the planet (e.g. climate change) is featuring more prominently within local, regional, provincial, and federal decision-making contexts to help shape investment priorities.

Where Matters II is a multi-sectoral (government, academia, industry) inter-disciplinary (public health, urban planning, transportation) collaboration. Primary funders are the Ministry of Transportation and Infrastructure, and the Real Estate Foundation of BC; who along with Metro Vancouver, TransLink, and the City of North Vancouver sponsored this project. WMII leverages and spatially integrates physical environment data with health outcome and travel data to assess causal impacts of transportation and land use actions on chronic disease, and associations with travel patterns and GHG emissions.

Walkability was measured consistently in 2006, 2011, and 2016 creating the ability to document how lower mainland communities have changed over time. This data along with greenspace and other social environment predictors was spatially joined with health outcome and travel data (see Figure 0-1).



Figure 0-1: Health and Climate Impacts of the Built and Natural Environment

Where Matters II provides a blueprint to track how communities are changing over time; and tracking how these changes impact public health and climate change. Tracking physical changes to the built environment over time and linking it with travel and health outcome data provides planners and decision-makers with a tool that links the health of a population and the environment with community design. WMII utilizes the Vancouver Walkability Index[1], TransLink's 2017 travel survey data, the BC Generations Health Survey, Metro Vancouver's Greenspace data, and air quality

[1] Developed by Dr. Lawrence Frank and researchers at the Health & Community Design Lab (HCDL). Dr. Frank led this work as the Bombardier Chair in Sustainable Transportation over a 17 year period at the University of British Columbia.

data from the Canadian Urban Environmental Health Research Consortium (CANUE). The conceptual study design shown in Figure 0-2 captures how transportation, land use, pedestrian design, and greenspace investments through travel and activity patterns affect our behaviours and exposures. These factors result in biological responses such as weight, inflammation, and stress which through time impact physical and chronic disease and downstream costs.

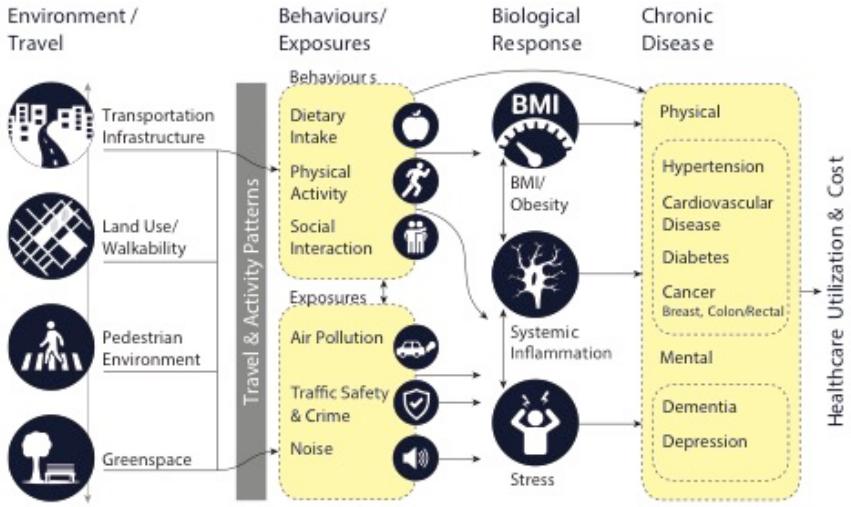


Figure 0-2: Conceptual Framework [2]

Where Matters found significant reductions in diabetes, and cardiovascular disease rates and increases in sense of community for those living in more walkable areas of the Vancouver region. Where matters II builds on this work and connects the same measures of walkability and community design with climate impacts. It also provides the ability to evaluate if health relationships with the built environment are causal. We can connect health outcomes more accurately to a person's neighbourhood and assess if a change in neighbourhood results in a change in health.

Tracking Walkability Changes

Figure 0-3 shows changes in the four main components of walkability between 2011 and 2016 across Metro Vancouver. Increases in residential density were largely concentrated in the urban centres and frequent transit development areas in the region. Changes in commercial floor area ratio (FAR) were widespread for areas with existing commercial and retail land uses with concentrated pockets of high change in some outlying areas in Richmond, Surrey, and Langley.[3] Land use mix shows relatively stable patterns across existing established mixed-use areas in Vancouver, Burnaby, and New Westminster, with larger changes in outlying and suburban areas. This is due to the fact that these previously single-use areas (e.g., residential subdivisions) are becoming more mixed with floor area from different land uses. Lastly, relatively limited change in intersection density was detected for the region with the exception of those outlying areas with greenfield development and significant new updates to the road network, especially in areas like Burke Mountain in Coquitlam and South Surrey.

[2] Frank, L. D., Iroz-Elardo, N., MacLeod, K. E., Hong, A. The pathways from built environment to health: Connecting behavior and exposure-based impacts. 2016. Journal of Transport and Health.

[3] Note that these areas may not exhibit high levels of commercial Floor Space Ratio (FSR); but have become more neighbourhood retail oriented.

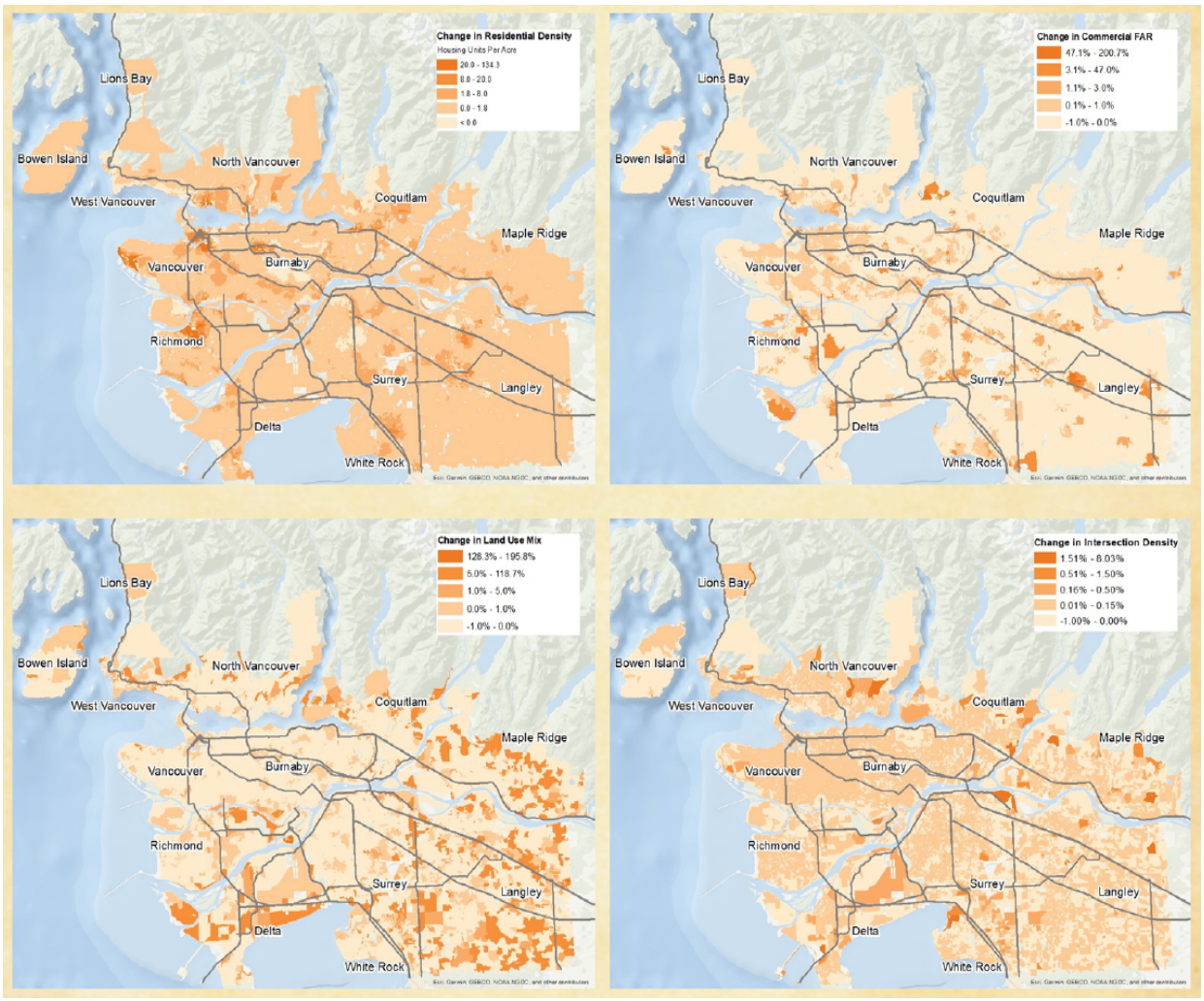


Figure 0-3: Longitudinal changes (2011-2016) by each component of walkability in Metro Vancouver.

Changes in residential density for four key areas experiencing the most population between 2011 and 2016 are shown in Figure 0-4 and include Downtown Richmond, Lonsdale in North Vancouver, False Creek/Olympic Village in Vancouver, and UBC. Similar findings can be mapped and quantified for the other metrics where changes were the greatest.



Figure 0-4: Longitudinal changes (2011-2016) in residential density for four key areas in the region.

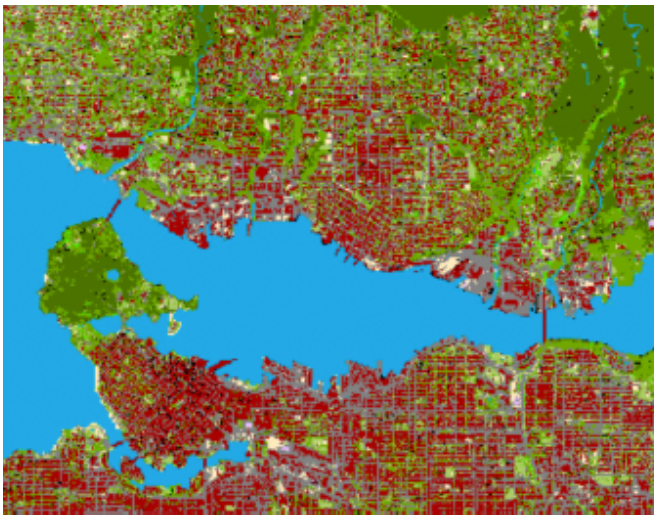
The Where Matters II conceptual framework (Figure 0-2) and subsequent analyses show that changes in walkability metrics (e.g. residential density) result in changes in travel and related downstream health and GHG outcomes. Increased density creates demand for

and proximity to shops and services which increases land use mix. Density and mix along with connected street networks and retail built up to the sidewalk without large surface parking lots (higher retail FAR) supports walking and physical activity, less driving and sedentary time, and reduced vehicle emissions.

A 2021 walkability surface is now being created for Metro Vancouver providing measurement of these same walkability metrics at a 4th time points spanning a 15-year period. Tracking how communities are changing around these key walkability metrics supports the potential for piloting a performance-based approach to transportation funding and once again making the Lower Mainland a global leader in progressive land use and transportation planning. This would explore the prioritization of active transportation and transit funding based on local government achievement of performance-based goals to meet health and GHG reduction objectives. This is a form of performance-based funding that has been used in education and public health and can fuse a stronger link between regionally and provincially led transportation funding with local government-controlled land use planning.

Greenspace Access & Exposure

Figure 0-5: Metro Area Land Cover



Road-based network buffers were developed to analyze Metro Vancouver's Land Cover data layer which allowed us to more accurately measure the proportion of different types of natural and developed land uses accessible to an individual. Three greenspace indicators were utilized for this study: 1) tree canopy coverage, 2) Normalized Difference Vegetation Index (NDVI), and 3) access to developed parks. Metro Vancouver had a median proportion of about 25% tree canopy coverage varying from <1% to 96% coverage[4] at the postal code level. Nearly all postal codes evaluated (98.5%) were within 1 kilometre of a park 1-hectare in size or larger. Seventy-four percent of postal codes had a park at least 1-hectare in size within 400 metres. Greenspace was used to predict physical and mental health outcomes.

Travel & Climate Change

Travel data from TransLink's 2017 travel survey on over 28,000 households containing 200,000 trips reported over a 2-day period was used to evaluate how travel habits and travel-related emissions relate with walkability and other factors. Higher levels of walkability are associated with increased walking and transit use, and fewer motor vehicle

[4] Median tree canopy coverage for the region was 24% for 400 metre buffer neighbourhoods and 26% for 1-kiolmetre buffer neighbourhoods.

trips (Figure 0-6). The proportion of trips by car declined from 92 to 44 percent and walking increased from 5 to 35 percent and transit rose from 3 to 17 percent from the least to the most walkable areas of the region. Chapter 4 results convey that overall relationships between travel patterns and walkability remain significant after controlling for regional accessibility, vehicle ownership, income, and other factors. Results also show that mean per capita vehicle kilometers traveled declined from 11.92 to 5.83 per day from the least to the most walkable areas of the region.

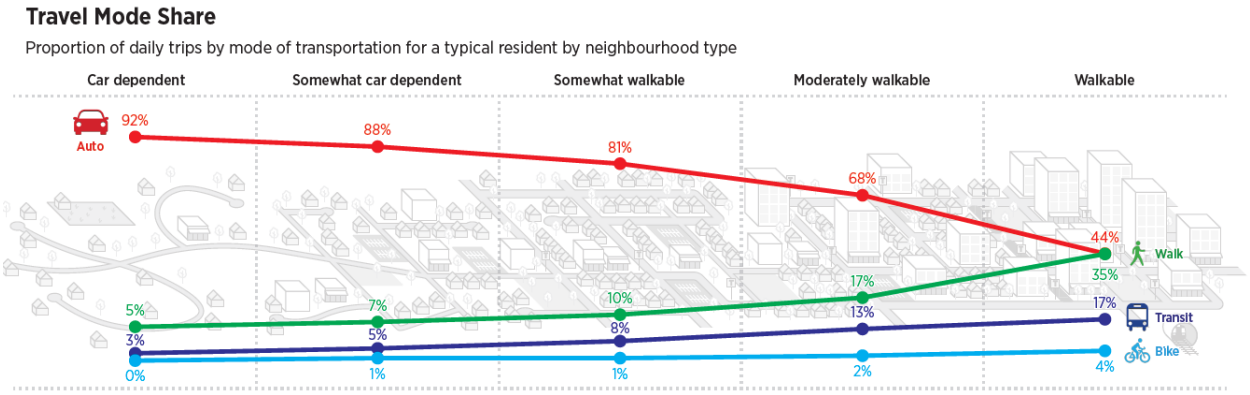


Figure 0-6: Travel mode share by walkability

Time in cars is a sedentary activity while walking and biking are forms of physical activity. Figure 0-7 shows a decline from 37 to 19 minutes of time in cars and a reduction from 23 to 9 kilometres traveled from the least to the most walkable areas. Conversely, walk and bike time rose from 2 to 14 minutes per day from the least to the most walkable areas.

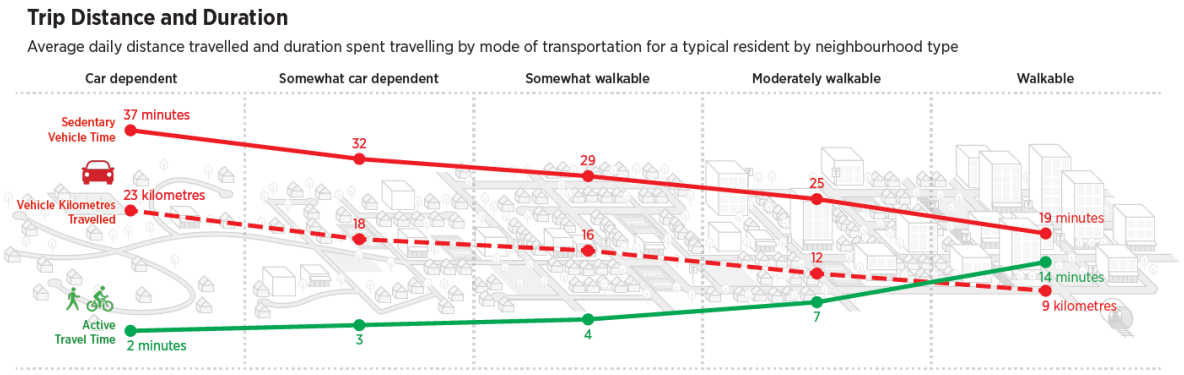


Figure 0-7: Distance and Duration

Comprehensive lifecycle emissions estimates were generated for each reported trip, and models were developed of daily greenhouse gas and local air pollutant emissions, dependent on the same explanatory variables. Model results in Chapter 5 show that emissions were significantly lower in more walkable neighbourhoods when adjusting for regional accessibility, vehicle ownership, income, and other factors. Travel-related GHG emissions declined nearly threefold from 17 to 6 kilograms per person / day (Figure 0-8).

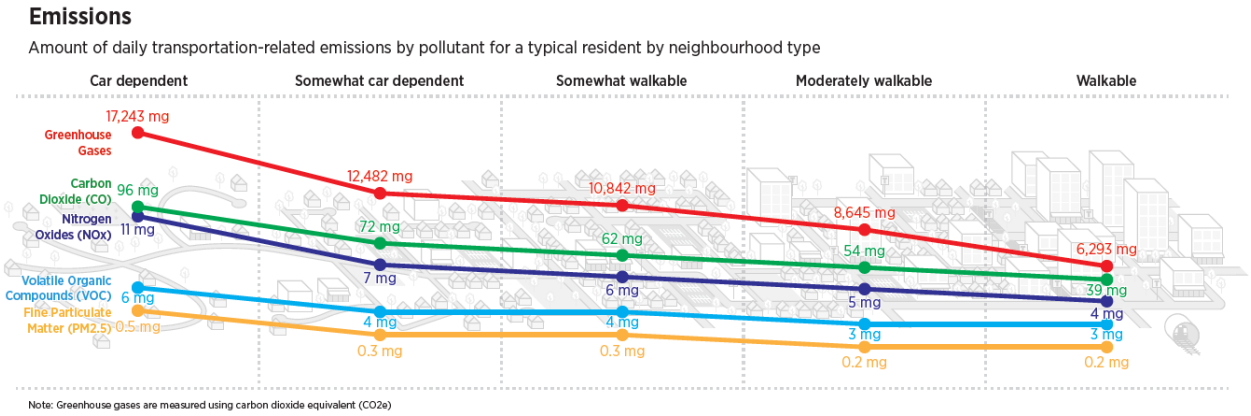


Figure 0-8: Average daily emissions from travel by quintile of walkability

Travel-related vehicle emissions have well-documented adverse health impacts. Where Matters estimated per capita daily travel-related amounts of Volatile Organic Compounds (VOCs), Oxides of Nitrogen (NOx), Small Particulate Matter (PM2.5), and Carbon Monoxide (CO). Overall, those living in walkable areas generated between half to a third as much of these pollutants as those in the most car-dependent areas of the region (see Figure 0-8). CO declined from 96 to 39, NOx declined from 11 to 4, VOC declined from 6 to 3, and PM 2.5 declined from 5 to 2 milligrams per day. Detailed emissions estimates that account for vehicle type and fuel, congestion level, vehicle occupancy, and other key factors.

Community Health Impacts

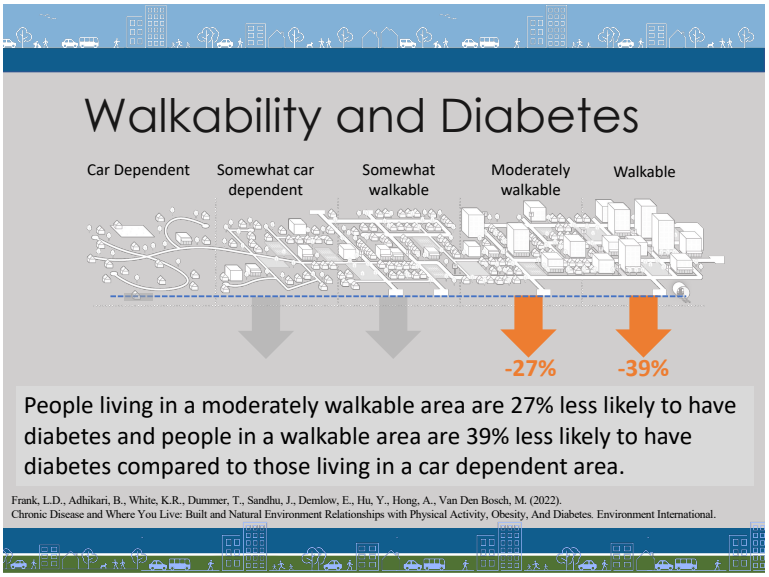
Chronic disease relationships with and impacts of the built and natural environment were estimated using the BC Generations Project (BCGP), a database of 30,000 British Columbians aged 35-69 years which represents. BCGP is a component of the Canadian Partnership for Tomorrow's Health (CanPath) Pan-Canadian prospective health cohort. This dataset was established over the past decade as a research platform for evaluating the genetic, behavioural and environmental causes of cancer and other chronic diseases. BCGP collects health, lifestyle, occupation, residential history, diet and physical activity, socio-demographic, behavioural and health-related data. Walkability datasets were linked with BCGP participants allowing us to investigate the causal impact of exposure to walkable versus car-dependent environments over time and how changes in walkability impact chronic disease and health behaviours.

Obesity, Hypertension & Diabetes

Obesity and obesity-related diseases continue to adversely impact health and economic indicators across low, middle and high income countries. Overweight and obesity are linked to increased risk of numerous chronic conditions including type 2 diabetes mellitus (T2DM) and high blood pressure (HBP), which are leading causes of cardiovascular disease and premature mortality globally. Living in walkable environments has been linked to significantly higher levels of physical activity via active travel. Among the Metro

Vancouver sample, obesity showed a 16% prevalence rate, with 12% being treated for hypertension, and only 2% being treated for type 2 diabetes.

We evaluated how changes in walkability over time impacted obesity. A reduction in the prevalence rate of obesity was observed with increased levels of walkability. **A 1-unit increase in the walkability change score was associated with a 9% reduction in odds of becoming obese.** When compared to the least walkable areas, those participants living in the most walkable areas had a 51% lower odds of becoming obese. This association was further reinforced by now-published evidence from Where Matters I. Figure 0-9 shows residents in the most walkable areas of the region have a 39 percent lower odds of having diabetes compared with those in the most car-dependent areas.



This relationship was tested longitudinally in the current study where change in walkability over a short time frame (5.5 years) was found to be an insufficient duration of exposure to cause downstream chronic health impacts such as type 2 diabetes or hypertension (at the 95% confidence level). However, other studies have begun to document causal relationships.

Figure 0-9: Walkability & Diabetes Risk[5]

Cancer Risk

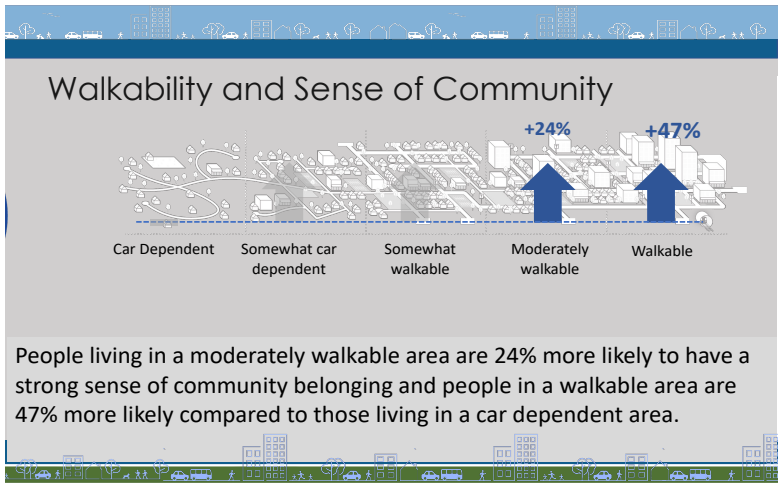
Cancer is the leading cause of death in Canada with lung, breast, colorectal, and prostate cancer accounting for approximately half of the cancer cases diagnosed. Two out of five Canadians are expected to receive a diagnosis of cancer in their lifetime resulting in one in four cancer-related deaths after diagnosis. Despite advances in detection and treatment, lung cancer is the leading cause of death in Canada with a 5-year survival of 19%. Little research has effectively linked built or natural environment features with Cancer outcomes. We found that increases in walkability were linked with decreasing trends for lung cancer hazards while a decreasing trend in risk for colorectal cancer was observed for participants with higher NDVI exposures but neither result was significant at the 95 percent confidence level. Potential protective trends for greenness and walkability were identified for certain cancer types but more research is needed on a larger sample.

[5] Frank, L.D., Adhikari, B., White, K.R., Dummer, T., Sandhu, J., Demlow, E., Hu, Y., Hong, A., Van Den Bosch, M. (2022). Chronic Disease and Where You Live: Built and Natural Environment Relationships with Physical Activity, Obesity, And Diabetes. Environment International. Http://Doi.Org/10.1016/J.Envint.2021.106959

Mental Health and Sense of Community

Mental disorders have a significant impact on the global burden of disease, affecting communities and people of all ages in both high and low-income countries. Sense of community and concern over social isolation has become a major mental issue in recent years.

Figure 0-10: Walkability & Sense of Community



In 2023, the US Surgeon General released a major report on social isolation and similar policy discussions are underway in Canada. Where Matters I found participants living in the most walkable areas of the Vancouver region were 47% more likely to report having a strong sense of community compared with those in the most car-dependent areas. Figure 0-10 reports these statistically significant results.[6] Depression stands as a significant public health issue affecting 344 million individuals globally in 2019, and 4.7% of Canadians aged 15 and older exhibited it in 2012. Anxiety disorders stand as the second most common mental disorder globally, affecting approximately 301 million individuals in 2019, and 14% of Canadians aged 12 in the same year. We did not observe any significant association between walkability and depression.

However, participants in the most walkability areas were 1.74 times more likely to report experiencing anxiety compared to those living in the least walkability areas. Participants living in areas with very high walkability had statistically significant increased odds of experiencing anxiety, even after adjusting for demographic, lifestyle, and health-related variables. These results are counter to results suggesting a higher sense of community and social capital in more walkable areas. More work is needed to understand the underlying mechanisms of this potential relationship and its generalizability.

[6] Results are based on My Health My Community Survey Data Collected by Vancouver Coastal Health Authority. Where Matters I: Health & Economic Impacts of Where We Live, University of British Columbia, 2019.

Summary and Conclusions

Findings presented in this report support GHG reduction and health promotion policies at the Provincial and Regional levels. Transportation and public health constitute two of the biggest Provincial responsibilities and perhaps the largest expenditures. These two issues are interrelated; yet institutionally separated. Both benefit from walkability and are adversely impacted by car dependence. Transportation investment decisions have considerable public health consequences. Results support Metro Vancouver's Regional Growth Strategy and TransLink's Transport 2050: Regional Transportation Strategy. Results further underpin the Ministry of Transportation and Infrastructure's CleanBC Roadmap to 2030. Findings support recently enacted Provincial bills 44, 46 & 47 which include a wide range of actions to increase density across most of BC municipalities primarily in association with transit. Bill 44 requires local governments to amend zoning bylaws to increase permitted density in areas currently zoned single-family or duplexes.

Residents within the more walkable areas of the lower mainland generated a third to half as much emissions as those in the most car-dependent areas and are at lower risk of several obesity-related chronic diseases. However, the most walkable parts of the lower mainland are also the least affordable and the less fortunate are priced out of the places with the best health outcomes. The promotion of walkability as a population health and GHG reduction solution requires mechanisms to make it more affordable to the less fortunate. Chronic disease is concentrated in the most underserved and constitutes a massive economic burden in BC and across Canada.

In 2015, the estimated cost of chronic disease was $7.8 billion and significant portion of the overall provincial budget (BCCDC). Where Matters I documented higher rates of chronic disease in the most car-dependent areas of the lower mainland. The estimated costs of chronic disease are massive. One study by the Chronic Disease Alliance of Canada in 2017 found that the direct cost of Chronic Disease accounts for about 58% of the annual health spending in Canada (CDPAC / APMCC 2017). Transportation and health care constitute two of the biggest Provincial expenditures. Findings from Where Matters I and II studies documents currently externalized direct and indirect health-related impacts and costs of transportation and land development decisions. It presents a dynamic 5-year surveillance approach to quantify and internalize impacts into future decision-making processes.

A broad range of findings presented confirm these relationships built around a dynamic model where changes to walkability over time are captured and related to health and travel-related climate change outcomes. Living in a more walkable environment is associated with generating less harmful emissions, more physical activity, and lower obesity, diabetes, and cardiovascular disease rates. Where Matters provides a model for tracking key features of the physical environment that impact health and climate change – two of the most pressing societal / provincial mandates. Where Matters has measured walkability at the postal code level using parcel-level land use data at what will soon be 4 time points and linked with the census in a consistent manner. This project shows how changes in walkability impact obesity and is presented as a test case. Tracking changes

in access to greenspace can also be done consistently over time and along with walkability can be linked with a broader array of travel, emissions, and health outcomes.

Tracking changes in those features of the built and natural environment that logically impact health and climate change is arguably a necessary form of surveillance given the broad array of population-level consequences of these actions. A dynamic change detection framework is presented that can further be used as a decision support tool to guide infrastructure investments and land use actions. A performance-based approach to transportation funding could be introduced whereby at least some portion of investments in transportation infrastructure is awarded based on the achievement of positive changes to the built and natural environment. This concept is presented as one method to further strengthen the link between local government-led land use decisions and regional and provincially-led transportation investment processes.

Table of Contents

EXECUTIVE SUMMARY 4

Tracking Walkability Changes 5
Travel & Climate Change Impacts 7
Community Health Impacts 9
Obesity, Hypertension & Diabetes 9
Cancer Risk 10
Summary and Conclusions 12

1. PROJECT PURPOSE & REPORT OVERVIEW 23

1.1. Background 25
1.2. Measuring & Achieving Regional Strategy Goals 26
1.3. Policy Framework: Regional & Provincial Strategies 27
1.3.1. Metro Vancouver Regional Growth Strategy 27
1.3.2. Metro Vancouver Regional Transportation Strategy 27
1.3.3. Province of British Columbia CleanBC Strategy 28
1.3.4. Changes in Regulatory Approaches 28

2. TRACKING CHANGE IN WALKABILITY AND REGIONAL ACCESSIBILITY 30

2.1. The Walkability Index 30
2.2. Defining the Neighbourhood 32
2.3. Longitudinal Walkability Data 33
2.3.1. Intersection Density 34
2.4. Net Residential Density 36
2.4.1. Commercial Floor Area (FAR) 37
2.4.2. Land Use Mix 38
2.5. Regional Accessibility 40
2.6. Summary 43

3. GREENSPACE ACCESS & EXPOSURE 44

3.1. Health Impacts of Greenspace Access and Exposure 44
3.2. Built and Natural Environment Exposures 46
3.2.1. Land Cover 47
3.2.2. Tree Canopy 47
3.2.3. Normalized Difference Vegetation Index 48
3.2.4. Park Access 48
3.3. Exposure Buffers 49
3.4. Statistical Analysis 50
3.5. Results 50
3.5.1. Natural Land Cover 50
3.5.2. Tree Canopy 51
3.5.3. Normalized Difference Vegetation Index 51
3.5.4. Park Access 52
3.5.5. Comparison of Buffer Types 52
3.5.6. Comparison of Greenspace Metrics 52
3.6. Discussion 52
3.7. Implications 54

4. TRAVEL BEHAVIOUR RELATIONSHIPS WITH WALKABILITY – THE ASSOCIATION OF BUILT ENVIRONMENT FACTORS ON ACTIVE AND SEDENTARY TRAVEL BEHAVIOUR: A CROSS-SECTIONAL TRAVEL DIARY STUDY 60

4.1. Background 60

4.2. Methods 60
4.2.1. Data source, survey design, and ethics 60
4.2.2. Study sample and study variables 61
4.2.3. Statistical Analysis 61
4.3. Results 62
4.3.1. Walking 62
4.3.1. Cycling 64
4.3.1. Transit 66
4.3.1. Vehicle 68
4.4. Discussion 70
4.5. Conclusions 70
4.6. References 70

5. GREENHOUSE GAS EMISSIONS AND WALKABILITY 71

5.1. Background 71
5.2. Methods 75
5.3. Results 82
5.4. Discussion 92
5.5. Conclusions 93
5.6. References 93

6. OBESITY, DIABETES & HYPERTENSION WITH WALKABILITY – LONGITUDINAL ADULT ASSOCIATIONS BETWEEN WALKABILITY AND INCIDENT OBESITY, HYPERTENSION, AND TYPE 2 DIABETES 96

6.1. Background 96
6.2. Methods 97
6.2.1. Analytic sample 97
6.2.2. Exposure Variable 97
6.2.3. Outcome Variables 97
6.2.4. Covariates 98
6.2.5. Statistical Analysis 98
6.3. Results 98
6.3.1. Descriptive statistics 98
6.3.2. Model results 99
6.4. Discussion 102
6.5. Conclusions 103
6.6. References 103

7. MENTAL HEALTH WITH WALKABILITY & GREENSPACE – MULTIFACETED IMPACTS OF GREEN SPACE AND WALKABILITY ON MENTAL HEALTH: DEPRESSION AND ANXIETY IN FOCUS 104

7.1. Background 104
7.2. Methods 105
7.3. Results 107
7.4. Discussion 111
7.5. Conclusions 112
7.6. References 112

8. CANCER RISK WITH WALKABILITY & GREENSPACE - THE EFFECT OF RESIDENTIAL GREENNESS AND WALKABILITY ON CANCER RISK IN THE GREATER VANCOUVER REGION 113

8.1. Background 113
8.2. Methods 113
8.3. Results 115
8.4. Discussion 119
8.5. Conclusions 121

8.6. References 122

9. REGULATORY & FISCAL APPROACHES TO TRANSPORTATION & LAND USE INVESTMENT 123

9.1. Changes to Municipal & Regional Regulatory Environment 123
9.2. Performance-Based Funding 126
9.2.1. Description of Existing PBF Literature 126

10. MAIN DOCUMENT REFERENCES 128

11. APPENDIX A: PERFORMANCE-BASED FUNDING 140

11.1.1. Performance-Based Funding (PBF): Differences in Application Across Sectors 140
11.1.2. Performance-Based Approaches in Global Development Financing and Aid 140
11.2. Incentive-Based Funding Mechanisms in Higher Education 148
11.3. Incentivizing Results in Social Service Delivery 151
11.3.1. Outcomes-Based Grants and Contracts 152
11.3.2. Pay for Success Initiatives 152

12. APPENDIX B: COMMUNITY DESIGN CHARACTERISTICS – WALKABILITY: EXPLORING THE RELATIONSHIP BETWEEN WALKABILITY AND NEIGHBOURHOOD CHANGE 154

12.1. Introduction 154
12.2. Neighbourhood Change 155
12.3. Theoretical Debates on Neighbourhood Change 155
12.3.1. Residential Migration as Neighbourhood Change 155
12.3.2. Neighbourhood Change as Demographic Shifts 156
12.3.3. Neighbourhood Change as in situ upgrading process 156
12.4. Measuring Neighbourhood Change 157
12.4.1. Indicators of Neighbourhood Change 157
12.5. Gaps in Existing Walkability and Neighbourhoods Change Literature 158
12.6. Analysis Methodology 158
12.6.1. Measuring Walkability 158
12.6.2. Measuring Longitudinal Changes in Walkability: Grand Mean Method 160
12.6.3. Measuring Neighbourhood Change 161
12.7. Summary 164
12.8. Analysis 165
What was the baseline walkability of the study area in 2006? 167
How did walkability change by municipality during the study period? 168
12.1. Detailed Review of Change in The Walkability Index: 2006 to 2016 172
12.1.1. Intersection Density 176
12.1.1. Net Residential Density 181
12.1.2. Commercial Floor Area (FAR) 185
12.1.3. Land Use Mix 189
12.1. Regional Accessibility 193
12.2. Walkability Summary 199
12.3. Neighbourhood Change in Metro Vancouver 199
12.3.1. Olympic Village, Vancouver 200
12.3.2. Willingdon Heights, Burnaby 205
12.3.3. Brighouse, Richmond 210
12.3.4. Morgan Heights, Surrey 214
How have patterns of gentrification varied across the region during the study period? 219
Measuring gentrification using the Social Status Index 219
Exploring the relationship between walkability and neighbourhood change 221
Baseline Walkability and Social Status Index 221
Baseline Walkability and Changes in Individual Indicators of Gentrification 223

Differences in gentrification in high and low walkability neighbourhoods *224*
How are changes in walkability associated with neighbourhood change? *226*
12.4. Discussion 227
12.5. Conclusion 228
12.5.1. Limitations and Future Research 229

13. APPENDIX C: COMMUNITY DESIGN CHARACTERISTICS – GREENSPACE: HOW DOES NEIGHBOURHOOD WALKABILITY RELATE TO GREENSPACE EXPOSURE, PARK ACCESS, AND SOCIAL AND MATERIAL DEPRIVATION? 231

13.1.1. Introduction 231
13.1.2. Material and Social Deprivation Index 232
13.1.3. Statistical Analysis 232
13.2. Results 232
13.2.1. Comparison of Walkability and Greenspace Metrics 232
13.2.2. Neighbourhood Social and Material Deprivation, Walkability and Tree Canopy 234
13.3. Discussion 235
13.4. Implications 236

14. APPENDIX D: HEALTH IMPACTS - FULL ARTICLE - LONGITUDINAL ASSOCIATIONS BETWEEN WALKABILITY AND INCIDENT OBESITY, HYPERTENSION, AND TYPE 2 DIABETES AMONG ADULTS IN VANCOUVER, CANADA 237

14.1. Background 237
14.2. Methods 238
14.2.1. Analytic sample 238
14.2.2. Exposure variable 238
14.2.3. Outcome Variables 239
14.2.4. Covariates 239
14.2.5. Statistical analysis 239
14.3. Results 240
14.3.1. Descriptive statistics 240
14.3.2. Model Results 242
14.4. Discussion 245
14.4.1. Strengths and Limitations 247
14.5. Conclusions 248
14.6. References 248

15. APPENDIX E: HEALTH IMPACTS - FULL ARTICLE - MULTIFACETED IMPACTS OF GREEN SPACE AND WALKABILITY ON MENTAL HEALTH: DEPRESSION AND ANXIETY IN FOCUS 279

15.1. Background 279
15.1.1. Problem statement: 279
15.2. Methods 283
15.2.1. Data sources: 283
15.2.2. Green space assessment: 283
15.2.3. Walkability assessment: 284
15.3. Results 286
15.4. Discussion 306
15.5. Conclusion 311
15.5.1. Limitations and Future Directions 311
15.5.2. Policy Implications 312
15.6. References 312

16. APPENDIX F: HEALTH IMPACTS - FULL ARTICLE - THE EFFECT OF RESIDENTIAL GREENNESS AND WALKABILITY ON CANCER RISK IN THE GREATER VANCOUVER REGION 343

16.1. Background 343

16.2. Methods 344
16.3. Results 348
16.4. Discussion 353
16.5. Conclusion 356
16.6. References 356

17. APPENDIX G: TRAVEL & CLIMATE IMPACTS - FULL ARTICLE - THE ASSOCIATION OF BUILT ENVIRONMENT FACTORS ON ACTIVE AND SEDENTARY TRAVEL BEHAVIOUR: A CROSS-SECTIONAL TRAVEL DIARY STUDY 360

17.1. Background 360
17.2. Methods 360
17.2.1. Data source, survey design, and ethics 360
17.2.2. Study sample and study variables 361
17.2.3. Statistical analysis 362
17.3. Results 363
17.4. Discussion 374
17.5. Conclusions 375
17.6. References 376

18. APPENDIX H: TRAVEL & CLIMATE IMPACTS - FULL REPORT - TRANSPORTATION EMISSIONS ESTIMATES FOR INTEGRATED ENVIRONMENT-HEALTH MODELLING 377

18.1. Methods for emission estimates 377
18.1.1. Data sources 377
Trip Diary Data 377
Regional travel model data 379
Transit system operations data 381
18.2. Automobile trips 381
Vehicle information 382
Occupancy 386
Operating emissions 387
Non-operating (upstream & downstream) emissions 393
Deadheading 398
Combining the phases 398
18.3. Public transit trips 399
Operating emissions 399
Non-operating (upstream & downstream) emissions 403
Occupancy 405
18.4. Other modes 406
Walking, wheelchair, and cycling 406
School bus (609 trips) 407
Motorcycle, moped, and scooter (236 trips) 408
Shuttle and charter bus (105 trips) 408
Aqua bus, boat, and tram (47 trips) 409
Bowen Island ferry (18 trips) 410
Other/unclassified modes (143 trips) 410
18.5. Multimodal trips 412
18.6. Marginal emissions adjustments 415
Calculation of marginal adjustment factors 415
Elasticity of vehicle to passenger travel in Vancouver 416
Application to TDD emissions estimates 418
18.7. Results of emissions estimates 419
18.7.1. Segment emissions 419
18.8. Trip emissions 422
18.9. Person and Household emissions 425

18.10. EXTERNAL COMPARISONS 426
18.11. MARGINAL EMISSIONS 428
18.12. ANALYSIS OF STATISTICAL RELATIONSHIP BETWEEN EMISSIONS AND WALKABILITY 439
Study sample and study variables *439*
Statistical analysis *440*
18.13. REFERENCES 448

List of Figures

Figure 1-1: The key goal of the project is to link built and natural environment characteristics with health and climate impacts. ____ *23*
Figure 1-2: provides a conceptual framework used to link built and natural environmental features with behaviours and exposures and climate impacts and their biological responses, chronic disease outcomes, and associated costs. ____ *25*
Figure 2-1: Network-based buffer area used to calculate the walkability index. ____ *31*
Figure 2-2: Change in the walkability index (2006-2016) in Metro Vancouver. ____ *31*
Figure 2-3: Continuum of walkability across five place types in Metro Vancouver. ____ *32*
Figure 2-4 Linkage of Postal Code Level Walkability Measures ____ *33*
Figure 2-5 Description of Intersection Density ____ *35*
Figure 2-6: Change in Intersection Density 2011-2016 ____ *36*
Figure 2-7: Change in Net Residential Density 2011-2016 ____ *37*
Figure 2-8: Change in Commercial FAR 2011-2016 ____ *38*
Figure 2-9: Change in Land Use Mix 2011-2016 ____ *39*
Figure 2-11: Metro Vancouver Regional Growth Strategy Destinations ____ *41*
Figure 2-12: Health & Community Design Lab Regional Growth Strategy Destinations ____ *42*
Figure 2-12: Map of 2016 Mean AM Transit Travel Time ____ *42*
Figure 2-13: Map of 2016 Mean Mid-Day Auto Transit Travel Time ____ *43*
Figure 3-1: Example of Land Cover in Metro Vancouver. ____ *47*
Figure 3-2: Example of Tree Canopy Coverage in Metro Vancouver. ____ *47*
Figure 3-3: Example of NDVI in Metro Vancouver. ____ *48*
Figure 3-4: Example of Park Access in Metro Vancouver. ____ *49*
Figure 3-5 Conceptual model showing the organization of each of the five analyses conducted. ____ *56*
Figure 5-1. Emissions modelling framework ____ *75*
Figure 5-2. Average emissions intensity per PKT by primary mode ____ *84*
Figure 5-3. Comparison of our emission estimates for automobile trips (boxplots) to rates in BC Provincial guidance (green diamonds); including upstream fuel cycle emissions for BEV and hybrid powertrains for comparability ____ *86*
Figure 5-4. Trip-level attributional (average-rate) versus consequential (marginal-rate) emissions by primary trip mode; bounds truncated for legibility; blue dashed line denotes equivalent values ____ *88*
Figure 5-5. Illustration of GHG model results by walkability bin (assuming median GHG emissions for the middle bin) ____ *92*
Figure 6-1: Incident obesity, HBP and T2DM ____ *99*
Figure 6-2: Incident obesity by change in walkability quintiles ____ *100*
Figure 6-3: Incident obesity by demographic subgroups. ____ *101*
Figure 8-1: BCGP Sample and Cancer Case Distribution ____ *114*
Figure 12-1: Walkability surface for the Metropolitan Vancouver Region, 2016 ____ *159*
Figure 12-2: Walkability Index Score of Census Tracts (2006) Histogram ____ *166*
Figure 12-3: Change in Walkability Index Scores (2006 - 2016) ____ *166*
Figure 12-4: Distribution of Baseline Walkability of Metro Vancouver Census Tracts. ____ *167*
Figure 12-5: Distribution of Changes in Walkability of Metro Vancouver CTs (2006-2016). ____ *169*
Figure 12-6: Changes in Walkability Index Scores 2006 – 2016 ____ *171*

Figure 12-7: Capilano 5 Reserve had the highest Walkability Index score in Metro Vancouver in 2016 (Image Source: District of West Vancouver Planning Department) 172
Figure 12-8: Distribution of Changes in Walkability 2006-2016. 173
Figure 12-9 Sankey Diagram of Changes in Walkability 2006 - 2011- 2016 174
Figure 12-10 Metro Vancouver Change in Walkability Index Score 2006 - 2011 175
Figure 12-11 Metro Vancouver Change in Walkability Index Score 2006 - 2016 175
Figure 12-12 Metro Vancouver Change in Walkability Index Score 2011 – 2016 176
Figure 12-13 Description of Intersection Density 177
Figure 12-14: Intersection Density 2006-2016 177
Figure 12-15: Change in Intersection Density 2006-2011 178
Figure 12-16: Change in Intersection Density 2011-2016 179
Figure 12-17 Member Jurisdiction Change in Intersection Density: 2006-2016 180
Figure 12-18: Net Residential Density 2006-2016 181
Figure 12-19: Change in Net Residential Density 2006-2011 182
Figure 12-20: Change in Net Residential Density 2011-2016 183
Figure 12-21 Member Jurisdiction Change in Net Residential Density: 2006 - 2016 184
Figure 12-22: Commercial FAR 2006-2016 186
Figure 12-23: Change in Commercial FAR 2006-2011 186
Figure 12-24: Change in Commercial FAR 2011-2016 187
Figure 12-25 Member Jurisdiction Change in Commercial Floor Area Ratio: 2006 - 2016 188
Figure 12-26: Land Use Mix 2006-2016 190
Figure 12-27: Change in Land Use Mix 2006-2011 191
Figure 12-28: Change in Land Use Mix 2011-2016 191
Figure 12-29 Member Jurisdiction Change in Land Use Mix: 2006 - 2016 192
Figure 12-30 Metro Vancouver Regional Growth Strategy Destinations 194
Figure 12-31 Health and Community Design Lab Determined Destinations 194
Figure 12-32 Map of 2011 Mean AM Transit Travel Time 195
Figure 12-33: Map of 2016 Mean AM Transit Travel Time 196
Figure 12-34: Map of 2011 Mean Mid-Day Auto Transit Travel Time 197
Figure 12-35: Map of 2016 Mean Mid-Day Auto Transit Travel Time 198
Figure 12-36 Map of Case Study Neighbourhoods 200
Figure 12-37 Walkability Profile of Olympic Village 201
Figure 12-38 Olympic Village Changes from 2006 (left) to 2016 (right) 202
Figure 12-39 Demographic Profile of Olympic Village 204
Figure 12-40 Walkability Profile of Willingdon Heights 206
Figure 12-41 Changes in Willingdon Heights from 2006 (left) to 2016 (right) 207
Figure 12-42 Changes in Willingdon Heights from 2006 (top) to 2016 (bottom) 208
Figure 12-43 Demographic Profile of Willingdon Heights 209
Figure 12-44 Walkability Profile of Brighouse 211
Figure 12-45 Changes in Brighouse from 2006 (left) to 2016 (right) 211
Figure 12-46 Changes in Brighouse from 2006 (left) to 2016 (right) 212
Figure 12-47 Demographic Profile of Brighouse 213
Figure 12-48 Walkability Profile of Morgan Heights 215
Figure 12-49 Changes in Morgan Heights from 2006 (left) to 2016 (right) 216
Figure 12-50 Changes in Morgan Heights from 2006 (left) to 2016 (right) 216
Figure 12-51 Demographic Profile of Morgan Heights 219
Figure 12-52: Changes in Social Status in Metropolitan Vancouver CTs, 2006 – 2016 220
Figure 12-53: Distribution of Baseline Walkability Index Score (2006) and Social Status Index Changes (2006-2016) 223
Figure 12-54: Principal Component Loading Matrix of High-High CTs (Left) and High-Low CTs (Right) 225
Figure 13-1: Pearson correlation coefficients between walkability and greenspace metrics for 1000m network buffers 233

Figure 13-2: Pearson correlation coefficients between walkability and greenspace relationships for 400m network buffers 234
Figure 16-1: BCGP Sample and Cancer Case Distribution 346
Figure 18-1. Urban (orange) and rural (green) link settings, based on Metro land use designations 380
Figure 18-2. Vehicle sizes in the TDD 390
Figure 18-3. Distribution of Model Factor (MF) values 391
Figure 18-4. Literature values for bus vehicle cycle emissions 404
Figure 18-5. Comparison of TDD and routed estimates of trip duration 407
Figure 18-6. SVM-inferred modes for 143 uni-modal trips with mode designated as "Other/unclassified" 412
Figure 18-7. SVM-inferred modes for 86 legs of multi-modal trips with mode designated as "Other/unclassified" 414
Figure 18-8. Mean emissions intensity per PKT by segment mode 421
Figure 18-9. Average emissions intensity per PKT by primary mode 424
Figure 18-10. Comparison of our emission estimates for automobile trips (boxplots) to rates in BC Provincial guidance (green diamonds); including upstream fuel cycle emissions for BEV and hybrid powertrains for comparability 427
Figure 18-11. Segment-level attributional (average-rate) versus consequential (marginal-rate) emissions by segment mode; bounds truncated for legibility; blue dashed line denotes equivalent values 435
Figure 18-12. Trip-level attributional (average-rate) versus consequential (marginal-rate) emissions by primary trip mode; bounds truncated for legibility; blue dashed line denotes equivalent values 436
Figure 18-13. Mean consequential and attributional daily household GHG by income tier 439

List of Tables

Table 1-1: Summary of organization of analysis sections. 25
Table 2-1: Summary of average walkability component values for Metro Vancouver in 2006, 2011 and 2016. 34
Table 3-1: Mean residential postal code proportion and standard deviation of land cover types 50
Table 3-2: Descriptive statistics of each greenspace metric by buffer type and size 51
Table 3-3: Summary of organization of analysis sections. 59
Table 4-1: Odds of walking trips across walkability quintiles 63
Table 4-2: Odds of cycling trips across walkability quintiles 65
Table 4-3: Odds of transit trips across walkability quintiles 67
Table 4-4: Odds of vehicle trips across walkability quintiles 69
Table 5-1. Summary of past studies investigating personal GHG from travel survey data 74
Table 5-2. Modal distribution of trips in the TDD 76
Table 5-3. Occupancy, PKT, and GHG intensity by segment mode 83
Table 5-4. Mean GHG emissions per trip by primary mode (g CO2e) 83
Table 5-5. Average trip CAC emissions (g) by primary mode 84
Table 5-6. Person- and household-level aggregate GHG measures 85
Table 5-7. MAER applied to the TDD emissions estimates 87
Table 5-8. CO2e emissions (g/day) model estimation results 91
Table 6-1: Odds ratios, p-values, and 95% confidence intervals for models 102
Table 7-1: Univariable and multivariable logistic regression using complete cases (n=5085) for the relationship between walkability index and anxiety condition 109
Table 7-2: Univariable and multivariable linear regression using complete cases (n=5085) for the relationship between walkability index and the total score of anxiety 109
Table 7-3: Unadjusted, minimally adjusted and fully adjusted linear regression using complete cases (n=5085) for the relationship between walkability index and the scores of anxiety components separately 110
Table 8-1: Results for lung cancer: Hazard ratio using Cox proportional models 117
Table 8-2: Results for colorectal cancer: Hazard ratio using Cox proportional models 117
Table 8-3: Results for breast cancer: Hazard ratio using Cox proportional models 118
Table 8-4: Results for prostate cancer: Hazard ratio using Cox proportional models 119
Table 12-1: Baseline (2006) Walkability Index Scores of Metro Vancouver Municipalities 168
Table 12-2: Change in Walkability of Metro Vancouver Municipalities (2006-2016) 170
Table 12-3: Change in Social Status Index in Metropolitan Vancouver by Location, 2006 - 2016 221

Table 12-4: Changes in Individual Indicators of Neighbourhood Change for Neighbourhoods with High and Low Walkability Index Scores 224
Table 12-5: Loading Factors of First Principal Component of High-High and High-Low CTs 226
Table 17-1: Odds of walking trips across walkability quintiles 365
Table 17-2: Odds of cycling trips across walkability quintiles 366
Table 17-3: Odds of transit trips across walkability quintiles 370
Table 17-4: Odds of vehicle trips across walkability quintiles 373
Table 18-1. Modal distribution of trips in the TDD 378
Table 18-2. Mapping of RTM to MOVES road types for the network data 381
Table 18-3. Passenger vehicle information reported in the TDD and assumptions used in analysis 382
Table 18-4. Summary of missing vehicle information for trips by household vehicles 383
Table 18-5. Number of unique household vehicles (out of 8086) matching multiple entries in the NRCAN fuel economy dataset for a given make, model, and year 385
Table 18-6. Car-share services and vehicles 385
Table 18-7. Variables used to calculate automobile operating emissions 387
Table 18-8. Upstream & downstream emissions parameters[1] 396
Table 18-9. Reference values for vehicle lifetime in vehicle-kilometres travelled (VKT) 398
Table 18-10. Fuel consumption rates by transit service 400
Table 18-11. GHG intensity of transit fuels 401
Table 18-12. Transit operating GHG emissions rates 402
Table 18-13. Rail vehicle cycle emissions in g CO2e per car-km 405
Table 18-14. Median trip lengths for uni-modal trips used in weighting for multi-modal trips 413
Table 18-15. Elasticities for calculation of MAER 416
Table 18-16. Summary of data used to estimate vehicle to passenger travel elasticity 417
Table 18-17. Cumulative GHG emissions by segment mode (kg CO_2e) 420
Table 18-18. Occupancy, PKT, and GHG intensity by segment mode 422
Table 18-19. Mean GHG emissions per trip by primary mode (g CO2e) 423
Table 18-20. Average trip CAC emissions (g) by primary mode 425
Table 18-21. Person- and household-level aggregate GHG measures 426
Table 18-22. Elasticity regression model results 430
Table 18-23. MAER applied to the TDD emissions estimates 434
Table 18-24. Model of personal factors influencing difference between consequential and attributional emissions estimates 437
Table 18-25. Model of household factors influencing difference between consequential and attributional emissions estimates 438
Table 18-26. Estimated model of individual daily g CO_2e emissions (attributional) from travel 443
Table 18-27. Estimated model of individual daily g CO emissions from travel 443
Table 18-28. Estimated model of individual daily g NO_x emissions from travel 445
Table 18-29. Estimated model of individual daily g $PM_{2.5}$ emissions from travel 446
Table 18-30. Estimated model of individual daily g VOC emissions from travel 447

1. Project Purpose & Report Overview

Phase I of the Where Matters study evaluated associations between built and natural environment features and health outcomes from the My Health, My Community (MHMC) survey and the data from the BC Generations project. Phase II aims to connect health with climate change impacts of built and natural environment features and where possible, document causal impacts on chronic disease outcomes. The overall goal is to provide evidence to inform local and regional policy actions by examining the pathways shown in Figure 1-1 linking the built environment, activity patterns, chronic diseases, and mental health. This second phase builds on this work by incorporating more extensive environmental exposure data and additional health outcomes (e.g., cancer incidence). The current study uses spatially linked existing detailed built environment data and integrates a wide range of health-related data from the BC Generations Project.

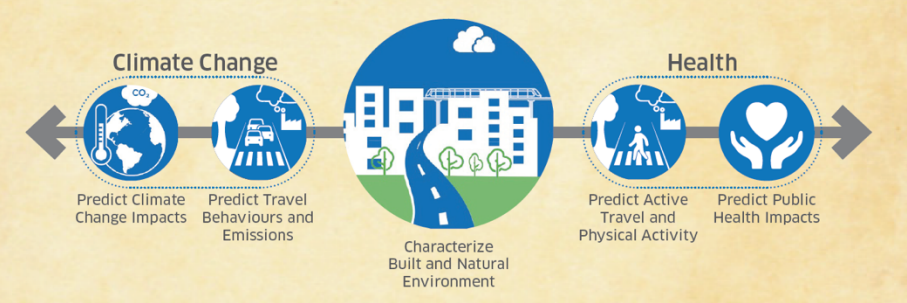


Figure 1-1: The key goal of the project is to link built and natural environment characteristics with health and climate impacts.

Data linkages were also established with the most recent TransLink Travel Survey to provide detailed information on travel behaviour and emissions. Where Matters II also leverages consistently measured environmental conditions at multiple time points to allow for longitudinal health impact analyses. Results from this study informs and supports policies and strategies mentioned above designed to reduce car dependence by further quantifying reductions in chronic disease and generation of GHG emissions in the Metro Vancouver region. Five different analyses were conducted linking environmental data with travel and vehicle emissions and health outcome data.[7]

[7] Ethics approval from the Behavioral Research Ethics Board of the University of British Columbia was granted to all researchers accessing these unique health and travel behaviour datasets required for this study.

Table 1-1 provides an overview of the organization of the analysis sections included in this report including key outcomes examined and study design characteristics. Additional information on each individual study design and the data sources utilized is reviewed in the research analysis sections of this report. For each study, an accompanying full-length manuscript has been developed in draft form, in process towards publication in leading scientific journals. These manuscripts are included as appendices focused on travel patterns, vehicle emissions, obesity and chronic conditions, cancer, and mental health.

Table 1-1: Summary of organization of analysis sections.

Analyses	**Theme**	**Travel Activity**		**Health Outcomes**		
	Impacts	Impacts on Human Behaviour & Air Quality		Impacts on Human Health		
	Sector	**Travel Behaviour**	**Travel & Emissions**	**Obesity & Chronic Disease**	**Mental Health**	**Cancer**
	Title	The Association Between Built Environment Factors with Active and Sedentary Travel Behaviour	Transportation Emissions Estimates for Integrated Environment-Health Modelling	Longitudinal Adult Associations Between Walkability and Incident Obesity, Hypertension, and Type 2 Diabetes	Multifaceted Impacts of Green Space and Walkability on Mental Health: Depression and Anxiety in Focus	The Effect of Residential Greenness and Walkability on Cancer Risk in the Greater Vancouver Region
	Key Outcomes	Physical Activity, Sedentary Time	Emissions by Mode	Obesity, Hypertension, Type 2 Diabetes	Depression, Anxiety	Cancers: Lung, Breast, Colorectal, Prostate
	Study Design	Cross-Sectional	Cross-Sectional	Longitudinal	Cross-Sectional	Longitudinal
	Report Section	4	5	6	7	8

1.1. Background

Where Matters is a collaboration of researchers and practitioners from health, transportation, and urban planning evaluating potential public health and climate change "co-benefits" from creating walkable communities with access to greenspace. Relationships between the built and natural environment where people live, travel and related vehicle emissions, and the prevalence of physical and mental chronic diseases were evaluated. Health and economic benefits of transit and active transportation strategies and walkable community design are not captured in cost-benefit processes that shape transportation investments.[8]

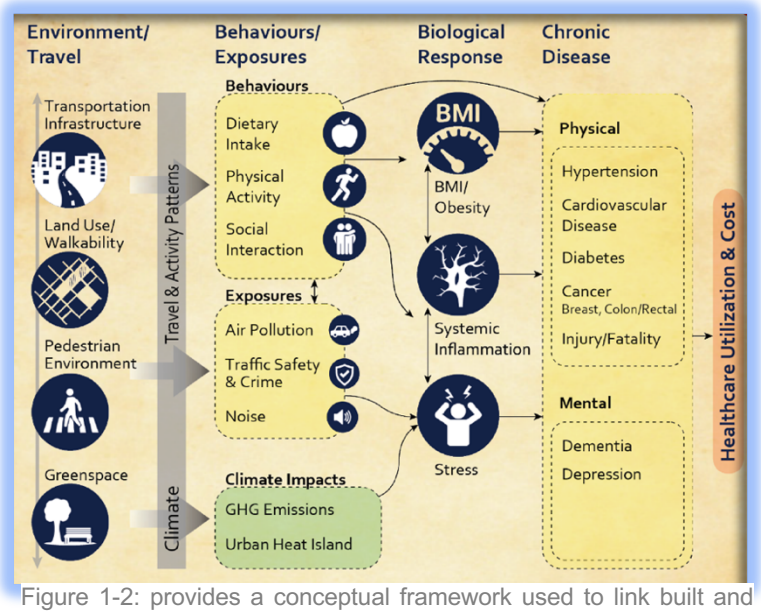


Figure 1-2: provides a conceptual framework used to link built and natural environmental features with behaviours and exposures and climate impacts and their biological responses, chronic disease outcomes, and associated costs.

[8] Adapted From: Frank, L. D., Iroz-Elardo, N., MacLeod, K. E., Hong, A. The pathways from built environment to health: Connecting behavior and exposure-based impacts. 2016. *Journal of Transport and Health.*

1.2. Measuring & Achieving Regional Strategy Goals

Where Matters II is based on a high-resolution, geospatial database of environmental metrics. These environmental metrics are categorized into two broad domains: 1) Built Environment including land use, transportation, and walkability-related measures, and 2) Natural Environment containing a series of measures focusing on access to greenspace including park access and regional vegetative cover. The environmental metrics, developed as part of Where Matters II, provide the opportunity to directly inform the strategic goals and objectives of Metro 2050, Transport 2050, and the CleanBC Strategy.

These data are a resource to Metro Vancouver, TransLink, the Province of British Columbia, and local municipalities. It provides objective measurement to track the success of policies and strategies over time. These data provide detailed information about the distribution of housing, employment, amenities, and services within the region. These data can help planners assess whether communities are 'complete' and identify areas for improvement. Walkability metrics can be enhanced to include measurement of the pedestrian-friendliness of neighbourhoods, including the availability and quality of sidewalks, lighting, street furniture, proximity to amenities, and safety. This can help measure progress toward Metro 2050's goal of creating vibrant neighbourhoods. Metro 2050 and Transport 2050 emphasize importance of sustainable transportation choices, regional accessibility, and effectiveness of transit-oriented development strategies.

The database resource included as part of Where Matters II can be used to directly measure the impact of Metro 2050 by comparing the current state of the region with the goals outlined in the strategy. For example, Metro 2050 includes regional targets such as protecting over half of the land base for nature, expanding tree canopy cover in urbanized areas, and ensuring minimum standards for new and redeveloped housing units in urban centres and frequent transit development areas are affordable, and prioritizing rental housing. These geospatial data can provide a quantitative measure of progress towards these targets and can consistently track changes in environmental conditions over time. These data were added to the Performance Monitoring Dashboard[9] used by Metro Vancouver to track changes in key metrics over time.

Study results from Where Matters I were used to support Metro Vancouver's 30-year plan: Regional Greenways 2050.[10] The plan maps out 830 kilometres of greenways, connecting with other multi-use corridors, such as TransLink's major bike network and municipal greenways. The results from Where Matters I showed that proximity to green space or parks is associated with less chronic disease and lower health care costs. In summary, accurate, high-resolution geospatial data is a powerful tool for measuring the success of Metro 2050. It provides a wealth of information that can be used to assess progress toward the strategy's goals and objectives and to guide future planning decisions. By providing a clear picture of the current state of the region, this data can ensure that Metro Vancouver continues to move towards a more sustainable, equitable, and livable future.

[9] Performance Monitoring Dashboard, Metro Vancouver, 2023.
[10] Regional Greenways 2050, Metro Vancouver, 2020.

1.3. Policy Framework: Regional & Provincial Strategies

1.3.1. Metro Vancouver Regional Growth Strategy

As the main governing body in the region responsible for land use, Metro Vancouver is mandated with developing, maintaining, and updating the Regional Growth Strategy. The Metro Vancouver Regional Growth Strategy, known as Metro 2050[11], is a long-range, strategic land use plan aimed at advancing the region's livability and sustainability goals and preparing for anticipated future growth. Led by Metro Vancouver, a collaborative development process was used to craft the Regional Growth Strategy (RGS) which includes extensive engagement and interaction with all member municipalities, TransLink, Provincial ministries, First Nations, and other regional organizations.

Metro 2050 provides a framework for concentrating growth into compact, walkable, complete communities, that rely on transit-oriented development, and a range of accessible housing choices that are close to jobs, amenities, and services. The strategy aligns projected long-term growth with transportation and infrastructure planning while protecting agricultural, rural, ecologically sensitive, and industrial lands. The strategy has five regional goals which are supported by corresponding strategies and policy actions: 1) Create a Compact Urban Area, 2) Support a Sustainable Economy, 3) Protect the Environment, 4) Respond to Climate Change Impacts, and 5) Enhance Community Well-being. The RGS aims to shape long-term growth and development in the region in a way that protects the natural environment, fuels economic prosperity, provides diverse and affordable housing choices, ensures the efficient provision of utilities and transit, reduces greenhouse gas emissions, improves resilience to climate change and natural hazards.

1.3.2. Metro Vancouver Regional Transportation Strategy

As the main governing body in the region responsible for transportation, TransLink has led the development of the Regional Transportation Strategy. The Metro Vancouver Transportation Strategy, known as Transport 2050 is a comprehensive plan that outlines the region's vision for sustainable transportation over the next 30 years. The strategy closely integrates with Metro 2050 while maintaining a focus on the transportation sector. As with Metro 2050, Transport 2050, was developed in direct collaboration with member municipalities in the region, Metro Vancouver, provincial ministries, First Nations, and other regional organizations. The vision for Transport 2050 is to create a future where every person in the region can easily access the people, places, and opportunities they need to prosper. Transport 2050 aims to provide transportation choices that are reliable, affordable, safe, comfortable, and carbon-free. The key goals of Transport 2050 include: 1) Expansion of the Rapid Transit Network, 2) Completing a Major Bikeway Network, 3) Promoting the Use of Electric and Shared Vehicles, and 4) Goods Movement that Supports Sustainable Economic Growth. The main initiatives in the strategy aim to bolster the current bike network and support the development of traffic-calmed streets for walking, biking, rolling, and transit.

[11] Metro 2050: The Regional Growth Strategy, Metro Vancouver, 2023.

1.3.3. Province of British Columbia CleanBC Strategy

The Ministry of Transportation & Infrastructure plays an important role in guiding strategic province-wide goals and providing support tools and investment for municipalities to help reach these goals. One of the key guiding strategies developed by the province is the CleanBC Strategy[12]. The CleanBC Strategy is a comprehensive approach by the province of British Columbia to reduce greenhouse gas emissions and build a sustainable, low-carbon economy.

The Ministry of Transportation has emphasized the importance of supporting active transportation uptake in BC as a key component in reducing greenhouse gas emissions.[13] The Ministry is working towards making active transportation an accessible and safe option for more people, thereby reducing carbon pollution, and building healthier communities. Some of the key initiatives include: 1) investing over $60 million over the next three years to help communities build over 400 active transportation projects, including new paths, bike lanes and crosswalks across the province, 2) working with communities to create policies and plans that enable and support complete active transportation networks, and 3) developing the Clean Transportation Action Plan for 2023[14] focusing on five pillars: reducing distance traveled, increasing mode shift, improving vehicle efficiency, adopting zero-emission vehicles, and using clean fuels.

In summary, the CleanBC Strategy, with its focus on active transportation, represents a significant step towards achieving a sustainable, low-carbon future for British Columbia. The Ministry of Transportation and Infrastructure's commitment to investing in active transportation infrastructure is a testament to the province's dedication to achieving the strategic goals and objectives of CleanBC.

1.3.4. Changes in Regulatory Approaches

Over the past couple of years, the regulatory landscape regarding land-use planning in BC has undergone significant and far-reaching changes. The provincial government, with the enactment of Bills 44, 46, and 47 and other measures, now has the power to override municipal authority in land-use planning and promote densification across municipalities. The new legislation, which applies to municipalities with a population over 5,000, mandates amendments to zoning bylaws to increase densification, introduces new development financing tools, and designates transit-oriented development areas. These initiatives align with the Homes for People action plan, aiming to streamline housing delivery and eliminate restrictive zoning policies. Additionally, the province emphasizes active transportation and public transit infrastructure investments to meet emission reduction targets, collaborating with municipalities and federal programs such as the Active Transportation Fund. However, there is a need to balance densification efforts with the preservation of greenspaces and urban tree canopy cover, which may require regulatory mandates, incentives, and coordination between government levels to ensure

[12] CleanBC: Roadmap to 2030, Province of British Columbia, 2021.
[13] Active Transportation, Ministry of Transportation & Infrastructure, Province of BC, 2023.
[14] Clean Transportation Action Plan, Province of British Columbia, 2023.

sustainable development. The remaining report is organized in the following sections and then followed by several appendices:

- Community Design Characteristics
  - Built Environment (Walkability)
  - Natural Environment (Greenspace)

- Travel & Climate Impacts
  - Travel Behaviour with Walkability
  - Greenhouse Gas Emissions with Walkability

- Health Impacts
  - Obesity, Diabetes & Hypertension with Walkability
  - Mental Health with Walkability & Greenspace
  - Cancer Risks with Walkability & Greenspace

- Regulatory & Fiscal Approaches

2. Tracking Change in Walkability and Regional Accessibility[15]

2.1. The Walkability Index

Walkability is one of the key independent variables in communities by which we are analyzing health outcomes in *Where Matters II.* Walkability is a measure of the physical characteristics of the urban environment at the neighbourhood level that support walking. The Walkability Index is a composite measure of neighbourhood walkability capturing proximity to and connectivity between destinations and their composition and is comprised of four equality-weighted main component measures[16]: 1) net residential density, 2) commercial floor space ratio (FSR) or floor area ratio (FAR), 3) land use mix, and 4) intersection density.

Net Residential Density: The concentration of dwelling units. Higher values indicate a greater number of dwelling units relative to residential land area.

Commercial Floor Area Ratio (FAR): The ratio between the total commercial floor area of a building to the land area of the property it is built on. Higher values indicate less surface parking and buildings set close to sidewalks and the street.

Land Use Mix: The balance between building floor areas of six land uses (retail, entertainment/recreation, civic/educational, office, single family and multi-family residential), providing more opportunities for different activities in the same neighbourhood.

Intersection Density: Measures route directness. Higher values indicate smaller block lengths and a greater number of intersections and shorter distances.

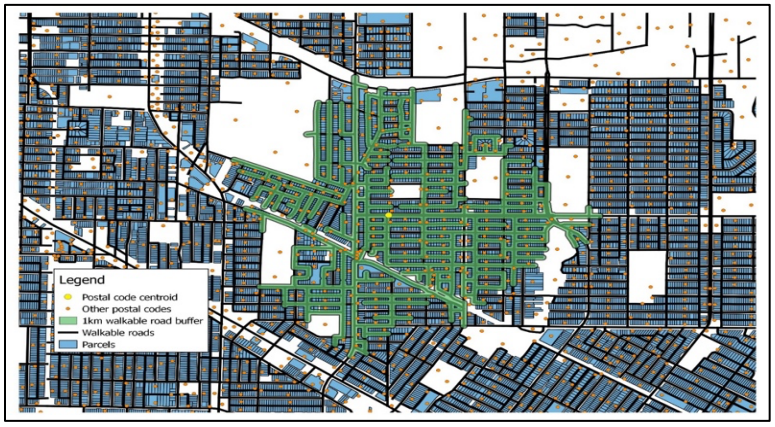
Sidewalk Coverage: Measures the proportion of local street network within a walkable distance (1 km) with sidewalks on one or both sides of the street.

These measures were calculated for every postal code (appx 60,000) in Metro Vancouver at 3 time points thus far. The calculations were conducted within a 1-kilometre road network buffer from postal code centroids, following a walkable road network. Measures were created for each postal code in Metro Vancouver as shown in Figure 2.1.

[15] For more details on the development of the walkability surface, please see Appendix B.

[16] Different combinations of component measures may comprise the walkability index. For instance, Where Matters II also utilized a secondary walkability index that also included the percentage of sidewalk coverage. Several iterations of the land use mix may be used that typically include between four and six land use types. In some instances, some component measures may also be weighted over others.

Figure 2-1: Network-based buffer area used to calculate the walkability index.



The network buffers are then used to capture each component measure, which are then converted to standardized value (z-scores) which allows them to be summed into a composite walkability index. Figure 2-2 shows a map of the change in walkability from 2006-2016. The final walkability index is the amalgam of a normalized z-score value for each component measure. Each of these walkability metrics are highly correlated with each other making the effect of each component on travel, health, and emissions difficult to isolate from another. This creates the need to roll them into an index to enable statistical analyses to proceed. Arguably, each of these features align with other factors and work as a system to shape travel and activity pattern.

The most walkable places in the region have a mix of housing types ranging from moderate to denser residential development, retail stores, and highly connected streets; also known as complete communities within a 15-minute travel time on foot via compact mixed-use development.

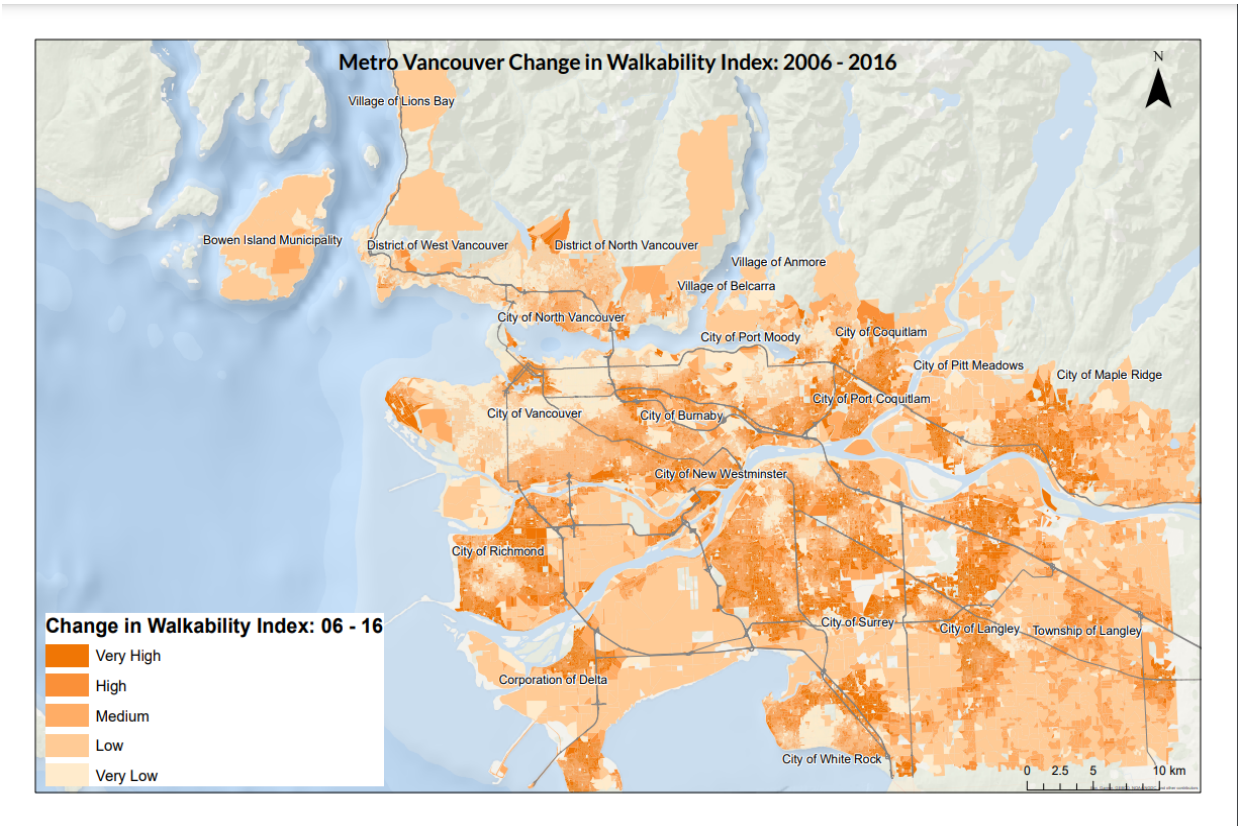


Figure 2-2: Change in the walkability index (2006-2016) in Metro Vancouver.

Figure 2-3 lays out a continuum from the most car dependent to the most walkable areas of the region along with aerial and street level images.

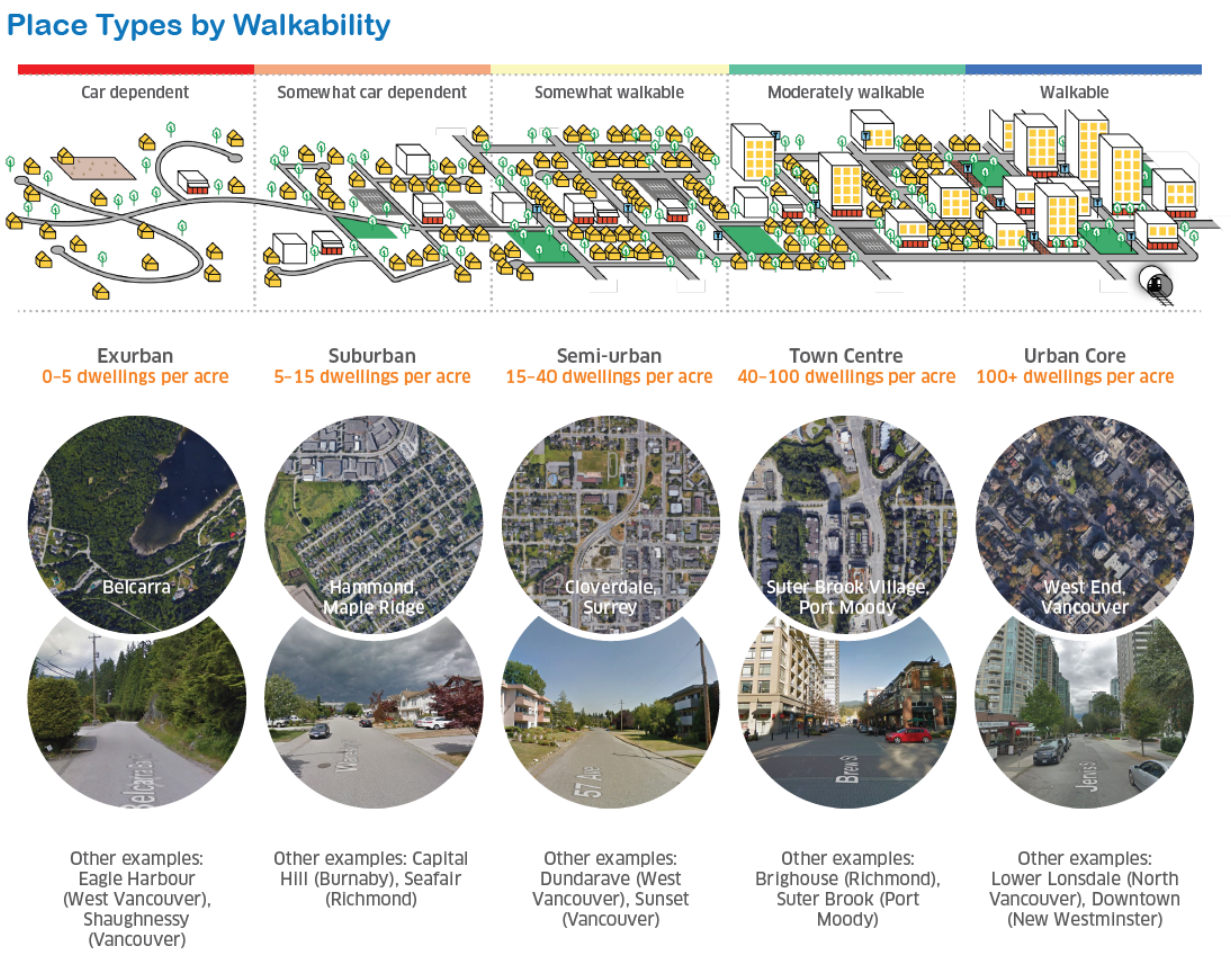


Figure 2-3: Continuum of walkability across five place types in Metro Vancouver.

2.2. Defining the Neighbourhood

Conceptualization and consistent definition of a neighbourhood boundary are important when creating a built environment metric using spatial data. This is primarily because of the Modifiable Area Unit Problem (MAUP). The MAUP arises when there is variation in the results of a spatial analysis based on the spatial unit used to collect the data. In the creation of each walkability index, this is explicitly addressed using spatial units derived from a walkable road network and consistent buffering techniques. Each postal code is given a 1-kilometre neighbourhood or walkshed using a network buffer, which corresponds to 10 to 15 minutes of walking time (Colabianchi et al., 2007). This boundary is defined by a network buffer that travels along a closely matched and updated walkable road network for each study year.

The figure below shows the approach used to define neighbourhood boundaries for 2006, 2011 and 2016 walkability indices using the 1km distance. In all three indices, street network buffers were used instead of a crow-fly (also called straight line) distance buffer. Street network buffers represent the actual built environment experienced by the pedestrian as they follow a road network that is known to be accessible by walking.

2.3. Longitudinal Walkability Data

With three waves (2006, 2011, 2016) of the walkability index completed using the methods outlined above, the longitudinal analysis of changes in the built environment in the Metro Vancouver region has become possible. This begins with the construction of a walkable road network. All roads that are not walkable by a pedestrian are removed from the road network to accurately reflect the pedestrian environment. Data from BC Assessment reflecting development across the region is then cleaned and analyzed to facilitate the calculation of the land-use mix, commercial floor area, and net residential density variables. The walkable neighbourhood for each postal code is then defined by a network buffer that travels along the walkable road network and measures intersection density, land-use mix, commercial floor area, and net residential density. Using these methods has allowed the comparison of neighbourhoods in the Metro Vancouver Region at the postal code level through the linkage of each postal code through a unique identifier.

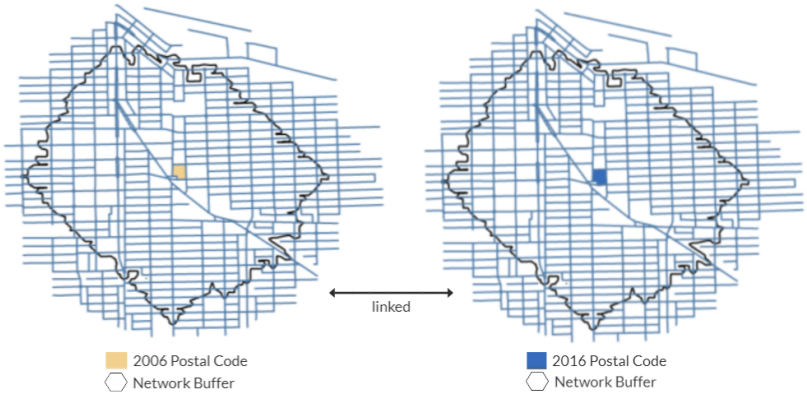


Figure 2-4 Linkage of Postal Code Level Walkability Measures

Assessing the longitudinal changes in walkability in Metro Vancouver is done using two methods. The first looks at the difference in each component measure from 2006 to 2016. Using this method, the change in each built environment variable of land use mix, commercial floor area ratio, net residential density, and intersection density is shown in absolute terms. The second method uses the changes in each component measure and normalizes each across 2006, 2011, and 2016, to create a walkability index using the grand mean and standard deviation of the entire dataset. The combined z-scores of each component measure are added together to create a normalized distribution of walkability from 2006, 2011, and 2016 that can be compared (See Appendix B for more details on the methodological development of the Metro Vancouver walkability surface). For each section below, changes between 2011-2016 are highlighted (for more detailed maps and descriptions of changes between 2006-2011 and 2006-2016 see Appendix B).

Table 2-1 provides a summary of the average Metro Vancouver regional values for each core component of walkability for 2006, 2011 and 2016. Each of the components show an increasing trend at subsequent time points with the section of a slight reduction in land use mix in 2016. In general, larger increasing trends in some components of walkability, such as intersection density and net residential density, were exhibited between 2006 and 2011, while others such as commercial FAR showed more consistent growth trends between both 2006-2011 and 2011-2016.

Table 2-1: Summary of average walkability component values for Metro Vancouver in 2006, 2011 and 2016.

Community Design Characteristic	Year		
	2006	2011	2016
Intersection Density (intersections/sq. km.)	45	63	65
Net Residential Density (units/acre)	10	16	18
Commercial FAR	0.345	0.348	0.350
Land Use Mix	0.275	0.375	0.325

The section that follows provides more detail on the changes in each component of walkability over time.

2.3.1. Intersection Density

The road network defines how we navigate the GVRD, what is accessible, and where development is happening. The road network in many areas of Metro Vancouver is well-established, gridded and many decades old. However, changes in land use patterns, especially in outlying suburban areas, have spurred changes reducing connectivity in the network structure. Major developments can require new roads to access housing, amenities, and the rest of the region. This is reflected in the changes in intersection density over the 10 years between 2006 and 2016 which have gone from a regional average of 45 intersections per kilometre in 2006 to 65 in 2016.

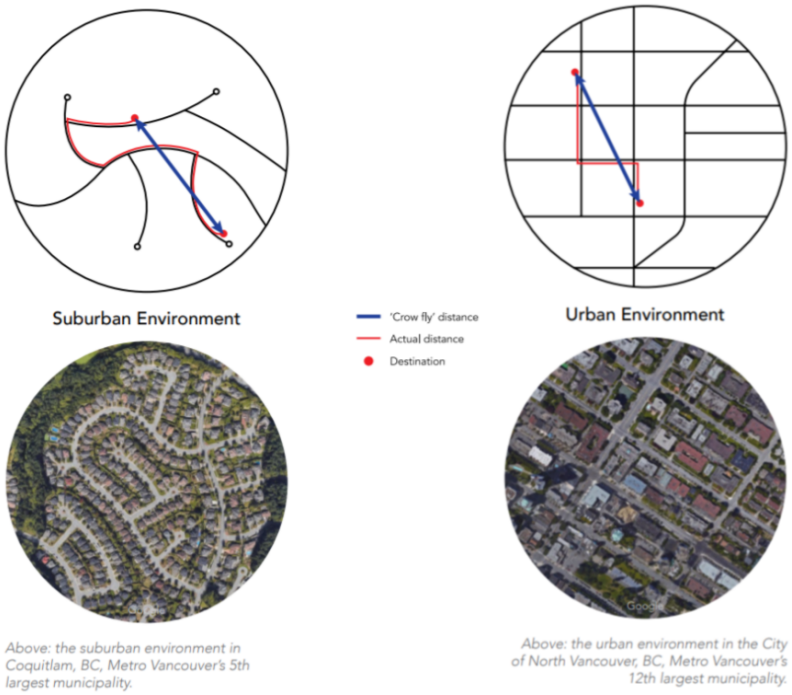


Figure 2-5 Description of Intersection Density

Intersection density is beginning to show a plateauing trend which may be attributed to stagnating greenfield development and new road building in the region. Many of the areas experiencing major development across the region such as Olympic Village and the Cambie corridor are infill or densification projects that require relatively limited changes to the road network. These areas already have a high road connectivity.

Many of the significant changes in intersection density across Metro Vancouver between 2006 to 2011 were in suburban areas of the region. Then from 2011-2016 the map shows that there is far less change across the region, especially in the suburban areas (Figure 2-6). Looking at the differing rates of intersection density change across the member jurisdictions, we can see that the suburban areas have experienced higher increases. Improved intersection density in rural areas may indicate suburban subdivisions which may have low connectivity even if increasing over time. It is also important to remember that some areas of the region, especially those designated for agricultural lands, are not intended for urban development.

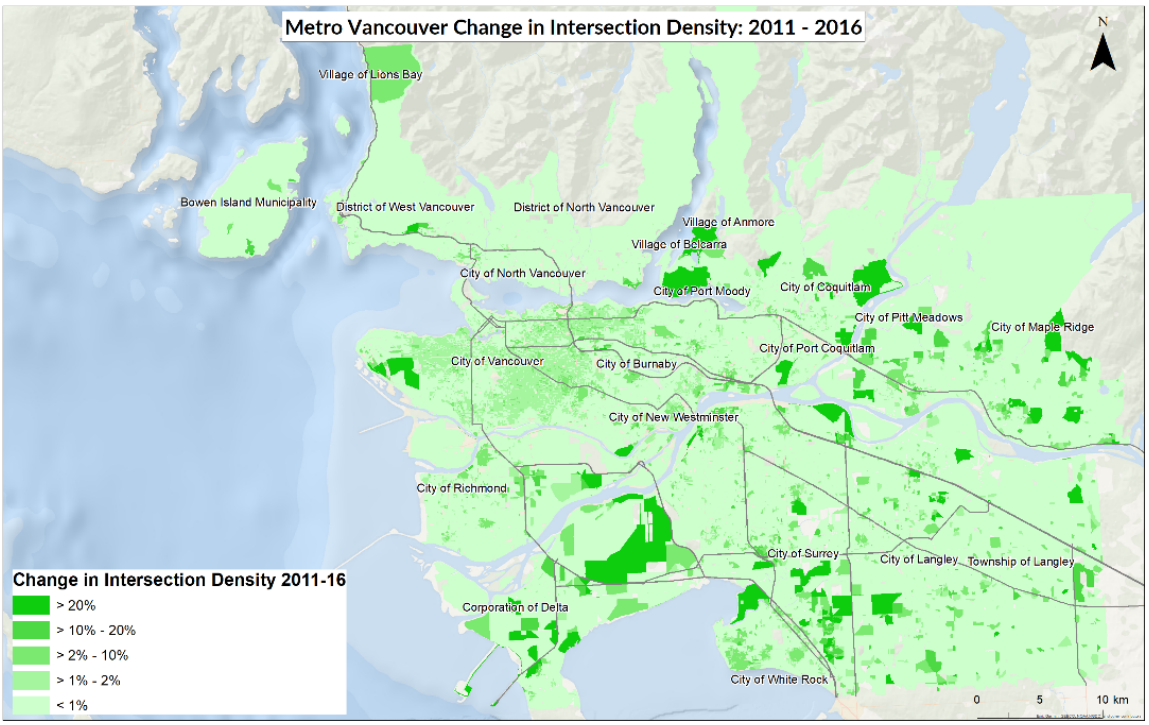
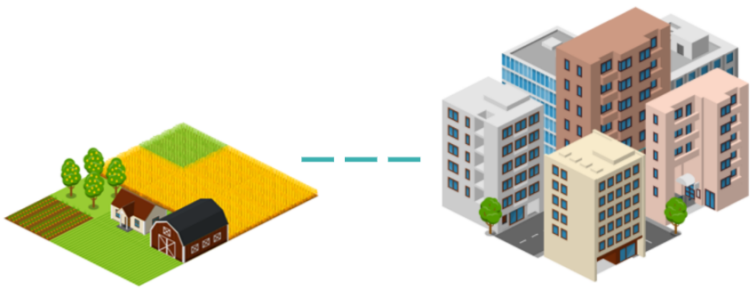


Figure 2-6: Change in Intersection Density 2011-2016

2.4. Net Residential Density

Residential compactness is one of the hallmarks of urban areas. Dense urban forms allow for more agglomeration of goods and services while facilitating social interaction and well-connected transportation networks.



Net residential density has continued on an upward trajectory from 2006-2016 (Figure 2-7). This can be attributed to increasing density in the urban areas of Metro Vancouver and residential development in the suburbs. Places such as the City of North Vancouver, Port Moody, the UBC Main Campus, Richmond, and Vancouver show some of the highest increases in net residential density from 2011 – 2016.

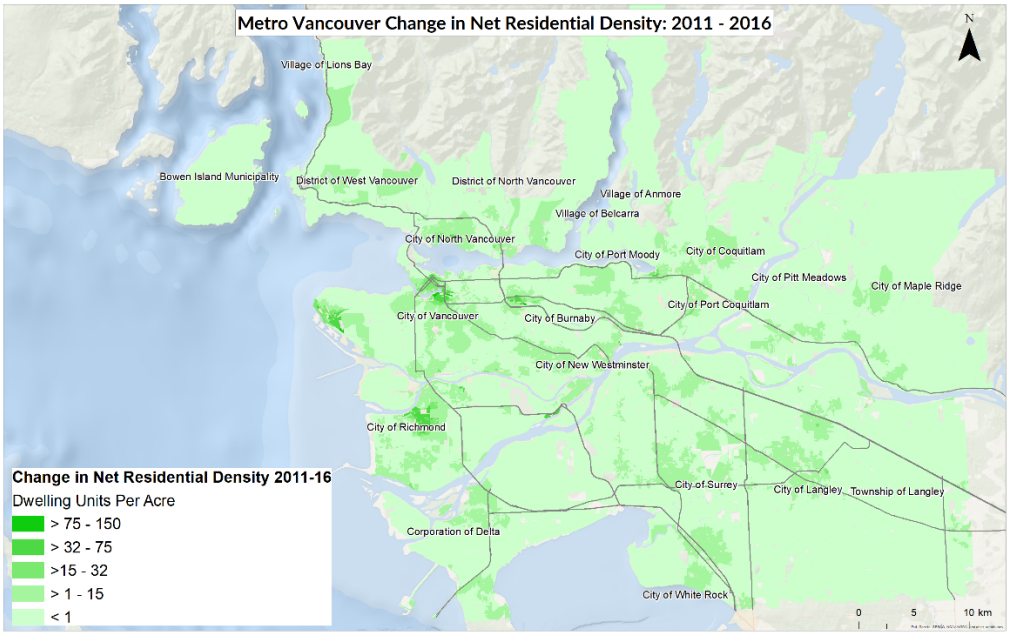
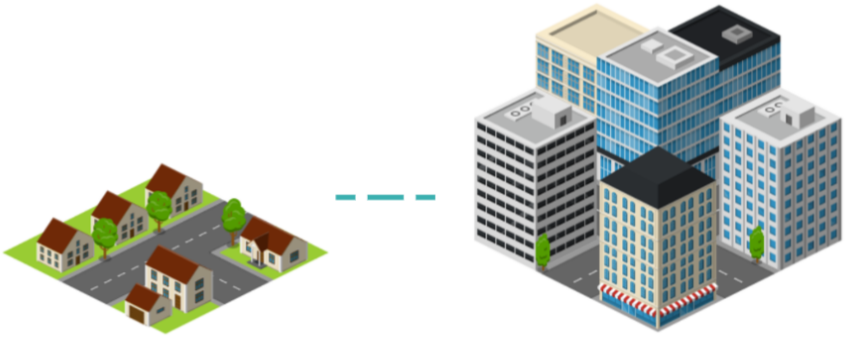


Figure 2-7: Change in Net Residential Density 2011-2016

2.4.1. Commercial Floor Area (FAR)

Commercial floor rea ratio (FAR) of a neighbourhood describes the intensity of commercial development. Neighbourhoods with high commercial FAR are generally more urban, have reduced parking and are typically orientated towards more neighbourhood retail allowing residents to easily access goods and amenities.



Regionally, commercial FAR has stayed at a consistent level on average. From 2006 to 2016 it is showing a levelling off trend which could be attributed to widespread increases across the metro region from before 2006 and through to 2011. This indicates that much

of the land use that is commercial in the region had been zoned to this use early in the development of the region. From 2006 – 2011 the region experienced the highest rates of change for each component measure, in many of the same areas, which could indicate a period of development in which commercial, residential, and road network development were completed in tandem.

From 2011-2016, the highest rates of changes in commercial FAR were no longer in the most urban areas of Metro Vancouver (Figure 2-8). Many of the largest changes were experienced in concentrated areas in Surrey, the City of Langley, Tsawwassen, and the City of North Vancouver. This is reflected when looking at the differing levels of change in the Member Jurisdictions of Metro Vancouver.

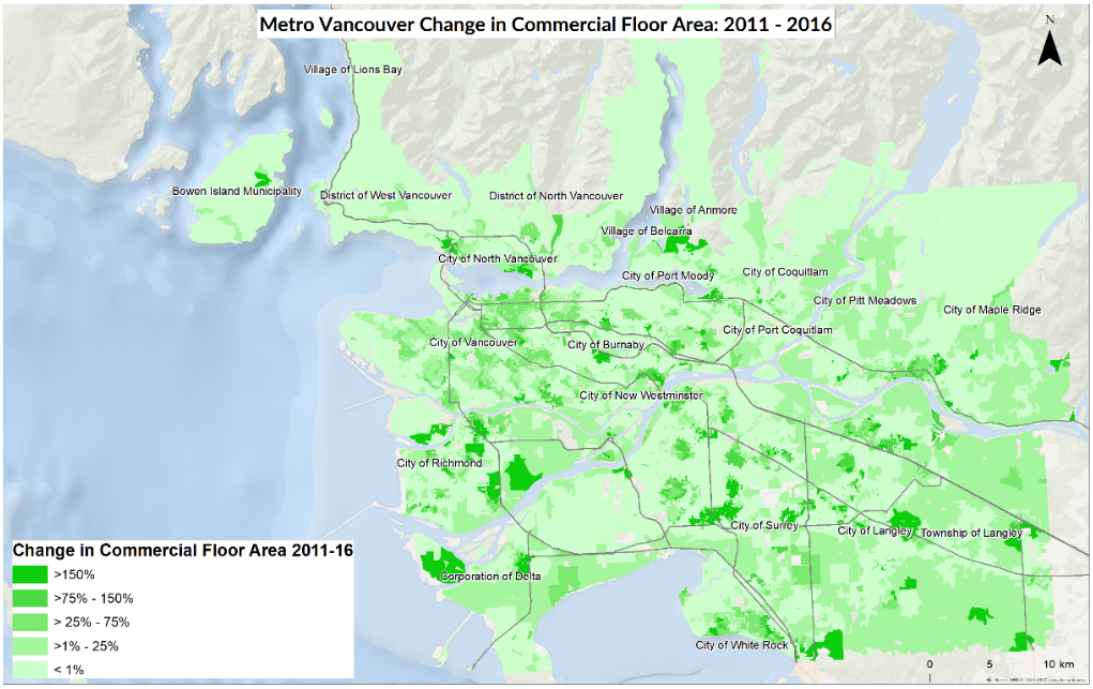
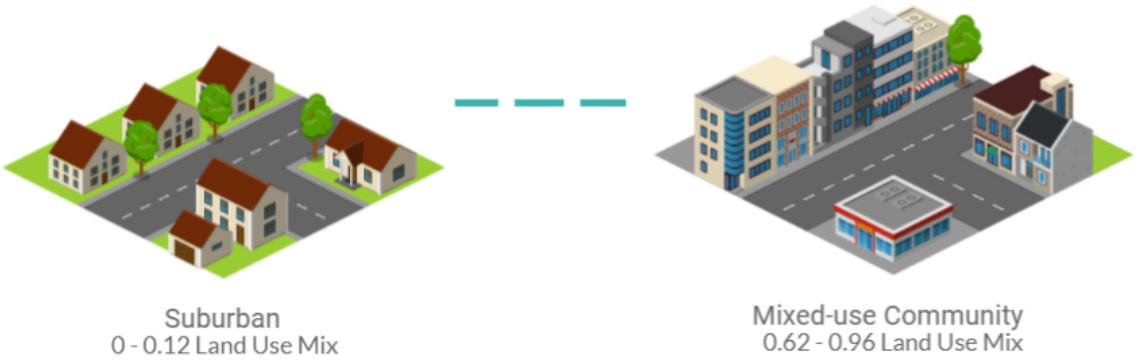


Figure 2-8: Change in Commercial FAR 2011-2016

2.4.2. Land Use Mix

Think of some of your favorite places to visit and walk around. Many of the neighbourhoods you thought of probably have a variety of businesses, amenities, and residences. This is what land use mix measures. Land Use Mix shows the evenness of square footage distribution across residential, commercial (including retail and services), entertainment, and office development within a neighbourhood buffer.



From 2006 to 2011 the changes in land use mix show that development across the region in these land use types became more balanced (Figure 2-9). This indicates that within a neighbourhood, new development included retail, residential, office, and entertainment land uses more equally. This can be seen in the trajectory of change in the land use mix measure as well as the consistent upward trend of commercial FAR and net residential density from 2006-2011.

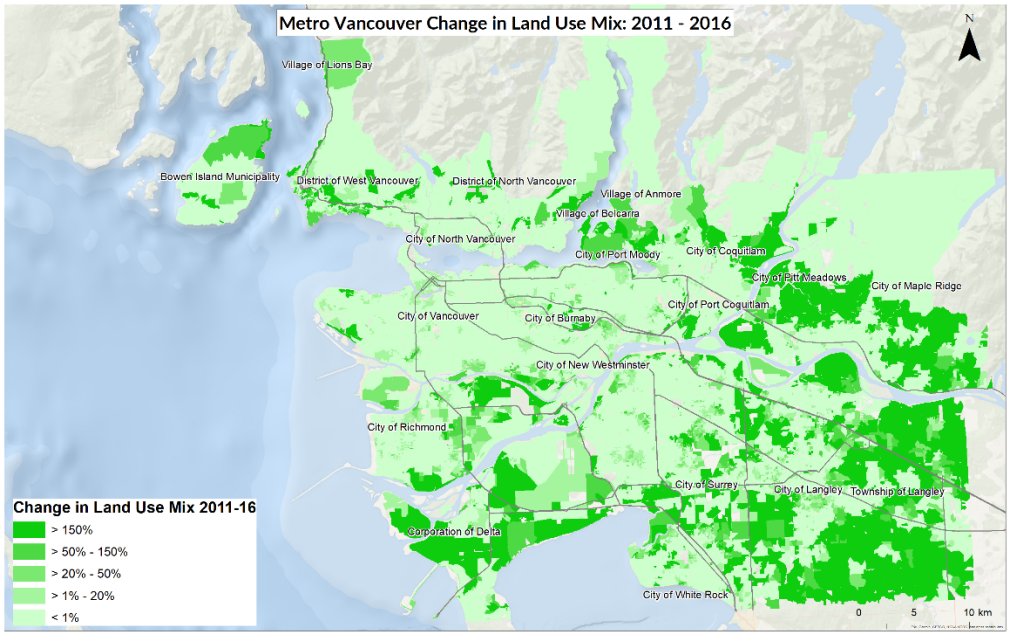


Figure 2-9: Change in Land Use Mix 2011-2016

Figure 2-9 shows that changes in land use mix from 2011 – 2016 have shifted into the southern and easternmost suburban areas where greenfield development of communities is still possible. Elsewhere in the region, changes in net residential density have kept a modest pace while commercial FAR has begun to plateau. This explains the downward trajectory of land use mix from 2011-2016 as the intensification of one land use type over another result in a less even distribution within a neighbourhood buffer. Further, denser

urban forms such as apartment buildings with ground-level retail and residences above can result in lower land use mix scores due to the increases in residential density.

2.5. Regional Accessibility

The Walkability Index describes neighbourhood level local accessibility but does not address accessing destinations beyond a 15–20-minute walk. A definition of describing Regional Accessibility is required to analyze how disparate areas of the region are connected. Both local and regional accessibility impact travel and activity patterns. Using Generalized Transit Feed Specification (GTFS) data from TransLink average travel times for auto and transit at peak AM and mid-day times were determined for the region for 2011 and 2016. These travel times are based on a variety of regional destinations and include Metro Vancouver Regional Growth Strategy destinations (Figure 2-10), those determined by the Health and Community Design Lab (HCDL), and Metro Vancouver and UBC destinations combined. Additional destinations (Figure 2-11) were added by the HCDL based on their importance to regional transportation using criteria such as volume and proximity to regional centers. An example of this is the Commercial Drive Station transportation hub which is one of the most heavily used transit corridors in the region[17]. The destinations are outlined in the tables below.

[17] TransLink. (n.d.). 2019 TSPR - Rail Summaries [Interactive]. Tableau Public. Retrieved August 12, 2021, from https://public.tableau.com/app/profile/translink/viz/2019TSPR-RailSummaries/TableofContents

#	Destination Name	Municipality	Type
1	Downtown Vancouver	Vancouver	Metropolitan Core
2	Surrey Centre	Surrey	Suburban Metro Core
3	Oakridge	Vancouver	Municipal Town Centre
4	Metrotown	Burnaby	Regional City Centre
5	Columbia Skytrain	New Westminster	Regional City Centre
6	Richmond Brighouse	Richmond	Regional City Centre
7	Lonsdale Quay	North Vancouver	Regional City Centre
8	Brentwood Town Centre	Burnaby	Municipal Town Centre
9	Lougheed Town Centre	Burnaby	Municipal Town Centre
10	Coquitlam Town Centre	Coquitlam	Regional City Centre
11	Edmonds	Burnaby	Municipal Town Centre
12	Newton	Surrey	Municipal Town Centre
13	Guildford Town Centre	Surrey	Municipal Town Centre
14	Willowbrook Centre	Langley City	Regional City Centre
15	Downtown Port Moody	Port Moody	Municipal Town Centre
16	Downtown Port Coquitlam	Port Coquitlam	Municipal Town Centre
17	Downtown Maple Ridge	Maple Ridge	Regional City Centre
18	Fleetwood	Surrey	Municipal Town Centre
19	Downtown Pitt Meadows	Pitt Meadows	Municipal Town Centre
20	Ambleside	West Vancouver	Municipal Town Centre
21	Lynn Valley Centre	DNV	Municipal Town Centre
22	Semiahmoo Centre	White Rock	Municipal Town Centre
23	Cloverdale	Surrey	Municipal Town Centre
24	Aldergrove Centre Mall	Township of Langley	Municipal Town Centre
25	Ladner	Delta	Municipal Town Centre
26	Willoughby	Township of Langley	Municipal Town Centre

Figure 2-10: Metro Vancouver Regional Growth Strategy Destinations

#	Destination Name	Municipality	Type
1	Commercial Dr. Station	Vancouver	Transportation Hub
2	Central Broadway	Vancouver	Transportation Hub
3	UBC	UEL	Educational
4	YVR	Richmond	Transportation Hub
5	Clearbrook	Abbotsford	Regional City Centre
6	Cottonwood Centre	Chilliwack	Municipal Town Centre
7	Mission City	Mission	Municipal Town Centre

Figure 2-11: Health & Community Design Lab Regional Growth Strategy Destinations

To calculate the travel times for each postal code, travel times acquired from the GTFS data were linked to each postal code based on the traffic analysis zone it falls within. The travel times for each destination were then aggregated and divided by the total number of destinations to arrive at mean AM and mid-day travel times for auto and transit. The resulting travel times for all Metro Vancouver and Health and Community Design Lab destinations are visualized in maps below (Figure 2-12 and Figure 2-13).

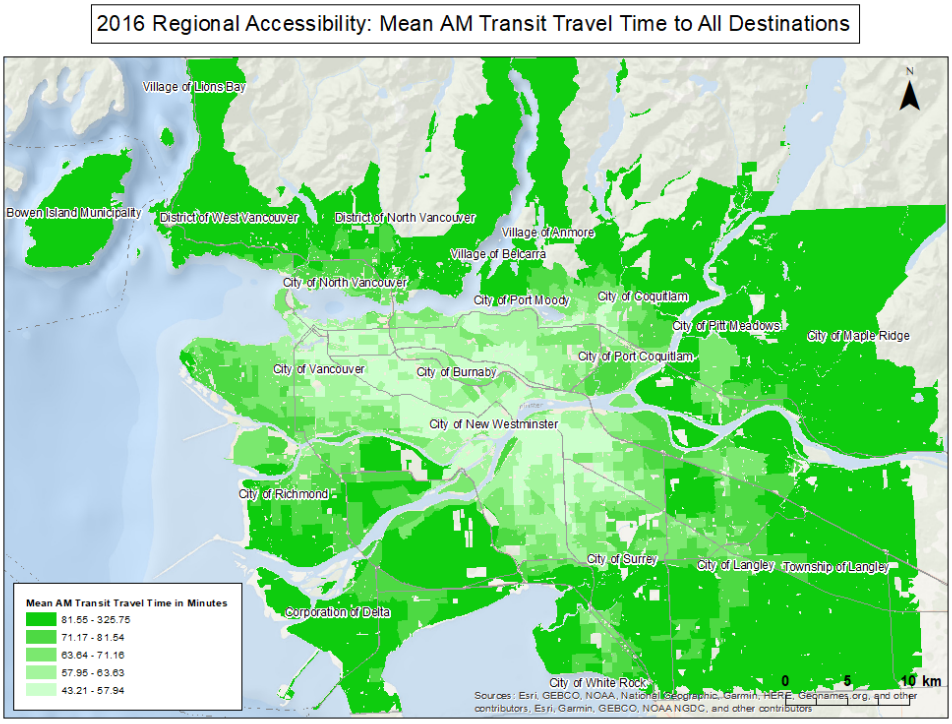


Figure 2-12: Map of 2016 Mean AM Transit Travel Time

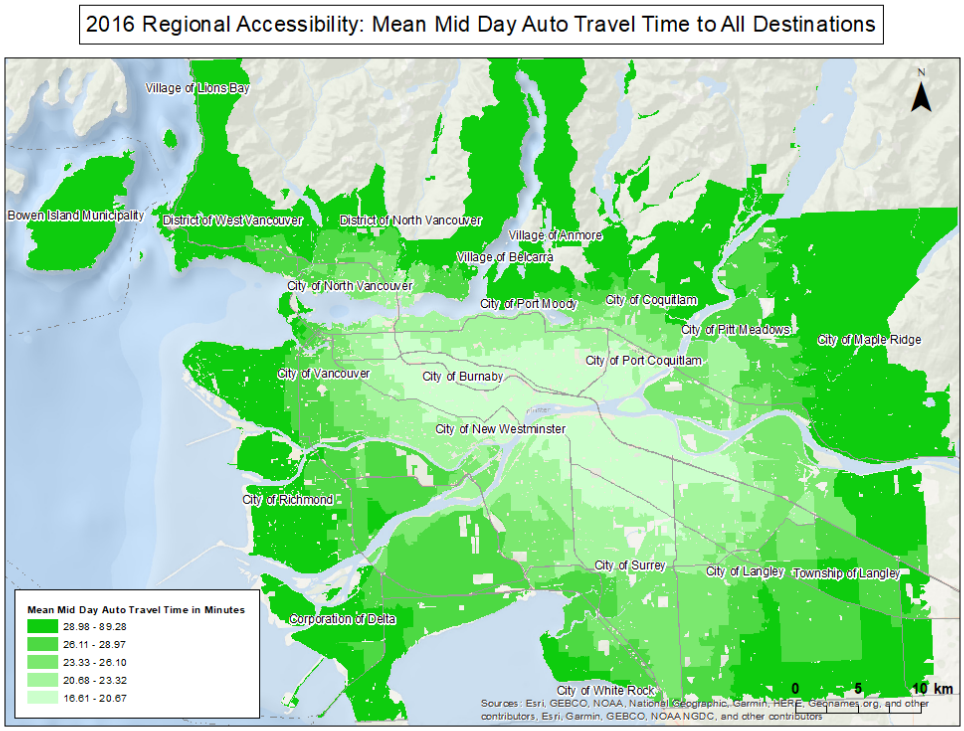


Figure 2-13: Map of 2016 Mean Mid-Day Auto Transit Travel Time

The transit travel time maps consistently show the lowest travel times for transit where transportation is easily accessible. This is apparent on the downtown peninsula of Vancouver, East Vancouver at Commercial Dr. Station, in New Westminster, and areas of Port Moody and Coquitlam where transit is concentrated. Transit travel time increases in car dependent areas with poor transportation connection. This is shown in suburban areas such as Anmore, Belcarra, Maple Ridge, and Lions Bay where transportation investment has historically been low. Auto travel times exhibit similar patterns regionally due to most destinations being closer to the downtown core of Vancouver. Some suburban areas exhibit travel times like those found closer to the downtown core of Vancouver due to transportation design differences. Many suburban areas were built as car dependent enclaves with well-connected highways, while areas within the City of Vancouver have transitioned to more transit and active transportation friendly modes of travel. As transportation policies evolve in the region, we would expect to see transit travel times decrease allowing greener more equitable travel across Metro Vancouver.

2.6. Summary

The analysis of changes in the component variables which comprise the walkability index allows policy decision makers to examine how changes in the built environment over time shape each neighbourhood and the collective region. These changes show, at the postal code level, the development trajectory of Metro Vancouver with policy relevant measures. When neighbourhood walkability is improved, the culmination of these changes has been shown to be a factor in living healthier more environmentally friendly lifestyles.

3. Greenspace Access & Exposure[18]

3.1. Health Impacts of Greenspace Access and Exposure

Related to walking-supportive features of the built environment, the proximity to greenspace within neighbourhoods is a core component of access to the natural environment. The role of access and exposure to greenspaces and the resulting human health impacts has been the topic of many studies, reviews, and systematic analyses. There is an abundance of literature that has established a relationship between greenspaces and various health behaviours and health outcomes. Increased exposure to greenness has been associated with health-promoting behaviours, such as increased physical activity and social interaction (Peters et al., 2010; Sugiyama et al., 2008). Studies have shown a positive relationship between greenspace proximity and specific health outcomes, such as lower prevalence of diabetes (Bodicoat et al., 2014; Mazumdar et al., 2021; Yang et al., 2019), reduced hypertension and CVD (Dzhambov et al., 2018; Jia et al., 2018), and lessened symptoms of depression, anxiety, and stress (Beyer et al., 2014). In addition, greenspaces have been shown to promote general health (Brindley et al., 2019) and reduce overall mortality (Rojas-Rueda et al., 2019). However, not all studies have found access or exposure to greenspace to benefit health. Some studies find no relationship (when controlling for other variables) or find greenspace exposure associated with adverse health outcomes (for example, increased asthma hospitalization) (Amato et al., 2011; Dales et al., 2004, 2008). It has been suggested that the use of diverse greenspace metrics, the varied quality of these metrics, and the specific methods used to quantify exposure or access, may contribute to these inconsistent findings (James et al., 2015; Lachowycz & Jones, 2011).

Despite the considerable existing literature examining the role of greenspace (in addition to other built and natural environmental exposures), there is no standardized definition of greenspace. Although there are some commonly used metrics to quantify greenspace, this overarching term may be used to refer to the ability to access any greenspace, the number of accessible park spaces, the percentage of local tree canopy cover, the proportion of natural land cover types, or the amount of healthy vegetation within a specified pixel size (e.g., Normalized Difference Vegetation Index (NDVI)). To further complicate this situation, a recent review of 125 greenspace articles, reported that less than 50% of these publications satisfactorily explained how “greenspace” was defined in their study (Taylor & Hochuli, 2017). This makes it difficult to compare across studies using greenspace as an exposure.

When greenspace exposure is sufficiently operationalized, the use of different metrics may yield diverse results in terms of health outcomes. Thus, the choice of greenspace metric could therefore unintentionally influence the result on health outcomes. This

[18] For more details on the development of greenspace access and exposure surface, please see

Appendix C.

happens when a statistically significant relationship between greenspace access or exposure and the health behaviour or outcome of interest is found. For example, one study examined Dutch adults to determine the relationship between various greenspace metrics and both the odds of being overweight and the odds of engaging in at least 150 minutes of outdoor activity. It found that the choice of how access or exposure to greenspace was measured (e.g., NDVI, land-use database, or distance to nearest park space) determined whether greenspace was significantly associated with the odds of a participant being overweight (BMI 30 or higher) or engaging in at least 150 minutes of weekly outdoor activity (Klompmaker et al., 2018). In this study, the use of NDVI as the exposure metric resulted in the strongest and most consistent associations with reduced odds of being overweight and increased odds of engaging in the recommended amount of outdoor activity. Another study found inconsistency in the correlations between different greenspace metrics when using various criteria and buffer sizes. This study in New South Wales, Australia reported correlations (Kendall's Tau) of between 0.09-0.38 when comparing both 100m and 10-minute walking buffers using NDVI, park land use, and tree canopy (Mazumdar et al., 2020). In addition to the inconsistency between these various quantitative measures of greenspace, there also tends to be a mismatch between these measures and perceptions by residents. Many objective measures of greenspace do not correspond to individual perceptions of greenspace (Larkin & Hystad, 2019; Li et al., 2015; Mazumdar et al., 2020). However, expert ratings of neighbourhood greenness (in this case Environmental Psychologists) tended to be highly correlated with NDVI (Rhew et al., 2011).

There are also various methods to determine the appropriate scale and location of greenspaces one could reasonably be exposed to or have access to. The selection of the area from which to measure exposure may have a significant influence on the "amount" of exposure that is ascribed to an area or individual. In large ecological studies, an entire city or census geographical areas may be used to determine the amount of exposure, such as in some early works on air pollution and mortality (Dockery et al., 1993) or extreme heat-related deaths (Medina-Ramón et al., 2006). However, for many environmental exposures, a smaller geographical area, encompassing the area that an individual would regularly engage with during their daily activities is desirable or necessary. In these cases, buffers are commonly used to define the area an individual may encounter from their place of residence or work. Previous studies have used several different buffering methods and a wide range of buffering distances to determine relative access or exposure to greenspace associated with a specific location or individual (Mazumdar et al., 2021; Rugel et al., 2019). The most used buffering methods are circular buffers (also called Euclidean or crow-fly) which require no additional data to calculate and rely on simple distance calculations, and network buffers, which utilize roadway or sidewalk infrastructure data to determine the area that is accessible from a specific location. Circular buffers use a simple process to measure a specified radius from a central point of interest, or centroid, to create a circular buffer area. Due to simplicity, and not requiring any additional data (such as the roadway or sidewalk infrastructure necessary to calculate network buffers), this method is commonly used in research and by other planning authorities (Coutts et al., 2010, 2013; Moseley et al., 2013). As circular buffering does not include roadway or sidewalk connectivity, or the possibility of other

impassable obstacles (e.g., highways, or private property), this method may over-estimate the distance an individual is able to travel under real-world conditions.

Buffer distances commonly range from 100-3000 metres and may be selected *a priori* to examine a specific hypothesis or multiple distances may be utilized in the analysis to determine the most predictive or strongest association with the health outcome of interest. Similar to the discrepancies that arise from comparing different greenspace metrics, using different buffering methods and distances may also result in different conclusions when examining the association between these exposures and health outcomes. While there is much existing work that has applied these various greenspace metrics within environmental epidemiological analysis, there has been far less emphasis on how these various metrics compare to one another. Even less attention has been focused on the potential discrepancies in exposure calculation when utilizing circular rather the network buffer methods.

Previous work has directly compared various buffering techniques, both circular and network, as well as the various methods to create network buffers, in relation to physical activity and walkability (Frank et al., 2017; Oliver et al., 2007). A study that compared 1 km circular buffers and line-based road network buffers found that the use of the network buffer method resulted in a stronger association between land use type and leisure and transport walking for respondents. (Oliver et al., 2007). To date, less work has focused on examining the impact of buffer method choice on the resulting association between greenspace and health outcomes.

3.2. Built and Natural Environment Exposures

In order to consider the effect of greenspace on health outcomes, we must create a spatial measure. The greenspace metrics were calculated from the centroid of each 6-digit postal code in the study area. The 6-digit postal code represents a spatially precise unit and is commonly used in Canadian environmental epidemiology studies (Labib et al., 2020b; Rugel et al., 2019). In urban neighbourhoods a postal code typically corresponds to one side of a city-block or a single high-rise building. Across urban and rural postal code areas studied, there was a median population of 19 and a mean of 41 residents, rural postal code areas tended to be larger, and the average corresponding population was higher in rural areas (el Emam et al., 2011). The use of postal code centroid as a proxy measure for full residential street address was found to be most accurate for high-rise or multi-unit residential buildings, with less accuracy in more rural areas (Healy & Gilliland, 2012; Khan et al., 2018). Each environmental exposure metric outlined below was calculated from the centroid of each unique postal code, using both 400m and 1000m circular and network buffers.

3.2.1. Land Cover

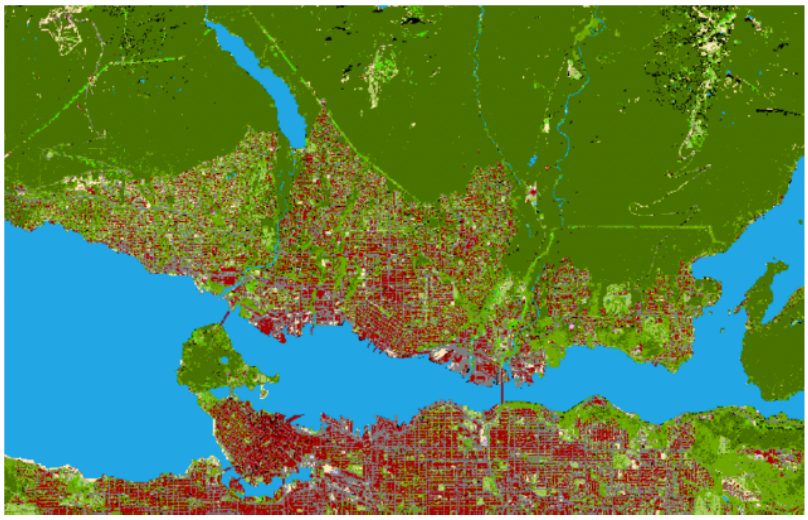


Figure 3-1: Example of Land Cover in Metro Vancouver.

The study area was classified into 13 urban land cover types using a geographic object-based image analysis which combined airborne laser scanning and RapidEye high-spatial-resolution imagery collected in 2016 (Metro Vancouver, 2020) (Figure 3-1). This method had a reported overall accuracy of 88% (kappa 0.87). These land cover types were mapped at a 2m spatial resolution, with some areas mapped at a 5m spatial resolution. The full methods are described elsewhere (Williams et al., 2018). The land cover types included 5 types of green land cover: coniferous (containing >75% coniferous tree species); deciduous (containing >75% deciduous tree species); shrub (vegetation taller than grass but shorter than tree, approximately < 3-4m tall); modified grass-herb (e.g., agricultural crops, golf course greens, park space, lawns); and natural grass-herb (e.g., meadows, grassland, or wetlands). These 5 green land cover types were analyzed individually and as a composite "total green" exposure variable (Jarvis, 2020). This data also contains 8 categories that were not included in the aggregate total green land cover: buildings; paved; other built (e.g., sport surfaces or transit and rail areas); barren; soil; non-photosynthetic vegetation (e.g., dead grass); water; shadow (e.g., an artifact of the method).

3.2.2. Tree Canopy

Tree canopy values were calculated from the Metro Vancouver Open Data "EcoHealth Indicators – Canopy and Imperviousness" data layer (Figure 3-2). This data was summarized by census dissemination block throughout the study area and was generated from the Land Cover Classification (5m, hybrid) data collected in 2016. Tree canopy was calculated as a proportion of the buffer area, including the ground area covered by leaves and branches as visible from the air (Metro

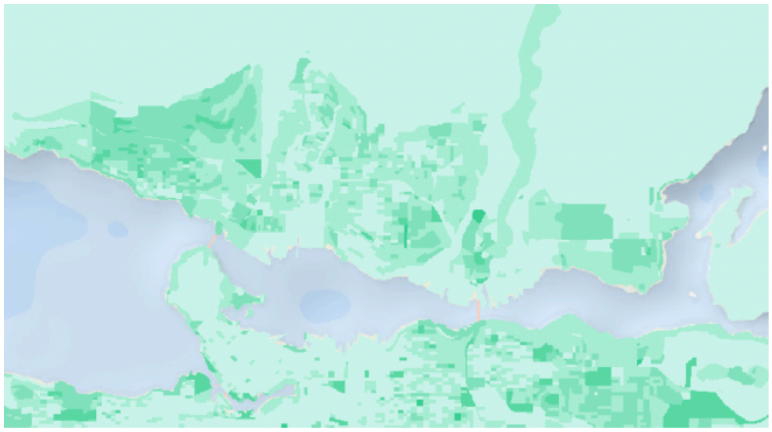


Figure 3-2: Example of Tree Canopy Coverage in Metro Vancouver.

Vancouver, 2020). Tree canopy cover is distinct from land cover data, due to this metric quantifying the proportion of buffer area covered by tree canopy, rather than the specific land cover types which may be predominant underneath the canopy (which may contain other types of vegetative and impervious land cover).

3.2.3. Normalized Difference Vegetation Index

Normalized Difference Vegetation Index (NDVI) was calculated using NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data (Figure 3-3). This data was obtained through the Application for Exacting and Exploring Analysis Ready Samples (AppEEARS) portal, and utilized 16-day averages data, at 250m resolution, collected in 2016 (U.S. Geological Survey, 2021). These resulting NDVI values were calculated using the following formula:

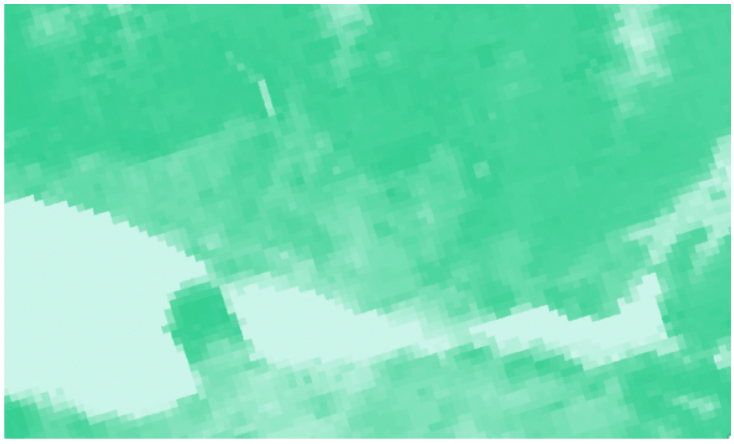


Figure 3-3: Example of NDVI in Metro Vancouver.

$$NDVI = \frac{\rho NIR - \rho Red}{\rho NIR + \rho Red}$$

This formula is intended to assess the proportion of healthy live vegetation within a specified pixel of land area. The resulting values range from -1 to +1, with low positive values indicative of barren areas, moderate positive values (0.2-0.3) indicating areas with shrub and grass, and high positive values indicating healthy dense forested areas. Negative values typically indicate areas covered with water. The buffer average NDVI value was used for subsequent analysis.

3.2.4. Park Access

Park access was calculated using the Metro Vancouver 2016 Land Use Classification data layer (Figure 3-4). Each parcel in this data layer is classified by the official land use

(Metro Vancouver, 2020). Parcels coded as “Recreation, Open Space and Protected Natural Areas” were identified as potential park areas. Only parks with at least 1 hectare of total area were considered in this analysis to ensure that these areas would be appropriate for active recreation and physical activity, which is consistent with the exclusion of smaller park spaces in previous work (Annerstedt Van Den Bosch et al., 2016). The inclusion of only 1 hectare and larger park spaces prevents the inadvertent inclusion of greenspaces where recreation would be unlikely such as roadway or sidewalk medians with vegetation, but as a result also excludes intentionally designed parklets and small urban open spaces less than 1 hectare, where residents may recreate and engage in social interaction.

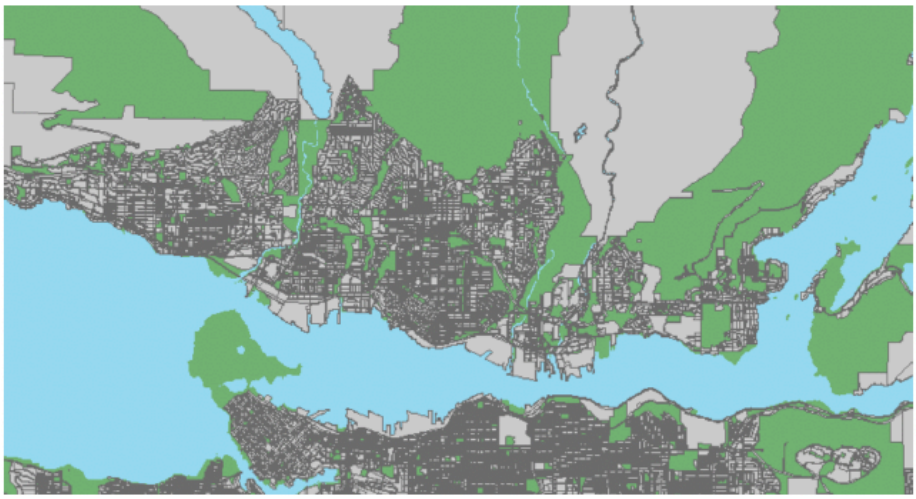


Figure 3-4: Example of Park Access in Metro Vancouver.

3.3. Exposure Buffers[19]

Two sizes of buffers were created surrounding each postal code in the study area (n = 57,430) using both circular and network buffers (with methods described below). 400m corresponds to an approximately 5-minute walk and is used by many local and regional planning authorities as a benchmark for access to greenspaces in the region (e.g., City of Vancouver, 2015). 1000m buffers, corresponding to approximately 10-15 minutes of walking, are also commonly used within walkability and environmental exposure literature (Labib et al., 2020). Distances between 400-1000m are often referenced as a distance that individuals are willing and able to walk to access neighbourhood amenities or services. The discrepancies between the same distance of circular and network buffer are reduced in areas with a more developed and connected walkable roadway network.

The centroid or center most point of each 6-digit postal code area was used as the starting point for the creation of each buffer, this is a common method in environmental epidemiology as it allows for greater de-identification of respondent/research participant’s specific location. In urban areas of Canada, postal code centroids are within 200m of the corresponding residential location in nearly 90% of addresses, and therefore make for a reasonable location proxy while increasing the protection of confidentiality for

[19] Portions of this study on greenspace access and exposure in Metro Vancouver derived from an excerpt from: White, K.R. (2021). A comparison of greenspace metrics and measurement methods, walkability, and social and material deprivation in Metro Vancouver. [MSc Thesis, University of British Columbia]. UBC Theses and Dissertations Open Collections: https://dx.doi.org/10.14288/1.0402572

respondents (Bow et al., 2004). Circular buffers were created using a straight-line radius of 400m and 1000m centered on each postal code centroid.

Network buffers were also applied to the centroid of each 6-digit postal code. These buffers incorporate the existing pedestrian road network developed in the Health and Community Design Lab. The pedestrian road network dataset includes all pedestrian-accessible road segments, including roadways with existing sidewalk infrastructure (including pathways or walkable road shoulders). All controlled access roads, divided highways/dual lane roads, and on/off-ramps were excluded. The resulting pedestrian road network was then applied to identify a comprehensive set of all possible "walking" routes from the 6-digit postal code centroid to the specified distance (400m and 1000m). The resulting buffer polygon vector layers were then applied to each greenspace exposure layer to determine the exposure estimates for each greenspace metric. All spatial data preparation was completed in ArcMap 10.8.1 (Esri, 2020) and QGIS 3.18 (QGIS Development Team, 2021).

3.4. Statistical Analysis

To measure the correlation of each greenspace metric all variables outlined above were joined by a unique 6-digit postal code. The postal-code level values were then compared for the 400m and 1000m distances for both the circular and network buffers. Correlation matrices were created, for the 400m and 1000m circular and network buffers, using the "Hmisc" package (Harrell Jr, 2021). To display the series of relationships heatmap visualizations were created using the "corrplot" package (Wei & Simko, 2021). All analyses were performed using R version 3.6.1 (R Core Team, 2019).

3.5. Results

3.5.1. Natural Land Cover

The aggregate or "total green" land cover type was calculated by combining the coniferous, deciduous, modified-grass herb, natural-grass herb, and shrub land cover types, these composite measures ranged from a mean of 0.33-0.41 of buffer areas. Throughout the region, the most prevalent category of green land cover was deciduous trees, with mean proportions from 0.157 (400m network buffer) to 0.187 (1000m circular buffer) of buffer area depending on size and type. The least prominent category of green land cover was natural grass-herb, a category that includes meadows, grasses and bogs/wetlands that have not been modified by human activity. The mean proportion and standard deviation of each land cover type are shown in Table 3-1.

Table 3-1: Mean residential postal code proportion and standard deviation of land cover types

	Circular Buffers		**Network Buffers**	
	400m	**1000m**	**400m**	**1000m**
Coniferous	0.070 (0.088)	0.075 (0.091)	0.059 (0.078)	0.059 (0.069)

Deciduous	0.186 (0.096)	0.187 (0.080)	0.157 (0.093)	0.162 (0.073)
Shrub	0.006 (0.011)	0.007 (0.009)	0.004 (0.009)	0.004 (0.006)
Modified grass-herb	0.129 (0.083)	0.136 (0.082)	0.108 (0.076)	0.114 (0.062)
Natural grass-herb	0.001 (0.007)	0.002 (0.007)	0.001 (0.008)	0.001 (0.005)
Aggregated green	0.393 (0.169)	0.408 (0.160)	0.330 (0.159)	0.340 (0.133)

3.5.2. Tree Canopy

The proportion of tree canopy cover within each postal code buffer was very diverse, from a minimum of <1% to a maximum of 96% in most tree-covered postal code buffers (see Table 3-2). The median proportion of tree canopy cover was 24% for 400m buffers, and 26% for 1000m buffers.

Table 3-2: Descriptive statistics of each greenspace metric by buffer type and size

	Buffer Type	Min	Max	Median	Mean	SD	*r*	*p*-value
Park Count								
1000m	**Circular**	0	23	8	8.37	3.56	0.66	< .01
	Network	0	21	4	4.54	2.15		
400m	**Circular**	0	13	2	2.09	1.41	0.66	< .01
	Network	0	16	1	1.17	1.00		
Proportion of Tree Canopy Cover								
1000m	**Circular**	<0.01	0.96	0.26	0.31	0.19	0.92	< .01
	Network	<0.01	0.96	0.26	0.30	0.17		
400m	**Circular**	<0.01	0.98	0.24	0.29	0.18	0.86	< .01
	Network	<0.01	0.96	0.24	0.29	0.17		
Proportion of Aggregate Green Land Cover Type								
1000m	**Circular**	0.01	0.99	0.39	0.41	0.16	0.81	< .01
	Network	<0.01	0.99	0.31	0.34	0.13		
400m	**Circular**	0.00	1.00	0.37	0.39	0.17	0.78	< .01
	Network	<0.01	0.99	0.30	0.33	0.16		
NDVI								
1000m	**Circular**	-0.08	0.92	0.55	0.55	0.12	0.80	< .01
	Network	-0.10	0.97	0.54	0.55	0.11		
400m	**Circular**	-0.10	0.95	0.55	0.55	0.12	0.54	< .01
	Network	-0.10	0.97	0.54	0.51	0.18		
Note: *r* and *p*-values for the correlation coefficient of the relationship between circular and network buffer for the same distance								

3.5.3. Normalized Difference Vegetation Index

Similar to tree canopy, there was a vast range of mean NDVI values across the region. Maximum NDVI values ranged from 0.92 (1000m circular buffer) to 0.97 (400m and 1000m network buffer), which indicates a buffer almost entirely covered with healthy

dense vegetation. This greenspace metric had the greatest difference (between buffer sizes) in correlation coefficients when comparing circular and network buffer methods at the 400m (r = 0.54, p < .01) and 1000m (r = 0.80, p < .01) buffer sizes.

3.5.4. Park Access

The majority (99.6%, n = 57,222 circular buffer; 98.5%, n = 56,580 network buffer) of postal code centroids were within 1000m of at least one park of 1-hectare or larger, with (90.1%, n = 51,720 circular buffer; 73.8%, n = 42,397 network buffer) within 400m of at least one park. There was a moderate correlation when circular and network buffer methods were compared (r = 0.66, p < .01).

3.5.5. Comparison of Buffer Types

For all greenspace metrics, the correlation coefficients for the relationship between the results when using circular or network buffers were positive; however, these results ranged from moderate to strong (see Table 3-2). The circular and network buffer results were most highly correlated for the tree canopy metric (1000m r = 0.92; 400m r = 0.86, p < .01), while park count had the weakest correlation between methods overall (1000m r = 0.66; 400m r = 0.66, p < .01).

3.5.6. Comparison of Greenspace Metrics

Total green land cover type (the composite measure of all vegetative land cover), proportion of tree canopy cover, and average NDVI were all moderately to strongly positively correlated. Park count was weakly correlated to the other greenspace metrics (with this relationship weakly positive when using the circular buffer method, and weakly negative when using the network buffer method).

3.6. Discussion

These findings show that using a measure of total green land cover, average NDVI, or tree canopy, results is moderate to strong association between these greenspace exposure estimates, in the MVRD. However, quantifying postal code level greenspace exposure through the number of accessible parks (e.g., park count) was only weakly positively correlated with the other three greenspace metrics when 1000m circular buffers (NDVI r = 0.12; total green land cover r = 0.07; tree canopy r = 0.14, p < .01) were used, when 1000m network buffers (NDVI r = -0.34; total green land cover r = -0.12; tree canopy r = 0.05, p < .01) were used two of the correlations became weakly to moderately negative.

When comparing the results for the circular and network buffer methods applied to estimating greenspace exposure and access, the results range from moderately to highly correlated. The greenspace metric for which these buffering methods are most highly correlated is tree canopy cover (1000m r = 0.92; 400m r = 0.86, p < .01). This indicates that the choice of buffering method may have less of an impact when tree canopy is the exposure metric of choice utilized in studies of health behaviours or outcomes. For tree

canopy, NDVI and total green land cover, the choice of buffering methods seems to be more influential at smaller distances, as the results for these metrics became more correlated at the 1000m compared to 400m distance. Overall, the results for park count were the least strongly correlated when the circular and network buffering methods were compared, suggesting that future work should be intentional about which buffering method is used when access to parks is the chosen greenspace exposure.

When the circular and network methods are only moderately correlated (such as in the case of park count, $r = 0.66$, $p < .01$), the use of circular buffers may tend to overestimate the real-world access to park spaces as this method does not take into consideration the walkable roadway network or physical barriers which may prevent convenient access to these spaces. The MVRD contains a diverse mix of urban, suburban, and rural areas, so these results may not be consistent in areas with a different mix of land uses. As circular and network buffers are less consistent in "less walkable", typically more suburban and rural areas, it may be more important to be intentional about the choice of buffering method used in these types of neighbourhoods. For example, in a neighbourhood with a limited walkable roadway network, or with obstacles (e.g., highway or watercourse), a park within a 500m circular buffer may require a much longer walking route distance to access. This would not be taken into consideration when using a circular buffer and therefore both access and estimated exposure may be overestimated.

Previous work has typically shown a lack of a strong relationship between green land cover type and park access in the Metro Vancouver region (Jarvis et al., 2020), as well as in other cities (Cusack et al., 2017). These current findings are consistent, with park access not being highly correlated to other greenspace metrics. This report contributes to the existing knowledge regarding the lack of a strong association between various greenspace metrics commonly used to quantify exposure to predict health outcomes in environmental epidemiology studies.

Previous work has compared circular and network buffering methods (Mazumdar et al., 2021; Oliver et al., 2007), however, no studies to date have compared these methods across several greenspace metrics. These findings may provide evidence for researchers when determining which buffer method is most appropriate for their specific research questions, and which types of greenspace metrics may be most influenced by buffering method.

Due to the scope of this report, and the focus on quantitative metrics of greenspace access and exposure, no measures of perceived greenspace were included. Given that some studies have found that individual perception of greenspace is more predictive of health behaviours, additional examination of how quantitative metrics of greenspace exposure relates to individual perceptions of their own access and exposure to residential greenness is warranted (Bai et al., 2013). This future work may provide evidence that perception of greenness can be adequately measured through a proxy quantitative metric.

This study also did not include measures of biodiversity or species richness within each park or greenspace. Previous work has found that increased species richness (measured

through in person sampling of plant, butterfly, and bird species) was associated with an increase in psychological well-being of greenspace visitors, over and above the benefits associated with the size of the greenspace (Fuller et al., 2007). Methods have been developed to estimate biodiversity using remote sensing data; however, this type of analysis is more common in environmental and natural resources research and is less often included when examining environmental exposure and health outcomes (Madonsela et al., 2018).

3.7. Implications

Future work using greenspace as an environmental exposure should be intentional about which greenspace metric and buffering method most accurately estimate the potential pathway by which greenspace is hypothesized to impact human health. The selection of buffering method may be particularly influential when park count (rather than tree canopy, NDVI or land cover) data is utilized to quantify greenspace access and exposure. This is important, as the use of circular buffers may overestimate the accessibility of greenspace or the likely exposure during local outings, as this method does not consider potential obstacles (such as highways or watercourses). Future work should examine the differences in greenspace metric results when using circular and network buffers in other diverse geographic areas to determine if these same relationships are found.

Travel & Climate Impacts

A key focus of Where Matters II was to expand on the work completed in Where Matters I by providing further advancements into the new research avenues using local data for Metro Vancouver. Applying the wide range of the built and natural environmental measures discussed in the sections above, a series of research applications were performed. Figure 3-5 conceptualizes the organization of five research analyses conducted as part of this project. Each research study is broadly categorized into two types: 1) analyses that examine impacts on human health using health outcomes, or 2) analyses on travel activity that examines human behaviour and pollution and air quality impacts. Three main health sectors were examined: 1) obesity and chronic diseases, such as hypertension and type 2 diabetes, 2) mental health including depression and anxiety and 3) four types of risks of cancer: a) lung, b) breast, c) colorectal, and d) prostate. Leveraging regional trip diary data, studies related to travel activity examined 1) travel emissions from automobiles and transit vehicles, and 2) travel behaviour related to types of household trips by mode and associated physical activity and sedentary time. While all five research studies evaluate built environment impacts on the dependent variables, two of the studies on mental health and cancer risk also integrate measures of green space related to the natural environment.

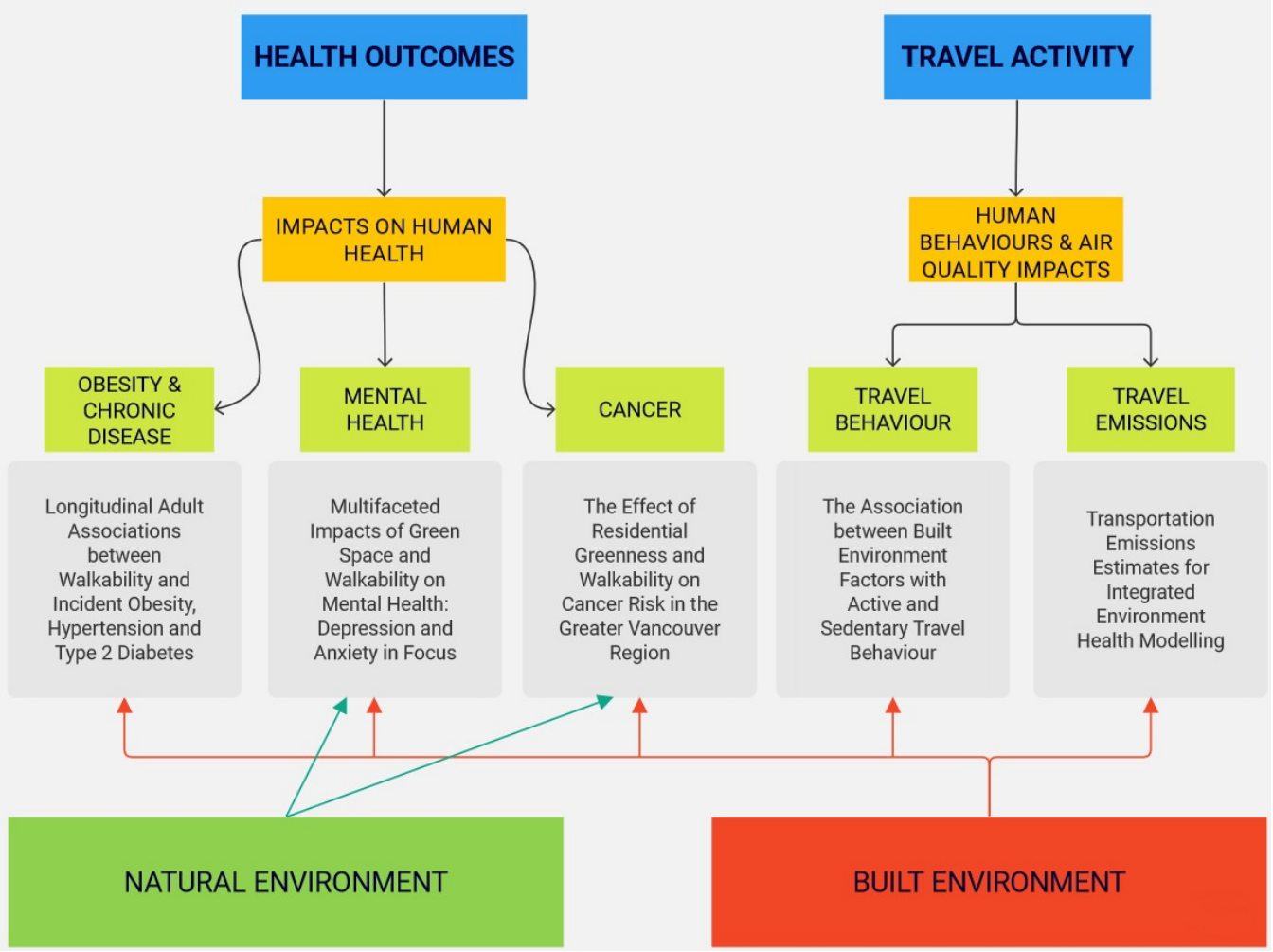


Figure 3-5 Conceptual model showing the organization of each of the five analyses conducted.

Where Matters II expands on the work done previously by evaluating the impact of the built environment on chronic disease and health behaviours. A central resource for our work is the BC Generations Project (BCGP), a database comprising 30,000 British Columbians aged 35-69 years which represents BC's largest-ever population health longitudinal cohort study. BCGP is a regional component of the Canadian Partnership for Tomorrow's Health (CanPath), the Pan-Canadian prospective health cohort, established over the past decade as a research platform for evaluating the genetic, behavioural and environmental causes of cancer and other chronic diseases.

BCGP collected baseline data (health, lifestyle, occupation, residential history, diet and physical activity) from participants using questionnaires. This included a wide range of socio-demographic, behavioural and health- related questions, such as: age, marital status, ethnicity, education, employment, income, personal and family health history. Health- related behavioural questions included tobacco use and exposure to second-hand smoke, sun exposure, daily servings of fruits and vegetables, alcohol consumption and physical activity. Physical measures (height, weight, waist and hip circumference, percentage body fat) and biological samples (venous blood) were obtained from 90% of participants.

Participant follow-up in BCGP is through active recontact for additional survey information (three follow-up questionnaires have been completed to-date), and passive follow-up via linkage to administrative health datasets, for which all participants have consented. Through this administrative linkage 1,678 incident cancer diagnoses since recruitment have been identified, including the following top five cancer types: 411 breast, 235 prostate, 135 colorectal, 111 lung and 105 melanoma skin.

Environmental data has been linked to BCGP participants through a collaboration with the Canadian Urban Environmental Health Research Consortium (CANUE). This includes traffic-related air pollution and greenspace. Walkability datasets generated by the Where Matters team for three timepoints is being linked to historical address information through a CANUE/ Statistics Canada collaboration, allowing us to investigate the impact of changing walkability over time on chronic disease and health behaviours.

Table 3-3 provides an overview summary of each of these research analyses and their components. Two of the analyses present longitudinal studies that systematically compare both health outcomes and environmental conditions at multiple time points to examine causation. The remaining three research studies examine the dependent variables cross-sectionally using the most recently available health and travel survey data combined with current environmental conditions.

Table 3-3: Summary of organization of analysis sections.

Analyses	**Theme**	**Travel Activity**		**Health Outcomes**		
	Impacts	Impacts on Human Behaviour & Air Quality		Impacts on Human Health		
	Sector	**Travel Behaviour**	**Travel & Emissions**	**Obesity & Chronic Disease**	**Mental Health**	**Cancer**
	Title	The Association Between Built Environment Factors with Active and Sedentary Travel Behaviour	Transportation Emissions Estimates for Integrated Environment-Health Modelling	Longitudinal Adult Associations Between Walkability and Incident Obesity, Hypertension, and Type 2 Diabetes	Multifaceted Impacts of Green Space and Walkability on Mental Health: Depression and Anxiety in Focus	The Effect of Residential Greenness and Walkability on Cancer Risk in the Greater Vancouver Region
	Key Outcomes	Physical Activity, Sedentary Time	Emissions by Mode	Obesity, Hypertension, Type 2 Diabetes	Depression, Anxiety	Cancers: Lung, Breast, Colorectal, Prostate
	Study Design	Cross-Sectional	Cross-Sectional	Longitudinal	Cross-Sectional	Longitudinal
	Report Section	4	5	6	7	8
Outcomes/ Activity	**Data Source Organization**	TransLink		BC Cancer Agency, BC Cancer Foundation, Canadian Partnership Against Cancer		
	Source Database	Regional Trip Diary		BC Generations Project		
	Database Year	2017		2009-2016; 2016-2019	2016-2019	2009-2016; 2016-2019
Environment	**Environmental Variables**	Built Environment	Built Environment	Built Environment	Built Environment; Natural Environment	Built Environment; Natural Environment
	Source Database	UBC SPPH Metro Vancouver Environmental Surface				
	Database Year	2016	2016	2006, 2011, 2016	2016	2006, 2011, 2016
	Source Database	-	-	-	Canadian Urban Environmental Health Research Consortium (CANUE)	
	Database Year	-	-	-	2016	2006, 2011, 2016

The sections that follow review the linkages of built and natural environmental conditions on health and travel activity outcomes in Metro Vancouver. These provide abbreviated summaries for each of the individual studies with supplementary information included for the full manuscript analysis in their respective appendix sections.

4. Travel Behaviour Relationships with Walkability – The Association of Built Environment Factors on Active and Sedentary Travel Behaviour: A Cross-Sectional Travel Diary Study[20]

4.1. Background

In North American we are currently facing both an epidemic of sedentary behaviour as well as a need to reduce greenhouse gas (GHG) emissions to mitigate further climate change. Initiatives to reduce the reliance on private vehicle travel, and instead promote the use of active travel modes (walking and cycling) and public transportation, may serve as a strategy to promote public health, and mitigate GHG emissions. Previous work has found a number of built environment factors to be associated with the amount of active travel (E. J. Kim et al., 2020; Koohsari et al., 2017; Liao et al., 2020; Thielman et al., 2015). This current study builds upon these previous works by utilizing detailed trips diary data from a regionally representative sample of households as well as more robustly attributing neighbourhood walkability through the use of the previous described walkability index.

The aim of this study is to examine the association between neighbourhood walkability and travel behaviour across mode (walking, biking, transit, and vehicle). We hypothesize that living in a more walkable neighbourhood would be associated with more trips made by an active mode (walking, biking, and/or transit) whereas living in a less walkable neighbourhood would be associated with more trips made by a sedentary mode (vehicle).

4.2. Methods

4.2.1. Data source, survey design, and ethics

This cross-sectional analysis utilized regionally representative data collected through TransLink's 2017 Trip Diary Data (TDD)[21]. Households through the Metro Vancouver Regional District (MVRD) and Fraser Valley Regional District (FVRD) were recruited through a random sample with approximately 2.5% of households in the region completing the survey (83% via web survey and 17% using smartphone app). The TDD collected data on weekday travel patterns for all individuals living in the recruited households between September 15 and December 12, 2017. In addition to information about the origins and destination, travel mode, and trip purposes, household and individual demographic data was collected.

[20] For the full article associated with this study, please see Appendix G.
[21] https://public.tableau.com/app/profile/translink/viz/Trip_Diary_2017/TripDiary2017

4.2.2. Study sample and study variables

The Walkability Index is a composite measure of neighbourhood walkability, comprised of four component measures (net residential density, commercial floor area, intersection density, and land use mix). Within this current analysis, the walkability value for each household was defined as the composite index value within a 1-kilometre network buffer, which follow a walkable road network, surrounding the location of the home (as defined by home 6-digit postal code). The values for each component measure were calculated beginning at the home postal code location and were then converted to z-scores to calculate the overall walkability index. The 1-km network buffer size was selected to represent the distance individuals could reasonably travel in a 10–15-minute walking trip and has been previous used to define the home "neighbourhood" area. (Colabianchi et al., 2007).

Individual and household demographic data were obtained from the TDD. For this current analysis the following variables were utilized and categorized as follows: gender (dichotomized as female or male), age (categorized as child/youth [age 5-18], adult [age 19-64], and older adult [65+]), driver's license status (dichotomous yes/no), car share status (continuous 0-4, the number of car share membership participants reporting having), employment status (categorized as 'full time employed', 'full time student', 'part time worker or student, or self-employed' or 'non-worker/non-student'), household income (categorized as <$50,000, $50,000-100,000, and >$100,000), household size (continuous 1-10), number of household bicycles (continuous 0-10), number of vehicles per adult in the home (dichotomized as less vehicles than adults [vehicles < adults] and 1 or more vehicle per adult in the home [vehicles > = adults]).

In addition to neighbourhood walkability, regional accessibility and sidewalk connectivity were calculated at the 6-digit postal code level and linked to the residential location. Regional accessibility was calculated by the mean number of minutes to travel to regional locations from the home location in morning peak traffic. These values were calculated for both vehicle travel, which provides an estimation of peak travel time from the home location if traveling by vehicle, as well as for transit travel, which conversely provides as estimation of peak travel time from the home if traveling by transit. Additionally, sidewalk connectivity, a measure of the completeness of the pedestrian infrastructure, was calculated using methods similar to the walkability index in the 1-km network buffer surrounding the home.

4.2.3. Statistical Analysis

All analyses were completed in R version 3.6.1; we used the 'glmer' function within the 'lme4' package to run generalized linear mixed-effect models. Adjusted odds ratios (OR) and 95% confidence intervals (CI) were calculated using logistic regression and three iterations of adjustment variables. Three adjustment models were developed based on existing literature and conceptual understanding of individual and environmental factors associated with travel behaviour. Multi-level (or mixed effects) models were developed to account for the hierarchical nature of the TDD (e.g., multiple participants living in the same household). A two-level model was used to account for clustering of participants within

households. Additionally, survey weights obtained from the TDD were utilized in these analyses.

4.3. Results

4.3.1. Walking

Certain individual and household characteristics increased the odds of reporting walking trips (Table 4-1). Numerous individual variables were significantly associated across each iteration of these analyses including gender, age, employment status, car share status, and driver's licence status. Female participants had 1.22 times the odds of males to make a walking trip in the minimally adjusted model. When accounting for additional variables these results were attenuated, but remained statistically significant. Younger participants reported the most walking trips, with a 15% increase in odds of walking compared to adults (in the fully adjusted model). Participants who reported non-worker/non-student status reported the most walking trips, with 11% increase in odds of walking compared to full time workers. Conversely, participants who reported having a driver's licence had 14% reduced odds of reporting a walking trip compared to those without a driver's licences.

Regional accessibility did not have a significant effect on walking trips; however increased sidewalk connectivity did have a small but significant association with walk trips. There was a graded relationship between walkability and walking. For each increase in walkability there was a corresponding increase in walking trips, with this association being significant across each level of walkability. Participants in the most walkable neighbourhoods reported 13% increased odds in making a walk trip compared to those living in the least walkable neighbourhoods.

Table 4-1: Odds of walking trips across walkability quintiles

	Mod 1		Mod 2		Mod 3	
	OR	95% CI	OR	95% CI	OR	95% CI
Gender						
Male	REF		REF		REF	
Female	**1.22**	**1.15, 1.30**	**1.02**	**1.01, 1.03**	**1.03**	**1.02, 1.03**
Age						
5-18	**2.32**	**1.98, 2.72**	**1.14**	**1.12, 1.17**	**1.15**	**1.12, 1.18**
19-64	REF		REF		REF	
65+	**0.54**	**0.48, 0.62**	**0.97**	**0.95, 0.98**	**0.97**	**0.95, 0.98**
Drivers License						
No	REF		REF		REF	
Yes	**0.30**	**0.27, 0.33**	**0.85**	**0.84, 0.87**	**0.86**	**0.84, 0.87**
Car share						
+1	**2.73**	**2.55, 2.94**	**1.10**	**1.08, 1.12**	**1.09**	**1.08, 1.11**
Status						
Full time employed	REF		REF		REF	
Full time student	**1.23**	**1.07, 1.41**	**1.03**	**1.01, 1.05**	**1.03**	**1.01, 1.05**
Part time or self-employed	**1.43**	**1.29, 1.58**	**1.05**	**1.03, 1.06**	**1.05**	**1.03, 1.06**
Non-worker/non-student	**2.09**	**1.87, 2.35**	**1.11**	**1.09, 1.12**	**1.11**	**1.09, 1.11**
Household income						
< $50,000	REF		REF		REF	
$50,000 - $100,000	**0.78**	**0.70, 0.87**	**0.98**	**0.97, 0.99**	0.98	0.97, 1.00
>$100,000	**0.89**	**0.80, 0.99**	**0.98**	**0.96, 0.99**	0.98	0.99, 1.00
Household size						
+1	**0.75**	**0.73, 0.77**	**0.99**	**0.98, 0.99**	0.99	0.99, 1.00
Household vehicles						
Vehicles < Adults	-		REF		REF	
Vehicles > = Adults	-		0.95	0.90, 1.00	0.96	0.91, 1.01
Bicycles						
+1	-		**1.02**	**1.01, 1.04**	**1.03**	**1.01, 1.04**
Regional Accessibility						
Vehicle	-		1.00	1.00, 1.00	1.00	1.00, 1.00
Transit	-		0.99	0.99, 0.99	0.99	0.99, 0.99
Sidewalk connectivity					**1.05**	**1.01, 1.09**
Walkability						
1	-		-		REF	
2	-		-		**1.04**	**1.01, 1.06**
3	-		-		**1.07**	**1.04, 1.10**
4	-		-		**1.11**	**1.08, 1.14**
5	-		-		**1.13**	**1.08, 1.19**

Notes: bolded results indicate statistical significance at p<0.05

Model 1 adjusted for gender, age, having a driver's licence, car share membership, employment status, household income, and household size. Model 2 adjusted for Model 1 variables, plus ratio of household vehicles to number of adults in household, number of household bicycles, and vehicle and transit regional accessibility. Model 3 adjusted for Model 2 variables, plus, sidewalk connectivity and 1km-network based walkability surrounding residential location.

Vehicle regional accessibility = AM vehicle trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations; Transit regional accessibility = AM transit trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations

4.3.1. Cycling

The patterns for cycling trips differed considerably compared to the trends for walking trips (Table 4-2). Females had 58% decreased odds of making a bike trip, and full-time students reported lower odds of cycling trips (81% decrease in odds) compared to full time workers. Participants in households with more bicycles reported increased odds in making a cycling trip. There was no significant association between neighbourhood walkability and odds of participants making a cycling trip.

Table 4-2: Odds of cycling trips across walkability quintiles

	Mod 1		Mod 2		Mod 3	
	OR	95% CI	OR	95% CI	OR	95% CI
Gender						
Male	REF		REF		REF	
Female	**0.37**	**0.31, 0.45**	**0.41**	**0.41, 0.42**	**0.42**	**0.30, 0.58**
Age						
5-18	**1.46**	**0.88, 2.43**	**4.86**	**4.85, 4.86**	**4.72**	**1.83, 12.2**
19-64	REF		REF		REF	
65+	**0.38**	**0.24, 0.59**	**0.73**	**0.73, 0.73**	0.68	0.32, 1.42
Drivers License						
No	REF		REF		REF	
Yes	**0.67**	**0.47, 0.95**	**0.56**	**0.56, 0.56**	**0.55**	**0.30, 0.99**
Car share						
+1	**3.29**	**2.86, 3.80**	**2.74**	**2.74, 2.74**	**2.71**	**1.94, 3.77**
Status						
Full time employed	REF		REF		REF	
Full time student	**0.42**	**0.28, 0.67**	**0.18**	**0.18, 0.18**	**0.19**	**0.07, 0.48**
Part time or self-employed	0.79	0.58, 1.05	**0.69**	**0.68, 0.69**	0.68	0.39, 1.19
Non-worker/non-student	0.98	0.67, 1.41	**1.37**	**1.37, 1.37**	1.40	0.73, 2.67
Household income						
< $50,000	REF		REF		REF	
$50,000 - $100,000	0.84	0.59, 1.20	**1.39**	**1.39, 1.39**	1.39	0.68, 2.85
>$100,000	1.15	0.82, 1.63	**1.34**	**1.34, 1.34**	1.31	0.64, 2.68
Household size						
+1	0.81	**0.73, 0.88**	**0.97**	**0.96, 0.97**	0.95	0.81, 1.11
Household vehicles						
Vehicles < Adults	-		REF		REF	
Vehicles > = Adults	-		0.47	0.09, 2.31	0.52	0.08, 3.47
Bicycles						
+1	-		**4.75**	**4.75, 4.76**	**4.75**	**3.56, 6.34**
Regional Accessibility						
Vehicle	-		**1.04**	**1.04, 1.04**	1.02	0.95, 1.01
Transit	-		**0.97**	**0.97, 0.97**	0.98	0.95, 1.01
Sidewalk connectivity	-		-		2.66	0.73, 9.68
Walkability						
1	-		-		REF	
2	-		-		0.83	0.39, 1.73
3	-		-		0.84	0.36, 1.98
4	-		-		0.42	0.12, 1.42
5	-		-		1.76	0.53, 5.85

Notes: bolded results indicate statistical significance at p<0.05
Model 1 adjusted for gender, age, having a driver's licence, car share membership, employment status, household income, and household size. Model 2 adjusted for Model 1 variables, plus ratio of household vehicles to number of adults in household, number of household bicycles, and vehicle and transit regional accessibility. Model 3 adjusted for Model 2 variables, plus, sidewalk connectivity and 1km-network based walkability surrounding residential location.
Vehicle regional accessibility = AM vehicle trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations
Transit regional accessibility = AM transit trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations

4.3.1. Transit

Female participants reported increased odds (17%) of making a transit trip compared to male participants (Table 4-3). Both child/youth respondents and older adult participants had lower odds of transit trips compared to adult participants. Similar to the effects for both walking and cycling travel mode, participants with a driver's license had lower odds of transit trips (89%), while participants with car share memberships were more likely to make a transit trip (119%). There was a large effect for employment status, with full-time student participants reporting 12.8 times (95% CI 10.6, 15.4) the odds of making a transit trip compared to participants who were employed full time. Unlike walking and cycling, income was associated with odds of participants reporting a transit trip, with higher income associated with lower odds of transit trips (45% decrease in the middle-income category, and 37% decrease in the higher income category compared to the lower income category), with these results remaining significant in the fully adjusted model. Increased neighbourhood walkability was also associated with greater odds of transit use. However, these results were less consistent across the levels of walkability when compared to the trends for walking trips. Participants with neighbourhood walkability in the 4th and 5th levels (e.g., the most walkable and second most walkable), reported greater odds of making a transit trip when compared to participants living in the least walkable neighbourhoods. However, these results do not follow the same graded response as for walking trips.

Table 4-3: Odds of transit trips across walkability quintiles

		Mod 1		Mod 2		Mod 3
	OR	95% CI	OR	95% CI	OR	95% CI
Gender						
Male	REF		REF		REF	
Female	**1.18**	**1.11, 1.26**	**1.15**	**1.05, 1.26**	**1.17**	**1.07, 1.28**
Age						
5-18	**0.01**	**0.01, 0.02**	**0.01**	**0.01, 0.02**	**0.02**	**0.01, 0.02**
19-64	REF		REF		REF	REF
65+	**0.73**	**0.64, 0.83**	**0.82**	**0.68, 0.99**	**0.81**	**0.67, 0.98**
Drivers License						
No	REF		REF		REF	
Yes	**0.09**	**0.08, 0.11**	**0.10**	**0.09, 0.12**	**0.11**	**0.10, 0.13**
Car share						
+1	**2.15**	**2.00, 2.30**	**2.30**	**1.98, 2.67**	**2.19**	**1.88, 2.55**
Status						
Full time employed	REF		REF		REF	
Full time student	**12.0**	**10.5, 13.7**	**13.8**	**11.4, 16.6**	**12.8**	**10.6, 15.4**
Part time or self-employed	0.93	0.84, 1.03	1.07	0.93, 1.25	1.08	0.93, 1.25
Non-worker/non-student	**0.60**	**0.53, 0.68**	**0.52**	**0.44, 0.63**	**0.53**	**0.44, 0.63**
Household income						
< $50,000	REF		REF		REF	
$50,000 - $100,000	**0.51**	**0.46, 0.57**	**0.56**	**0.47, 0.66**	**0.57**	**0.48, 0.67**
>$100,000	**0.54**	**0.48, 0.60**	**0.61**	**0.51, 0.73**	**0.63**	**0.53, 0.75**
Household size						
+1	**0.89**	**0.86, 0.92**	**0.93**	**0.89, 0.98**	**0.95**	**0.91, 0.99**
Household vehicles						
Vehicles < Adults	-		REF		REF	
Vehicles > = Adults	-		**0.18**	**0.08, 0.41**	**0.28**	**0.13, 0.60**
Bicycles						
+1	-		**0.75**	**0.66, 0.85**	**0.74**	**0.65, 0.84**
Regional Accessibility						
Vehicle	-		**1.08**	**1.06, 1.10**	**1.07**	**1.05, 1.09**
Transit	-		**0.94**	**0.93, 0.95**	**0.94**	**0.94, 0.95**
Sidewalk connectivity			-		**2.13**	**1.44, 3.16**
Walkability						
1	-		-		REF	
2	-		-		1.10	0.88, 1.38
3	-		-		1.22	0.95, 1.58
4	-		-		**1.78**	**1.32, 2.42**
5	-		-		**1.58**	**1.02, 2.44**

Notes: bolded results indicate statistical significance at $p<0.05$

Model 1 adjusted for gender, age, having a driver's licence, car share membership, employment status, household income, and household size. Model 2 adjusted for Model 1 variables, plus ratio of household vehicles to number of adults in household, number of household bicycles, and vehicle and transit regional accessibility. Model 3 adjusted for Model 2 variables, plus, sidewalk connectivity and 1km-network based walkability surrounding residential location.

Vehicle regional accessibility = AM vehicle trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations; Transit regional accessibility = AM transit trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations

4.3.1. Vehicle

Individual and household characteristics that were associated with participants reporting a vehicle trip (either as the driver or passenger) differed considerably from the other modes of travel. Both child/youth participants and older adult participants reported significantly increased odds of making a vehicle trip compared to participants aged 19-64 years, with children/youth reporting the greatest odds of making a vehicle trip (Table 4-4). Reporting being employed full time was associated with the greatest odds of vehicle travel, with full time students (86% reduced), part time employed/student or self-employed (33% reduced), and non-worker/non-student (51% reduced) categories reporting reduced odds of any vehicle trip. Unlike the other modes of travel, higher income was associated with greater odds of making a vehicle trip (this is opposite to transit travel, where there was no significant association for income and either walking or cycling trips). Additionally, participants with a driver's license had over 15 times the odds of taking a vehicle trip (either as the driver or passenger), compared to participants without a driver's licence. In the fully adjusted model, the ratio of household vehicles to adults in the home was not significantly associated with vehicle trips. Participants in the least walkable neighbourhoods reported the greatest odds of vehicle travel; however, only the 4th walkability level was associated with a significant decrease in odds of vehicle travel.

Table 4-4: Odds of vehicle trips across walkability quintiles

	Mod 1		Mod 2		Mod 3	
	OR	95% CI	OR	95% CI	OR	95% CI
Gender						
Male	REF		REF		REF	
Female	**1.10**	**1.03, 1.18**	1.08	0.98, 1.18	1.07	0.97, 1.17
Age						
5-18	**9.06**	**7.69, 10.7**	**8.37**	**6.68, 10.5**	**7.72**	**6.16, 9.66**
19-64	REF		REF		REF	
65+	**1.34**	**1.17, 1.53**	**1.29**	**1.06, 1.57**	**1.29**	**1.06, 1.58**
Drivers License						
No	REF		REF		REF	
Yes	**14.5**	**13.0, 16.3**	**16.5**	**14.0, 19.4**	**15.7**	**13.3, 18.4**
Car share						
+1	**0.46**	**0.43, 0.50**	**0.60**	**0.51, 0.71**	**0.63**	**0.53, 0.74**
Status						
Full time employed	REF		REF		REF	
Full time student	**0.18**	**0.16, 0.20**	**0.13**	**0.11, 0.16**	**0.14**	**0.11, 0.17**
Part time or self-employed	**0.91**	**0.82, 1.01**	**0.67**	**0.57, 0.79**	**0.67**	**0.57, 0.79**
Non-worker/non-student	**0.71**	**0.62, 0.79**	**0.49**	**0.41, 0.58**	**0.49**	**0.41, 0.59**
Household income						
< $50,000	REF		REF		REF	
$50,000 - $100,000	**2.10**	**1.87, 2.35**	**1.85**	**1.55, 2.21**	**1.82**	**1.52, 2.18**
>$100,000	**2.31**	**2.06, 2.60**	**2.31**	**1.91, 2.80**	**2.24**	**1.85, 2.72**
Household size						
+1	**1.14**	**1.10, 1.17**	0.96	0.91, 1.01	**0.95**	**0.90, 0.99**
Household vehicles						
Vehicles < Adults	-		REF		REF	
Vehicles > = Adults	-		**2.23**	**1.08, 4.62**	1.93	0.93, 3.98
Bicycles						
+1	-		**1.31**	**1.14, 1.51**	**1.33**	**1.16, 1.53**
Regional Accessibility						
Vehicle	-		**0.93**	**0.91, 0.95**	**0.93**	**0.91, 0.95**
Transit	-		**1.07**	**1.06, 1.08**	**1.06**	**1.05, 1.07**
Sidewalk connectivity			-		**0.41**	**0.26, 0.63**
Walkability						
1	-		-		REF	
2	-		-		0.91	0.71, 1.17
3	-		-		0.76	0.57, 1.02
4	-		-		**0.59**	**0.42, 0.82**
5	-		-		0.69	0.42, 1.14

Notes: bolded results indicate statistical significance at p<0.05
Model 1 adjusted for gender, age, having a driver's licence, car share membership, employment status, household income, and household size. Model 2 adjusted for Model 1 variables, plus ratio of household vehicles to number of adults in household, number of household bicycles, and vehicle and transit regional accessibility. Model 3 adjusted for Model 2 variables, plus, sidewalk connectivity and 1km-network based walkability surrounding residential location.

Vehicle regional accessibility = AM vehicle trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations
Transit regional accessibility = AM transit trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations

4.4. Discussion

This chapter describes the relationship between individual, household, and neighbourhood factors and trip mode reported in TransLink's 2017 Trip Diary Data. Overall, these analyses found an increase in active travel mode trips completed (in particular walking trips) and a reduction in sedentary modes (vehicle trips) as neighrbouhood walkability increased, when adjusting for other individual, households, and neighbourhood factors. This effect was most apparent for walking trips, with each increase in niehgbourhood walkability associated with a further significant increase in walking trips. These results are consistent with previous work which found an increase in walking trips completed in more walkable neighbourhoods (Kim et al., 2020), additionally, similar individual and household characteristics were found, with women, younger age, and lower household incomes associated with completing more walking trips. This same pattern was also seen when examining utilitarian walking trips across urban areas in Canada, with increased walking trips reported in more walkable neighbourhoods (Wasfi et al., 2016). Additionally, previous work which looked at components of walkability, found that residential density and land use mixed were also independently associated with increased transportation walking (Eriksson et al., 2012).

Similar to previous work (Riggs & Sethi, 2020), there were increased odds of transit trips in more walkable neighbourhoods, however, this effect was only significant and in the two most walkable quintiles. Previous work also tended to find more biking trips complete in more walkable areas, however this was only seen in the most walkable quintile in this current analysis.

There are a number of strengths of this current work, including the generalizability to the population of the MVRD. However, the cross-sectional nature of these data limit the ability to determine cause and effect, and therefore these results represent correlations rather than causal relationships.

4.5. Conclusions

Analysis results showed that individual, household, and neighbourhood characteristics are all associated with trip mode. When controlling for other factors, living in more walkable areas was associated most strongly with reporting walking trips.

4.6. References[22]

[22] The full set of references used for this analysis are provided in the References section in Appendix G.

5. Greenhouse Gas Emissions and Walkability[23]

5.1. Background

Transportation contributes roughly one third of greenhouse gas (GHG) emissions in Canada, with the majority associated with passenger travel (Environment and Climate Change Canada, 2021). Mitigating the climate impacts of transportation is an ethical, existential imperative, and aligns with strategic plans of TransLink, British Columbia, and Canada (B.C. Ministry of Environment and Climate Change Strategy, 2021; TransLink, 2022b). Despite decades of efforts to reduce motor vehicle emissions through efficiency gains, steady increases in the quantity of travel have led to a net increase in GHG

1.1. [23] For the full article associated with this study, please see References

Eriksson, U., Arvidsson, D., Gebel, K., Ohlsson, H., & Sundquist, K. (2012). Walkability parameters, active transportation and objective physical activity: Moderating and mediating effects of motor vehicle ownership in a cross-sectional study. *International Journal of Behavioral Nutrition and Physical Activity*, *9*(1), 123. https://doi.org/10.1186/1479-5868-9-123

Kim, E. J., Kim, J., & Kim, H. (2020). Does Environmental Walkability Matter? The Role of Walkable Environment in Active Commuting. *International Journal of Environmental Research and Public Health*, *17*(4), 1261. https://doi.org/10.3390/ijerph17041261

Koohsari, M. J., Owen, N., Cole, R., Mavoa, S., Oka, K., Hanibuchi, T., & Sugiyama, T. (2017). Built environmental factors and adults' travel behaviors: Role of street layout and local destinations. *Preventive Medicine*, *96*, 124–128. https://doi.org/10.1016/j.ypmed.2016.12.021

Liao, Y., Lin, C.-Y., Lai, T.-F., Chen, Y.-J., Kim, B., & Park, J.-H. (2019). Walk Score® and Its Associations with Older Adults' Health Behaviors and Outcomes. *International Journal of Environmental Research and Public Health*, *16*(4), 622. https://doi.org/10.3390/ijerph16040622

Riggs, W., & Sethi, S. A. (2020). Multimodal travel behaviour, walkability indices, and social mobility: How neighbourhood walkability, income and household characteristics guide walking, biking & transit decisions. *Local Environment*, *25*(1), 57–68. https://doi.org/10.1080/13549839.2019.1698529

Thielman, J., Rosella, L., Copes, R., Lebenbaum, M., & Manson, H. (2015). Neighborhood walkability: Differential associations with self-reported transport walking and leisure-time physical activity in Canadian towns and cities of all sizes. *Preventive Medicine*, *77*, 174–180. https://doi.org/10.1016/j.ypmed.2015.05.011

Wasfi, R. A., Dasgupta, K., Eluru, N., & Ross, N. A. (2016). Exposure to walkable neighbourhoods in urban areas increases utilitarian walking: Longitudinal study of Canadians. *Journal of Transport & Health*, *3*(4), 440–447. https://doi.org/10.1016/j.jth.2015.08.001

Appendix H.

emissions from the transportation sector. Clearly, new and more effective strategies are needed.

GHG emissions are only one of the critical externalities of motor vehicle travel. Motor vehicles are also a major source of local air pollution, a leading cause of death through crashes, and a contributor to the myriad negative health effects of sedentary lifestyles. The core goal of the project "Where Matters II: Health and Climate Change Impacts of Transportation and Land Use Actions" (WMII) is to integrate the consideration of health and climate impacts of passenger transportation to inform land use planning in Metro Vancouver and beyond.

This chapter contributes to the emissions component of the WMII project by developing detailed emission estimates from travel survey data, and examining their association with neighbourhood walkability features. We generate emissions estimates for trips reported in TransLink's 2017 travel survey data using state-of the art estimation methods, and then summarize the estimated GHG and CAC emissions at the person and household levels. Subsequently, we use these estimates to investigate how walkability and transit accessibility relate to person- and household-level GHG emissions from travel, moderated by personal and household characteristics. Previous work has found a number of built environment factors to be associated with the amount of active travel (E. J. Kim et al., 2020; Koohsari et al., 2017; Liao et al., 2020; Thielman et al., 2015). We hypothesize that living in a more walkable neighbourhood is associated with lower transport emissions, due to the ability for more trips to be completed through walking, cycling, and transit, with fewer trips/short distance trips completed with private vehicle.

A variety of methods can be used to quantify the emissions impacts of travel. Directly measuring emissions from motor vehicles is currently impractical in a large-scale survey. Even if direct measurement were possible (such as with Portable Emissions Measurement Systems or PEMS attached to every participant's vehicle), it would only capture the tailpipe emissions during vehicle operation, and only for personally-owned private vehicle trips, which is a small scope of analysis for passenger transportation.

Emissions estimation methods enable more comprehensive analysis by relying, explicitly or implicitly, on a combination of abstractions and assumptions, which we can describe as an emissions model. The utility of the emissions estimates for subsequent analysis or decision-making depends on the relevance and consistency of the modeling method. Emissions modelling is an analysis process involving trade-offs of precision and accuracy, requiring an understanding of the uncertainties and biases associated with each data source, assumption, and modelling tool. For these reasons, we precede the description of our methodology with a brief discussion of the principles and priorities motivating our modelling approach. These principles are informed by both the WMII project objectives and the state-of-the-art in emissions modeling methods represented in the literature (Al-Rijleh et al., 2018; BC Ministry of Environment and Climate Change Strategy, 2022; Bel & Rosell, 2017; A. Bigazzi, 2019; Cerqueira et al., 2020; M. Chester & Horvath, 2009; Lee & Lee, 2020; Saleh & Hatzopoulou, 2020; Shekarrizfard et al., 2020; U.S. Environmental Protection Agency, 2022b; Venigalla et al., 2018; A. Wang et al., 2018, 2023; Xiao et al., 2017).

1. The first priority is **precision**: the estimates should as closely as possible represent the quantity of emissions attributable to observed travel in the survey data. Precision is maximized by using modelling tools that match the specificity of vehicle and travel information provided in the travel survey data. This priority also motivates use of the most temporally (October 2017) and geographically (metro Vancouver) relevant modelling data and assumptions.
2. The second priority is for **consistent accuracy** across trips in the travel survey data, to ensure comparability and avoid biasing subsequent analysis of the factors influencing person- and household-level emissions. This priority motivates the use of consistent modelling tools and assumptions across trips wherever possible, and so may require trade-offs against the first priority of precision. To avoid introducing bias, missing data should be imputed using the best available information, rather than excluded from the estimates.
3. Enabling subsequent analysis also leads to the third priority, which is incorporating **variability in emissions rates over the factors of interest**, to address the emissions implications of travel behaviour and the built environment. Relevant factors in this and the broader WMII analysis include travel mode, vehicle type, and destinations, among others. As above, this priority may require trade-offs with precision or accuracy.
4. Because the project aims to address climate impacts, the emissions estimates should include **lifecycle emissions** of passenger travel, and not be limited to operating or on-road emissions.
5. Furthermore, because the project aims to inform decision-making, the analysis should use a **consequential emissions accounting framework**, so that the GHG estimates represent the additional or marginal climate impacts of changes or differences in the observed passenger travel.

Applied to the travel survey data, the implication of these principles for modelling decisions is to explicitly account for: vehicle type, vehicle occupancy, traffic congestion, upstream and downstream activities in the vehicle and fuel lifecycles, and non-service activity of non-private vehicles. The emission estimates do not include the guideway lifecycle (i.e., road/track construction and maintenance), for which consequential attribution to person-level travel activity is highly uncertain.

To situate our methods in the literature, Table 5-1 summarizes the scope of a sample of past studies using household travel survey data to estimate personal GHG emission from daily travel. It excludes studies that only considered automobile emissions (Choi & Zhang, 2017) or only included a subset of trips such as commuting (Yang et al., 2019). Few studies have accounted for vehicle-cycle emissions, and only three others used large-sample regional travel surveys (including a very large sample from Toronto). Very few studies have employed dynamic emissions rates within modes, either, with most relying on fixed emission rates by mode. We aim to produce emissions estimates more sensitive to trip attributes by using dynamic vehicle occupancy and emission factors, sensitive to vehicle make, congestion, and other factors.

Table 5-1. Summary of past studies investigating personal GHG from travel survey data

Source	Data year	Location	Number of households	Number of persons	Number of trips	Emission scope
This study	2017	Vancouver	27,980	57,431	224,525	Fuel- and vehicle-cycle
(A. Wang et al., 2023)	2016	Toronto	162,708	395,885	798,093	Fuel-cycle
(Wu et al., 2019)	2017	Twin cities	NR	360	NR	Operating
(L. Xu et al., 2018)	2015	Xiamen City	1,125	NR	NR	Operating
(Al-Rijleh et al., 2018)	2012	Philadelphia	9,235	20,216	NR	Fuel- and vehicle-cycle
(Des Rosiers et al., 2017)	2006	Quebec City	33,859	NR	209,849	Operating
(Bel & Rosell, 2017)	2006	Barcelona	NR	24,605	93,864	Operating
(Reichert et al., 2016)	2008	Germany	25,922	60,712	NR	Fuel-cycle
(Kotval-K & Vojnovic, 2015)	2008	Detroit	NR	940	15,392	Operating
(Ma et al., 2014)	2007	Beijing	NR	1,026	NR	Operating
(Wilson et al., 2013)	2007	Halifax	1,920	NR	NR	Operating
(Barla et al., 2011a)	2002-2006	Quebec City	250	400	15,000	Operating
(L. D. Frank, Stone, et al., 2000)	1996	Seattle	~1,700	NR	~30,000	Operating

NR: Not Reported

Data partially drawn from Wang et al. (2023)

All past analyses of household emissions have used an attributional accounting framework that explicitly or implicitly assigns vehicle emissions to vehicle occupants in equal proportions (often with assumed occupancy). This approach is the most appropriate for creating an emissions inventory, because the aggregation of all person-trip emissions is expected to equal the total system emissions. In contrast, a consequential accounting framework represents the impacts of specific actions or agents within a system on total system emissions. These two frameworks produce different results when there are fixed emissions-generating activities in a system, or when vehicle activity does not change proportionally with passenger travel. Consequential accounting is more appropriate for policy analysis and decision-making because it represents how system emissions change in response to an intervention (Brander et al., 2018; Brander & Ascui, 2015; Corradi et al., 2021; Thomassen et al., 2008).

The Where Matters II project aims to quantify how the climate impacts of passenger travel are influenced by the built and natural environment. The research questions are essentially consequential, with an explicit aim to inform decision-making. The emissions estimates are only aggregated to sampled households in the analysis, and although expansion factors could be used to estimate regional emissions, there is no explicit inventory calculation in the study. Therefore, we believe a consequential accounting framework is the most appropriate for this study. However, we also acknowledge that consequential accounting is new in the transportation field (A. Bigazzi, 2019, 2020), and has been the subject of long debate in the climate analysis literature (World Resources Institute (WRI), 2014, 2015). Therefore, we calculate and report emissions estimates using both attributional and consequential accounting frameworks.

5.2. Methods

Key components of our emissions modelling framework are illustrated in Figure 5-1. Three main local data sources from TransLink are used in the emissions estimates: the Regional Travel Model (RTM), 2017 Trip Diary Data (TDD), and transit system operations data. The next section provides further information on these data sources. Auto and transit emission rate look-up tables are generated from MOVES modelling and transit system operations data, respectively. MOVES, the MOtor Vehicle Emissions Simulator, is a detailed modal motor vehicle emissions model developed by the U.S. Environmental Protection Agency from extensive data recorded from on-road and off-road vehicles (U.S. Environmental Protection Agency, 2022b). Although developed for the USA, MOVES is widely used in Canada due to its precision, adaptability using local input data, large volume of vehicle test data, and the harmonized Canada-USA vehicle fleet (Environment and Climate Change Canada, 2022; Ghafghazi & Hatzopoulou, 2014; Le Hong & Zimmerman, 2021; Requia et al., 2018; J. Xu et al., 2019). Operating auto and transit emissions are calculated by applying vehicle-and route-specific emission rates to observed trips in the TDD. Fuel economy data from Natural Resources Canada (2022) are used to adjust for variations by vehicle make and model within the MOVES vehicle type categories. Vehicle operating emissions are augmented with upstream emissions for lifecycle estimates, and then attributed to vehicle occupants and adjusted for marginality. Finally, trip emissions are aggregated up to the person and household for relational analysis. Given the complexity of the modelling and the scope of details needed to provide a replicable description of the methods, we have provided a lengthy appendix to this chapter reporting complete methodological details. The remainder of the Methods section provides a higher-level overview of the emissions estimation methods.

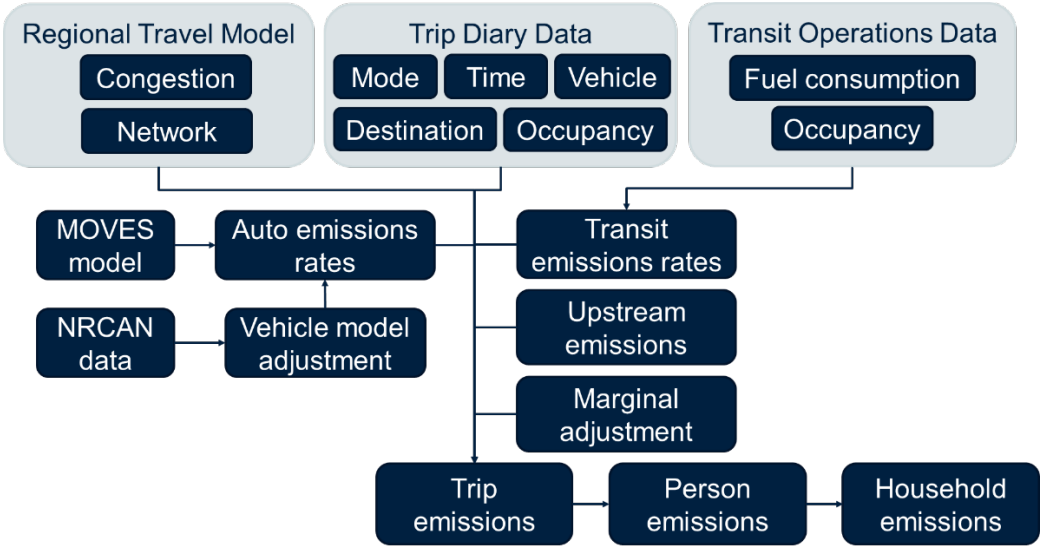


Figure 5-1. Emissions modelling framework

5.2.1. Data Sources

The main source of travel information is TransLink's 2017 Trip Diary Data (TDD) (Ipsos, 2018). Sample households for the TDD were recruited from Grater Vancouver Regional District and Fraser Valley Regional District by a pre-notification letter and followed up by telephone recruitment. Approximately 2.5% of households in the region completed the survey (83% via web survey and 17% using smartphone app). A travel diary instrument was used to record all travel by members of the sampled households over 1 day (or 3 days if they used the smartphone app) between September 15 and December 12, 2017. Person and household sampling weights are included in the TDD to account for representation differences between the sample and the regional population (as indicated by census data).

In total, the TDD consist of 224,525 trips by 57,431 persons in 27,980 households, who collectively own 37,148 motor vehicles and 35,146 bicycles. Based on the geographic study scope (see above), 1333 trips (0.59%) were excluded, leaving 223,192 trips for analysis. The primary mode shares for the analyzed trips were auto driver (55%), auto passenger (14%), walk (15%), transit (13%), and bicycle (2%) – see Table 5-2. Some trips reported in the TDD involved the use of multiple modes of travel. The TDD defines the "primary" mode as the mode that was most likely used for the largest proportion of the trip, with a hierarchy of rail transit, bus transit, then automobile and other modes for multi-modal trips (TransLink, 2013b). For emissions estimation, we disaggregate multi-modal trips into modal "segments", as described below.

Table 5-2. Modal distribution of trips in the TDD

Primary mode	Single mode	Multi-mode	Total	
Auto Driver	122,880	142	123,022	55.1%
Auto Passenger	31,336	68	31,404	14.1%
Taxi	518	3	521	0.2%
Transit Bus	11,867	819	12,686	5.7%
Sky Train	6,919	9,061	15,980	7.2%
Westcoast Express	69	161	230	0.1%
Handy Dart	150	3	153	0.1%
Sea Bus	97	90	187	0.1%
Walk	33,516	0	33,516	15.0%
Bike	4,266	5	4,271	1.9%
School bus	609	21	630	0.3%
Other mode	591	1	592	0.3%
Total	212,818	10,374	223,192	100.0%

TransLink's regional travel model (RTM) is a four-step, trip-based travel model, implemented in EMME software (TransLink, 2018). The current version of the RTM was estimated using data from TransLink's 2011 trip diary data (the predecessor to the TDD) (TransLink, 2013b). The RTM provides link-level information on peak and off-peak period

road and transit network congestion levels. The RTM road network consists of 20,043 links with an average length of 61.5 m, and the RTM transit network consists of 16,214 links with an average length of 390 m. The transit network includes all of the regularly serviced transit lines in the region, including bus, Sky Train, Sea Bus, and West Coast Express services (i.e., road, rail, and marine transit). The RTM transit network data were enhanced with TransLink's General Transit Feed Specification (GTFS) data for the period September to December 2017, including transit line attributes (TransLink, 2022a).

TransLink transit system operation data were used to generate regional, fleet-specific vehicle emission factors and vehicle occupancy (i.e., passenger loads) for metro Vancouver. These data were taken from the 2019 Transit Service Performance Review (TransLink, 2019).

5.2.2. Emissions estimates for automobile trips

Emissions for private or shared (car-share and taxi/ride-hail) automobile trips are calculated as the summation of operating (start and running) and non-operating (fuel and vehicle lifecycles) emissions processes. Non-operating emissions are attributed to vehicle-trips based on the amount of fuel and proportion of vehicle-life consumed by the trip. Vehicle-trip emissions are then attributed to person-trips based on vehicle occupancy (excluding working drivers for ride-hail services). All four automobile emission components are vehicle-dependent, and the operating emissions also vary with facility type, congestion level, and temperature.

In the TDD, auto driver and passenger trips were self-reported as made by a household vehicle (96%), another household's vehicle (3.3%), a car-share vehicle (0.4%), or a taxi/ride-hail vehicle (0.3%). For trips made as the driver of a household vehicle, the TDD includes self-reported information on the vehicle's make, model, model-year, and fuel type. The TDD includes trips made by 8,086 unique combinations of vehicle make-model-year-fuel, to which we added supplementary vehicle information from other sources (Insurance Corporation of British Columbia (ICBC), 2020; Natural Resources Canada, 2022; Transport Canada, 2021). See the full report in the appendix for details about assumptions and imputations for missing vehicle data.

Total person-trip emissions are calculated by summing the start and running vehicle emissions (by link), adjusted for deadheading, and then dividing by vehicle occupancy. Vehicle occupancy (excluding the driver for taxi/ride-hail trips) was reported for automobile trips in the TDD. If occupancy was missing, occupancy was assumed to be 1.24 for taxi trips (TransLink, 2013a), and 1.60 for all other automobile trips (the average occupancy in the TDD). For taxi/ride-hail trips, a deadheading adjustment is applied to each reported trip to account for the induced vehicle kilometres travelled (VKT) without the traveller present in the vehicle. The deadheading rate is the percent of operating VKT for taxis without a passenger present. Relevant literature reports deadheading rates of 41% to 61%, with a mean of 55% (Cramer & Krueger, 2016; Li et al., 2020, 2022; San Francisco County Transportation Authority, 2017; Sun & Ertz, 2021). We apply this value to scale up running and upstream (not start) emissions for all taxi trips in the TDD.

MOVES2014, the latest version of the MOVES model at the time of analysis (U.S. Environmental Protection Agency, 2022b), was used to create emission rate lookup tables for application to the TDD. MOVES input data were obtained from Metro Vancouver's Air Quality and Climate Change team (Metro Vancouver, 2018), augmented by data sources on vehicle fleets (Insurance Corporation of British Columbia (ICBC), 2020; Natural Resources Canada, 2022; Statistics Canada, 2010; Transport Canada, 2021), vehicle activity (TransLink, 2013a, 2013b, 2018), and archived weather station data for meteorology (Environment and Climate Change Canada, 2020; Pacific Climate Impacts Consortium, 2020; Weather Underground, 2022).

Because MOVES emission rates are uniform within vehicle type categories (for a given model-year and fuel type), we apply a make/model-specific adjustment factor to the MOVES rates (separately for city and highway road types), based on model-specific fuel economy test data. This approach enables us to leverage both the link-level congestion-sensitive emission rates from the MOVES model (by vehicle type, fuel type, model-year, and road type), and the more detailed vehicle make/model information in the TDD to account for efficiency differences by model within a given vehicle class. Model-specific fuel economy data were taken from NRCAN data (Natural Resources Canada, 2022), averaged across variations in engine size or transmission type within a given make-model-year as necessary.

Automobile trips were routed from origin to destination on the road network data as represented in the RTM. Precise locations (latitude – longitude) for origins and destinations were "snapped" (orthogonal projection) to the nearest centroid connector within their respective TAZ. The network shortest (time) path sequences of links were determined using R software (R Core Team, 2019) with the package igraph (Csárdi et al., 2023).

The non-operating emissions accounted in this analysis include those attributable to 1) upstream activities for fuel provision (i.e., "well-to-tank" (WTT) emissions), and 2) upstream (production), downstream (disposal/scrappage), and non-operating in-use (maintenance) phases of the vehicle lifecycle. Fixed upstream emission rates (in kg CO_2e per unit fuel type) are applied to the operating fuel consumption, taken from GHGenius ((S&T) Squared Consultants Inc., 2022) for petrol fuels and the B.C. Ministry of Environment and Climate Change Strategy (2022) for electricity. Non-operating emissions attributable to the vehicle cycle are calculated using the emission estimation framework applied in Kannangara et al. (2021). This framework is highly parameterized, enabling adaptability with model-specific weight and size parameters, in addition to local energy factors.

5.2.3. Public transit trips

The 29,236 reported transit trips in the TDD (65% uni-modal) were 55% by Sky Train, 43% by transit bus, and the other 2% divided among West Coast Express, Sea Bus, and Handy Dart. Emissions for transit trips are calculated as the summation of operating and non-operating (fuel and vehicle lifecycle) components. Operating and non-operating emissions are attributed to transit vehicle operation (per VKT) based on emission and fuel

consumption rates and vehicle lifecycle, and then attributed to person-trips by transit based on the transit vehicle passenger occupancy (excluding working drivers).

Per-VKT emission rates for criteria air contaminants (CAC) from buses are estimated using MOVES, as described above for automobile trips. Fuel consumption and GHG emissions for transit vehicles are based on TransLink reporting of measured transit fleet fuel consumption data for the year 2019. Annual fleet fuel consumption and GHG emissions are attributed equally to annual service km (by mode) using TransLink reported annual operations data (TransLink, 2019, 2020a). The service km exclude deadheading, but the fuel consumption data do not, and so this approach incorporates deadheading emissions into the operations-phase emissions rates. Reported fuel consumption is converted into both operating and upstream GHG emissions using BC guidance on emissions intensity by fuel (B.C. Ministry of Energy, Mines and Petroleum Resources, 2017; BC Ministry of Environment and Climate Change Strategy, 2022, 2022; (S&T) Squared Consultants Inc., 2022; TransLink, 2020b).

Transit trip routing was undertaken using the r5r package in R (Pereira et al., 2021) for all modes except Handy Dart trips (the on-demand paratransit service), which were routed using the same procedure as automobile trips. The link cost function for transit used trip purpose-specific walking, transfer, and waiting time penalties from the Regional Travel Model (RTM) (TransLink, 2018).

For transit vehicle-cycle emissions, we include the same three elements as for automobiles (manufacture, maintenance, and end-of-life), attributing lifecycle emissions equally across a vehicle's operating life VKT. Transit vehicle-cycle emissions rates are based on the literature for bus (Chan et al., 2013; M. V. Chester, 2008; Condon & Dow, 2011; Cooney et al., 2013; Lajunen & Lipman, 2016; Nordelöf et al., 2019; Pourahmadiyan et al., 2021; Spreafico & Russo, 2020; Zhao et al., 2022), rail (M. V. Chester, 2008; Del Pero et al., 2015; Gulcimen et al., 2021; Lederer et al., 2016) and ferry (Istrate et al., 2022; Schmidt & Watson, 2014).

For transit bus and Sea Bus, average peak loads by line-direction are taken from the 2019 TSPR (TransLink, 2019), with missing values imputed from non-missing values for the line. Rail occupancy was extracted from station boarding and alighting data in the TSPR with a higher spatial resolution of station-by-station rather than line-average (still by line, direction, day, and hour).

5.2.4. Other modes

Walking trips (33,516) and trips by wheelchair (41) were assumed to have zero emissions and GHG impact. Lifecycle (all upstream) GHG emissions for the 4,266 bicycle trips were calculated from the trip distance using a factor of 10.5 g CO_2e per km, based on (Sun & Ertz, 2021). There was no way to distinguish electric bicycle trips from non-motorized cycles, but they were probably a small portion (<5%) of the reported trips (Hassanpour & Bigazzi, 2023). Bicycle trips were routed on the OSM network using the r5r package in R (Pereira et al., 2021).

Motorcycle, school bus, shuttle bus, and charter bus emissions rates were generated from MOVES using the same modelling approach described above for automobile trips, supplemented with fuel-cycle and vehicle-cycle rates from the literature. See the appendix for details on the estimates for these trips, as well as the Aqua Bus, boat, and ferry trips.

The primary mode was designated as "Other/unclassified" for 143 uni-modal trips. We developed and applied a Support Vector Machine (SVM) classification algorithm with a 92% success rate to infer a mode for these trips, and then applied the relevant GHG estimation method.

5.2.5. Multimodal trips

The TDD include 10,374 trips (4.6%) reported as multi-modal, but without specific mode-change locations. We use one of two approaches to disaggregate these trips into uni-modal segments for emissions estimation. For trips including fixed-route services (e.g., rail transit, Sea Bus), we use the r5r routing function in R described above, input with the reported mode sequence for the trip. Emissions are then estimated for each of the modal segments of the trip and then summed. For trips without fixed-route services, we assume that trip segment distances for each mode in a multi-modal trip are proportional to their respective typical trip distances for uni-modal trips, and so aggregate multi-modal trip emissions as a weighted average of each constituent mode. For 86 segments of multi-modal trips designated as "Other/unclassified" mode, we use the same SVM algorithm to infer a mode as for uni-modal trips.

5.2.6. Marginal emissions adjustments

The methods up to this point have used an attributional accounting framework, apportioning vehicle emissions equally across vehicle occupants. To our knowledge, consequential emissions accounting has never been applied to household travel data, but we can build on previous work that estimated marginal emissions rates for passenger travel (consequential accounting) from average emissions rates (attributional accounting) using system-level data (A. Bigazzi, 2019). In this approach, the marginal/average emissions ratio, MAER, is calculated from two factors: the elasticity of vehicle to passenger kilometres travel (ε_v^p), and the elasticity of vehicle fuel or emission rates (per VKT) to vehicle occupancy (ε_e^θ). The MAER is estimated from local data and literature values, and then used to scale the attributional (average-rate) estimates. Details of the method are described in the appendix.

We can calculate local values of ε_v^p where dynamic vehicle occupancy data are available. From the TDD and TSPR, we do this for automobile, bus, and rail transit trips. For other modes and for ε_e^θ, we rely on the U.S.-average values reported in Bigazzi (2019, 2020). Local estimates for ε_v^p are generated from a regression model of VKT as a function of passenger kilometres travelled (PKT) and contextual factors. Automobile ε_v^p is estimated using automobile VKT and PKT from the TDD aggregated to the household (N=21,430). , and bus and rail VKT and PKT from the TSPR. Bus ε_v^p is estimated using cross-sectional data from the 2019 TSPR of bus trips and boardings per hour, which are reported by line,

direction, day type, season, and time period. A multi-level (mixed effects) model is estimated with random effects by line for 216 unique lines, with a total of 12,315 complete observations. Rail ε_v^p is estimated using cross-sectional data from the 2019 TSPR of train passenger volumes per hour, which are reported by service, station, direction, day type, and hour of the day. The TSPR data are augmented with average train (vehicle) trips per hour over the same segmenting variables, derived from the GTFS data for September through December 2019. A multi-level (mixed effects) model is estimated with random effects by station for 55 unique stations, with a total of 6,268 complete observations. All elasticity models are estimated using the plm package in R (Croissant & Millo, 2008), with heteroscedasticity-consistent standard errors estimated using the lmtest package (Zeileis & Hothorn, 2002).

5.2.7. Contextual Variables for Modelling

The *Walkability Index* is a composite measure of neighbourhood walkability, comprised of four component variables (net residential density, commercial floor area, intersection density, and land use mix). Within this current analysis, the walkability value for each household was defined as the composite index value within a 1-kilometre network buffer, which follow a walkable road network, surrounding the location of the home (as defined by home 6-digit postal code). The values for each component measure were calculated beginning at the home postal code location and were then converted to z-scores to calculate the overall walkability index. The 1-km network buffer size was selected to represent the distance individuals could reasonably travel in a 10–15-minute walking trip and has been previous used to define the home "neighbourhood" area. (Colabianchi et al., 2007).

In addition to neighbourhood walkability, regional accessibility and sidewalk connectivity were calculated at the 6-digit postal code level and linked to the residential location. Regional accessibility was calculated by the mean number of minutes to travel to regional locations from the home location in morning peak traffic. These values were calculated for both vehicle travel, which provides an estimation of peak travel time from the home location if traveling by vehicle, as well as for transit travel, which conversely provides as estimation of peak travel time from the home if traveling by transit. Additionally, sidewalk connectivity, a measure of the completely of the pedestrian infrastructure, was calculated using methods similar to the walkability index in the 1-km network buffer surrounding the home.

Individual and household demographic data were obtained from the TDD. For this current analysis the following variables were utilized and categorized as follows: gender (dichotomized as female or male), age (categorized as child/youth [age 5-18], adult [age 19-64], and older adult [65+]), driver's license status (dichotomous yes/no), car share status (continuous 0-4, the number of car share membership participants reporting having), employment status (categorized as 'full time employed', 'full time student', 'part time worker or student, or self-employed' or 'non-worker/non-student'), household income (categorized as <$50,000, $50,000-100,000, and >$100,000), household size (continuous 1-10), number of household bicycles (continuous 0-10), number of vehicles

per adult in the home (dichotomized as less vehicles than adults [vehicles < adults] and 1 or more vehicle per adult in the home [vehicles > = adults]).

5.2.8. Statistical Analysis

We calculated descriptive statistics to characterize the study sample stratified by neighhourhood walkability. Adjusted associations and 95% confidence intervals (CI) were calculated using linear regression and three iterations of adjustment variables. Three adjustment models were developed based on existing literature and conceptual understanding of individual and environmental factors associated with travel behaviour. Multi-level (mixed effects) models were developed to account for the hierarchical nature of the TDD (e.g., multiple participants living in the same household). A two-level model was used to account for clustering of participants within households. Additionally, survey weights obtained from the TDD were utilized in these analyses. All analyses were completed in R version 3.6.1; we used the *glmer()* function within the 'lme4' package to run generalized linear mixed-effect models (Bates et al., 2015).

5.3. Results

This section summarizes the emission estimation results for the observed trips in the TDD. A subsequent chapter investigates relationships between these emissions quantities and household and environmental attributes. The summary values for the TDD emissions are unweighted unless stated otherwise (i.e., without applying sampling or expansion weights), and so are not representative of regional emissions.

5.3.1. Attributional emissions

Table 5-3 summarizes the segment-level occupancy, PKT, and emissions intensity by segment mode. The values are aggregated across segments (not weighted by distance). Start and running emissions are combined to give per-PKT operating emissions. The table shows that emissions intensity varies widely across trips, especially for the automobile and main transit modes (bus and rail), for which dynamic occupancy values were used. Occupancy is a key determinant of per-PKT emissions intensity. Per-VKT emission rates vary as well, depending on vehicle type, fuel, congestion level, and other factors (varying across modes). The varying emissions intensities within modes is a strength of this analysis, which produced emissions estimates more sensitive to trip attributes than the more common approach of applying fixed per-PKT emissions rates by mode.

Table 5-3. Occupancy, PKT, and GHG intensity by segment mode

Segment mode	Occupancy (persons/vehicle)		PKT		Operating (g CO2e/PKT)		Non-operating fuel (g CO2e/PKT)		Non-operating vehicle (g CO2e/PKT)	
	mean	s.d.[1]	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
Auto driver	1.38	0.68	10.04	11.52	257.53	216.11	91.83	71.46	69.28	26.09
Auto passenger	2.45	0.85	8.60	10.93	121.97	141.48	43.15	44.07	33.03	10.38
Taxi	1.24	0.00	7.28	8.91	130.03	24.36	37.37	5.70	192.73	0.00
Motorcycle	1.15	0.00	9.81	13.53	243.60	74.84	88.39	25.65	55.68	0.00
Transit bus	35.26	16.29	4.67	5.07	42.38	43.76	13.05	12.27	6.13	5.32
School bus	56.00	0.00	10.37	12.53	18.97	11.28	6.36	3.68	4.52	0.00
Shuttle	21.37	0.00	13.49	22.76	38.80	4.15	13.63	1.45	7.77	0.00
SkyTrain	40.19	31.89	8.54	6.79	0.00	0.00	3.90	4.03	9.70	10.02
Westcoast Express	120.47	71.70	19.95	14.92	19.70	18.34	8.28	6.38	6.96	10.84
SeaBus	124.82	23.39	2.78	1.10	185.46	36.81	58.10	11.53	11.05	2.19
Aqua Bus	4.00	0.00	5.87	7.15	56.34	0.00	36.51	0.00	3.64	0.00
Ferry	366.00	0.00	11.12	8.56	191.08	0.00	59.86	0.00	7.30	0.00
HandyDart	1.31	0.00	7.96	5.60	467.97	60.00	161.40	0.00	126.72	0.00

[1] standard deviation

Table 5-4 gives GHG emissions estimates per trip by primary mode. Figure 5-2 illustrates these values normalized by PKT to illustrate GHG intensity by primary mode. Note that the trip-aggregated values include emissions from other modal segments in the trips. For example, the Sky Train generates no operating emissions, but Sky Train trips that are accessed by automobile or transit bus include those operating emissions.

Table 5-4. Mean GHG emissions per trip by primary mode (g CO2e)

Primary mode	Number of trips	PKT	Operating (running)	Operating (start)	Non-operating (fuel)	Non-operating (vehicle)	Total
Auto Driver	123021	10.1	2079	109	797	714	3699
Auto Passenger	31404	8.6	785	52	304	287	1428
Taxi	521	7.3	790	47	247	1408	2491
Transit bus	12686	7.8	310	7	101	52	471
Sky Train	15980	15.1	300	15	145	176	635
West Coast Express	230	36.1	1668	77	605	456	2806
Sea Bus	187	8.6	996	30	338	197	1560
Handy Dart	153	8.1	3579	95	1296	1019	5988
School bus	630	10.6	206	5	70	54	335
Bike	4271	4.5	1	0	0	48	49
Walk	33516	1.0	0	0	0	0	0
Other mode	591	11.0	1379	54	526	366	2325
Total	223190	8.6	1306	70	502	456	2334

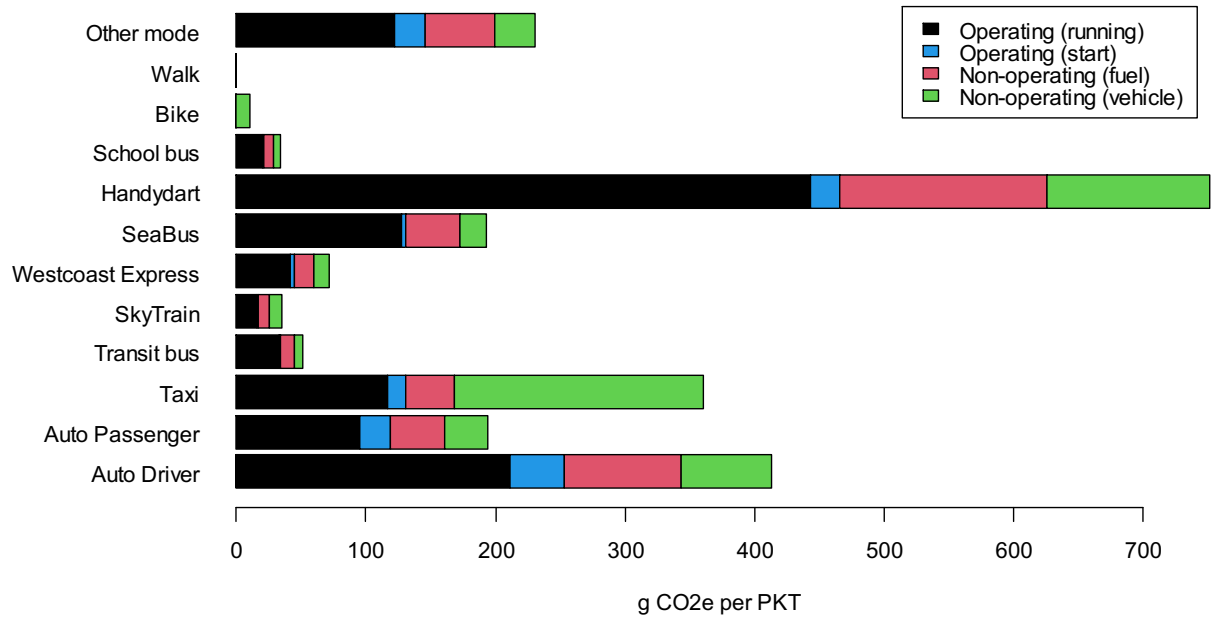


Figure 5-2. Average emissions intensity per PKT by primary mode

Table 5-5 gives average CAC emissions per trip by the same set of primary modes – again aggregating emissions from all trip segments.

Table 5-5. Average trip CAC emissions (g) by primary mode

Primary mode	CO	NOx	VOC	$PM_{2.5}$
Auto Driver	21.905	2.011	1.311	0.097
Auto Passenger	6.220	0.469	0.362	0.034
Taxi	2.987	0.165	0.204	0.073
Transit bus	1.825	0.786	0.125	0.027
Sky Train	2.195	0.572	0.145	0.022
West Coast Express	8.344	0.638	0.493	0.037
Sea Bus	4.541	0.419	0.288	0.022
Handy Dart	107.546	14.212	6.391	0.437
School bus	0.850	1.011	0.223	0.097
Bike	0.007	0.000	0.000	0.000
Walk	0.000	0.000	0.000	0.000
Other mode	41.020	2.402	4.649	0.090
Total	13.414	1.280	0.809	0.063

Table 5-6 reports summary statistics for further aggregated emissions up to the person and household levels, as both total daily GHG and GHG intensity per PKT. Emissions rates across the TDD sample vary widely, with interquartile ranges larger than the mean values. The 75th percentile persons and households are generating 8 to 10 times the daily

emissions of the 25th percentile persons and households. Some of this is due to higher PKT, but emissions intensity (g CO2e per PKT) also varies by a factor of 3 to 5.

Table 5-6. Person- and household-level aggregate GHG measures

Measure	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
Person-level total PKT	0.10	11.47	26.01	40.02	51.92	672.33
Household-level total PKT	0.16	21.59	47.95	73.10	96.60	1,463.80
Person-level total daily GHG (g CO2e)	0	1,347	5,483	10,814	14,158	396,433
Household-level total daily GHG (g CO2e)	0	3,502	11,964	19,753	26,562	589,654
Person-level GHG intensity (g CO2e per PKT)	0	82	232	251	385	2,700
Household-level GHG intensity (g CO2e per PKT)	0	122	269	265	388	2,406

Applying the TDD person and household sampling weights, the weighted mean daily PKT is 36.91 per person and 91.39 per household, generating weighted mean emissions of 10.18 kg CO_2e per person and 25.21 kg CO_2e per household. Weighted mean GHG intensity of travel is 251.6 or 276.6 g CO_2e per PKT, averaged at the person or household levels, respectively. The weighted median daily PKT is 21.22 per person and 61.80 per household, generating weighted median emissions of 3.90 kg CO_2e per person and 16.12 kg CO_2e per household. Weighted median GHG intensity of travel is 234.2 or 283.3 g CO_2e per PKT, averaged at the person or household levels, respectively. The household weighting has a greater impact than person weighting, due to a stronger relationship between weights and emissions at the household level. Household and person weights both range from 0.169 to 808.696, with median values of 26.087 and 24.453 and mean values of 47.736 and 39.569 for person and household weights, respectively. Person weights have a correlation of 0.052 with person-level GHG, whereas household weights have a correlation of 0.202 with household-level GHG.

As an external validation, in Figure 5-3 we compare our running emissions estimates to the emission rates from BC's Provincial emission factors by vehicle type and fuel type, which applied in 2017 (BC Ministry of Environment and Climate Change Strategy, 2022). Upstream fuel cycle emissions are included for battery electric and hybrid vehicles only, for comparability to the reference BC data. The central values are similar, but with greater variation in our estimates due to the inclusion of additional influencing factors (vehicle make, speed, road type, etc.).

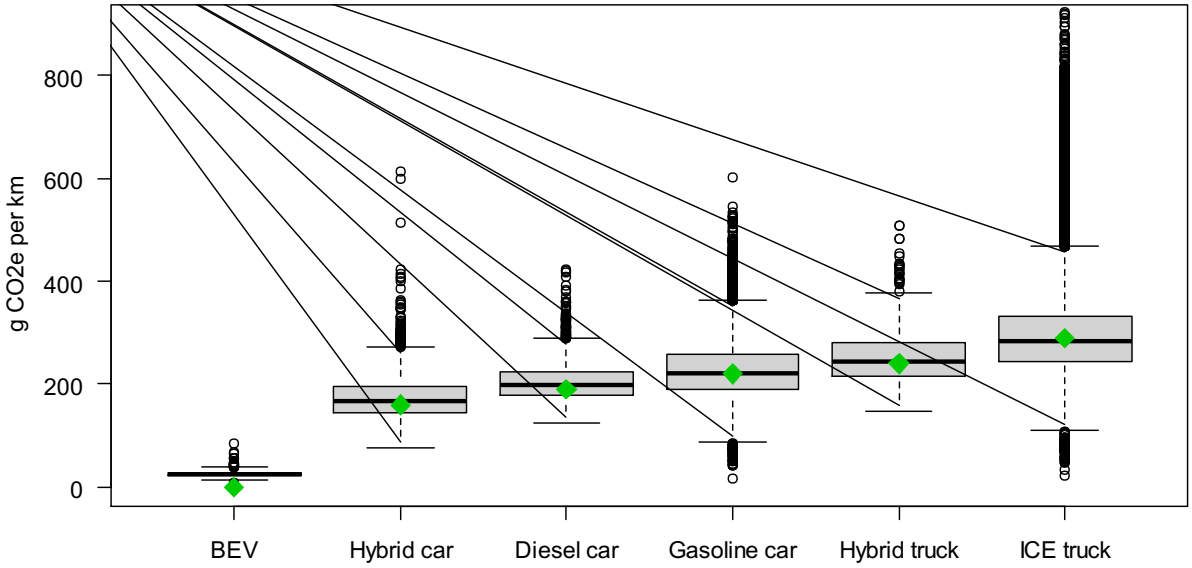


Figure 5-3. Comparison of our emission estimates for automobile trips (boxplots) to rates in BC Provincial guidance (green diamonds); including upstream fuel cycle emissions for BEV and hybrid powertrains for comparability

As another external validation, Wang et al. (2023) computed daily GHG emissions for the sample of trips in Toronto's 2016 household travel survey data. They report median personal daily GHG emissions from travel of 6.5 kg CO2e, and median GHG intensity of travel of 210 g CO2e per PKT. In comparison, we calculate median values of 5.5 kg CO2e/person/day and 232 g CO2e per PKT for the TDD. These values are similar, providing a good external validation on the estimates, despite different regions of analysis (Toronto is a larger but less dense region). In addition, there were several important differences in the estimation methods, including:

1. We include vehicle cycle emissions while they do not,
2. We include vehicle make/model adjustments to MOVES-modeled fuel efficiency by vehicle class/fuel, which they do not,
3. We use vehicle-specific fuel and powertrain types (gasoline, diesel, HEV, PHEV, and BEV) rather than assuming all passenger vehicles are gasoline-fuelled and all buses are diesel-fuelled,
4. We include dynamic passenger occupancy for automobile (from the TDD) and the primary transit modes (from operational data) rather than fixed occupancy by mode and time period (extracted from a travel demand model),
5. Our transit emission factors (per VKT) are based on measured fuel consumption data, rather than MOVES estimates (petrol buses) or manufacturer information (electric buses and trains),
6. We use a fixed GHG intensity for Provincial electricity *consumption*, rather than a dynamic GHG intensity for Provincial electricity *production*,

7. We attribute automobile emissions equally to all vehicle occupants, rather than only to the driver, and
8. We estimate emissions from all reported trips (with necessary assumptions) rather than excluding "other" modes.

Note also that due to skewed distributions and varying trip lengths and household sizes, these aggregate measures vary greatly if using mean versus median values, or aggregating by trip, person, or household. For further comparisons, mean daily GHG emissions per person from travel has been reported as 6.8 kg CO2e in Quebec City in the early 2000's (Barla et al., 2011a), and just 0.6 kg CO2e in Xiamen City, China in 2015 (L. Xu et al., 2018).

5.3.2. Consequential emissions

Applying the estimated local values and literature elasticities we generate the MAER (marginal to average emissions ratios) given in Table 5-7. The MAER scaling factors are applied to trip segments by mode (multiplying by the previously-calculated attributional g CO_2e), and then summed to trip total consequential (marginal) emissions estimates in g CO_2e.

Table 5-7. MAER applied to the TDD emissions estimates

Mode	ε_e^θ	ε_v^p	MAER
Auto driver or passenger	0.040	0.977[1]	0.978
Motorcycle or taxi	0.040	0.977[1]	0.978
Transit bus	0.160	0.365[1]	0.467
SkyTrain	0.050	0.332[1]	0.365
Westcoast Express	0.050	0.135[1]	0.178
School bus	0.160	0.365[1]	0.467
Shuttle	0.100	0.858	0.872
SeaBus, Aqua Bus, ferry	0.050	0.431	0.459
HandyDart	0.100	0.763	0.787
Bicycle, walk, wheelchair	0.000	1.000	1.000

[1] From local data; others from Bigazzi (2019, 2020)

Figure 5-4 illustrates the consequential versus attributional (i.e., marginal versus average rate) emissions estimates by trip. The trip-level comparison aggregates segment-level differences of multi-modal trips, which is particularly relevant for transit trips with substantial (high-emitting) access and egress segments. Figure 5-4 shows that the consequential and attributional accounting frameworks generate substantially different emissions estimates for some but not all trips. The ratio of consequential to attributional emissions estimates by trip averages 0.91 (0.97 if emissions-weighted) and ranges from 0.18 to 1.00, with 25th, 50th, and 75th percentile values of 0.98 (due to the preponderance of automobile trips).

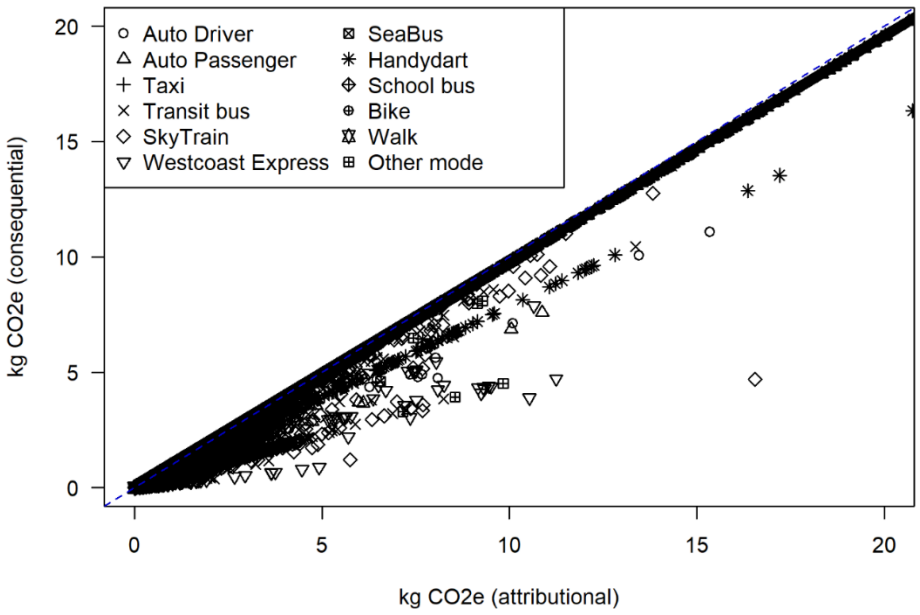


Figure 5-4. Trip-level attributional (average-rate) versus consequential (marginal-rate) emissions by primary trip mode; bounds truncated for legibility; blue dashed line denotes equivalent values

Given the variability in the effect of accounting framework on trip-level emissions, we estimated a regression model to examine the relationships between person and household-level factors and the difference between the two types of emissions estimates (in g CO2e). The results show that differences between the estimates are larger for people and households who use more low-MAER modes (particularly transit). Applying a consequential (vs. attributional) framework disproportionately increases the apparent climate impacts of travel for licensed drivers, younger (<19 years of age) and older (≥65 years of age) travellers, and households with more vehicle ownership or higher income, and disproportionately decreases the apparent climate impacts of travel for car-share members, larger households and renters.

5.3.3. Relationship between Emissions and Walkability

Table 5-8 shows the association between individual, household, and built environment factors and individual daily GHG emissions from travel (g CO_2e). Results of similar model specifications for local air pollution emissions (CO, PM2.5, and NOx) and the consequential CO_2e emissions are given in Appendix H

References

Eriksson, U., Arvidsson, D., Gebel, K., Ohlsson, H., & Sundquist, K. (2012). Walkability parameters, active transportation and objective physical activity: Moderating and mediating effects of motor vehicle ownership in a cross-sectional study. *International Journal of Behavioral Nutrition and Physical Activity*, *9*(1), 123. https://doi.org/10.1186/1479-5868-9-123

Kim, E. J., Kim, J., & Kim, H. (2020). Does Environmental Walkability Matter? The Role of Walkable Environment in Active Commuting. *International Journal of Environmental Research and Public Health*, *17*(4), 1261. https://doi.org/10.3390/ijerph17041261

Koohsari, M. J., Owen, N., Cole, R., Mavoa, S., Oka, K., Hanibuchi, T., & Sugiyama, T. (2017). Built environmental factors and adults' travel behaviors: Role of street layout and local destinations. *Preventive Medicine*, *96,* 124–128. https://doi.org/10.1016/j.ypmed.2016.12.021

Liao, Y., Lin, C.-Y., Lai, T.-F., Chen, Y.-J., Kim, B., & Park, J.-H. (2019). Walk Score® and Its Associations with Older Adults' Health Behaviors and Outcomes. *International Journal of Environmental Research and Public Health*, *16*(4), 622. https://doi.org/10.3390/ijerph16040622

Riggs, W., & Sethi, S. A. (2020). Multimodal travel behaviour, walkability indices, and social mobility: How neighbourhood walkability, income and household characteristics guide walking, biking & transit decisions. *Local Environment*, *25*(1), 57–68. https://doi.org/10.1080/13549839.2019.1698529

Thielman, J., Rosella, L., Copes, R., Lebenbaum, M., & Manson, H. (2015). Neighborhood walkability: Differential associations with self-reported transport walking and leisure-time physical activity in Canadian towns and cities of all sizes. *Preventive Medicine*, *77,* 174–180. https://doi.org/10.1016/j.ypmed.2015.05.011

Wasfi, R. A., Dasgupta, K., Eluru, N., & Ross, N. A. (2016). Exposure to walkable neighbourhoods in urban areas increases utilitarian walking: Longitudinal study of Canadians. *Journal of Transport & Health*, *3*(4), 440–447. https://doi.org/10.1016/j.jth.2015.08.001

Appendix H Across each type of emissions analyzed, reduced emissions are consistently associated with living in more walkable areas. Walkability results are presented as change in travel-related emissions compared to the reference level of least walkable areas. A graded relationship (dose-response) was shown across walkability bins for CO_2 emissions – with each increase in walkability associated with further reductions in CO_2 emissions, all of which were significantly different from the reference level. Levels 3 through 5 are also significantly different from level 2. The results for consequential CO_2 emissions are similar to those for attributional CO_2 emissions, but with a slightly stronger relationship to walkability. For $PM_{2.5}$ and NOX, more walkable (e.g., all walkability bins compared to the reference "least walkable" level) neighbourhoods were also associated with statistically significant reductions in emissions. However, although CO and VOC emissions were reduced across all walkability bins compared to the reference level, the reductions were not monotonic nor statistically significant across all walkability bins.

Conversely, more greenness around the home location was associated with higher travel emissions. After adjusting for walkability and greenness, sidewalk connectivity around the home location was not statistically significant, but regional transit and vehicle accessibility were both associated with significantly higher travel-related emissions.

Across all models and emissions, reporting female gender (compared to male) was associated with lower emissions, as was being in the youngest age group (5-18). Having a driver's licence, and a higher ratio of vehicles to adults living in the home, were also associated with significantly higher emissions estimates across all models. Higher household income tended to be associated with higher emissions, however these results were not consistently statistically significant. Additionally, being a full-time student, or a non-worker/non-student was associated with significantly lower emissions across all models compared to full-time workers.

Table 5-8. CO2e emissions (g/day) model estimation results

		Model 1[1]	Model 2	Model 3
Gender				
	Male	Reference	Reference	Reference
	Female	**-4512**	**-4490**	**-4501**
Age				
	5-18	**-2904**	**-3112**	**-3215**
	19-64	Reference	Reference	Reference
	65+	-246	-464	-537
Driver's License				
	No	Reference	Reference	Reference
	Yes	**12295**	**12037**	**11892**
Car share				
	+1	**-652**	-461	-224
Status				
	Full time employed	Reference	Reference	Reference
	Full time student	**-5461**	**-5555**	**-5608**
	Part time employed/student or self-employed	**-2680**	**-2865**	**-2946**
	Non-worker/non-student	**-11007**	**-11196**	**-11323**
Household income				
	< $50,000	Reference	Reference	Reference
	$50,000 - $100,000	**1686**	**1250**	**1045**
	>$100,000	**3336**	**2390**	**2022**
Household size				
	+1	**-564**	**-507**	**-686**
Household vehicles				
	Vehicles < Adults	-[3]	Reference	Reference
	Vehicles > = Adults	-	**3438**	**3054**
Bicycles				
	+1	-	**1025**	**862**
Regional Accessibility[2]				
	Vehicle	-	32	**74**
	Transit	-	**103**	**59**
Sidewalk connectivity				-1113
Walkability				
	1	-	-	Reference
	2	-	-	**-1657**
	3	-	-	**-3168**
	4	-	-	**-4394**
	5	-	-	**-4561**
Greenness				
	1	-	-	Reference
	2	-	-	**1331**
	3	-	-	**1236**
	4	-	-	**2679**
	5	-	-	**3357**

[1] Bolded values indicate statistical significance at $p<0.05$

[2] Vehicle regional accessibility = AM vehicle trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations; Transit regional accessibility = AM transit trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations

[3] '-' indicates variables not included in the model specification

Figure 5-5 illustrates the model results, relative to the median daily GHG emission rate of 5.48 kg CO_2e per day (applied to the middle bin 3). Daily GHG emissions are half as high in bin 4 versus bin 1, with only a small reduction between the 4th and 5th bins. In percentage terms, emissions rates fall by 19 to 22% at each successive walkability tier until bin 5, at which they fall by 4%.

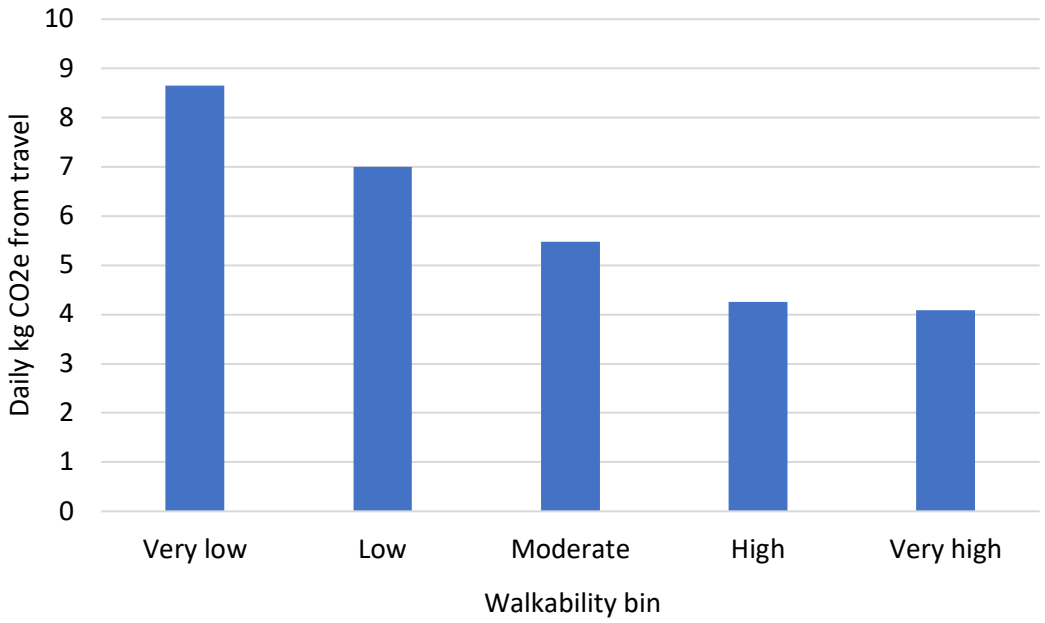


Figure 5-5. Illustration of GHG model results by walkability bin (assuming median GHG emissions for the middle bin)

5.4. Discussion

This chapter described the process of generating emissions estimates for all household travel reported in TransLink's 2017 Trip Diary Data. These emissions estimates were then used to investigate the factors influencing travel-related emissions in Metro Vancouver, which are presented in a subsequent chapter. To provide the best possible information for the statistical analysis, the estimation methods prioritized precision, consistency, sensitivity, and comprehensiveness. We used state-of-the-art models and the best available data to produce emissions estimates that are sensitive to vehicle make and type, occupancy, congestion, and other factors.

The statistical analysis results are consistent with previous findings in other locations which tended to find both individual and neighbourhood factors were associated with the individual emissions generated for daily travel purpose. Previous work across multiple locations have found that individuals and households living in more walkable neighbourhoods tended to generate lower travel related emissions, which may be attributed to the features of these neighbourhoods promoting the use of active travel modes, as opposed to private vehicles, being used to make daily trips (Darwish et al., 2023; L. D. Frank, Jr, et al., 2000, p. 200; Rickwood et al., 2008; Steemers, 2003; A. Wang et al., 2023; Wu et al., 2019). Additionally, these current results found similar

patterns in individual characteristics which tended to be associated with emissions generates, including that higher income households tend to produce higher travel based emissions, which has previously been attributed to these households making more driving trips and owning more household vehicles (Barla et al., 2011b; Brand & Preston, 2010; Kahn, 1998; Ko et al., 2011; Sider et al., 2013).

Two novel aspects of our methodology are applying a vehicle-model adjustment to the MOVES-modelled emissions rates to account for both congestion/roadway effects and sub-vehicle-class variation in efficiency, and accounting for dynamic transit vehicle occupancy in attributing vehicle emissions to passengers. In contrast to the more common method of using fixed per-PKT emission rates by mode, our approach reveals highly dynamic intra-modal emissions intensity. This sensitivity to trip and traveller attributes beyond trip distance and mode is important for the subsequent analysis of the factors that influence emissions from household travel.

In addition, to our knowledge this is the first study to apply a consequential accounting framework to estimate the climate impacts of household travel. By reporting both attributional and consequential values, the results provide insights into the bias that can result from application of an inappropriate framework. We hope this methodical innovation advances the state of practice in climate analysis for the transportation sector.

Despite these strengths, the emissions data must be qualified with the caveat that they are estimates only, relying on the TDD, modelling tools (e.g., MOVES), additional data sets (e.g., NRCAN fuel economy database), and various assumptions (e.g., imputing missing vehicle data). Each model and data source has its own uncertainties, which are compounded in a modelling effort such as this (Dey et al., 2019; Frey, 2007). We have employed measured data wherever possible (e.g., transit operations), but a comprehensive accounting requires best estimates where direct information is lacking.

5.5. Conclusions

Modelling results showed that individual, household, and neighbourhood characteristics are all associated with travel-related emissions. When controlling for other factors, living in more walkable areas was associated with generating lower travel-related emissions. The largest emissions reductions are obtained by increasing walkability over the first 4 bins, with roughly half the daily emissions for bin 4 versus bin 1; the emissions benefits of increasing walkability further to bin 5 are much smaller (a 4% reduction).

5.6. References[24]

1.2. [24] The full set of references used for this analysis are provided in the References section in References

Eriksson, U., Arvidsson, D., Gebel, K., Ohlsson, H., & Sundquist, K. (2012). Walkability parameters, active transportation and objective physical activity: Moderating and mediating effects of motor vehicle ownership in a cross-sectional study. *International Journal of Behavioral Nutrition and Physical Activity*, *9*(1), 123. https://doi.org/10.1186/1479-5868-9-123

Kim, E. J., Kim, J., & Kim, H. (2020). Does Environmental Walkability Matter? The Role of Walkable Environment in Active Commuting. *International Journal of Environmental Research and Public Health*, *17*(4), 1261. https://doi.org/10.3390/ijerph17041261

Koohsari, M. J., Owen, N., Cole, R., Mavoa, S., Oka, K., Hanibuchi, T., & Sugiyama, T. (2017). Built environmental factors and adults' travel behaviors: Role of street layout and local destinations. *Preventive Medicine*, *96*, 124–128. https://doi.org/10.1016/j.ypmed.2016.12.021

Liao, Y., Lin, C.-Y., Lai, T.-F., Chen, Y.-J., Kim, B., & Park, J.-H. (2019). Walk Score® and Its Associations with Older Adults' Health Behaviors and Outcomes. *International Journal of Environmental Research and Public Health*, *16*(4), 622. https://doi.org/10.3390/ijerph16040622

Riggs, W., & Sethi, S. A. (2020). Multimodal travel behaviour, walkability indices, and social mobility: How neighbourhood walkability, income and household characteristics guide walking, biking & transit decisions. *Local Environment*, *25*(1), 57–68. https://doi.org/10.1080/13549839.2019.1698529

Thielman, J., Rosella, L., Copes, R., Lebenbaum, M., & Manson, H. (2015). Neighborhood walkability: Differential associations with self-reported transport walking and leisure-time physical activity in Canadian towns and cities of all sizes. *Preventive Medicine*, *77*, 174–180. https://doi.org/10.1016/j.ypmed.2015.05.011

Wasfi, R. A., Dasgupta, K., Eluru, N., & Ross, N. A. (2016). Exposure to walkable neighbourhoods in urban areas increases utilitarian walking: Longitudinal study of Canadians. *Journal of Transport & Health*, *3*(4), 440–447. https://doi.org/10.1016/j.jth.2015.08.001

Appendix H.

Health Impacts

6. Obesity, Diabetes & Hypertension with Walkability – Longitudinal Adult Associations Between Walkability and Incident Obesity, Hypertension, and Type 2 Diabetes[25]

6.1. Background

Obesity and obesity-related diseases continue to adversely impact health and economic indicators across low, middle, and high income countries (Shekar & Popkin, 2020; World Health Organization (WHO), 2016). The prevalence of obesity worldwide has tripled in the last 50 years and is responsible for nearly three million premature deaths annually (World Health Organization (WHO), n.d.). Overweight and obesity are linked to increased risk of numerous chronic conditions including type 2 diabetes mellitus (T2DM) and high blood pressure (HBP), which are leading causes of cardiovascular disease and premature mortality globally (Leon & Maddox, 2015; Mills et al., 2020), as well as many cancers.

Living in walkable environments has been linked to significantly higher levels of PA and active travel across multiple age groups (Carlson et al., 2017; Cerin et al., 2017; L. Frank et al., 2016; Grasser et al., 2012; J. Sallis et al., 2016). Research has shown several macro-level, built environment features support walkability, including, having a mix of land uses in close proximity (i.e. destination diversity), greater residential density, higher retail floor area ratio, and a well-connected road network (L. D. Frank et al., 2005; Saelens & Handy, 2008). Among adults, there is growing evidence linking GIS-measured walkability to lower prevalence of obesity and metabolic disorders. Several recent reviews show generally consistent inverse relationships between walkability and body weight or obesity, hypertension and diabetes (S. Barbosa et al., 2019; Chandrabose, Cerin, et al., 2019; L. D. Frank et al., 2022; Jones et al., 2021; J. Sallis et al., 2016; Tarlov et al., 2020a), though findings are mixed. Obesity is the most studied of these outcomes, although most research to date has been cross-sectional. Longitudinal studies have commonly utilized a single baseline walkability measure, with repeated health measures over time. This chapter aims to contribute to our understanding of temporal relationships between longitudinal, objectively measured walkability and reported health outcomes.

Using data from an observational, longitudinal cohort in British Columbia, this study investigated associations between change in objectively-measured walkability and incident obesity, HBP, and T2DM. We hypothesized that walkability would be inversely related to odds of becoming obese or starting treatment for HBP or T2DM at follow up. In secondary analyses, we additionally studied whether relationships differed across demographic characteristics, including sex, age, and income.

[25] For the full article associated with this study, please see Appendix D.

6.2. Methods

6.2.1. Analytic sample

The current study used data from the British Columbia Generations Project (BCGP), the largest longitudinal health study in British Columbia. Details have been published elsewhere but, in brief, BCGP prospectively follows a cohort of nearly 30,000 adults from 35 to 69 years of age (Dhalla et al., 2019). This analysis includes data only from participants residing in the Metro Vancouver and Fraser Valley Regional Districts to maximize potential change in walkability over time (n=12,181). Between 2009 and 2013, participants were recruited to complete baseline questionnaires on health, lifestyle factors and medical histories and roughly half of the full sample had physiological measures collected in person at an assessment center. From 2016 to 2019, participants were invited to complete follow-up surveys on health and lifestyle factors, with approximately three-quarters of the original sample contributing data.

6.2.2. Exposure Variable

GIS-based walkability index: Participant-level walkability was assessed using a validated composite index which includes four built environment features: land use mix ((LUM) diversity of destinations), intersection density ((IDENS) street connectivity), net residential density ((NRD) housing density), and commercial floor-to-area ratio ((CFAR) ratio of floor area to lot size) (L. D. Frank et al., 2010a). A walkability score was created for each postal code which, on average, covers roughly 19 Canadian households and has been shown to provide acceptable positional accuracy, especially in urban areas (Khan et al., 2018; Pinault et al., 2020). The index was applied to a 1km road network buffer from participants' postal code centroid. Participants provided their residential history since childhood. An average of each walkability component feature was calculated for participants' residential locations from 2000-2006 (baseline) and 2012-2016 (follow up). We created the baseline and follow up walkability indices by calculating z-scores for each of the 4 components (LUM, IDENS, NRD, CFAR) using 2006 mean and standard deviations for the main urbanized areas of the region excluding rural hinterlands (*Statistics Canada*, n.d.). Standardizing to baseline regional walkability provides a measure of how individuals' walkability compares to the region and how it has changed over time. Change in walkability was the sum of zCFAR + zLUM + zIDENS + zNRD at follow up minus the sum in baseline. We additionally quintiled the change in walkability score to explore the relationship between walkability and the outcomes of interest in more depth.

6.2.3. Outcome Variables

Obesity: At baseline, participants (n=8,100) had height and weight measured at an assessment center; participants (n=3,696) not attending an assessment center provided self-reported height and weight. At follow up, all height and weight data were self-reported. BMI was calculated as the weight in kilograms divided by the height in metres squared and a binary obesity variable was created (BMI ≥30 or BMI <30). Incident obesity was defined as shifting from not obese at baseline to obese at follow up.

Hypertension: At both baseline and follow up, participants were considered to have prevalent hypertension if they reported currently being treated for high blood pressure or hypertension. Those not treated for hypertension at baseline and treated at follow up were considered to have incident hypertension.

Diabetes: At baseline, participants were considered to have type 2 diabetes if they reported being currently under treatment for diabetes and having been diagnosed with type 2 diabetes. At follow up, participants reported whether they were currently under treatment for type 2 diabetes. Incident T2DM was defined as a change from not being treated at baseline to currently being treated for at follow up.

6.2.4. Covariates

Participant demographics were collected through the health and lifestyle questionnaire and included age, male/female sex. Racial and ethnic descent was classified as "White or European", "Some other descent", or "Unknown". Baseline income was dichotomized into "≤74,999" or "≥$75,000", to approximate above or below median income in the Vancouver area during baseline data collection. We also adjusted models for the length of time (in years) between the baseline and follow up assessment.

6.2.5. Statistical Analysis

Descriptive statistics compared baseline participant characteristics across change in walkability quintiles using ANOVA for continuous and χ^2 for categorical variables. We used mixed effects regression models to assess associations between change in walkability (as a continuous variable) with binary incident obesity, T2DM, and HBP status, in separate models. We also modeled change in obesity status by quintiled change in walkability. Mixed model analyses allow for missing observations in studies with repeated measures, avoiding bias associated with complete case analysis (Gabrio et al., 2022). To account for non-independence of repeated measures, we included participant ID as a random effect. We assessed clustering by Forward Sortation Area (the geographical unit designated by the first 3 digits in Canadian postal codes) and found it accounted for less than 1% of total variance so did not include it in models. All models adjusted for sex, age, racial/ethnic descent, baseline income, and length of time between assessments. We conducted a sensitivity analysis including only those with self-reported height and weight data at both assessments to test the robustness of results. We additionally explored associations within individual subgroups, including sex (female/male), age (above/below 60 years), and baseline income (above/below $75,000). All analyses were conducted in Stata Version 16.1 (StataCorp, College Station, TX).

6.3. Results

6.3.1. Descriptive statistics

We included those participants with walkability data at both time points (N=9,932). The time between study assessments ranged from 2.7 to 9.3 years, with a mean 5.5 years. At baseline, participants were on average 55 years of age, and nearly 70% were female.

The majority (80%) were White or of European descent, and roughly 60% had an income over $75,000 CAD. Approximately 16% of the sample were obese, and 12% and 2% were being treated for hypertension and T2DM at baseline, respectively. There were differences in age, length of follow up and education level across change in walkability quintiles, though no obvious pattern was discernible. We did not observe any differences in baseline obesity, HBP or T2DM across change in walkability groups. As expected, those living in the most walkable neighbourhoods at baseline had the least change in walkability between study assessments.

6.3.2. Model results

Odds ratios and confidence intervals for all models are presented in Table 6-1, whereas the figures show the effect size and 95% CIs. Change in walkability was inversely associated with incident obesity in both unadjusted and adjusted models (Figure 6-1). In adjusted analyses, a 1-unit increase in the walkability change score was associated with a 9% reduction in odds of becoming obese (OR=0.91, 95% CI 0.85, 0.98). In those with self-reported height and weight data only, there was a slightly larger decrease in odds of incident obesity (OR 0.88, 95% CI 0.79,0.98). Change in walkability was not associated with incident HBP or T2DM in unadjusted or adjusted models.

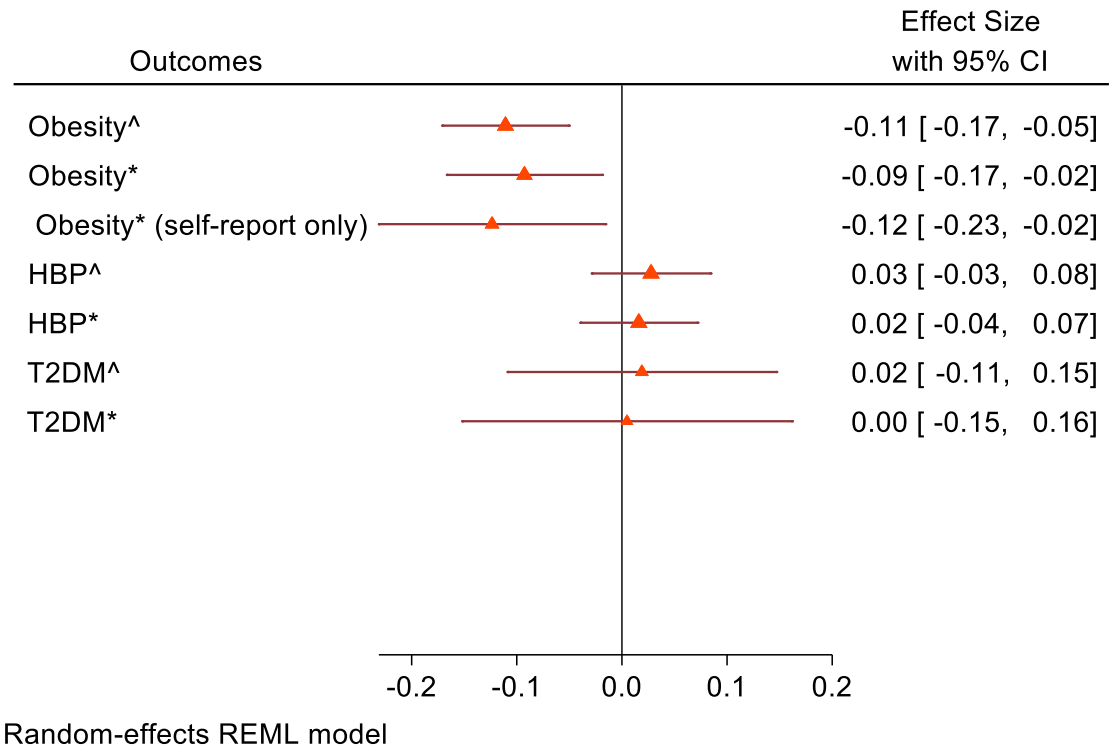


Figure 6-1: Incident obesity, HBP and T2DM

^Unadjusted models

*Adjusted for sex, age, racial/ethnic descent, baseline income, and length of time between assessments.

Figure 6-2 shows the association between change in walkability quintiles and incident obesity. Compared to quintile 1, those in quintile 5 had a 51% reduction in odds of becoming obese (OR=0.49, 95% CI 0.27, 0.88). Confidence intervals overlapped the null value for other quintiles, though the reduction in odds of incident obesity suggested a graded inverse association with greater change in walkability.

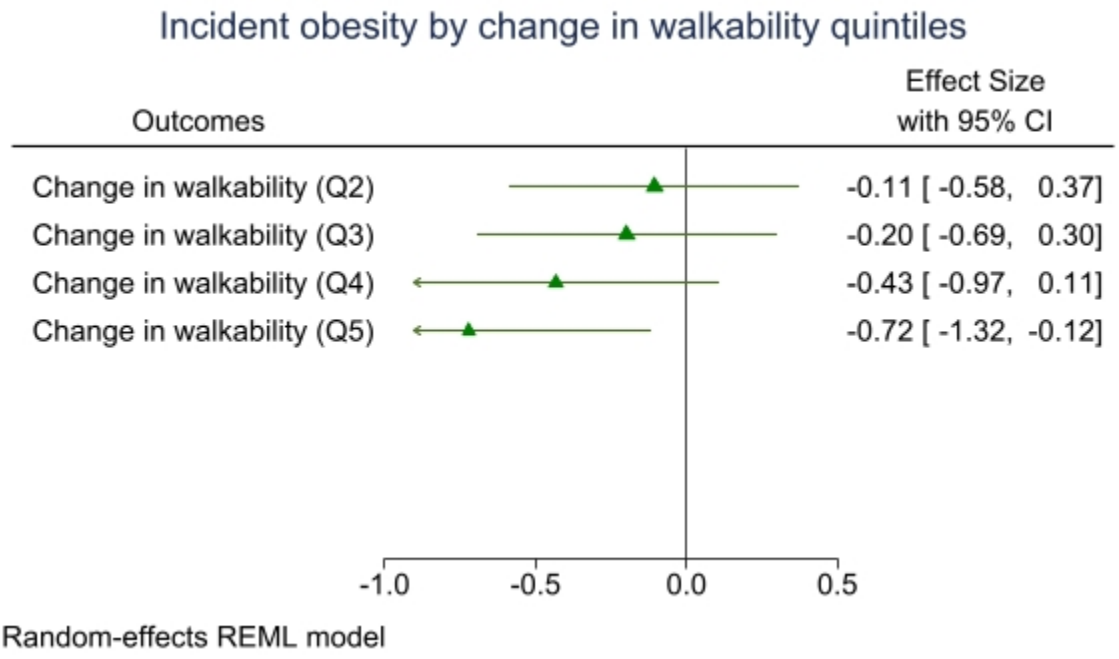


Figure 6-2: Incident obesity by change in walkability quintiles

All models adjusted for sex, age, racial/ethnic descent, baseline income, and length of time between assessments.

Change in walkability was associated with an 10% reduction in the odds of becoming obese in females (OR=0.90, 95% CI 0.82,0.98), while results among males were imprecise (Figure 6-3). A similar reduction in odds of obesity at follow up was observed among those who were less than 60 years old at baseline (OR=0.91, 95% CI 0.83,0.99), while this relationship was imprecise in older adults. Results by income were imprecise though suggestive that higher household income was associated with a slightly greater reduction in odds of obesity (OR=0.91, 95% CI 0.83, 1.0) compared to the lower income group.

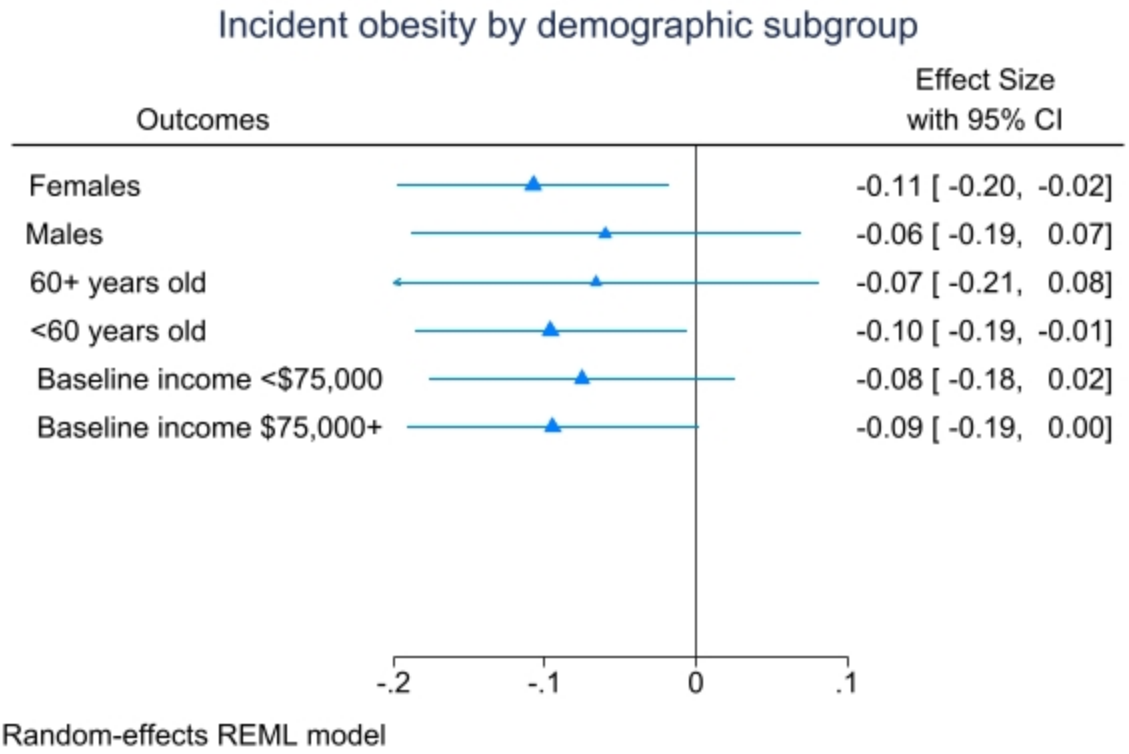


Figure 6-3: Incident obesity by demographic subgroups.

All models adjusted for sex, age, racial/ethnic descent, baseline income, and length of time between assessments.

Table 6-1: Odds ratios, p-values, and 95% confidence intervals for models

	Odds Ratio	p-value	95% CI	95% CI
Becoming obese[+]	**0.895**	**0.000**	**0.843**	**0.951**
Becoming obese*	**0.911**	**0.014**	**0.847**	**0.981**
Becoming obese (self-report only)*	0.884	0.025	0.794	0.984
Treated for HBP[+]	1.028		0.972	1.088
Treated for HBP*	1.016	0.571	0.961	1.074
Treated for T2 Diabetes[+]	1.019	0.771	0.897	1.158
Treated for T2 Diabetes*	**1.005**	0.952	0.859	1.175
Incident obesity by change in walkability quintiles				
Quintile 2	0.899	0.663	0.558	1.449
Quintile 3	0.820	0.431	0.500	1.344
Quintile 4	0.649	0.115	0.379	1.111
Quintile 5	**0.486**	**0.018**	**0.268**	**0.884**
Incident obesity by age				
60 and over	0.936	0.377	0.809	1.084
Under 60	**0.908**	**0.035**	**0.830**	**0.993**
Incident obesity by sex				
Female	**0.898**	**0.019**	**0.821**	**0.982**
Male	0.942	0.360	0.828	1.071
Incident obesity by income				
Baseline income <$75,000	0.927	0.141	0.839	1.025
Baseline income $75,000+	**0.910**	**0.052**	**0.827**	**1.001**

6.4. Discussion

We found change in walkability was associated with a significant reduction in obesity. The effect was strongest among women, adults 60 years and younger, and those with higher incomes. The risk of becoming obese decreased with greater change in walkability over time. We did not observe a relationship between walkability and incident HBP or T2DM. It is likely that the follow up period may have been insufficient to observe changes in these longer-term, chronic disease outcomes. Much of the research on walkability and health outcomes has been cross-sectional or utilized a single baseline measure of walkability with repeated health outcomes (Chandrabose, Rachele, et al., 2019a; Lai et al., 2023). The current study expands the longitudinal evidence supporting urban design as an effective approach to reducing the significant public health burden of obesity and obesity-related conditions.

6.5. Conclusions

This unique study provides longitudinal evidence on the benefits of increased neighbourhood walkability on reduced incidence of obesity in urban dwelling adults. While we found no evidence of impact on downstream chronic disease the analysis was limited by relying on self-reported blood pressure and diabetes incidence, as well as insufficient follow up. Longer monitoring would help elucidate this relationship and the length of exposure required to modify risk. As obesity remains a significant public health concern, policies and investments to support walkable communities are justified.

6.6. References[26]

[26] The full set of references used for this analysis are provided in the References section in
Appendix D.

7. Mental Health with Walkability & Greenspace – Multifaceted Impacts of Green Space and Walkability on Mental Health: Depression and Anxiety in Focus[27]

7.1. Background

Mental health refers to the overall state of an individual's well-being and their capacity to positively impact the community, while effectively managing the everyday challenges of stress ((WHO), 2022). The term "mental health conditions" encompasses mental disorders, psychosocial disabilities, and other mental states characterized by considerable distress, impaired functioning, or a potential risk of self-harm (Perrino et al., 2019). Mental disorders have a significant impact on the global burden of disease, affecting communities and people of all ages in both high and low-income countries (WHO (World Health Organization), 2018).Depression stands as a significant public health issue affecting 344 million individuals globally in 2019 ("GBD Mental Disorders Collaborators. Global, Regional, and National Burden of 12 Mental Disorders in 204 Countries and Territories, 1990–2019: A Systematic Analysis for the Global Burden of Disease Study 2019," 2022). Based on the 2012 Canadian Community Health Survey (CCHS), approximately 4.7% of Canadians aged 15 and above exhibited symptoms consistent with a diagnosis of major depression (C. Pearson et al., 2013a).

The research indicates that depression is estimated to affect approximately 10.8% of the global population throughout their lifetime (Lim et al., 2018). While it is estimated that about 11.3% of Canadians experienced a major depressive episode at some point in their lives (C. Pearson et al., 2013b). Depression is identified by symptoms such as a loss of interest or enjoyment in activities, decreased energy levels, and depressed mood (World Health Organization, 2017) (2). Depression differs from normal mood fluctuations and daily emotional responses. During a depressive episode, individuals experience persistent feelings of sadness, irritability, or emptiness, along with reduced interest in activities, lasting for most of the day, nearly every day, for at least two weeks. Additional symptoms include difficulty concentrating, overwhelming guilt or low self-esteem, a sense of hopelessness about the future, thoughts of death or suicide, disrupted sleep, appetite changes, and persistent fatigue (Perrino et al., 2019).

Anxiety disorders stand as the second most common mental disorder globally, affecting approximately 301 million individuals in 2019 (Núñez-González et al., 2020). These disorders are characterized by intense feelings of fear and worry, accompanied by associated behavioral disturbances. The severity of these symptoms is significant enough to cause either notable distress or substantial impairment in daily functioning (Perrino et al., 2019). In the Canadian context, the prevalence of diagnosed mood and anxiety disorders has shown a notable increase. In 2019, it was estimated that about 4.4 million Canadians, or 14% of those aged 12 and older residing in the provinces, had a diagnosed

[27] For the full article associated with this study, please see Appendix E.

mood or anxiety disorder. This shows an increase from 3.7 million individuals, or 12%, in 2015. Importantly, this rise has been particularly significant among young adults aged 18 to 34, where the prevalence increased from 13% in 2015 to 17% in 2019 ("Statistics Canada. Canadian Community Health Survey, 2019: Mental HealthStatistics. Canada Catalogue No. 11–001-X," 2020).

Mental health is influenced by a multifaceted interplay of factors, extending beyond individual characteristics to encompass a range of health determinants. These include elements at the individual, family, community, and structural levels, all of which can either bolster or compromise mental well-being (Perrino et al., 2019; Shen, 2014; *World Health Organization (WHO). Mental Health Action Plan 2013–2020*, 2013). Hirschfeld and Weismann (2002) identified several risk factors for depression, such as being female, having medical illnesses, experiencing early-life trauma, and facing adverse life events. These risk factors encompass various individual-level attributes, underscoring the significance of investigating environmental risk factors as well in understanding this major public health concern (Hirschfeld & Weissman, 2002). The association of built and natural environment with mental health remains an underexplored domain. While some studies have found a positive correlation between increased walkability or green space and reduced levels of depression and anxiety (Beyer et al., 2014; Hartig et al., 2014), the relationships are often not straightforward, and the mechanisms underlying these associations are not fully understood (McCormack & Shiell, 2011).

The primary objective of this study is to investigate the relationship between key elements of the urban environment—specifically, walkability and green space—and clinically diagnosed depression and anxiety. Complementing this, the secondary objective delves into the underlying mechanisms that drive these associations.

7.2. Methods

Data sources:

The study integrated data from three sources: BC Generations Project (BCGP) (BCGP, 2019), the Canadian Urban Environmental Health Research Consortium (CANUE) (CANUE, n.d.), and the Where Matters: Health & Economic Benefits Study (*Where Matters: Health & Economic Benefits Study*, n.d.).

Green space assessment:

The normalized difference vegetation index (NDVI) is a widely used measure to assess the health and density of vegetation in an area, and it is derived from satellite imagery. The NDVI for the residential neighbourhood was derived from the CANUE dataset. The categories applied for NDVI as a categorical variable are obtained from NDVI quintiles. The NDVI levels used are as follows: very low – 1st quintile (0.22,0.316], low – 2nd quintile (0.316,0.39], medium - 3rd quintile (0.316,0.39], high - 4th quintile (0.39,0.48], very high - 5th quintile (0.48,0.81].

Walkability assessment:

The Where Matters Study (*Where Matters: Health & Economic Benefits Study*, n.d.) constructed a walkability index for the Greater Vancouver region in British Columbia, utilizing postal codes. This index was developed by integrating data from different sources, including Statistics Canada (StatsCan, n.d.) and CanMap (*DMTISpatial. CanMap® GIS Data for GIS Mapping Software - DMTI Spatial.*, n.d.), and it is specifically linked to the BCGP cohort, focusing on residential postal codes. In comparison to the CANUE walkability index, the Where Matters index incorporates extra factors to evaluate walkability and has been established for the years 2006, 2011, and 2016, utilizing the following measures:

a) Residential Density: The number of residential units per acre within a neighbourhood.

b) Commercial Density: The area designated for commercial use within a neighbourhood.

c) Land use mix: A measure of the different purposes of land use in a neighourhood. A higher value indicates even distribution between purposes of land use such as residential, commercial, entertainment, and office development.

d) Street Connectivity: The number of street intersections in a neighourhood. A larger number of intersections would lead to increased connectivity and movement.

The walkability index used in the current study is the sample standardized walkability index. The categories applied for the walkability index as a categorical variable are obtained from walkability index quintiles. The walkability index levels used in the analysis are as follows: very low – 1st quintile [-6.1,-1.86], low – 2nd quintile (-1.86,-0.363], medium - 3rd quintile (-0.363,1.25], high - 4th quintile (1.25,3.03], very high - 5th quintile (3.03,13.8].

Depression and anxiety were evaluated separately as both continuous variables and categorical variables, utilizing a cutoff score of 10 to distinguish between different levels. Descriptive statistics were used to summarize the characteristics of the study sample, including demographics and relevant variables. Univariate descriptive analysis was conducted to assess the distribution of variables of interest, which includes exposure variables (i.e., NDVI and walkability index), outcome variables (i.e., depression and anxiety), and covariates (i.e., income, education, marital status, health perception, alcohol intake, smoking, sleep duration, activity category). Continuous variables were analyzed to reveal means, standard deviations, and interquartile ranges, while categorical variables were presented in terms of frequencies. The study used bivariate analysis to examine the relationships between exposure and outcome variables, as well as the associations between covariates and both exposure and outcome variables. We employed generalized linear models for the multivariable analysis. We examined the relationship between green space and depression, as well as anxiety, and also looked at how walkability correlates with these mental health conditions. Logistic regression was used for analyzing relationships with categorical mental health outcomes, while linear regression was applied for continuous mental health scores. This included overall scores as well as individual components of depression and anxiety questionnaires. In the regression

analysis the following potential confounding variables were identified based on the literature: age, sex, education level, occupation, income, physical activity, sleep pattern, dietary intake, smoking habits, and alcohol intake and the variables retained in the final model were selected by backward selection using the Akaike Information Criteria (AIC). Model goodness of fit was assessed by Area Under the Curve (AUC) from Receiver Operating Characteristics (ROC). Sensitivity analysis was performed to compare the participants with complete data and participants with missing values.

7.3. Results

The initial sample collected in this study was 9,238. After removing the participants with missing data, a total of 5,085 participants with complete information were considered for the analysis, of which 213 (4.1%) were categorized as depressed, and 4872 (95.8%) as not depressed. The mean age of the overall sample was 61 years (SD = 9).

Table 7-1 presents the univariable and multivariable logistic regression analyses exploring the association between the walkability index and anxiety condition using complete cases (n=5085). Participants living in areas with very high walkability had a statistically significant increased odds of anxiety (OR=1.43, 95% CI: 1.03–1.98), indicating that people living in areas with very high walkability had increased odds of experiencing anxiety, even after adjusting for demographic, lifestyle, and health-related variables. Table 7-2 demonstrates the linear regression analyses on the relationship between walkability index and the total score of anxiety. The fully adjusted models revealed that individuals in areas with very high walkability had a statistically significant increase in the total anxiety score ($\beta=0.36$, $p<0.01$). This trend remained even after adjusting for confounding variables, indicating a strong positive association between high walkability and anxiety scores. Table 7-3 displays the results from the linear regression analyses exploring the relationship between walkability index and individual components of anxiety. For areas with very high walkability, the unadjusted analysis showed a statistically significant positive association across multiple components, such as 'Nervous' ($\beta=0.11$, $p<0.0001$), 'Worrying1' ($\beta=0.08$, $p<0.001$), and 'Afraid' ($\beta=0.05$, $p=0.01$). This relationship generally held in the minimally and fully adjusted models, particularly for the components 'Nervous' and 'Worrying1' ($p<0.01$).

Table 7-1: Univariable and multivariable logistic regression using complete cases (n=5085) for the relationship between walkability index and anxiety condition

Outcome: Anxiety (Yes – No)			
	Unadjusted model	**Minimally adjusted model[a]**	**Fully adjusted model[b]**
Independent variable	**OR (95%CI)**	**OR (95%CI)**	**OR (95%CI)**
Walkability index			
Very low	Ref	Ref	Ref
Low	1.28 (0.83 – 1.98)	1.18 (0.86 – 1.62)	1.22 (0.88 – 1.70)
Medium	1.32 (0.86 – 2.04)	1.02 (0.74 – 1.42)	1.03 (0.73 – 1.45)
High	1.12 (0.72 – 1.75)	0.96 (0.70 – 1.34)	1.02 (0.72 – 1.43)
Very high	**1.74 (1.16 – 2.64)**	**1.35 (1.00 – 1.84)**	**1.43 (1.03 – 1.98)**

[a] Minimally adjusted model is adjusted for age, sex, and income

[b] Fully adjusted model is adjusted for age, sex, income, education, health perception, alcohol, smoking, and sleep duration

Table 7-2: Univariable and multivariable linear regression using complete cases (n=5085) for the relationship between walkability index and the total score of anxiety

Outcome: Anxiety total score						
	Unadjusted model		**Minimally adjusted model[a]**		**Fully adjusted model[b]**	
Independent variable	**β**	**p-value**	**β**	**p-value**	**β**	**p-value**
Walkability index						
Very low	Ref		Ref		Ref	
Low	0.16	0.23	0.10	0.47	0.10	0.43
Medium	0.04	0.76	0.14	0.53	-0.12	0.37
High	0.12	0.36	-0.01	0.95	-0.01	0.92
Very high	**0.46**	**<0.001**	**0.39**	**<0.01**	**0.36**	**<0.01**

[a] Minimally adjusted model is adjusted for age, sex, and income
[b] Fully adjusted model is adjusted for age, sex, income, education, health perception, alcohol, smoking, and sleep duration

Table 7-3: Unadjusted, minimally adjusted and fully adjusted linear regression using complete cases (n=5085) for the relationship between walkability index and the scores of anxiety components separately

Outcome: Anxiety component scores							
	Unadjusted analysis						
	Nervous	**Worrying1**	**Worrying2**	**Relax**	**Restless**	**Annoyed**	**Afraid**
	β (p-value)	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**
Walkability index							
Very low	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Low	0.02 (0.51)	0.03 (0.21)	0.02 (0.52)	0.03 (0.21)	0.01 (0.71)	0.03 (0.19)	0.02 (0.25)
Medium	0.00 (0.89)	0.00 (0.86)	-0.02 (0.45)	0.02 (0.41)	0.01 (0.52)	0.02 (0.49)	0.02 (0.33)
High	0.03 (0.34)	0.02 (0.36)	0.00 (0.90)	0.03 (0.19)	0.00 (0.89)	0.02 (0.32)	0.03 (0.21)
Very high	**0.11 (<0.0001)**	**0.08 (<0.001)**	**0.06 (0.02)**	**0.09 (<0.001)**	0.03 (0.18)	**0.06 (0.01)**	0.05 (0.01)
	Minimally adjusted analysis[a]						
	Nervous	**Worrying1**	**Worrying2**	**Relax**	**Restless**	**Annoyed**	**Afraid**
	β (p-value)	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**
Walkability index							
Very low	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Low	0.00 (0.95)	0.02 (0.38)	0.00 (0.98)	0.02 (0.36)	0.00 (0.81)	0.03 (0.27)	0.02 (0.37)
Medium	-0.02 (0.38)	-0.01 (0.57)	-0.05 (0.09)	0.01 (0.82)	0.00 (0.88)	0.00 (0.89)	0.00 (0.87)
High	0.01 (0.77)	0.00 (0.96)	-0.02 (0.42)	0.02 (0.45)	-0.02 (0.36)	0.00 (0.86)	0.00 (0.84)
Very high	**0.1 (<0.001)**	**0.07 (0.01)**	0.05 (0.09)	**0.08 (<0.01)**	0.02 (0.36)	**0.05 (0.05)**	0.04 (0.09)
	Fully adjusted analysis[b]						
	Nervous	**Worrying1**	**Worrying2**	**Relax**	**Restless**	**Annoyed**	**Afraid**
	β (p-value)	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**
Walkability index							
Very low	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Low	0.01 (0.71)	0.02 (0.33)	0.00 (0.89)	0.03 (0.31)	0.01 (0.75)	0.02 (0.31)	0.02 (0.43)
Medium	-0.02 (0.39)	-0.02 (0.38)	**-0.54 (0.04)**	0.00 (0.86)	-0.01 (0.79)	-0.01 (0.82)	0.00 (0.97)
High	0.01 (0.79)	0.00 (0.95)	-0.03 (0.33)	0.02 (0.53)	-0.02 (0.36)	0.00 (0.89)	0.01 (0.76)
Very high	**0.09 (<0.001)**	**0.07 (0.01)**	0.04 (0.12)	**0.07 (<0.01)**	0.02 (0.36)	**0.05 (0.04)**	0.03 (0.18)

[a] Minimally adjusted model is adjusted for age, sex, and income

[b] Fully adjusted model is adjusted for age, sex, income, education, health perception, alcohol, smoking, and sleep duration

7.4. Discussion

Our study investigated the relationship between the walkability index and depression. We did not observe any significant association between walkability and depression as defined by the depression score. However, in the continuous outcome analysis, measured as the total score of depression, higher walkability was associated with a higher depression score in unadjusted analysis, reaching statistical significance for high and very high levels of walkability. However, these associations were considerably attenuated in both minimally adjusted and fully adjusted models. The lack of a significant association in the minimally adjusted model, which considered age, sex, and income, suggests that these factors may be confounding the relationship between walkability and depression. This is in line with previous literature that has identified age, sex, and income as significant determinants of mental health. The fully adjusted model further attenuated the relationship between walkability and depression, underscoring the possible role of other variables such as education, health perception, history of depression, alcohol consumption, smoking, and sleep duration in influencing this association. On the other hand, the unadjusted regression model on the association between the walkability index and various components of depression showed significant associations between high and very high walkability indices and multiple depression components, namely interest, depressed mood, confidence, concentration, and suicidal thoughts. However, these associations were attenuated in the minimally adjusted and fully adjusted models, suggesting that confounding variables may be playing a considerable role.

For anxiety, in the unadjusted analysis, participants residing in areas with a "very high" walkability index were 1.74 times more likely to report experiencing anxiety compared to those living in areas with a "very low" walkability index. Although the magnitude of the relationship attenuated with adjustment, the association remained statistically significant in the fully adjusted model. This suggests that while confounding variables play a role, there is a unique and positive association between high walkability and the likelihood of experiencing anxiety. Similarly, in the linear regression model examining continuous anxiety scores, a significant association was observed in the "very high" walkability index category. In the unadjusted model, living in a "very high" walkable area was associated with a higher total anxiety score. This association remained robust in both minimally adjusted and fully adjusted models, indicating that high walkability is associated with increased total anxiety scores, irrespective of the covariates adjusted for. The study also assessed the relationship between walkability indices and various components of anxiety. In the unadjusted analysis, a significant association was observed only in the "very high" walkability index category across multiple anxiety components, such as nervousness, worrying1, worrying2, relaxation, annoyance, and fearfulness. After adjusting for age, sex, and income in the minimally adjusted model, we noticed a slight attenuation but the significance was maintained for many of the anxiety components like nervousness, worrying1, and relaxation, particularly in very high walkability areas. Further adjustments for education, health perception, history of depression, alcohol intake, smoking, and sleep duration in the fully adjusted model did not dramatically alter the outcome, especially in the "very high" walkability index category. This suggests that walkability may indeed have

a unique relationship with individual components of anxiety, independent of several other factors.

This study was designed to investigate the relationship between presence of green space, measured through NDVI and various measures of depression. While some analyses suggested a potential protective effect of green space on depression, most of the results indicated no consistent association between green space and depression. Such inconsistent findings present a complex narrative and underscore the multi-faceted impact of green spaces on mental health. For instance, the availability of green space might help improve concentration and confidence but not necessarily sleep quality. This multifaceted impact has implications for public health interventions and urban planning. This complex relationship is also highlighted by other studies. A cross-sectional study by Cottagiri et al in 2021 showed an inverse association between self-reported clinical diagnosis of depression in relation to an increase of NDVI within a 500 m buffer of the participant's residence (Cottagiri et al., 2022). There are plenty of research showing the inverse relationship between green space and depression (Cottagiri et al., 2022; Gariepy et al., 2014; Krols et al., 2022; Liu et al., 2019; R. Wang et al., 2019). Interesting, a longitudinal study by Astell-Burt et al in Australia in 2022 revealed that a 10% increase in green space was associated with higher levels of antidepressant prescription (Astell-Burt et al., 2022). In addition, a study by Helbich et al in 2021 showed there was no statistically significant evidence that people with less urban residential greenness had higher depression or anxiety scores than those exposed to higher levels (Helbich et al., 2021).

7.5. Conclusions

The complexities unveiled in our studies have significant implications for urban planning and healthcare policies. A one-size-fits-all approach to public health interventions based on walkability or green spaces would be insufficient. Policymakers and healthcare providers should adopt a multidimensional approach that accounts for these intricate relationships.

7.6. References[28]

[28] The full set of references used for this analysis are provided in the References section in Appendix E.

8. Cancer Risk with Walkability & Greenspace - The Effect of Residential Greenness and Walkability on Cancer Risk in the Greater Vancouver Region[29]

8.1. Background

Cancer is the leading cause of death in Canada with lung, breast, colorectal, and prostate cancer accounting for approximately half of the cancer cases diagnosed[1,2]. Two out of five Canadians are expected to receive a diagnosis of cancer in their lifetime resulting in one in four cancer-related deaths after diagnosis. Furthermore, due to aging population demographics, Canada is expected to face an increased burden of cancer[1]. Despite advances in detection and treatment, lung cancer is the leading cause of death in Canada with a 5-year survival of 19%[1]. While estimated mortality rates for breast cancer declined by 49% from 1986 to 2020[2], improvements are mainly limited to women with early-stage cancers[3,4]. The incidence of colorectal cancers is lowest among persons under 50 years but is increasing in younger age groups[1,5,6]. Similarly, the incidence of prostate cancer has been decreasing since 2007, yet it is the most commonly diagnosed cancer in men accounting for 20% of new cases in 2021[1,3]. Cancer morbidity and mortality can be mitigated by interventions reducing exposure to risk factors. Smoking, alcohol consumption, physical activity, and diet have been shown to affect cancer risk[15], but interventions to influence these factors are focused on individual-level behavior change which can be ineffective if they fail to account for multi-faceted socio-cultural barriers to change[7,8]. The built environment, which influences behaviors, can be altered to reduce cancer incidence[7].

With studies mainly focusing on the built environment and mortality rates, the mixed associations reported for NDVI, and the lack of research for walkability with cancer risk, it is essential to further investigate the causal associations using longitudinal study designs. Through this study, we examined the effect of residential greenspace and walkability on the risk of lung, colorectal, breast, and prostate cancers. We hypothesize that after accounting for socio-demographic and other individual factors, the built environment with infrastructure promoting healthier lifestyles such as increased physical activity, or access to urban green space would lead to a lower risk of cancer outcomes compared to areas with poorly built infrastructures. However, the decreased risk could potentially be offset by collinear factors such as increased air, noise, and light pollution.

8.2. Methods

Data Sources: We conducted a longitudinal analysis using secondary data merged from multiple sources, *viz.* the BCGP cohort, Where Matters project, and environmental exposures from CANUE described earlier. We additionally used data from the British

[29] For the full article associated with this study, please see Appendix F.

Columbia Cancer Registry. Based on passive annual follow-up, the British Columbia Cancer Registry provided information on mortality and cancer diagnoses which were categorized according to the International Classification of Diseases for Oncology, third edition (ICD-O-3) site codes. Only primary cancer diagnoses for each cancer type were considered for their individual analysis.

A total of 10,929 BCGP participants were included in the study sample (Figure 8-1). To be eligible, participants had to be residing in the Greater Vancouver region. Participants who developed cancer prior to enrolment and with missing information about the year of enrolment, were excluded from the analysis.

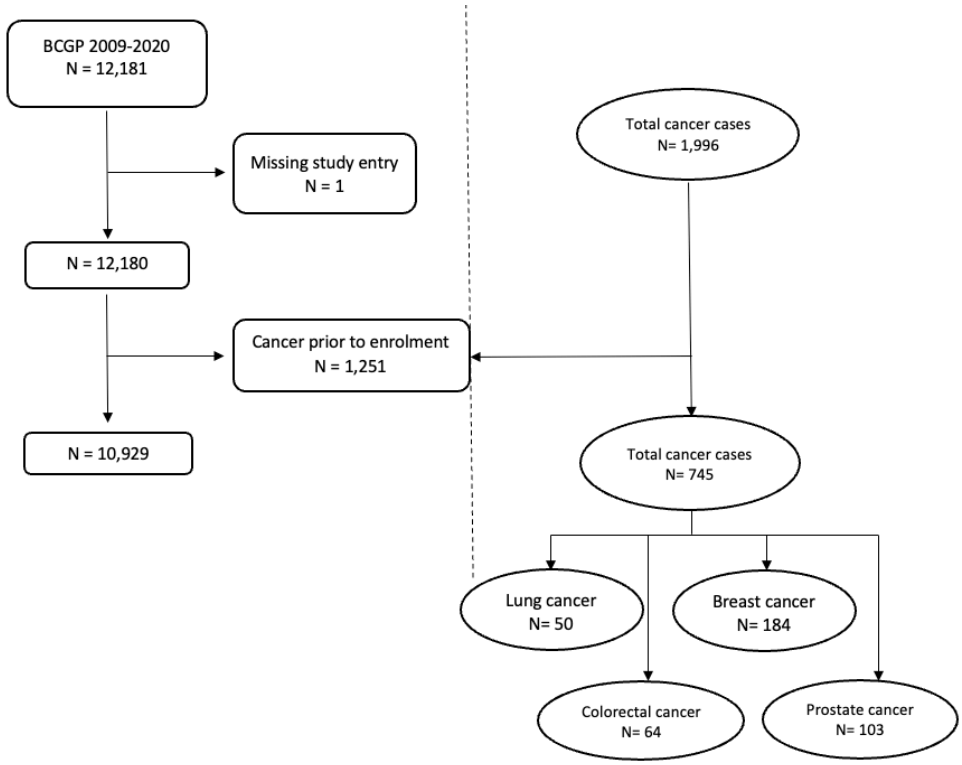


Figure 8-1: BCGP Sample and Cancer Case Distribution

Statistical Analysis: We conducted separate time-varying Cox proportional hazards models to assess the hazard ratio for the primary diagnosis of each cancer type based on the annual environmental exposures. Participants were censored at the year of cancer diagnosis, death, or end of follow-up in 2020. The analyses for lung and colorectal cancers were conducted in the entire sample, while the analyses for breast and prostate cancers were restricted to females and males respectively. The environmental exposures were classified into three groups of high, medium, and low exposures based on approximately equal sample size. Age, sex, race, marital status, education level, and income were considered as socio-economic and demographic factors, while alcohol intake, smoking habits, hormonal replacement therapy (HRT), contraceptive use, family history of the primary cancer diagnosis, and air pollution factors (NO_2) were considered as risk factors. Variables were selected for each cancer type based on established risk

factors, researcher assumptions, and change in effect estimates. Due to the limited number of incident cases, the number of variables in the models estimating the hazard ratio for lung and colorectal cancers were limited to a maximum of 7 and 9, respectively. After variable selection, a second model was created which accounted for collinear environmental exposures. NO_2 concentrations were adjusted in NDVI models, while NDVI and NO_2 exposures were included in walkability models. The assumption of proportional hazards was verified by using Schoenfeld residuals. In case of deviations from the proportional hazards assumption, we introduced interaction terms with time for continuous variables and stratified by categorical variables.

8.3. Results

The eligible study sample consisted of 10,298 participants. The average age of the participants was 55 years and were mostly female (70%). The majority of the participants (83%) had a level of education greater than high school. Approximately 83% of the population was Caucasian and 61% had moderate to high total family income of ≥$75,000. Only 5% of the participants were current smokers while 90% were current drinkers. The average length of follow-up was 9 years with participants accounting for a total of 97,083 person-years. A total of 50 lung cancer, 64 colorectal cancer, 184 breast cancer, and 103 prostate cancer cases were developed over follow-up. The results from the Cox analyses studying the association between the primary environmental exposures and individual cancer risks are presented in Tables 2-5.

Associations with lung cancer risk

There was no significant association between NDVI and lung cancer risk in the primary model (

Table 8-1). Similarly, the CanALE walkability index showed no significant associations while comparing the lung cancer risk in moderate (HR = 0.94, 95% CI = 0.46 - 1.89) and high (HR = 0.76, 95% CI = 0.37 - 1.58) walkable regions to the lowest walkable regions. Results for the Where Matters walkability index were similar to those of the CanALE estimates in magnitude and trend. Although the findings were not statistically significant, an increase in both CANUE and Where Matters walkability metrics showed noticeable decreasing trends for lung cancer hazards. Model 2, which was additionally adjusted for collinear environmental exposures showed similar estimates and trends to those from Model 1.

Table 8-1: Results for lung cancer: Hazard ratio using Cox proportional models

N = 10,929	Lung Cancer (N= 50)		
Environmental Exposures	**Model 1[a]**	**Model 2**	**Cases (N)**
Normalized Difference Vegetation Index			46 (10,261)
Medium	0.78 (0.37, 1.63)	0.76 (0.36, 1.62)[b]	
High	0.94 (0.48, 1.86)	0.92 (0.45, 1.89)[b]	
Canadian Active Living Environment			45 (10,124)
Medium	0.94 (0.46, 1.89)	0.91 (0.45, 1.87)[c]	
High	0.76 (0.37, 1.58)	0.73 (0.32, 1.64)[c]	
Where Matters Walkability Index			44 (10,026)
Medium	0.94 (0.43, 2.04)	0.93 (0.42, 2.03)[c]	
High	0.89 (0.42, 1.86)	0.83 (0.37, 1.89)[c]	

a: adjusted for age, sex, race, family history of lung cancer, and smoking history

b: age, sex, race, family history of lung cancer, smoking history, tertiles of rolling averages of nitrogen dioxide concentrations

c: age, sex, race, family history of lung cancer, smoking history, and tertiles of NDVI and rolling averages of nitrogen dioxide concentrations

Associations with colorectal cancer risk

Colorectal cancer risk was not significantly associated with NDVI, the CanALE walkability index, and the Where Matters walkability index in the primary model (Table 8-2). However, there was a decreasing trend in risk when comparing participants with the higher NDVI exposures to those with the lowest NDVI exposure (HR = 0.73, 95% CI =0.37, 1.46. Adjusting for rolling averages of NO_2 in Model 2 did not result in changes in estimates for any of the exposures.

Table 8-2: Results for colorectal cancer: Hazard ratio using Cox proportional models

N = 10,929	Colorectal Cancer (N= 64)		
Environmental Exposure	**Model 1[a]**	**Model 2**	**Cases (N)**
Normalized Difference Vegetation Index			58 (9,856)
Medium	1.00 (0.54, 1.89)	0.99 (0.53, 1.84)[b]	
High	0.73 (0.37, 1.46)	0.70 (0.36, 1.35)[b]	
Canadian Active Living Environment			59 (9,912)
Medium	1.08 (0.57, 2.05)	1.02 (0.54, 1.96)[c]	
High	1.08 (0.57, 2.08)	0.96 (0.47, 1.96)[c]	
Where Matters Walkability Index			56 (9,824)
Medium	0.95 (0.46, 1.95)	0.93 (0.45, 1.93)[c]	
High	1.20 (0.61, 2.33)	1.15 (0.56, 2.37)[c]	

a: adjusted for age, sex, race, income, family history of colorectal cancer, alcohol intake, and smoking history

b: adjusted for age, sex, race, income, family history of colorectal cancer alcohol intake, and smoking history tertiles of rolling average of nitrogen dioxide concentrations.

c: adjusted for age, sex, race, income family history, alcohol and smoking history, and tertiles of NDVI and rolling average of nitrogen dioxide concentrations.

Associations with breast cancer risk

There were no statistically significant findings for breast cancer with any of the exposures of interest. However, models for NDVI showed protective point estimates across all levels of greenness [Medium vs. Low NDVI: HR =0.87, 95% CI=(0.59, 1.26) and High vs Low NDVI: HR=0.81, 95%CI= (0.55, 1.19)] (Table 8-3). Model 2 did not show any changes in estimates for any of the exposures.

Table 8-3: Results for breast cancer: Hazard ratio using Cox proportional models

N = 7,611	Breast Cancer (N= 184)		
Environmental Exposure	**Model 1[a]**	**Model 2**	**Cases (N)**
Normalized Difference Vegetation Index			162 (6,813)
Medium	0.87 (0.59, 1.26)	0.85 (0.58, 1.24)[b]	
High	0.81 (0.55, 1.19)	0.80 (0.54, 1.19)[b]	
Canadian Active Living Environment			161 (6,727)
Medium	1.26 (0.87, 1.85)	1.25 (0.85, 1.84)[c]	
High	0.99 (0.66, 1.48)	0.93 (0.60, 1.45)[c]	
Where Matters Walkability Index			157 (6,653)
Medium	0.89 (0.60, 1.32)	0.87 (0.58, 1.30)[c]	
High	1.00 (0.67, 1.48)	0.94 (0.61, 1.44)[c]	

a: adjusted for age, marital status, income, education status, race, family history of breast cancer, alcohol intake, smoking history, history of oophorectomy/hysterectomy, history of hormone replacement therapy

b: adjusted for age, marital status, income, education status, race, family history of breast cancer, alcohol intake, smoking history, history of oophorectomy/hysterectomy, history of hormone replacement therapy, and tertiles of rolling averages of nitrogen dioxide concentrations

c: adjusted for age, marital status, income, education status, race, family history of breast cancer, alcohol intake, smoking history, history of oophorectomy/hysterectomy, history of hormone replacement therapy, and tertiles of NDVI and rolling averages of nitrogen dioxide concentrations

Associations with prostate cancer risk

There was no significant association between NDVI and prostate cancer risk in the results from Model 1 (medium vs. low NDVI: HR = 0.85, 95% CI =0.49, 1.46, high vs. low NDVI: HR = 1.12 95% CI =0.68, 1.83). Similarly, while analyzing the CanALE (medium vs. low walkability: HR = 1.27, 95% CI =0.76, 2.11, high vs. low walkability: HR = 1.24 95% CI =0.73, 2.12) and Where Matters (medium vs. low walkability: HR = 0.90, 95% CI =0.54,

1.49, high vs. low walkability: HR = 1.02 95% CI =0.62, 1.69) walkability indices, there were no significant associations or noticeable trends in prostate cancer risk. No significant associations were observed in Model 2 either after adjusting for collinear environmental exposures (Table 8-4).

Table 4. Results for prostate cancer: Hazard ratio using Cox proportional models

Table 8-4: Results for prostate cancer: Hazard ratio using Cox proportional models

N = 3,318	Prostate Cancer (N= 103)		
Environmental Exposure	**Model 1[a]**	**Model 2**	**Cases (N)**
Normalized Difference Vegetation Index			96 (3,116)
Medium	0.85 (0.49, 1.46)	0.80 (0.46, 1.38)[b]	
High	1.12 (0.68, 1.83)	1.01 (0.60, 1.69)[b]	
Canadian Active Living Environment			94 (3,070)
Medium	1.27 (0.76, 2.11)	1.32 (0.78, 2.22)[c]	
High	1.24 (0.73, 2.12)	1.57 (0.86, 2.86)[c]	
Where Matters Walkability Index			92 (3,052)
Medium	0.90 (0.54, 1.49)	0.96 (0.57, 1.62)[c]	
High	1.02 (0.62, 1.69)	1.22 (0.70, 2.14)[c]	

a: adjusted for age, income, education status, race, family history of prostate cancer, and alcohol intake

b: adjusted for age, income, education status, race, family history of prostate cancer, alcohol intake, and tertiles of NDVI

c: adjusted for age, race, family history of prostate cancer, smoking history, tertiles of NDVI and rolling average of nitrogen dioxide concentrations

8.4. Discussion

Our study investigates the association between residential environmental exposures of greenness (NDVI) and walkability with cancer risk using a longitudinal cohort design. Although none of the effects were statistically significant we observed some important trends.

Greenness and cancer risk

While there were no statistically significant associations between NDVI exposure levels and lung cancer risk both medium and high exposure to greenness showed protective estimates when compared to low exposure. Even though air pollution is a known lung carcinogen, the estimates were unchanged following adjustment for Nitrogen dioxide exposure, potentially due to the low levels of air pollution in British Columbia.). However, even at low concentrations air pollution is known to cause medical complications with increased hospitalizations and attributed deaths in British Columbia[36]. This highlights the importance of accounting for the effects of multiple collinear environmental exposures and emphasizes that in our urban sample the health benefits of greenspace are outweighed by increased air pollution. Medium NDVI exposure had no effect on colorectal

cancer risk. But a protective trend was noticed while comparing the highest NDVI exposure to the lowest exposure. Our analyses for lung and colorectal cancers were hampered by the low number of incident cases, 50 and 64 respectively. Previous research has shown a protective trend with lung cancer and no association with colorectal cancers, emphasizing the complexity of the impact of greenspace on health[24,30,31]. A study by Huang et al. (2022) found a 5% decrease in lung cancer risk using a Cox proportional hazards model with baseline covariates and lung cancer (HR: 0.95, 95% CI: 0.91–0.99)[28] while Kayyal-Tarabeia et al. (2022) found a 25% reduction in risk with a unit IQR increase in NDVI (HR = 0.75, 95% CI: 0.66–0.85)[29]. A third study by Sakhvidi et al. (2021) found no association between NDVI at a 100 m buffer and lung cancer risk (HR = 0.870, 95% CI= 0.691 - 1.095) but still exhibited a decreasing trend with increasing NDVI[32]. Both Huang et al. (2022) and Kayyal-Tarabeia et al. (2022) had a considerably larger number of cases and longer follow-up periods. Consequently, the finding of no statistically significant associations from the primary analysis could be a chance finding or an attribute of the limited number of cases developed in the cohort due to the short follow-up time. The proportional hazards Cox model performs better with more events and longer follow-up which helps in informed censoring.

While assessing breast cancer risk using measures of greenness, findings have been mixed. Sakhvidi et al. (2021) and Kayyal-Tarabeia et al. (2022) found a decreased risk of breast cancer incidence[29,32], while Huang et al. (2022) found no association with NDVI[28]. Our findings, although statistically non-significant, exhibited protective estimates with increased NDVI exposure. The estimates in the high and medium NDVI levels were similar to each other which could also suggest a plateauing of the effect of greenness on breast cancer risk. We also found no association between NDVI and incidence of prostate cancer. While using low NDVI as the reference group, high NDVI exposure had higher point estimates of prostate cancer compared to medium NDVI exposure (medium vs. low NDVI: HR = 0.85, 95% CI =0.49, 1.46, high vs. low NDVI: HR = 1.12, 95% CI =0.68, 1.83), but the estimates are likely the attribute of the wider confidence intervals, due to limited male sample size living in areas with the highest NDVI exposure, and not an actual increase in cancer risk. Moreover, the estimate in the participants with the highest NDVI exposure reduced to a null effect after accounting for air pollution (HR = 1.01, 95% CI: 0.60–1.69).

From our findings and previous research, we surmise that living in areas with increased green space can potentially decrease the risk of lung, colorectal and breast cancer. While we could account for NO_2 as an air pollution factor, there may be other significant collinear exposures, such as ambient night light and noise pollution that we have not considered in our analysis. Although NDVI is a popular method for measuring surrounding greenness[33], several other vegetation indices are available and [34.] the choice of metric, including using discrete measures such as park or tree count, impacts research findings. Depending on the type of greenness (urban greenspace amenities vs. dense vegetation), increased exposure could enhance health, through factors such as increased physical activity and other physiological and psychological impacts[35].

Walkability and cancer risk

To our knowledge, there are no longitudinal studies investigating the direct effect of residential walkability on the risk of lung, colorectal or prostate cancer risk in the general population, making our study the first of its kind. A recent study in a female population by India-Aldana et al. (2023) reported no association of colorectal cancer and reduced risk of post-menopausal breast cancer with increasing neighbourhood walkability[37]. Apart from the difference in the study population, their measure of walkability was based on averaged z-scores of the population and commercial densities in New York city, USA. A study by Keats et al. (2020) based on the Atlantic PATH cohort found no association between quintiles of the CanALE index and all-cancer risk[21]. Given that different cancer types have different etiologies, it is important to conduct epidemiologic studies for each cancer type an using incidence cancer cases that occur after the exposures were measured. Although statistically non-significant, while examining lung cancer risk we found protective estimates for all levels of walkability when compared to the lowest level in addition to decreasing risk with increasing walkability. We did not find any significant associations while examining the effect of walkability on colorectal and prostate cancer risk and the estimates presented with relatively wider confidence intervals precluding any extrapolation. While assessing breast cancer risk, all but one hazard ratio estimates were below or at the null effect of 1, potentially signaling no association between walkability with breast cancer risk. Given the dearth of research longitudinally examining walkability and cancer risk, future studies, with longer follow-up duration and consequently more cancer diagnoses, is required to assess these potential findings.

The differences in estimates from the CanALE and Where Matters walkability indices could be the result of multiple factors. One is the difference in geographical units utilized to estimate the exposure. The Where Matters walkability was created at the residential postal code level while the CanALE index was created by using dissemination areas (DA) as the smallest unit. Dissemination areas are larger geographical units comprised of multiple postal codes. Secondly, the WM index also considers commercial floor area and land use mix to measure walkability, in addition to the residential and intersection density assessed by CanALE. As a result, we believe the WM index captures greater variability in the exposure. Moreover, the WM index is longitudinal in nature and able to account for changes in the participant's exposure over time.

8.5. Conclusions

Through our study, we were able to identify potential protective trends for greenness and walkability on certain cancer types. Individual-level behaviour interventions can influence public health considerably. As an example, due to effective public health campaigns about the ill effects of smoking, we have seen decreasing trends in tobacco-use and lung cancer incidence. However, lung cancer is still the leading cause of cancer death in Canada and other avenues, such as modifying the built environment, must be explored to reduce its burden on a wide-reaching scale. Given the complex nature of the built environment and

the potential for interaction between multiple environmental factors, further research is required to confirm our findings.

8.6. References[30]

[30] The full set of references used for this analysis are provided in the References section in Appendix F.

9. Regulatory & Fiscal Approaches to Transportation & Land Use Investment[31]

9.1. Changes to Municipal & Regional Regulatory Environment

Regulatory and fiscal approaches are two distinct strategies governments use to manage various economic, social, and environmental objectives. Regulatory policies involve the establishment and enforcement of laws, rules, and regulations by the government to guide behavior and address various social, economic, or environmental issues. Governments attempt to regulate markets and ensure fair competition, protect the environment, enforce health and safety standards and more. Fiscal approaches refer to government spending, taxation and borrowing to influence the economy. Some fiscal tools include subsidies, grants, gas taxes and congestion charges. Regulatory and fiscal policies are powerful tools that can shape how public transportation services are funded, managed, and operated. These tools also play a crucial role in shaping land use patterns, development decisions and the overall built environment. Governments have a tremendous amount of influence to guide development in ways that promote economic prosperity, environmental sustainability, social equity, and community well-being.

Prior to November 30, 2023, B.C.'s municipal governments had significant authority for shaping their land use policy and influencing development within their jurisdictions. However, following the Royal Assent of three new housing statues, Bill 44, 46 & 47, the provincial government has enacted major housing legislation that changes the powers of city councils, city planning officials and citizens and aims to increase density across most of BC municipalities. Bill 44 requires local governments to update zoning bylaws to allow either a minimum of one secondary suite or detached accessory dwelling unit, a minimum of three to four dwelling units, or a minimum of six dwelling units (near transit) on lots currently zoned for single-family homes and duplexes in municipalities above 5000 people. It also limits the use of public hearings for certain residential projects that are consistent with official community plans and zoning bylaws and requires municipal governments to update official community plans every five years with public input and in a manner that reflects projected housing needs. Bill 46 introduces amenity cost charges ("ACCs") as a new development financing tool to help local governments cover increased capital costs associated with providing or altering amenities to benefit development and any associated increase in population of residents or workers. Bill 47 requires municipalities to designate land within 800 metres of rapid transit stations and 400 metres of major bus exchanges as transit-oriented development areas, and to permit development in accordance with the prescribed minimum density levels within such areas. Through regulations, transit-oriented development (TOD) areas have now been defined. The regulations will prescribe 104 TOD Areas in 31 municipalities throughout B.C. within the first year of the legislation coming into effect. Bill 47 also removes most

[31] For more details on the review of performance-based funding (PBF), please see Appendix A.

parking requirements for developments in these areas. These bills override municipal government authority over land use planning.

The legislation and the accompanying regulations and guides are part of the Provinces' Homes for People action plan, which builds on the 2018 Homes for B.C. plan. These legislative changes are part of the provincial government's efforts to streamline the delivery of homes, services, and infrastructure for growing communities throughout BC and eliminate restrictive zoning policies. A report prepared by BC Stats shows that BC's population growth rate has surged over the past three years due to higher national immigration targets. Nearly 150,800 migrants came to the province in 2022, roughly 52,000 of whom were permanent immigrants. Assuming Canada strictly maintains its annual immigration targets, B.C.'s population is projected to steadily increase through 2046, from 5.5 million people in 2023 up to 7.9 million (+ 48.6%) in 4046. All development regions of BC are anticipated to see population growth; however, the most significant growth will be in the Mainland / Southwest region where most immigrants settle. The province and Metro Vancouver need to anticipate and plan for long-term challenges and opportunities associated with increased population growth,

Recently the provincial government had ventured into previous municipal jurisdiction over land-use planning with two other pieces of legislation, designed to support the Homes For People action plan. In September 2023, the Ministry of Housing selected ten municipalities to meet housing target orders under the authority of the Housing Supply Act (Bill 43), over the next five years between October 2023 and September 2028. Metro Vancouver municipalities that are affected by these housing targets are: City of Delta, City of Port Moody, City of Vancouver, District of North Vancouver, and District of West Vancouver. In 2022, legislation was passed to enable the Ministry of Transportation and Infrastructure to purchase land in areas near transit stations for the purpose of transit-oriented development. Previously, the ministry was only able to purchase land that was directly related to transit projects. Municipalities have traditionally had jurisdiction to oversee land use within their boundaries, but this has rapidly changed in BC with the Royal Assent of Bill 43 in November 2022.

The vision for Metro 2050 is to have a region of diverse and complete communities connected by sustainable transportation choices where residents live in neighbourhoods that offer a range of opportunities to live, work, play, and learn. This comprehensive plan recognizes that policies and strategies need to work together to ensure that land development and transportation planning are aligned. The Mayor's Council, the collective voice of Metro Vancouver mayors on transit and transportation, recognizes that the more people who use transit, the more cars we remove from the road, lowering GHG emissions and keeping our air clean. Encouraging densification and complete communities near transit hubs, promotes citizens to take transit. Furthermore, a well-functioning public transit system is a critical part of meeting federal and provincial climate action targets as outlined in the Federal government's 2030 Emissions Reduction Plan. To align with both federal and provincial targets of significantly lowered emissions by 2030, transit services and bike lanes need to be expanded and thus funded. An urgent transit expansion is required to keep up with the growth in the region.

Transportation infrastructure investments are the responsibility of the Provincial Government. The B.C. government has the goal to make 30% of all trips taken in the province by active transportation (AT) and public transit, essentially doubling the percentage of trips by 2030. Through funding to municipalities and partnerships with non-profits, the Ministry of Transportation and Infrastructure is spending money to build active transportation facilities, such as bike lanes, delivering education and encouragement programs, enforcing rules that make the roads safer for everyone and evaluating their progress to make sure they are on the right path. In 2019, the Ministry created an Active Transportation Design Guide which contains recommended policies, specifications, standards, and guidelines to be followed in the development of active transportation infrastructure in British Columbia. The goal of this free design guide is to help communities build safe, effective active transportation infrastructure. The province recognizes that making active transportation an option for more people will reduce gas emissions as is stated in the CleanBC Strategy. Provincial charitable non-profits such as Hub Cycling and the BC Cycling Coalition work with communities to promote safer and accessible cycling. On a federal level, the Government of Canada launched the Active Transportation Fund (ATF) in 2021, to invest $400 million over five years to build new and expanded networks of pathways, bike lanes, trails, and pedestrian bridges in addition to supporting active transportation planning and stakeholder engagement activities. Governments at every level recognize that expanding and promoting active transport, especially public transit, is crucial to meeting emissions reduction targets. WMII also demonstrates that active transportation has health benefits for the population.

Metro 2050 also includes regional targets for protecting half the land base for nature and expanding tree canopy cover. The provincial government also recognizes the importance of greenspace for improving the mental health and well-being of citizens and the need to preserve the natural environment by reducing urban sprawl (contained in the British Columbia Complete Communities Guide). What are the fiscal and regulatory strategies employed by government to support greenspace and urban tree canopy preservation? The unintended result of densification will be losing backyards and trees on private property. Zoning regulations can mandate minimum greenspace requirements for new developments or that a certain percentage of land within urban areas be dedicated to greenspaces such as parks. Grants or tax incentives could be provided to community organizations, municipal governments, or private landowners to ensure the preservation of a certain percentage of land for greenspace. Provincially, British Columbia has a system of areas managed by BC Parks. Municipalities have powers to establish parks and develop Official Community Plans (OCPs) that include provisions for greenspace protection and management. With the focus of the new provincial government legislation and Federal government housing policies on increasing housing supply through densification, municipalities must ensure greenspace conservation is not overlooked.

9.2. Performance-Based Funding

Where Matters proposes a Performance-Based Funding model for transportation and land use infrastructure investments. Performance-Based funding (PBF) is a mechanism in which a funder financially rewards an agent upon the achievement of pre-agreed upon results (Alshehri, 2016; Musgrove, 2011). PBF schemes include, but are not limited to, bonus payments, prizes, grants, loans or long-term financing contracts (Gold et al., 2014). In most cases, the funder delegates an aim or desired outcome to an agent, who is then responsible for the delivery of those aims and outcomes. One method of measuring performance could be based on evaluating the extent to which communities are becoming more walkable with a range of transportation options. Standardized, consistently measured data, such as those leveraged for Where Matters II, should be considered as a key resource to evaluate environmental change in communities over time.

PBF approaches to management, budgeting and resource allocation have been used for decades across many sectors with the goal of improving programmatic and financial efficiency and accountability. Governments, parliaments, citizens, the private sector, non-governmental organizations (NGOs), civil society, international organizations, and donors all commonly use performance funding mechanisms as an alternative to traditional forms of funding that disburse funds before delivery, or based on inputs (Rodriguez et al., 2014). PBF mechanisms can be contracts between organizations and governments, different levels of government, public or private service providers, governments and individuals, or society organizations. The primary strength of PBF is that it has a results-based structure used to provide timely and efficient guidance to projects. The term 'principal' in this section is used to refer to those responsible for designing and implementing the PBF mechanism, and 'agent' is used to describe those responsible for delivery of the desired objective.

9.2.1. Description of Existing PBF Literature

Although applications of PBF are common, literature and studies covering PBF are overwhelmingly concerned with a few key sectors: global development finance and aid, higher education, healthcare, and social service delivery. The global health sector has been a pioneer in implementing PBF mechanisms, followed by other sectors including education, energy, and climate (Rodriguez et al., 2014). In climate finance, PBF programs aimed at preserving or restoring ecosystem services have also grown in popularity over the last two decades (Snilsveit et al., 2019). In the Global North, healthcare systems have also been early adopters of PBF models over the last twenty years; Australia, Brazil, New Zealand, the US, and several European countries have all introduced some PBF to their national healthcare systems (Gold et al., 2014). In North America, the Social Service and Higher Education sectors have also been pioneers in implementing results-based mechanisms (Hawkins et al., 2019).

Literature on performance-based approaches to funding and financing has broad sectoral coverage. Generally, the earlier PBF was applied in individual fields or sectors, the more experiences were evaluated and documented in the literature (Warnecke et al., 2015). The most abundant literature on PBF is found in its use in global development and aid,

specifically in the climate, education, and health sectors (Martínez et al., 2012). There is also significant literature on performance-based approaches in higher education,(Baker et al., 2006; De Boer et al., 2015; Harnisch, 2011; Salmi & Hauptman, 2006) as well as its use in the delivery of social and health services (Barker et al., 2018; Gold et al., 2014; Hawkins et al., 2019; Zlatinov & Gillette, 2018).

Existing literature on PBF can be grouped into the following categories: specific project evaluations, reports on the implementation and monitoring challenges of PBF approaches (Johnson & Zajonc, 2006; OECD, 2020; M. Pearson et al., 2010; Perakis & Savedoff, 2015), and meta-evaluations of particular performance-based approaches (Vivid Economics, 2013). Other literature reviews (see Warnecke et al., 2015; Oxman & Fretheim, 2009) have connected the availability of literature on performance-based approaches to the experience with PBF in different sectors. Some findings and papers are sector-related, while other findings provide considerations and lessons that can be applied in different contexts (Oxman et al., 2009). The most common PBF literature, which covers results-based approaches to development finance and aid, mostly covers its application for meeting its desired aims or objectives (Johnson & Zajonc, 2006; Perakis & Savedoff, 2015, 2014); There is also a significant body of literature evaluating the efficiency and cost of performance-based approaches (Oxman et al., 2009; Poister et al., 2014; Warnecke et al., 2015). Although there is a significant body of literature documenting sector-specific experience with performance-based approaches, there are few resources that connect or compare PBF approaches across sectors, nor is there much information on PBF approaches in North America outside of healthcare, education, and social service delivery programs. Performance-oriented administration is a common practice in government in Europe and North America and has been rigorously studied (Bleyen et al., 2017); however, the literature on the mechanism connecting funding to performance is scarce compared to studies on the efficiency and outcomes of specific models. Despite performance-based funding being often used across many different sectors, there is currently a lack of PBF related to walkability studies.

When discussing PBF, one noteworthy program is The Livable Centers Initiative (LCI), developed by the Atlanta Regional Commission (ARC). Like Metro Vancouver, ARC is charged with considering issues from a regional perspective. The LCI program awards planning grants to local governments to prepare and implement plans to enhance existing activity centers and corridors thus incentivizing local jurisdictions to re-envision their communities as more walkable, mixed-use, and transit-friendly. The LCI program goals are threefold: Encourage a diversity of housing, employment, commercial, shopping and recreation land uses at the transit station, local and regional center level; enhance access to a range of travel modes including transit, roadways, walking and biking and increase roadway connectivity to provide optimal access to all uses within the study area; foster public-private partnerships and sustained community support through an outreach process. The program also awards Federal transportation funding to implement the transportation elements (i.e. streetscapes, pedestrian connections) of LCI studies. Since its creation in 2000, the LCI program has invested over $312 million in more than 130 communities throughout the Atlanta region, helping pay for planning studies and the construction of transportation projects such as sidewalks and intersection improvements, to bring those visions to life. In addition, the ARC board has allocated $600 million through

2050 for transportation projects resulting from completed LCI studies. The LCI process involves collaboration between local governments, the ARC, and community stakeholders. The program is unique in that, every December, the Land Use Coordinating Committee (LUCC) holds an Ideas Exchange meeting where counties are invited to attend, and then the formal application opens in early January. The LCI program is unique in that the various levels of government work in a coordinated effort to reward creating mixed-use development. Appendix A provides an overview of a wide range of local and international PBF case study examples reviewed as part of this study.

10. Main Document References

Adler, N. E., & Ostrove, J. M. (1999). Socioeconomic status and health: What we know and what we don't. *Annals of the New York Academy of Sciences*, *896*, 3–15. https://doi.org/10.1111/j.1749-6632.1999.tb08101.x

Agbai, C. O. (2021). Shifting neighborhoods, shifting health: A longitudinal analysis of gentrification and health in Los Angeles County. Social Science Research, 100, 102603. https://doi.org/10.1016/j.ssresearch.2021.102603

Alfonzo, M. A. (2005). To Walk or Not to Walk? The Hierarchy of Walking Needs. Environment and Behavior, 37(6), 808–836. https://doi.org/10.1177/0013916504274016

Allen, J., & Taylor, Z. (2018). A new tool for neighbourhood change research: The Canadian Longitudinal Census Tract Database, 1971-2016: Canadian Longitudinal Tract Database. The Canadian Geographer / Le Géographe Canadien, 62(4), 575–588. https://doi.org/10.1111/cag.12467

Amato, G., Rottem, M., Dahl, R., Blaiss, M. S., Ridolo, E., Cecchi, L., Rosario, N., Motala, C., Ansotegui, I., & Annesi-Maesano, I. (2011). Climate change, migration, and allergic respiratory diseases: An update for the allergist. *World Allergy Organization Journal*, *4*(7), 121–125. https://doi.org/10.1097/WOX.0b013e3182260a57

Andrews, G. J., Hall, E., Evans, B., & Colls, R. (2012). Moving beyond walkability: On the potential of health geography. Social Science & Medicine, 75(11), 1925–1932. https://doi.org/10.1016/j.socscimed.2012.08.013

Anguelovski, I., Connolly, J. J. T., Masip, L., & Pearsall, H. (2018). Assessing green gentrification in historically disenfranchised neighborhoods: A longitudinal and spatial analysis of Barcelona. Urban Geography, 39(3), 458–491. https://doi.org/10.1080/02723638.2017.1349987

Annunziata, A., & Garau, C. (2020). A Literature Review on Walkability and its Theoretical Framework. Emerging Perspectives for Research Developments. In O. Gervasi, B. Murgante, S. Misra, C. Garau, I. Blečić, D. Taniar, B. O. Apduhan, A. M. A. C. Rocha, E. Tarantino, C. M. Torre, & Y. Karaca (Eds.), Computational Science and Its Applications – ICCSA 2020 (pp. 422–437). Springer International Publishing. https://doi.org/10.1007/978-3-030-58820-5_32

Annerstedt Van Den Bosch, M., Egorov, A. I., Mudu, P., Uscila, V., Barrdahl, M., Kruize, H., Kulinkina, A., Staatsen, B., Swart, W., & Zurlyte, I. (2016). Development of an urban green space indicator and the public health rationale. *Scandinavian Journal of Public Health*, *44*(2), 159–167. https://doi.org/10.1177/1403494815615444

Ariffin, R. N. R., Rahman, N. H. A., & Zahari, R. K. (2021). Systematic Literature Review of Walkability and the Built Environment. Journal of Policy & Governance, 1–20. https://doi.org/10.33002/jpg010101
Atkinson, R., Wulff, M. G., & Australian Housing and Urban Research Institute. (2009). Gentrification and displacement: A review of approaches and findings in the literature. The Institute.
Bailey, N., van Gent, W. P. C., & Musterd, S. (2017). Remaking Urban Segregation: Processes of Income Sorting and Neighbourhood Change. Population, Space and Place, 23(3), e2013. https://doi.org/10.1002/psp.2013
Barton, M. (2016). An exploration of the importance of the strategy used to identify gentrification. Urban Studies, 53(1), 92–111. https://doi.org/10.1177/0042098014561723
Bartzokas-Tsiompras, A., Tampouraki, E. M., & Photis, Y. N. (2020). Is walkability equally distributed among downtowners? Evaluating the pedestrian streetscapes of eight European capitals using a micro-scale audit approach. International Journal of Transport Development and Integration, 4(1), 75–92. https://doi.org/10.2495/TDI-V4-N1-75-92
Bereitschaft, B. (2017). Equity in neighbourhood walkability? A comparative analysis of three large U.S. cities. Local Environment, 22(7), 859–879. https://doi.org/10.1080/13549839.2017.1297390
Beyer, K., Kaltenbach, A., Szabo, A., Bogar, S., Nieto, F., & Malecki, K. (2014). Exposure to neighborhood green space and mental health: evidence from the survey of the health of Wisconsin. *International Journal of Environmental Research and Public Health*, *11*(3), 3453–3472.
Bodicoat, D. H., O'Donovan, G., Dalton, A. M., Gray, L. J., Yates, T., Edwardson, C., Hill, S., Webb, D. R., Khunti, K., Davies, M. J., & Jones, A. P. (2014). The association between neighbourhood greenspace and type 2 diabetes in a large cross-sectional study. *BMJ Open*, *4*(12), 1–8. https://doi.org/10.1136/bmjopen-2014-006076
Boyle, A., Barrilleaux, C., & Scheller, D. (2014). Does walkability influence housing prices? Social Science Quarterly, 95(3), 852–867.
Bow, C. J. D., Waters, N. M., Faris, P. D., Seidel, J. E., Galbraith, P. D., Knudtson, M. L., & Ghali, W. A. (2004). Accuracy of city postal code coordinates as a proxy for location of residence. *International Journal of Health Geographics*, *3*, 1–9. https://doi.org/10.1186/1476-072X-3-5
Brindley, P., Cameron, R. W., Ersoy, E., Jorgensen, A., & Maheswaran, R. (2019). Is more always better? Exploring field survey and social media indicators of quality of urban greenspace, in relation to health. *Urban Forestry and Urban Greening*, *39*(January), 45–54. https://doi.org/10.1016/j.ufug.2019.01.015
British Columbia & Ministry of Community Services. (2006). Regional growth strategies: An explanatory guide. British Columbia Ministry of Community Services.
Brown, A. L., Khattak, A. J., & Rodriguez, D. A. (2008). Neighbourhood types, travel and body mass: A study of new urbanist and suburban neighbourhoods in the US. Urban Studies, 45(4), 963–988.
Buzar, S., Ogden, P., Hall, R., Haase, A., Kabisch, S., & Steinfiihrer, A. (2007). Splintering Urban Populations: Emergent Landscapes of Reurbanisation in Four European Cities. Urban Studies, 44(4), 651–677. https://doi.org/10.1080/00420980601185544
Cervero, R. (2001). Efficient urbanisation: Economic performance and the shape of the metropolis. Urban Studies, 38(10), 1651–1671.

Cervero, R., & Kockelman, K. (1997). Travel demand and the 3Ds: Density, diversity, and design. Transportation Research Part D: Transport and Environment, 2(3), 199–219. https://doi.org/10.1016/S1361-9209(97)00009-6
Chatman, D. G., Xu, R., Park, J., & Spevack, A. (2019). Does Transit-Oriented Gentrification Increase Driving? Journal of Planning Education and Research, 39(4), 482–495. https://doi.org/10.1177/0739456X19872255
Colabianchi, N., Dowda, M., Pfeiffer, K. A., Porter, D. E., Almeida, M. J. C. A., & Pate, R. R. (2007). Towards an understanding of salient neighborhood boundaries: Adolescent reports of an easy walking distance and convenient driving distance. *International Journal of Behavioral Nutrition and Physical Activity*, *4*, 1–4. https://doi.org/10.1186/1479-5868-4-66
Coutts, C., Chapin, T., Horner, M., & Taylor, C. (2013). County-level effects of green space access on physical activity. *Journal of Physical Activity and Health*, *10*(2), 232–240. https://doi.org/10.1123/jpah.10.2.232
Coutts, C., Horner, M., & Chapin, T. (2010). Using geographical information system to model the effects of green space accessibility on mortality in Florida. *Geocarto International*, *25*(6), 471–484. https://doi.org/10.1080/10106049.2010.505302
Cusack, L., Larkin, A., Carozza, S. E., & Hystad, P. (2017). Associations between multiple green space measures and birth weight across two US cities. *Health and Place*, *47*(December 2016), 36–43. https://doi.org/10.1016/j.healthplace.2017.07.002
Cutts, B. B., Darby, K. J., Boone, C. G., & Brewis, A. (2009). City structure, obesity, and environmental justice: An integrated analysis of physical and social barriers to walkable streets and park access. Social Science & Medicine, 69(9), 1314–1322. https://doi.org/10.1016/j.socscimed.2009.08.020
Dales, R. E., Cakmak, S., Judek, S., & Coates, F. (2008). Tree pollen and hospitalization for asthma in urban Canada. *International Archives of Allergy and Immunology*, *146*(3), 241–247. https://doi.org/10.1159/000116360
Dales, R. E., Cakmak, S., Judek, S., Dann, T., Coates, F., Brook, J. R., & Burnett, R. T. (2004). Influence of outdoor aeroallergens on hospitalization for asthma in Canada. *Journal of Allergy and Clinical Immunology*, *113*(2), 303–306. https://doi.org/10.1016/j.jaci.2003.11.016
Danyluk, M., & Ley, D. (2007). Modalities of the New Middle Class: Ideology and Behaviour in the Journey to Work from Gentrified Neighbourhoods in Canada. Urban Studies, 44, 2195–2210. https://doi.org/10.1080/00420980701520277
De Bourdeaudhuij, I., Sallis, J. F., & Saelens, B. E. (2003). Environmental correlates of physical activity in a sample of Belgian adults. American Journal of Health Promotion, 18(1), 83–92.
Dendup, T., Astell-Burt, T., & Feng, X. (2019). Residential self-selection, perceived built environment and type 2 diabetes incidence: A longitudinal analysis of 36,224 middle to older age adults. *Health & Place*, *58*, 102154. https://doi.org/10.1016/j.healthplace.2019.102154
Dockery, D., Pope, C., Xu, X., Spengler, J., Ware, J., Fay, M., Ferris, B., & Speizer, F. (1993). An association between air pollution and mortaltiy in six U.S. cities. *New England Journal of Medicine*, *328*, 1167–1172.

Duncan, D., Aldstadt, J., Whalen, J., & Melly, S. (2012). Validation of Walk Scores and Transit Scores for estimating neighborhood walkability and transit availability: A small-area analysis. GeoJournal, 78. https://doi.org/10.1007/s10708-011-9444-4
Duncan, D. T., Sharifi, M., Melly, S. J., Marshall, R., Sequist, T. D., Rifas, -Shiman Sheryl L., & Taveras, E. M. (2014). Characteristics of Walkable Built Environments and BMI z-Scores in Children: Evidence from a Large Electronic Health Record Database. Environmental Health Perspectives, 122(12), 1359–1365. https://doi.org/10.1289/ehp.1307704
Dzhambov, A. M., Markevych, I., & Lercher, P. (2018). Greenspace seems protective of both high and low blood pressure among residents of an Alpine valley. *Environment International*, *121*(August 2018), 443–452. https://doi.org/10.1016/j.envint.2018.09.044
el Emam, K., Buckeridge, D., Tamblyn, R., Neisa, A., Jonker, E., & Verma, A. (2011). The re-identification risk of Canadians from longitudinal demographics. *BMC Medical Informatics and Decision Making*, *11*(1). https://doi.org/10.1186/1472-6947-11-46
Ettema, D., & Nieuwenhuis, R. (2017). Residential self-selection and travel behaviour: What are the effects of attitudes, reasons for location choice and the built environment? Journal of Transport Geography, 59, 146–155. https://doi.org/10.1016/j.jtrangeo.2017.01.009
Ewing, R., Hajrasouliha, A., Neckerman, K. M., Purciel-Hill, M., & Greene, W. (2016). Streetscape Features Related to Pedestrian Activity. Journal of Planning Education and Research, 36(1), 5–15. https://doi.org/10.1177/0739456X15591585
Ewing, R., & Handy, S. (2009). Measuring the Unmeasurable: Urban Design Qualities Related to Walkability. Journal of Urban Design, 14(1), 65–84. https://doi.org/10.1080/13574800802451155
Feng, J., Glass, T. A., Curriero, F. C., Stewart, W. F., & Schwartz, B. S. (2010). The built environment and obesity: A systematic review of the epidemiologic evidence. Health & Place, 16(2), 175–190. https://doi.org/10.1016/j.healthplace.2009.09.008
Forsyth, A. (2015). What is a walkable place? The walkability debate in urban design. URBAN DESIGN International, 20(4), 274–292. https://doi.org/10.1057/udi.2015.22
Fotheringham, A. S., & Wong, D. W. S. (1991). The Modifiable Areal Unit Problem in Multivariate Statistical Analysis. Environment and Planning A: Economy and Space, 23(7), 1025–1044. https://doi.org/10.1068/a231025
Frank, L. D., & Engelke, P. (2005). Multiple Impacts of the Built Environment on Public Health: Walkable Places and the Exposure to Air Pollution. International Regional Science Review, 28(2), 193–216. https://doi.org/10.1177/0160017604273853
Frank, L. D., & Pivo, G. (1994). Impacts of mixed use and density on utilization of three modes of travel: Single-occupant vehicle, transit, and walking. Transportation Research Record, 1466, 44–52.
Frank, L. D., Fox, E. H., Ulmer, J. M., Chapman, J. E., Kershaw, S. E., Sallis, J. F., Conway, T. L., Cerin, E., Cain, K. L., Adams, M. A., Smith, G. R., Hinckson, E., Mavoa, S., Christiansen, L. B., Hino, A. A. F., Lopes, A. A. S., & Schipperijn, J. (2017). International comparison of observation-specific spatial buffers: Maximizing the ability to estimate physical activity. *International Journal of Health Geographics*, *16*(1), 1–13. https://doi.org/10.1186/s12942-017-0077-9
Frank, L. D., Saelens, B. E., Powell, K. E., & Chapman, J. E. (2007). Stepping towards causation: Do built environments or neighborhood and travel preferences explain physical

activity, driving, and obesity? *Social Science and Medicine*, *65*(9), 1898–1914. https://doi.org/10.1016/j.socscimed.2007.05.053
Frank, L. D., Sallis, J. F., Saelens, B. E., Leary, L., Cain, L., Conway, T. L., & Hess, P. M. (2010). The development of a walkability index: Application to the neighborhood quality of life study. *British Journal of Sports Medicine*, *44*(13), 924–933. https://doi.org/10.1136/bjsm.2009.058701
Freeman, L., & Braconi, F. (2004). Gentrification and Displacement New York City in the 1990s. Journal of the American Planning Association, 70(1), 39–52. https://doi.org/10.1080/01944360408976337
Fuller, R. A., Irvine, K. N., Devine-Wright, P., Warren, P. H., & Gaston, K. J. (2007). Psychological benefits of greenspace increase with biodiversity. *Biology Letters*, *3*(4), 390–394. https://doi.org/10.1098/rsbl.2007.0149
Gallimore, J. M., Brown, B. B., & Werner, C. M. (2011). Walking routes to school in new urban and suburban neighborhoods: An environmental walkability analysis of blocks and routes. Journal of Environmental Psychology, 31(2), 184–191.
Gibbs, K., Slater, S. J., Nicholson, L., Barker, D., & Chaloupka, F. J. (2012). Income disparities in street features that encourage walking. Bridging the Gap Program.
Gilderbloom, J. I., Riggs, W. W., & Meares, W. L. (2015). Does walkability matter? An examination of walkability's impact on housing values, foreclosures and crime. Cities, 42, 13–24. https://doi.org/10.1016/j.cities.2014.08.001
Glass, R. (1964). Aspects of change. The Gentrification Debates: A Reader, 19–30.
Glazier, R. H., Creatore, M. I., Weyman, J. T., Fazli, G., Matheson, F. I., Gozdyra, P., Moineddin, R., Shriqui, V. K., & Booth, G. L. (2014). Density, destinations or both? A comparison of measures of walkability in relation to transportation behaviors, obesity and diabetes in Toronto, Canada. *PLoS ONE*, *9*(1), 1–9. https://doi.org/10.1371/journal.pone.0085295
Greenberg, M. R., & Renne, J. (2005). Where does walkability matter the most? An environmental justice interpretation of New Jersey data. Journal of Urban Health, 82(1), 90–100.
Grigsby, W. (1986). The Dynamics of Neighborhood Change and Decline.
Gullón, P., Bilal, U., Cebrecos, A., Badland, H. M., Galán, I., & Franco, M. (2017). Intersection of neighborhood dynamics and socioeconomic status in small-area walkability: The Heart Healthy Hoods project. International Journal of Health Geographics, 16, 21. https://doi.org/10.1186/s12942-017-0095-7
Hackworth, J., & Smith, N. (2001). The changing state of gentrification. Tijdschrift Voor Economische En Sociale Geografie, 92(4), 464–477.
Hall, C. M., & Ram, Y. (2018). Walk score® and its potential contribution to the study of active transport and walkability: A critical and systematic review. Transportation Research Part D: Transport and Environment, 61, 310–324. https://doi.org/10.1016/j.trd.2017.12.018
Hamidi, S., & Ewing, R. (2014). A longitudinal study of changes in urban sprawl between 2000 and 2010 in the United States. Landscape and Urban Planning, 128, 72–82.
Hammel, D. J., & Wyly, E. K. (1996). A MODEL FOR IDENTIFYING GENTRIFIED AREAS WITH CENSUS DATA. Urban Geography, 17(3), 248–268. https://doi.org/10.2747/0272-3638.17.3.248

Hamnett, C. (1994). Social polarisation in global cities: Theory and evidence. Urban Studies, 31(3), 401–424.
Handy, S., Cao, X., & Mokhtarian, P. L. (2006). Self-selection in the relationship between the built environment and walking: Empirical evidence from Northern California. Journal of the American Planning Association, 72(1), 55–74.
Harrell Jr, F E, & with contributions from Charles Dupont and many others. (2021). *Hmisc: Harrell Miscellaneous.* (R package version 4.5-0.).
Healy, M. A., & Gilliland, J. A. (2012). Quantifying the magnitude of environmental exposure misclassification when using imprecise address proxies in public health research. *Spatial and Spatio-Temporal Epidemiology*, *3*(1), 55–67. https://doi.org/10.1016/j.sste.2012.02.006
Hedman, L. (2011). Residential mobility and neighbourhood effects: A holistic approach. Acta Universitatis Upsaliensis.
Heinen, E., van Wee, B., Panter, J., Mackett, R., & Ogilvie, D. (2018). Residential self-selection in quasi-experimental and natural experimental studies: An extended conceptualization of the relationship between the built environment and travel behavior. *Journal of Transport and Land Use*, *11*(1), 939–959. https://doi.org/10.5198/jtlu.2018.1165
Hochstenbach, C., & van Gent, W. P. (2015). An anatomy of gentrification processes: Variegating causes of neighbourhood change. Environment and Planning A: Economy and Space, 47(7), 1480–1501. https://doi.org/10.1177/0308518X15595771
Immergluck, D., & Balan, T. (2018). Sustainable for whom? Green urban development, environmental gentrification, and the Atlanta Beltline. Urban Geography, 39(4), 546–562. https://doi.org/10.1080/02723638.2017.1360041
Institut National de Sante Publique du Quebec. (2017). *The Challenges of Updating the Deprivation Index with Data from the 2011 Census and the National Household Survey (NHS)*. 1–7. https://www.inspq.qc.ca/sites/default/files/publications/2207_challenges_deprivation_index_date_20111_census.pdf
James, P., Banay, R. F., Hart, J. E., & Laden, F. (2015). A Review of the Health Benefits of Greenness. *Current Epidemiology Reports*, *2*(2), 131–142. https://doi.org/10.1007/s40471-015-0043-7
Jarvis, I., Gergel, S., Koehoorn, M., & van den Bosch, M. (2020). Greenspace access does not correspond to nature exposure: Measures of urban natural space with implications for health research. *Landscape and Urban Planning*, *194*(June 2019), 103686. https://doi.org/10.1016/j.landurbplan.2019.103686
Jia, X., Yu, Y., Xia, W., Masri, S., Sami, M., Hu, Z., Yu, Z., & Wu, J. (2018). Cardiovascular diseases in middle aged and older adults in China: the joint effects and mediation of different types of physical exercise and neighborhood greenness and walkability. *Environmental Research*, *167*(October 2017), 175–183. https://doi.org/10.1016/j.envres.2018.07.003
Kardan, O., Gozdyra, P., Misic, B., Moola, F., Palmer, L. J., Paus, T., & Berman, M. G. (2015). Neighborhood greenspace and health in a large urban center. *Scientific Reports*, *5*, 1–14. https://doi.org/10.1038/srep11610

Khan, S., Pinault, L., Tjepkema, M., & Wilkins, R. (2018). Positional accuracy of geocoding from residential postal codes versus full street addresses. *Health Reports*, *29*(2), 3–9.
Klompmaker, J. O., Hoek, G., Bloemsma, L. D., Gehring, U., Strak, M., Wijga, A. H., van den Brink, C., Brunekreef, B., Lebret, E., & Janssen, N. A. H. (2018). Green space definition affects associations of green space with overweight and physical activity. *Environmental Research*, *160*(May 2017), 531–540. https://doi.org/10.1016/j.envres.2017.10.027
King, A. C., Sallis, J. F., Frank, L. D., Saelens, B. E., Cain, K., Conway, T. L., Chapman, J. E., Ahn, D. K., & Kerr, J. (2011). Aging in neighborhoods differing in walkability and income: Associations with physical activity and obesity in older adults. Social Science & Medicine (1982), 73(10), 1525–1533. https://doi.org/10.1016/j.socscimed.2011.08.032
Knight, J., Weaver, R., & Jones, P. (2018). Walkable and resurgent for whom? The uneven geographies of walkability in Buffalo, NY. Applied Geography, 92(Complete), 1–11. https://doi.org/10.1016/j.apgeog.2018.01.008
Koschinsky, J., Talen, E., Alfonzo, M., & Lee, S. (2017). How walkable is Walker's paradise? Environment and Planning B: Urban Analytics and City Science, 44(2), 343–363. https://doi.org/10.1177/0265813515625641

Labib, S. M., Lindley, S., & Huck, J. J. (2020). Spatial dimensions of the influence of urban green-blue spaces on human health: A systematic review. *Environmental Research*, *180*(November 2019), 108869. https://doi.org/10.1016/j.envres.2019.108869
Lachowycz, K., & Jones, A. P. (2011). Greenspace and obesity: A systematic review of the evidence. *Obesity Reviews*, *12*(5), 183–189. https://doi.org/10.1111/j.1467-789X.2010.00827.x
Larkin, A., & Hystad, P. (2019). Evaluating street view exposure measures of visible green space for health research. *Journal of Exposure Science and Environmental Epidemiology*, *29*(4), 447–456. https://doi.org/10.1038/s41370-018-0017-1
Lee, C., & Moudon, A. V. (2006). The 3Ds+R: Quantifying land use and urban form correlates of walking. Transportation Research Part D: Transport and Environment, 11(3), 204–215. https://doi.org/10.1016/j.trd.2006.02.003
Lee, S., & Talen, E. (2014). Measuring Walkability: A Note on Auditing Methods. Journal of Urban Design, 19(3), 368–388. https://doi.org/10.1080/13574809.2014.890040
Lees, L. (2000). A reappraisal of gentrification: Towards a 'geography of gentrification.' Progress in Human Geography, 24(3), 389–408.
Ley, D. (1986). Alternative Explanations for Inner-City Gentrification: A Canadian Assessment. Annals of the Association of American Geographers, 76(4), 521–535. https://doi.org/10.1111/j.1467-8306.1986.tb00134.x
Ley, D. (2003). Artists, Aestheticisation and the Field of Gentrification. Urban Studies, 40(12), 2527–2544. https://doi.org/10.1080/0042098032000136192
Ley, D., & Dobson, C. (2008). Are There Limits to Gentrification? The Contexts of Impeded Gentrification in Vancouver. Urban Studies, 45(12), 2471–2498. https://doi.org/10.1177/0042098008097103
Leyden, K. M. (2003). Social capital and the built environment: The importance of walkable neighborhoods. American Journal of Public Health, 93(9), 1546–1551.

Li, X., Zhang, C., Li, W., Ricard, R., Meng, Q., & Zhang, W. (2015). Assessing street-level urban greenery using Google Street View and a modified green view index. *Urban Forestry and Urban Greening*, *14*(3), 675–685. https://doi.org/10.1016/j.ufug.2015.06.006
Liao, B., van den Berg, P. E. W., van Wesemael, P. J. V., & Arentze, T. A. (2020). Empirical analysis of walkability using data from the Netherlands. Transportation Research Part D: Transport and Environment, 85, 102390. https://doi.org/10.1016/j.trd.2020.102390
Lovasi, G. S., Neckerman, K. M., Quinn, J. W., Weiss, C. C., & Rundle, A. (2009). Effect of Individual or Neighborhood Disadvantage on the Association Between Neighborhood Walkability and Body Mass Index. American Journal of Public Health, 99(2), 279–284. https://doi.org/10.2105/AJPH.2008.138230
Madonsela, S., Cho, M. A., Ramoelo, A., Mutanga, O., & Naidoo, L. (2018). Estimating tree species diversity in the savannah using NDVI and woody canopy cover. *International Journal of Applied Earth Observation and Geoinformation*, *66*, 106–115. https://doi.org/10.1016/j.jag.2017.11.005
Markevych, I., Schoierer, J., Hartig, T., Chudnovsky, A., Hystad, P., Dzhambov, A. M., de Vries, S., Triguero-Mas, M., Brauer, M., Nieuwenhuijsen, M. J., Lupp, G., Richardson, E. A., Astell-Burt, T., Dimitrova, D., Feng, X., Sadeh, M., Standl, M., Heinrich, J., & Fuertes, E. (2017). Exploring pathways linking greenspace to health: Theoretical and methodological guidance. *Environmental Research*, *158*(February), 301–317. https://doi.org/10.1016/j.envres.2017.06.028
Marcuse, P. (1985). Gentrification, abandonment, and displacement: Connections, causes, and policy responses in New York City. Wash. UJ Urb. & Contemp. L., 28, 195.
Massey, D. S. (2004). SEGREGATION AND STRATIFICATION: A Biosocial Perspective. Du Bois Review: Social Science Research on Race, 1(1), 7–25. https://doi.org/10.1017/S1742058X04040032
Matthews, J. W., & Turnbull, G. K. (2007). Neighborhood street layout and property value: The interaction of accessibility and land use mix. The Journal of Real Estate Finance and Economics, 35(2), 111–141
Mazumdar, S., Chong, S., Astell-Burt, T., Feng, X., Morgan, G., & Jalaludin, B. (2021). Which green space metric best predicts a lowered odds of type 2 diabetes? *International Journal of Environmental Research and Public Health*, *18*(8). https://doi.org/10.3390/ijerph18084088
Mazumdar, S., Dunshea, A., Chong, S., & Jalaludin, B. (2020). Tree canopy cover is best associated with perceptions of greenspace: a short communication. *International Journal of Environmental Research and Public Health*, *17*(18), 1–9. https://doi.org/10.3390/ijerph17186501
McKinnish, T., Walsh, R., & White, T. K. (2010). Who Gentrifies Low-Income Neighborhoods? Journal of Urban Economics, 67(2), 180–193. https://doi.org/10.1016/j.jue.2009.08.003
Meegan, R., & Mitchell, A. (2001). “It’s not community round here, it’s neighbourhood”: Neighbourhood change and cohesion in urban regeneration policies. Urban Studies, 38(12), 2167–2194.
Meen, G., Nygaard, C., & Meen, J. (2012). The Causes of Long-Term Neighbourhood Change. In Understanding Neighbourhood Dynamics: New Insights for Neighbourhood Effects Research (pp. 43–62). https://doi.org/10.1007/978-94-007-4854-5_3

Medina-Ramón, M., Zanobetti, A., Cavanagh, D. P., & Schwartz, J. (2006). Extreme temperatures and mortality: Assessing effect modification by personal characteristics and specific cause of death in a multi-city case-only analysis. *Environmental Health Perspectives*, *114*(9), 1331–1336. https://doi.org/10.1289/ehp.9074
Metro Vancouver. (2020). *Open Data Catalogue*.
Metro Vancouver. (2011, July). Metro Vancouver 2040. http://www.metrovancouver.org/services/regional-planning/PlanningPublications/RGSAdoptedbyGVRDBoard.pdf
Metro Vancouver. (2022). About Us. http://www.metrovancouver.org/about/Pages/default.aspx
Moeller, J. (2015). A word on standardization in longitudinal studies: Don't. Frontiers in Psychology, 6. https://doi.org/10.3389/fpsyg.2015.01389
Moseley, D., Marzano, M., Chetcuti, J., & Watts, K. (2013). Green networks for people: Application of a functional approach to support the planning and management of greenspace. *Landscape and Urban Planning*, *116*, 1–12. https://doi.org/10.1016/j.landurbplan.2013.04.004
Newman, K., & Wyly, E. K. (2006). The Right to Stay Put, Revisited: Gentrification and Resistance to Displacement in New York City. Urban Studies, 43(1), 23–57. https://doi.org/10.1080/00420980500388710
Oliver, L. N., Schuurman, N., & Hall, A. W. (2007). Comparing circular and network buffers to examine the influence of land use on walking for leisure and errands. *International Journal of Health Geographics*, *6*, 1–11. https://doi.org/10.1186/1476-072X-6-41
Pampalon, R., Hamel, D., Gamache, P., Philibert, M. D., Raymond, G., & Simpson, A. (2012). An area-based material and social deprivation index for public health in Québec and Canada. *Canadian Journal of Public Health*, *103*(SUPPL.2). https://doi.org/10.1007/bf03403824
Peters, K., Elands, B., & Buijs, A. (2010). Social interactions in urban parks: Stimulating social cohesion? *Urban Forestry and Urban Greening*, *9*(2), 93–100. https://doi.org/10.1016/j.ufug.2009.11.003
Pivo, G., & Fisher, J. D. (2011). The Walkability Premium in Commercial Real Estate Investments. Real Estate Economics, 39(2), 185–219. https://doi.org/10.1111/j.1540-6229.2010.00296.x
Pollack, S., Bluestone, B., & Billingham, C. (2010). Maintaining diversity in America's transit-rich neighborhoods: Tools for equitable neighborhood change.
Punter, J. (2010). The Vancouver achievement: Urban planning and design. UBC Press.
QGIS Development Team. (2021). *QGIS Geographic Information System. Open Source Geospatial Foundation Project* (3.18).
Quastel, N., Moos, M., & Lynch, N. (2012). Sustainability-As-Density and the Return of the Social: The Case of Vancouver, British Columbia. Urban Geography, 33(7), 1055–1084. https://doi.org/10.2747/0272-3638.33.7.1055
R Core Team. (2019). *R: A Language and Environment for Statistical Computing* (3.6.1). R Foundation for Statistical Computing. https://www.r-project.org/
Ramos, H., Kaida, L., Singh, D., Pritchard, P., & Wijesingha, R. (2021). The power of a simple index of neighbourhood change: Challenging the perception that there is no such thing as simplicity in creating indexes. The Canadian Geographer / Le Géographe Canadien, n/a(n/a). https://doi.org/10.1111/cag.12711

Rauterkus, S. Y., & Miller, N. (2011). Residential land values and walkability. Journal of Sustainable Real Estate, 3(1), 23–43.
Riggs, W. (2016). Inclusively walkable: Exploring the equity of walkable housing in the San Francisco Bay Area. Local Environment, 21(5), 527–554. https://doi.org/10.1080/13549839.2014.982080
Rhew, I. C., vander Stoep, A., Kearney, A., Smith, N. L., & Dunbar, M. D. (2011). Validation of the Normalized Difference Vegetation Index as a Measure of Neighborhood Greenness. *Annals of Epidemiology*, *21*(12), 946–952. https://doi.org/10.1016/j.annepidem.2011.09.001
Rojas-Rueda, D., Nieuwenhuijsen, M. J., Gascon, M., Perez-Leon, D., & Mudu, P. (2019). Green spaces and mortality: a systematic review and meta-analysis of cohort studies. *The Lancet Planetary Health*, *3*(11), e469–e477. https://doi.org/10.1016/S2542-5196(19)30215-3
Rose, D. (1984). Rethinking Gentrification: Beyond the Uneven Development of Marxist Urban Theory. Environment and Planning D: Society and Space, 2(1), 47–74. https://doi.org/10.1068/d020047
Rothschild, S. (2019). An Exploratory Statistical Analysis of Gentrification and Neighborhood Change in Seattle. 42.

Rugel, E. J., Carpiano, R. M., Henderson, S. B., & Brauer, M. (2019). Exposure to natural space, sense of community belonging, and adverse mental health outcomes across an urban region. *Environmental Research*, *171*(January), 365–377. https://doi.org/10.1016/j.envres.2019.01.034
Saelens, B. E., & Handy, S. L. (2008). Built Environment Correlates of Walking: A Review. Medicine and Science in Sports and Exercise, 40(7 Suppl), S550–S566. https://doi.org/10.1249/MSS.0b013e31817c67a4
Sallis, J. F., Cerin, E., Conway, T. L., Adams, M. A., Frank, L. D., Pratt, M., Salvo, D., Schipperijn, J., Smith, G., Cain, K. L., Davey, R., Kerr, J., Lai, P.-C., Mitáš, J., Reis, R., Sarmiento, O. L., Schofield, G., Troelsen, J., Van Dyck, D., … Owen, N. (2016). Physical activity in relation to urban environments in 14 cities worldwide: A cross-sectional study. The Lancet, 387(10034), 2207–2217. https://doi.org/10.1016/S0140-6736(15)01284-2
Sallis, J. F., Slymen, D. J., Conway, T. L., Frank, L. D., Saelens, B. E., Cain, K., & Chapman, J. E. (2011). Income disparities in perceived neighborhood built and social environment attributes. Health & Place, 17(6), 1274–1283. https://doi.org/10.1016/j.healthplace.2011.02.006
Shields, R., Gomes da Silva, E. J., Lima e Lima, T., & Osorio, N. (2021). Walkability: A review of trends. Journal of Urbanism: International Research on Placemaking and Urban Sustainability, 0(0), 1–23. https://doi.org/10.1080/17549175.2021.1936601
Shuvo, F. K., Mazumdar, S., & Labib, S. M. (2021). Walkability and greenness do not walk together: Investigating associations between greenness and walkability in a large metropolitan city context. *International Journal of Environmental Research and Public Health*, *18*(9). https://doi.org/10.3390/ijerph18094429
Slater, T. (2011). Gentrification of the city. The New Blackwell Companion to the City, 1.
Song, Y., & Knaap, G.-J. (2003). New urbanism and housing values: A disaggregate assessment. Journal of Urban Economics, 54(2), 218–238.

Southworth, M., & Owens, P. M. (1993). The Evolving Metropolis: Studies of Community, Neighborhood, and Street Form at the Urban Edge. Journal of the American Planning Association, 59(3), 271–287. https://doi.org/10.1080/01944369308975880
Stevenson, M., Thompson, J., de Sá, T. H., Ewing, R., Mohan, D., McClure, R., Roberts, I., Tiwari, G., Giles-Corti, B., Sun, X., Wallace, M., & Woodcock, J. (2016). Land use, transport, and population health: Estimating the health benefits of compact cities. The Lancet, 388(10062), 2925–2935. https://doi.org/10.1016/S0140-6736(16)30067-8
Su, S. (2019). Auditing street walkability and associated social inequalities for planning implications. Journal of Transport Geography, 15.
Sugiyama, T., Leslie, E., Giles-Corti, B., & Owen, N. (2008). Associations of neighbourhood greenness with physical and mental health: do walking, social coherence and local social interaction explain the relationships? *Journal of Epidemiology and Community Health*, *62*(5), 6–11. https://doi.org/10.1136/jech.2007.064287
Sutherland JM, Liu G, Crump RT, Law M. (2016). Paying for volume: British Columbia's experiment with funding hospitals based on activity. Health Policy. Nov;120(11):1322-1328. https://doi.org/10.1016/j.healthpol.2016.09.010
Taylor, L., & Hochuli, D. F. (2017). Defining greenspace: Multiple uses across multiple disciplines. *Landscape and Urban Planning*, *158*, 25–38. https://doi.org/10.1016/j.landurbplan.2016.09.024
Temkin, K., & Rohe, W. (1996). Neighborhood Change and Urban Policy. Journal of Planning Education and Research, 15(3), 159–170. https://doi.org/10.1177/0739456X9601500301
Timmermans, E. J., Visser, M., Wagtendonk, A. J., Noordzij, J. M., & Lakerveld, J. (2021). Associations of changes in neighbourhood walkability with changes in walking activity in older adults: A fixed effects analysis. BMC Public Health, 21(1), 1323. https://doi.org/10.1186/s12889-021-11368-6
Twohig-Bennett, C., & Jones, A. (2018). The health benefits of the great outdoors: A systematic review and meta-analysis of greenspace exposure and health outcomes. *Environmental Research*, *166*(February), 628–637. https://doi.org/10.1016/j.envres.2018.06.030
Walks, R. A., & Maaranen, R. (2008). Gentrification, Social Mix, and Social Polarization: Testing the Linkages in Large Canadian Cities. Urban Geography, 29(4), 293–326. https://doi.org/10.2747/0272-3638.29.4.293
Williams, D. A. R., Matasci, G., Coops, N. C., & Gergel, S. E. (2018). Object-based urban landcover mapping methodology using high spatial resolution imagery and airborne laser scanning. *Journal of Applied Remote Sensing*, *12*(04), 1. https://doi.org/10.1117/1.jrs.12.046020
Wyly, E. K., & Hammel, D. J. (1998). Modeling the Context and Contingency of Gentrification. Journal of Urban Affairs, 20(3), 303–326. https://doi.org/10.1111/j.1467-9906.1998.tb00424.x
Yang, B. Y., Markevych, I., Heinrich, J., Bowatte, G., Bloom, M. S., Guo, Y., Dharmage, S. C., Jalaludin, B., Knibbs, L. D., Morawska, L., Qian, Z. (Min), Chen, D. H., Ma, H., Chen, D., Lin, S., Yang, M., Liu, K. K., Zeng, X. W., Hu, L. W., & Dong, G. H. (2019). Associations of greenness with diabetes mellitus and glucose-homeostasis markers: The 33 Communities Chinese Health Study. *International Journal of Hygiene and Environmental Health*, *222*(2), 283–290. https://doi.org/10.1016/j.ijheh.2018.12.001

Yu, C.-Y. (2014). Environmental supports for walking/biking and traffic safety: Income and ethnicity disparities. Preventive Medicine, 67, 12–16. https://doi.org/10.1016/j.ypmed.2014.06.028
Zandieh, R., Flacke, J., Martinez, J., Jones, P., & van Maarseveen, M. (2017). Do Inequalities in Neighborhood Walkability Drive Disparities in Older Adults' Outdoor Walking? International Journal of Environmental Research and Public Health, 14(7), 740. https://doi.org/10.3390/ijerph14070740
Zwiers, M., Kleinhans, R., & Van Ham, M. (2017). The Path-Dependency of Low-Income Neighbourhood Trajectories: An Approach for Analysing Neighbourhood Change. Applied Spatial Analysis and Policy, 10(3), 363–380. https://doi.org/10.1007/s12061-016-9189-z

11. Appendix A: Performance-Based Funding

11.1.1. Performance-Based Funding (PBF): Differences in Application Across Sectors

Innovative applications of PBF have resulted in an abundance of terms used to describe the various strategies through which it is applied, and there is no universal framework for aggregating, understanding and comparing PBF strategies across sectors (M. Brown et al., 2019; M. Pearson et al., 2010; Rodriguez et al., 2014). Different sectors use the same terminology for different PBF models, or different terminology for the same models. For instance, **contracting-for-results**, **results-driven contracting**, and **outcome-based contracting** are all terms for similar mechanisms in social service delivery (N. M. Brown, 2019; Hawkins et al., 2019). In some cases, the term 'performance' is a broad term synonymous with 'results' that encompasses 'inputs', 'outputs', and 'outcomes'; In other cases, 'performance' specifically refers to inputs and outputs, while only outputs are considered results. With the ambiguity of PBF, almost anything can be considered a performance measure (including inputs), however, applications of PBF in this document are narrowly focused on cases where financial or non-financial incentives have been explicitly linked to and dispersed based on targeted and measurable outcomes.

The following section summarizes the differences in application of common performance-based methods grouped by sector, with the intention of clarifying the similarities and differences in applications of PBF across sectors.

11.1.2. Performance-Based Approaches in Global Development Financing and Aid

In response to concerns surrounding the effectiveness of aid spending, performance and results-based approaches to development financing became popular mechanisms for development aid since the early 2000s (Perakis & Savedoff, 2014). Almost all foreign aid programs and projects have at least some specific outcomes and results monitoring processes, but some models are more direct in connecting their incentive structures to quantifiable results and outcomes (Janus et al., 2015). Financing institutions and organizations such as the British Department for International Development (DfID), German Kreditanstalt für Wiederaufbauthe (KfW), Swedish International Development Agency (SIDA), and the Australian Agency for International Development (AusAID) were early promoters of PBF instruments, as well as development agencies such as Center for Global Development (CGD) and the Global Partnership on Output-Based Aid (GPOBA) (Rodriguez et al., 2014).

Musgrove (2011) and Pearson (2010) have both created comprehensive glossaries of terminology related to PBF approaches in the development sectors, with the most common instruments being:

- Results-Based Financing;
- Results-Based Aid; and
- Challenge-Linked Financing.

Descriptions, examples, and case studies of these PBF models, as well as various sub-categories, are provided in the following section.

11.1.2.1. Results-Based Financing

Results-Based Financing (RBF) in global development refers to any program that rewards the delivery of one or more outputs or outcomes by one or more incentives (Musgrove, 2011). RBF is typically a contract between a national or sub-national government and an implementing agency such as an NGO, for-profit organization, non-profit organization, or sub-national government (Grittner, 2013). Most times, RBF payments are additional or 'top-ups' to traditional or current sources of funding (such as a results-based bonus). In these models, the relationship between results and payments can be both linear or non-linear (Musgrove, 2011

In the global development and aid literature, **Performance-Based Financing, Pay-for-Performance (P4P), Performance-Based Payment** and **Performance-Based Incentives (PBI)** can all be synonyms for RBF; however, the term "performance" in this context means that payments are only made to providers, not beneficiaries.). **Performance-Based Contracting (PBC)** is another subset of RBF that sets a fixed price for a desired output and adds a variable component that can either reduce payment for poor performance, or increase payment for good performance relative to the standard or benchmark defined in the contract (Hawkins et al., 2019).

RBF Program Examples:

- **The Global Fund,** which is an international financing partnership that aims to fight HIV, tuberculosis (TB), and malaria in 130 countries. The program uses a PBF mechanism that evaluates program performance, and funding is released based on progress towards country-owned targets and indicators. Performance data is used to stop grants, reduce funding, or accelerate funding (V. Y. Fan et al., 2013).

- **The World Bank's Conditional Cash Transfer Programs**, which are social assistance programs aiming to reduce poverty. In development finance, Conditional Cash Transfer Programs typically reward the behaviour of an individual, such as providing money to families contingent upon certain

verifiable actions, generally minimum investments in children's human capital such as regular school attendance or basic preventative health care (see World Bank Group's RBF for Health portal for specific projects at *www.rbfhealth.org*).

- **The World Bank's Voucher Programs**, where vouchers are handed out to targeted individuals who redeem them at service providers. Service providers then get reimbursed for the vouchers (see World Bank Group's RBF for Health portal for specific projects at *www.rbfhealth.org*).

RBF In-Depth Example 1: The Amazon Fund was the first large-scale international effort to promote forest conservation using a performance-based mechanism. The agreement between Norway and Brazil transferred development financing to Brazil on the basis of verified reductions in carbon emmisions from slowing the rate of deforestation. Norway pledged US $1 billion to the Amazon Fund for the period from 2008 to 2015. Transfers from Norway to Brazil were designed to reward an outcome (reduced emissions from deforestation) based on satellite imagery that measures changes in deforested area.

The agreement saw Norway pay Brazil a fixed amount for each "unit" of progress at US$5 per ton of CO2 emission reductions. Avoided deforestation rates were calculated based on data from Brazil's National Center for Space Research using satellite imagery, and 'avoided deforestation' was the change in the current years deforestation rates compared to the average between 1996 and 2005 (this 5 year period was shifted forward every five years to create a new baseline). The amount of reported reduced gas emissions was independently reviewed by a technical committee of independent experts. Brazil had full discretion over the way it reduced deforestation, and international funds were channelled through the Amazon Fund into environmental programs that would further contribute to forest conservation.

Information on annual deforestation rates, emissions reductions and payments can be found on both Norwegian and Brazilian official websites and the Norwegian International Climate and Forest Initiative (NICFI) websites.

Sources: (Correa et al., 2019; Forstater et al., 2013; Wertz-Kanounnikoff & Angelsen, 2009)

11.1.2.2. Result-Based Aid

Results-based aid (RBA) is a performance-based aid contract between a donor and a national or sub-national government (Grittner, 2013). In these models, the recipient of the fund achieves specific outcomes, and governments link the disbursement of the fund to the verification of the achievement of those outcomes (Perakis & Savedoff, 2015). In this context, **Output-based aid (OBA)** is accepted to be a synonym for RBA, and output does not usually include results better classified as outcomes (Musgrove, 2011). **Cash-on-Delivery (COD)** is a subset of RBA that refers to outcomes rather than just outputs and

is distinguished from RBA as the principal has minimal oversight of how the agent achieves the desired outcomes (Musgrove, 2011). RBA has been applied in most infrastructure sectors and social sectors (GPRBA, 2021).

RBA Program Examples:

- **The United States Millennium Challenge Corporation**, which allocates aid to 'reward' developing countries for a commitment to good governance and development as measured by a series of third-party policy indicators (see (GPRBA, n.d.) for specific projects).

- **The European Union's EU Budget Support Program**, which offers three budget support programs (Good Governance and Development Contracts, Sector Reform Contracts, and State Building Contracts) designed to address a specific development objective (see https://ec.europa.eu).

- **The World Bank's Program for Results**, which provides incentives to enhance the quality and availability of services and disbursement is linked to specified results (see https://www.worldbank.org/en/programs/program-for-results-financing).

Results-Based Aid In-Depth Example 1: The GAVI Alliance Immunization Services Support (ISS) Program was established in 2000 with the aim to increase immunizations in developing countries through a results-based funding mechanism between the World Health Organization, the World Bank, and many other private and public agencies. It was considered to be an innovative approach to funding vaccination programs and one of the first to pay governments for "units of progress".

The GAVI ISS program paid for increases in the number of immunized children, which represents a development outcome: vaccination is a strong proxy for improved child health and may be correlated with the quality of a country's healthcare system (Murray and Evans 2006). The ISS program provided a fixed payment of US$20 per additional child vaccinated. The program took country ownership seriously and did not impose specific requirements on how vaccination programs were to be rolled out or how reward funds were to be used.

A total of 62 countries received funding from the ISS Program between 2000 and 2010. The funding model was for five years, with the first three years as initial investment and in subsequent years, countries were paid based on increases in numbers of children immunized. The program gave countries wide discretion on how they would achieve increases in immunizations, and external evaluators monitored countries reporting on immunization progress.

Sources: (Gandhi, 2015; Perakis & Savedoff, 2015; Trap et al., 2011)

Results-Based Aid In-Depth Example 2: Salud Mesoamérica 2015 (SM2015) was a five-year RBA initiative aimed to reduce equity gaps in maternal and child health across Central America starting in 2010, funded by the Bill and Melinda Gates Foundation, the Inter-American Development Bank (IDB) and the Spanish Government. The pilot operated in seven countries, and a portion of funding to government was contingent upon progress toward health-related development goals. SM2015 was a large regional initiative, for which a portion of program funding is paid on the basis of measured results (up to 50% of counterpart funding, which is at least 50% of input-based funding provided by the project's donors). The program provides conventional investment funds alongside a performance component, and countries received grants but were also required to finance a portion of the program costs themselves. If the goals of the initiative were achieved, countries were reimbursed for 50% of the amount they contributed. Through this program, funding could only be used to implement specific evidence-based interventions in targeted areas, and activities were required to be targeted at the poorest 20% of the population.

The indicators directly measure outcomes (for example, reductions in prevalence of anemia) or outputs that are associated with desired outcomes (for example, increases in neonatal care provided within 24 hours of birth), and the program did not pay for a single outcome but instead uses 8 to 12 outcome and output indicators which measure important features of the countries' health systems in the areas of prenatal, neonatal, and maternal health. About 8 to 12 indicators were selected on average for each country, and five of which were common across countries in order to make regional comparisons. Examples of indicators used include contraceptive use, anemia prevalence, DTP3 vaccinations and antenatal care visits. SM2015 payments are made on the basis of targets rather than in proportion to progress.

The SM2015 website maintained by the IDB has published country-level information about the program.

Sources: (Bhushan & Calleja, 2015; El Bcheraoui et al., 2018; Mokdad et al., 2015, 2018; Perakis & Savedoff, 2015)

RBA In-Depth Example 2: United Kingdom Department for International Development (UK DFID) Cash-on-Delivery Pilot in the Ethiopian Education Sector was a project intended to improve access to and the quality of lower secondary education in Ethiopia through the use of COD Aid. UK DFID negotiated an RBA program with the government of Ethiopia, making it the first program to be directly inspired by the idea of COD Aid. In this pilot, the amount of aid provided was directly related to the magnitude of outcomes achieved, rather than activities provided or outputs produces (Tobin et al., 2015). The pilot aimed to improve access and quality of education of secondary students in specific regions of the country, specifically, the pilot intended to increase the number of grade 10 students sitting and passing the national examinations in 2012, 2013 and 2014. To incentivize these outcomes, the DFID offered the Government of Ethiopia a fixed dollar amount per student sitting and passing the national exams in these years.

Rewards payments were based on the number of additional sitters and passers within each region per year, compared to the number the previous year. The program paid for each additional boy or girl who sits the lower secondary exam and for each boy or girl who passes the exam, rewarding the Ethiopian government in proportion to the progress made on these measures. DFID contracted an independent consulting agent to verify results reported by the government. During this pilot, the DFID published independently conducted annual reviews as well as a final review (Tobin et al., 2015) and provided detailed performance data at the disaggregated level, available at its open data portal. In terms of accountability to British taxpayers, DFID has provided key information on its website, especially in terms of the program's budget and design.

Sources: (Bhushan & Calleja, 2015; Holzapfel & Janus, 2015; Perakis & Savedoff, 2014; Tobin et al., 2015)

11.1.2.3. Challenge-Linked Financing

Challenge-linked Financing (CLF) is a term for 'awards' or 'prizes' in the development sector, and includes funds or other rewards for development solutions, typically through a competitive process (Bhushan & Calleja, 2015). Notable CLF models include the Grand Challenge programs, the Small Medium Enterprise (SME) Innovation Trust Fund, and the USAID's Development Innovation Ventures. (Bhushan & Calleja, 2015).

CLF Program Examples:

- **The Global SME Finance Innovation Trust Fund**, which promotes innovative ways to provide sustainable financing of SMEs in low-income countries (see https://www.gpfi.org/publications/inception-report-sme-finance-forum-and-interim-progress-report-global-sme-finance-innovation-trust).

- **Bill and Melinda Gates Foundation Grand Challenges in Global Health**, which uses a family of grant programs to overcome bottlenecks in developing new tools and methods to improve health in the developing world (see https://gcgh.grandchallenges.org)

- **Canada, Bill and Melinda Gates Foundation, United Kingdom Grand Challenge Canada**, which supports innovative ideas to overcome health problems in low- and middle-income countries (see https://www.grandchallenges.ca)

- **Bill and Melinda Gates Foundation Grand Challenge Exploratio**n, which uses a tiered grant mechanism to support innovative ideas to solve key health and development problems for those most in need (see https://gcgh.grandchallenges.org/about)

- **United States Development Innovation Ventures**, which supports the discovery of new and innovative ways to address complex development problems (https://www.usaid.gov/div)

Challenge-Linked Financing In-Depth Example: The United States Millennium Challenge Corporation (MCC) provides economic assistance through a competitive selection process to developing nations that demonstrate positive performance in three areas: ruling justly, investing in people, and fostering economic freedom. MCC compacts are five-year grant agreements, proposed and implemented by well-governed countries. This PBF model is unique from others previously described as the disbursement-linked indicators are used to evaluate a country for initial funding based on past performance. Indicators used by the MCC include Political Rights, Girls Primary Education Completion Rate, Public Expenditure on Health, Fiscal Policy, and 1-Year Consumer Price Index. Indicators are monitored by independent auditors including the World Bank Institute, World Health Organization, and Heritage Foundation.

As of 2019, the MCC has signed 37 grant agreements, known as compacts, with 29 countries. The MCC provides detailed financial results and impact data for specific initiatives and links the financial and objective/outcome data at the initiative specific level and presents this through its own online data portal (Link data portal).

Sources: (N. M. Brown, 2019; Johnson & Zajonc, 2006)

11.2. Incentive-Based Funding Mechanisms in Higher Education

In the higher-education sector, PBF is a model of funding where the budget of an institution is linked to the performance of that institution, usually over a period of 2-4 years (Alshehri, 2016). PBF first appeared as a model for funding in higher education in the late 1970s, but was later abandoned by most governments (Harnisch, 2011). Many national and sub-national governments have re-adopted performance-based approaches to higher-education funding including Australia, Canada, Chile, Hong-Kong, and the United States as well as many European countries (Alshehri, 2016; De Boer et al., 2015; Jongbloed & De Boer, 2020; Miao, 2012).

PBF approaches in higher education vary in terms of what is considered 'performance' and how it is attached to funding. Common performance indicators include number of degrees attained, exams passed, credits earned, students from underrepresented groups, PhD graduates, and employability indicators (De Boer et al., 2015; Miao, 2012). There are two common performance-based approaches to funding in higher education:

- Performance Agreements; and
- Performance Set-Asides (Clark et al., 2018).

11.2.1. Performance Agreements

Performance Agreements, also known as **Performance Contracts**, are negotiated agreements between states and institutions to achieve results within a timeframe (De

Boer et al., 2015; Harnisch, 2011). The contracts are binding documents that are typically tailored to each university. In exchange for a funding allocation, institutions come to an agreement with the state regarding benchmarks and goals. In most cases, if these targets are not met, institutions lose all or a portion of the funding in the next round of performance agreements (D. W. Lang, 2016).

Examples of countries that use performance agreements:

- **Australia**, where 20% of budget for education and research is based on Mission-Based Compacts. In these Compacts, agreement to certain performance targets is a condition for funding (Australia Department of Education, 2020).

- **Ontario (Canada),** where about 2% of educational operating grants are linked to performance through Strategic Mandate Agreements (Ontario, 2018)

- **The Netherlands**, where 7% to 32% of budget for education and research at higher education institutions is linked to Performance Agreements (De Boer et al., 2015).

- **Scotland**, where 85% of budget for education and research at higher education institutions is connected to Outcome Agreements (Scottish Funding Council, 2020).

Performance Agreement In-Depth Example 1: The Netherlands

Since 2012, portion of higher education funding in the Netherlands has been based on performance agreements, where universities make agreements with government on how they will improve the education they provide. Performance agreements are aimed at improving the quality of education in higher education institutions with the goal of reducing drop-out rates, and situating Dutch higher education institutions among the most competitive knowledge economies (De Boer et al., 2015).

The agreements have specified indicators used to improve student success and education quality including: student degree completion, student drop out rates, share of Year 1 students switching programs, students in honors programs, teaching intensity and academic staff qualifications, and share of overhead costs. In terms of connecting these indicators to funding, a share of 7% of the education component of the institutions annual budget was tied to these agreements, with the remainder of funding allocated based on a standard formula. If institutions did not meet their targets at the end of the four-year period that the performance agreements covered, they stood to lose a portion of this funding during the next four years. Progress towards results was monitored by an independent review committee at a mid-term basis, based on reports provided by the institutions.

In 2017, performance agreements were replaced by quality agreements, which have a similar concept but are focused more on student outcomes.

Sources: (De Boer et al., 2015; Jongbloed & De Boer, 2020)

11.2.2. Performance Set-Asides

In Performance Set-Asides, a base funding is provided to all institutions, and a small portion is set-aside as a competitive fund for universities that produce results that meet or exceed certain performance targets (Miao, 2012). Performance Set-Asides may be a "bonus" fund or a separate portion of a regular state appropriation (Harnisch, 2011).

Example of Performance Set-Asides:

- **The Pennsylvania State System of Higher Education** sets aside 8% of its institutional budget, equivalent to about $36 million, to reward schools for meeting or exceeding eight performance measures that encompass a variety of key areas such as degree completion, retention, and faculty productivity. In this model, all targets need to be met in order for institutions to receive a share of these funds, and those that exceed requirements receive a larger portion (Miao, 2012).

Performance Set-Aside In-Depth Example 1: Ontario Strategic Mandate Agreements

Strategic Mandate Agreements (SMAs) are agreements between the Ontario Ministry of Training, Colleges and Universities (MTCU) and the publicly funded education institutions in the province. SMAs were first introduced in 2014, through which higher education institutions were required to articulate distinctive goals and report on outcomes annual. SMAs are intended to promote student success and institutional excellence through five priority areas: Enhancing the student experience to improve student success and outcomes; Innovation in teaching and learning excellence; improving access and equity for qualified students; enhancing applied research/research excellence; and innovation, economic development and community engagement. In total there are about 20 metrics, both system-wide metrics and institution-specific metrics. System-wide metrics include graduate employment rates, student satisfaction survey results, graduation and retention rates, and other equity-based metrics such as proportion of Aboriginal, first generation, students with disabilities, and francophone students at an institution. Institution-specific metrics include number of students studying abroad, spin-offs and highly-cited researchers.

SMAs were seen to be the first step in a process where the program would eventually evolve into one where funding is attached to institutions based on their successes at achieving their goals. As of 2020, funding is not tied to institutions meeting their SMA targets, however, the SMA program has presented an opportunity for the MTCU to engage in a dialogue with institutions about performance, with the intention that the program will transition to tying these metrics to outcomes based funding as part of the third round of SMAs.

Sources: (De Boer et al., 2015; Jongbloed & De Boer, 2020)

11.3. Incentivizing Results in Social Service Delivery

Performance-based approaches to social service delivery are used as a means to incentivize the goals and desired outcomes of specific social programs (Hawkins et al., 2019). In a 2013 national US survey, 22% of large non-profit organizations had performance-based mechanisms as all or partial funding sources (Gold et al., 2014). There are three common models for performance-based approaches to social service delivery and contracting:

- Outcomes-based grants and contracts;
- Incentive prizes and challenges; and
- Pay for Success initiatives.

A detailed description of these mechanisms as they relate to social service delivery and examples of how these mechanisms have been operationalized is provided below.

11.3.1. Outcomes-Based Grants and Contracts

Outcome-Based Grants and Contracts (OBCs) are bilateral agreements between a principal and a social service provider. Under these agreements, at least a portion of payment is connected to measurable outcomes, and the service providers payment is based on successfully achieving those outcomes (Barker et al., 2018). How OBCs are operationalized varies, but the critical component is that the service provider is paid on achievement of specified outcomes. For example, if a government was paying a service provider for a program to help unemployed persons find work, an OBC would connect payment to the achievement of that outcome, such as the quantity of unemployed persons who found sustained employment through the program (Zlatinov & Gillette, 2018). In contrast, a more traditional (non-OBC) arrangement would likely connect payment to the number of training classes delivered or persons who enrolled in the program (Zlatinov & Gillette, 2018).

Outcome Based Contract Example 1: Tennessee Department of Children's Services

The Tennessee Department of Children's Services (DCS) began exploring the use of performance measures in the early 2000's with the aim of reducing its reliance on out-of-home care and time it takes to place children in permanent homes. In 2005, the DCS began a year-long pilot with five service providers, with contracts that are grounded in a longitudinal database maintained by the Center for State Child Welfare Data, containing foster care trajectories of all children in out-of-home care. In these pilots, agencies were initially measured against their past performance rather than the performance of other agencies, and contracts were developed based on a 'baseline-target-actual' method to measure change in agency performance over time. These methods were agency specific, and metrics included exits-to-permanency, care days used, and rate of re-entry to care. In the decade following, the service evolved to include 'performance banding' where agencies were placed in to high-, mid- and low-performance bands.

The payment structure for the programs is developed into two parts, a blended rate per day and a performance bonus or penalty. When providers exceed their baseline performance rate, DCS returns apportion of the savings generated back to the provider. The program successfully improved agency performance and as of 2009, all DCS contract agencies work under the PBC protocol. Once fully implemented in 2010, Tennessee's new model nearly cut in half the average time a child spends in temporary care, from more than 22 months to 14.

Sources : (Barker et al., 2018; Hawkins et al., 2019)

11.3.2. Pay for Success Initiatives

Pay-for-Success Initiatives (PFS), also commonly referred to in the social service sector as **Social Impact Bonds (SIBs)**, are contracts that enable a principal to pay the service provider only when they meet certain targets or goals related to a desired outcome (Barker et al., 2018). A SIB is not a real 'bond' but a loan from private funders to service

providers (Harvard Kennedy School Government Performance Lab, 2017). In an SIB, an investor provides funds to the service provider until they achieve specific outcomes, at which point the investor plus interest is reimbursed to the investor by the principal. If the service provider does not achieve the target, they may not receive all or a portion of their initial funding. Examples of outcomes used in previous SIB programs include the number of former offenders that do not return to prison, or the number of unemployed individuals who are successful in finding sustained employment. The parties to the contract agree to the measured outcomes, and metrics used for the outcomes are evaluated by an independent auditor (Zlatinov & Gillette, 2018).

Examples of Pay for Success Initiatives:

- The world's first PFS in **Peterborough, England**, provided services designed to reduce recidivism for individuals being released from jail (RAND, 2016).

- **New York City** has an ongoing PFS project that provides cognitive behavioral therapy to juveniles incarcerated at Rikers Island (Hawkins et al., 2019)

- **British Columbia** hospitals introduced an activity-based funding policy as opposed to lump sum funding which resulted in a decreased volume of cases and an increased number of surgeries (Sutherland et al., 2016).

- **Connecticut** has an ongoing PFS project providing substance abuse treatment to parents in child-welfare-involved families with the goal of reducing out-of-home placements (Social Finance, 2016)

- **The DC Water Authority** issued the US's first environmental impact bond in 2016 to fund installation of green infrastructure intended to reduce stormwater and sewage runoff into polluted waterways (DC Water, 2016).

The literature and case studies reviewed in this report are not intended to be exhaustive, rather the goal is to provide a general overview of how performance-based approaches are operationalized across sectors.

12. Appendix B: Community Design Characteristics – Walkability: Exploring the Relationship Between Walkability and Neighbourhood Change

12.1. Introduction

Walkability is a measure of how supportive an area is of walking for both recreation and functional purposes. While generally a desirable neighbourhood characteristic, there is a growing body of research suggesting that those who need walkable neighbourhoods most, such as low-income residents, are increasingly unable to afford to live in them. The purpose of this paper is to explore the relationship between walkability and neighbourhood social change, investigating how walkability and gentrification have changed in Metro Vancouver during a 10-year period from 2006 to 2016, and how the two processes are related.

Using the Walkability Index as a measure of walkable urban environments, the analysis found that the most walkable neighbourhoods in the region were those nearest the urban core (downtown City of Vancouver); however, the greatest relative changes in walkability during the study period were in more suburban and rural municipalities.

Gentrification was evaluated using two methods, the David Ley Social Status Index and multiple individual indicators of change. Both comparative analysis methods found distinct patterns associated with walkability during the study period, with findings suggesting that while gentrification is taking place in both high and low walkability neighbourhoods, the actual social, economic, and demographic outcomes of the processes differ. There would be opportunity through further research to continue investigating the differences in these patterns and processes, perhaps using different measures of change and across additional time points.

A relationship between changes in walkability and gentrification couldn't be established using the analysis methods employed; however, future research could build on the early findings of this study to further investigate changes in walkability and gentrification using more advanced quantitative methods, adjust the temporal scope of the study.

The findings of this paper suggest that walkable neighbourhoods are a resource that is not equally accessible by all residents, that people who might need walkable environments the most might have unequal access to them. As the Metro Vancouver region and many of its member municipalities are emphasizing walkable neighbourhoods on their urban planning agendas, it is important to consider whether the strategies deployed to operationalize the region's policy goals are serving the regions diverse populations and how changes in built and social neighbourhood trajectories are connected.

12.2. Neighbourhood Change

In traditional urban theory, residential displacement is largely the root cause of shifts in changing neighbourhood dynamics, such as shifts in racial composition or population age (Freeman & Braconi, 2004), and that this displacement can lead to negative outcomes in both health and equity for displaced residents (Atkinson et al., 2009). The competition for space in desirable neighbourhoods can lead to existing residents being displaced by more affluent ones, and some scholars even argue that gentrification is an "overt revitalization strategy" that has been historically deployed by local governments, often in consortium with private developers (Hackworth & Smith, 2001; Lees, 2000; Ley, 2003).

Many debates have emerged over the last several decades about what constitutes and causes neighbourhood change. These critical debates have led to questions such as what exactly a neighbourhood constitutes, what is change, how should change be measured and over what time period. The following section provides a high-level overview of the prominent theoretical debates in neighbourhood change research, how neighbourhood change has been measured, as well as a discussion on the importance of context in scale in Canadian neighbourhood change research.

12.3. Theoretical Debates on Neighbourhood Change

Gentrification and neighbourhood change is a well-established area of research with significant theoretical divisions that have pervaded the literature for decades (Slater, 2003). While critical debates remain, a lot of the literature is concerned with two dominant drivers of urban change: class displacement, or demographic shift and economic restructuring that causes populations to change. The next section of this literature view covers some of the key debates in what constitutes neighbourhood change and gentrification.

12.3.1. Residential Migration as Neighbourhood Change

Discussions on residential migration dominate neighbourhood change literature, with much of the research focused on the characteristics of those moving in and out of neighbourhoods. Typically, the migration patterns follow more affluent population moving into an area for many reasons (real estate pressures, physical upgrades, proximity to cultural centers or jobs) and lower income and more socially vulnerable existing residents are displaced (Atkinson et al., 2009; Newman & Wyly, 2006; Wyly & Hammel, 1998). Marcuse (1985) distinguished between two forms of displacement, direct and indirect. Direct displacement is the process of lower income residents moving out because of evictions and rising rent prices, while indirect displacement is defined by lower-income residents being unable to afford to move into areas that they may have been able to previously (Marcuse, 1985).

Some researchers have historically argued that it is hard to draw a direct relationship between neighbourhood change as displacement, and that sometimes an influx of new residents does not always lead to low-income residents moving out (Lupton, 2004). Rose (1984) pointed out that some displacement is favorable for persons who own their home

and hope to capitalize on favorable real estate prices. In other cases, 'marginal-gentrifiers' are persons who move to affordable neighbourhoods as an entry point to the city's housing market, and the neighbourhood does not necessarily gentrify (Rose, 1984).

While displacement might be the dominant driver of urban social change, other processes are also often taking place that contribute to neighbourhood change such as in situ upgrading and generational demographic shifts (Hedman, 2011). Analyses evaluating neighbourhood change must address and attempt to isolate the process of displacement from other changes processes that may be at place by looking at regional trends and not neighbourhoods in isolation.

12.3.2. Neighbourhood Change as Demographic Shifts

Demographic shifts can also occur in cities where a younger middle-class population moves in and to an area that has a predominantly ageing working-class population. In studies that describe these shifts as a driver of neighbourhood change (Buzar et al., 2007; Hamnett, 1994), they argue that a growing number of young persons move to cities following graduation, and suggest some of the demographic shifts observed are because of higher death rates among an older working-class population than among a relatively young middle class (Bailey et al., 2017). In classic neighbourhood life-cycle theory, when a housing stock ages, younger and lower income households slowly replace more affluent residents who move away (Temkin & Rohe, 1996), which can be considered another process of urban change that is not necessarily gentrification and displacement.

At what point in the processes gentrification takes place is also important in understanding neighbourhood change and demographic shifts: a recently gentrified area may see a demographic outflow of older and (or) low-income households, but areas that are further along in the gentrification process may see an older cohort of gentrifies (Agbai, 2021). The implications of this for neighbourhood change research is that demographic shifts identified as an inflow of young persons may be a mark of early stage gentrification, while this shift may not mark late-stage gentrification.

12.3.3. Neighbourhood Change as in situ upgrading process

In situ upgrading is a process in which an existing residential population experiences a market compositional change, such as increased income or upward social mobility. Literature on in situ upgrading is scarce compared to residential migration, but some have pointed to it being a contributing factor to neighbourhood change in some cities, and being more prominent in working-class neighbourhoods with low turnover (McKinnish et al., 2010). In situ upgrading is also described as residents moving into a neighbourhood and being of an income below neighbourhood average, but subsequently experiencing steep income increases. In these cases, not all residents would experience income gains to the same extent, and the research on in situ upgrading has shown that it is typically young and highly educated persons that show substantial income gains following a period of in-migration (Hochstenbach & van Gent, 2015).

Isolating in situ neighbourhood change from other change process is challenging, as it requires measuring changing income composition of in-moving and out-moving households, instead of measuring changing income profiles in neighbourhoods and comparing them to regions or control neighbourhoods (Grigsby, 1986).

12.4. Measuring Neighbourhood Change

Based on the complexity of the debates on drivers of neighbourhood change, it would be hard to explain the phenomenon through a single decisive model of change. The three processes of urban change described in the previous section are not mutually exclusive, and all could be occurring within one neighbourhood at any given time, but the degree to which each is occurring would likely vary across neighbourhoods and regions.

What makes measuring neighbourhood change even more challenging is that the theoretical framework used to develop methodology for measuring change in one location may not be applicable to another. For example, Buzar (2007) suggested that social change in neighbourhoods within cities that are performing well economically vary significantly from declining or stable cities. Therefore, some means that underlying assumptions about certain indicators of gentrification, such as immigration status, education, and income, from other regions may not hold in Vancouver's regional context.

12.4.1. Indicators of Neighbourhood Change

In a systematic review of walkability literature, Anguelovski (2018) identified over 180 studies using various neighbourhood indexes to measure gentrification since 2000. There is no clear best practice for measuring neighbourhood change but there are some common methods where some may be more appropriate for certain contexts than others. Conceptualizations of gentrification historically focus on socioeconomic markers (e.g., income, housing values, education) (Glass, 1964; Slater, 2011), but more contemporary research argues neighbourhood change should be determined tough other factors such as macroeconomic trends, segregation, and housing stock (Meegan & Mitchell, 2001). Quantitative data used to measure change usually fall within the realm of the economic, sociocultural, and physical dimensions of neighbourhoods measured across time; and common indicators include median income, visible minority status, ethnicity, age, educational attainment, employment status, median home value, median rent, home ownership (Barton, 2016; Freeman, 2005; Hammel & Wyly, 1996; Walks & Maaranen, 2008). Less common quantitative indicators of neighbourhood change include age of home, mortgage information (lending), and counts of certain amenities and businesses such as coffee shops. Quantitative indicators are typically measured at the census tract level or equivalent due to data limitations and suppression (Barton, 2016). There is no definitive quantitively measures to measure urban change as a multidimensional process, but Hammel and Wyly (1996), among others, have argued that it is best to measure change across multiple indicators rather than just one variable to avoid an oversimplication of the phenomenon.

Some literature on neighbourhood change is concerned with whether relative or absolute change is the most relevant to measure in urban change (Lupton, 2004). Relative change

often considered what is important for equity purposes, because the difference between neighbourhoods is what matters. A neighbourhood may see an absolute increase in a certain variable of change, but this would be a less significant indicator of change if the rest of the city experienced the same increase (Glass, 1964; Slater, 2011).

12.5. Gaps in Existing Walkability and Neighbourhoods Change Literature

There are two distinct but related gaps in walkability and neighbourhood change literature. First, most studies related to walkability and neighbourhood characteristics are evaluated across a city or region at one point in time. Cross sectional studies cannot assess a temporal relationship between input and outcome, this raises the question whether an increase in neighbourhood walkability over time is associated with increased changes in other neighbourhood characteristics (Timmermans et al., 2021). One notable exception is a study by Quastel (2012), that measured change over time in Vancouver, however, this study assumed walkability to be static, rather than an aspect of neighbourhoods that also changes over time. In reality, neighbourhoods experience different processes both physical and social change over time, and that change, and its effects may be non-linear. Second, most literature on walkability and gentrification has focused on measuring the relationship between specific urban design features that contribute to pedestrian-supportive environments and a neighbourhood's social characteristics rather than 'walkability' as factor of the built environment.

The relationship between walkability and neighbourhood change is an important issue as policy in Metro Vancouver is specifically aimed at increasing walkability in particular parts of the city. Evaluating the influence of built environment changes on neighbourhood social trajectories is important, as it may help understand why some neighbourhoods experience change while others remain stable, and potentially help identify predictors of future processes of gentrification (Zwiers et al., 2017). Given the emphasis on walkable environments in urban planning policy including the Regional Growth Strategy for Metro Vancouver, it is important to consider how the social and physical characteristics influence each other during the short and long term (Quastel et al., 2012).

12.6. Analysis Methodology

12.6.1. Measuring Walkability

For this analysis, walkability was measured using the walkability index proposed by Frank et al. (2005) to quantify the walkability across the region at the census block level for all three time points. For each census block group, the walkability index is a derived function of net residential density, retail floor area ratio (FAR), land-use mix, and intersection density. Net residential density is the ratio of residential units to land area devoted to residential use; Retail FAR is the retail building floor area footprint divided by retail land floor area footprint, which is a proxy measure of retail urban design (a low ratio is a proxy

indicator of substantial surface parking and large setbacks); Intersection density measures the connectivity of the street network, measured as the ratio of number of intersections to land area of the block group. Land use mix is an entropy score based on five land use types (residential, retail, entertainment, office and institutional), with values normalized between 0 and 1, with 0 being single use and 1 indicating an even distribution of floor area across 5 uses (L. D. Frank et al., 2010b).

To develop the index, the z-scores of each variable are calculated so that the value distribution is normalized, and the walkability index is the sum of these scores for the four measures of urban form:

$$walkabiliy = \begin{bmatrix} (2 \times Z - intersection\ density) + (Z - net\ residential\ density) + \\ (Z - retail\ f\ loor\ area\ ratio) + (Z - land\ use\ mix) \end{bmatrix}$$

Calculating walkability across the region using this measure is then used to create a walkability surface for the metropolitan region, which are maps of walkability index values to visualize walkability across a geographic area. Walkability surfaces and the absolute values of the variables used to calculate the surfaces have been provided by UBC Health and Community Design Lab. The walkability surface for the 2016 study year is illustrated in Figure 12-1 with highly walkable neighbourhoods appearing in green and low walkability neighbourhoods appearing in red.

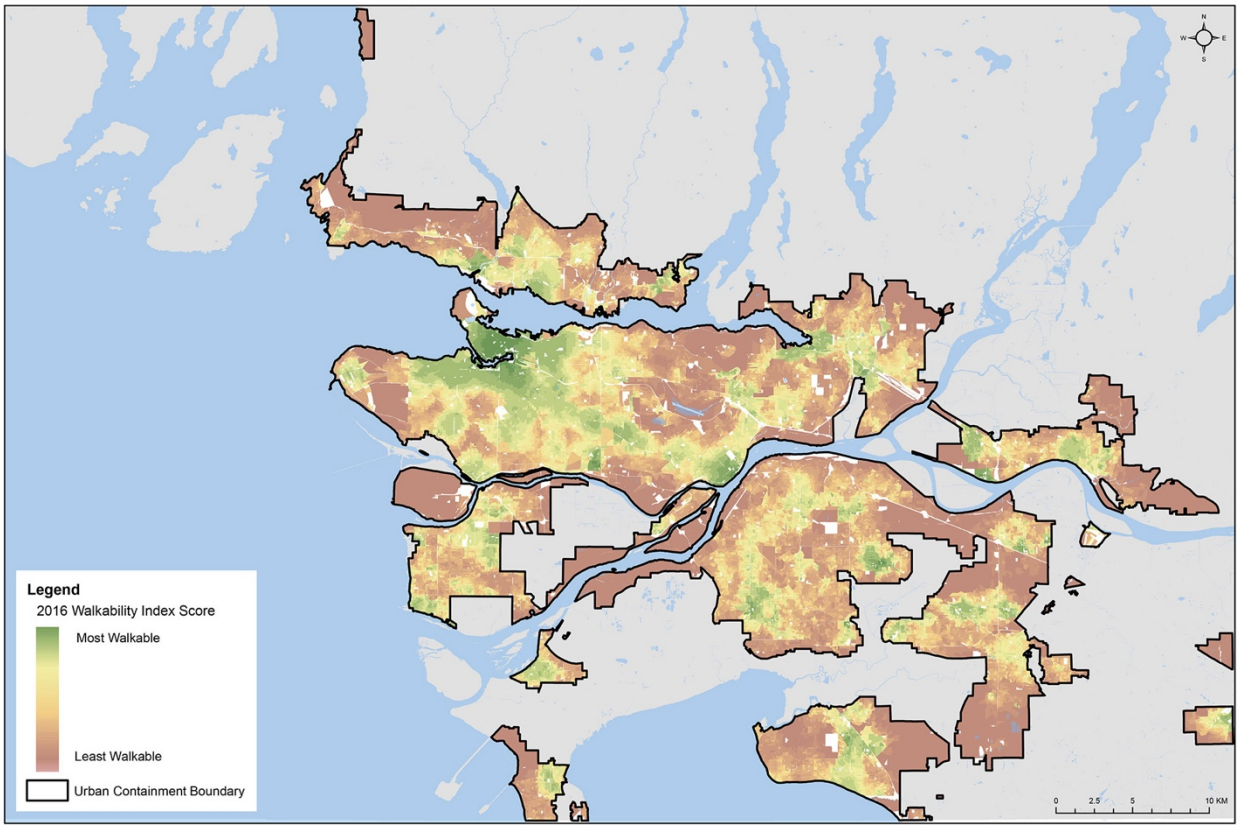


Figure 12-1: Walkability surface for the Metropolitan Vancouver Region, 2016

12.6.2. Measuring Longitudinal Changes in Walkability: Grand Mean Method

The original walkability index has been validated against actual travel behavior, with the weighting scheme of the urban form measures (each urban form measure is given equal weight, except intersection density has double the weight than others) determined through iterations of alternative schemes (L. D. Frank et al., 2010b). While the index does need to be modified for measuring longitudinal change, the results of the modified index would ideally involve little modification of the original index formula as well as the rank-order of the results (even if the magnitude changes). The preferable method would be the **grand mean method**, as this method is the most consistent with the original index formula. Using the grand mean to calculate the standard deviation and mean of the urban form measure z-scores means that the index formula itself does not need to be altered (as it would with POMS method). As the urban form measures are still standardized, the order on which they score cross sectionally isn't expected to change within each time point, even if the mean and standard deviation change, as they are all compared against the same values. Using POMS method or creating a "change in walkability" index would involve altering the original index formula, and how this would impact the validity of the index isn't known.

This method considered for measuring change in walkability was the **"Grand Mean"** method, where the z-scored values for each of the four variables would be calculated using the mean and standard deviation across all reference frames (study years). Using this method, the original walkability index would not be modified, but the new formula for calculating mean and standard deviation is shown below:

$$walkabiliy = \begin{bmatrix} 2 \cdot Z_{\substack{Intersection \\ Density}} + Z_{\substack{Net\ Residential \\ Density}} \\ + Z_{\substack{Retail \\ FAR}} + Z_{\substack{Land\ Use \\ Mix}} \end{bmatrix}$$

Where:

$$z - score = \frac{(x - \mu)}{\sigma}$$

$$\mu = \frac{\left(\sum x_{2006} + \sum x_{2011} + \sum x_{2016} \right)}{n_{2006} + n_{2011} + n_{2016}}, \text{ and}$$

$$\sigma = \sqrt{\frac{\left(\sum \left(x_{2006} - \mu\right)^2 + \sum \left(x_{2011} - \mu\right)^2 + \sum \left(x_{2016} - \mu\right)^2\right)}{n_{2006} + n_{2011} + n_{2016}}}$$

The benefit of calculating z-scores using a grand mean is that it would not require changing the walkability index formula, and it would be possible to calculate z-scores using standard deviation and mean across all time points. It is expected that the standard deviation and mean for each variable do not change much using this method, and the index scores themselves are not expected to vary significantly, meaning that rank order across time points would be maintained. However, a criticism of this method might be that standardization across observations across time points obscures information about relative rank of an observation across a given point in time.

Standardizing across time points obscures information about relative rank of an observation across a given time point, but this is not expected to be a significant issue as this method was only used to measure across time points, and not to determine the rank order within time points.

12.6.3. Measuring Neighbourhood Change

There is debate about what constitutes the spatial and social dimensions of a neighbourhood. For quantitative analysis, both census tract (CT) and dissemination area (DA) boundaries are commonly used as an aerial unit of analysis. Measuring data at the dissemination area was initially considered as it would be a more granular analysis and may be easier to interpret a relationship between neighbourhood change and walkability (which is measured at the census block level), but there were several issues with data suppression for some of the variables at this scale. Further, the dissemination area boundaries changed between census years, particularly in downtown Vancouver. CTs are a larger unit analysis but still a common measure of neighbourhoods in quantitative research, and the CT boundaries in the greater Vancouver area have been relatively stable over time. There were some instances when the CT boundaries did change, but these were adjusted using *The Canadian Longitudinal Census Tract Database, 1971—2016* (Allen & Taylor, 2018*).*

Many indexes and methods have been developed, but neighbourhood change is context-specific, and many of the inherent assumptions about the relationship between certain variables made when developing indexes do not necessarily track to Metropolitan Vancouver context. This eliminates the possibility of using many of the pre-existing

indicators and indexes of neighbourhood change found in United States and United Kingdom gentrification literature.

Several methods were explored for measuring neighbourhood change in Metropolitan Vancouver: (1) describing neighbourhood change using individual indicators, (2) using Principal Component Analysis to develop an index of change, and (3) using a gentrification index from the literature that has been previously validated in Canadian cities.

Using **individual indicators to measure change** is a simple and common method for measuring change in urban geography. Individual indicators, such change in demographic trends or change in median household income, is a straightforward and does not require interpreting any relationship between variables. The benefit of using this method is its simplicity, the relationship between individual indicators and walkability can be compared through discussion on how change in some indicators change in relation to change in walkability, or more walkable and less walkable environments. However, as discussed in the literature review, using a single indicator to measure neighbourhood change may oversimplify complex a phenomenon, which is why composite index of gentrification indicators across multiple variables is a popular method for understanding overall neighbourhood change.

Principal Component Analysis (PCA) is a popular method for studying social and economic change and the correlation of variables in urban geography research and has been used previously by Quastel et al. (2012) to measure neighbourhood change in Vancouver. PCA is an unsupervised method for transforming multiple correlated variables into a new set of uncorrelated principal components. A single principal component can include several variables that capture multiple dimensions of contemporary urban change, preserving as much variability as possible and translating variables into new components that are linear functions. In essence, PCA does the work of creating an index of change from many indicators of change and can often reveal relationships that were not previously suspected between variables (Rothschild, 2019).

PCA was considered as a method for measuring change, as it would be possible to create an index that captures several dimensions of contemporary urban change measured by occupational categories, household characteristics, and immigration status using indicators identified through the literature. However, the issue with using PCA for longitudinal change is that underlying relationship between variables (referred to as loading factors) such as median household income, educational attainment, employment status, race, and immigration status change significantly between the three study years. For reference, PCA was used to create principal components from common indicators of gentrification using 2006 and 2016 census data, comparing the biplots can show how the principal components and relationships between variables differ between these two time points:

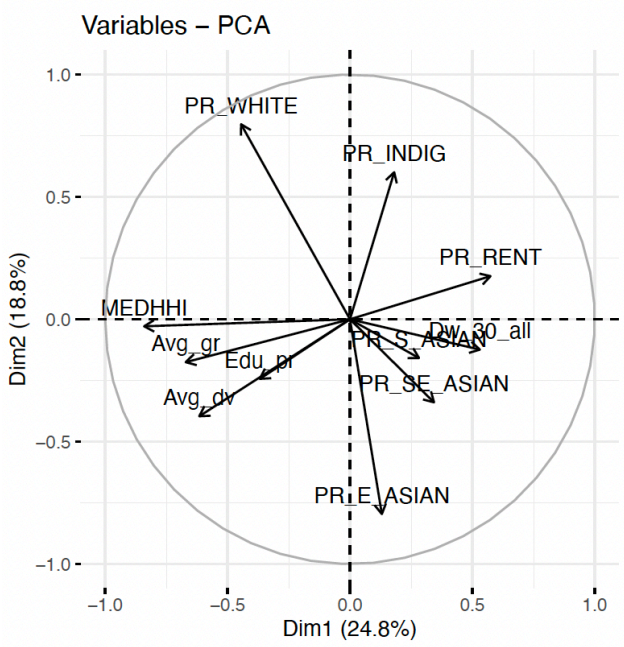


Figure 2: Biplot of Loading Matrix Variables 2006

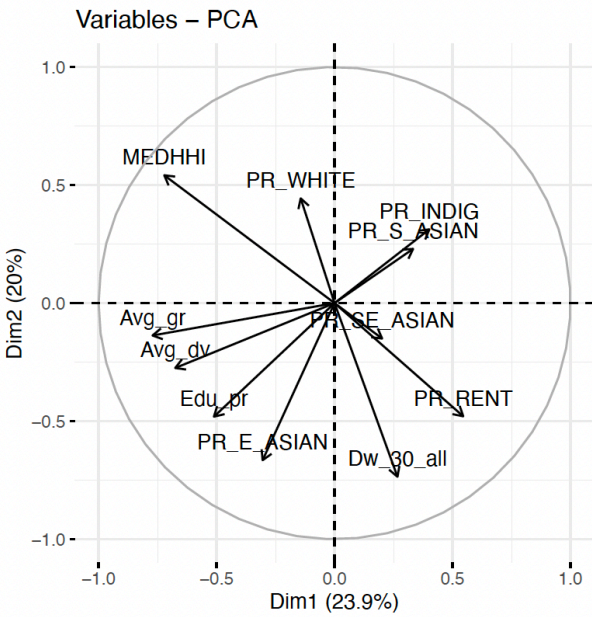


Figure 10: Biplot of Loading Matrix Variables 2016

As shown in the biplots above, the relationship between variables computed for two different time points are inconsistent, which means principal component analysis may not be able to create stable index of neighbourhood change across the study period.

The third method considered for measuring neighbourhood change was **using an established social status index** to measure neighbourhood change that has been validated in a Canadian, and preferably Metro Vancouver, context. David Ley's (1987, 1994) social status index is often cited in Canadian research and has been used to measure gentrification in Vancouver in several studies (Ley & Dobson, 2008). The index is a validated measure of neighbourhood social-economic status, and operationalizes gentrification in terms of social status, including measures of professional-managerial employment and the percentage of residents with post-secondary education across Census Tracts (CTs) (Ramos et al., 2021). The index is composed of only two indicators of social status, the percentage of population (aged 25+) with a college education and percentage of population working in managerial and professional occupations (Ley 1987; Ley 1994). These two percentages are added together and averaged across neighbourhoods over two time periods (e.g., 2006 and 2016), computed by averaging the percentage of professional managerial employment and post-secondary education:

$$Index = \frac{\left(\%\ Bachelors_{2} + \%\ Managerial_{2} \right)}{2} - \frac{\left(\%\ Bachelors_{1} + \%\ Managerial_{1} \right)}{2}$$

Subtracting the 2016 social status index from the 2006 index gives a measure of social status change in each census tract over the 10-year period, a change that is identified as an index of gentrification. The gentrification scores are then divided into quintiles to give a sense of the level of socioeconomic transformation that has occurred (Ramos et al., 2021).

The benefit of this method is that it's a simple interpretation of urban change that has been applied in the metropolitan Vancouver context. Validation of this index as a measure of socioeconomic status has been demonstrated in earlier research, showing strong correlations with other diagnostic variables like household income and monthly rent (Ley, 1986). One drawback of using this method is that in using only two indicators of social status to signify "neighbourhood change" does not offer the multidimensional interpretation of urban change that using PCA or more complex indices may. The method could capture residential displacement but may not capture in situ upgrading or demographic shifts, as demographic indicators like age and economic indicators like income are not incorporated in the index.

12.7. Summary

Three methods have been contemplated for measuring neighbourhood change: measuring the change of individual indicators, creating a change index using PCA, or using an index from the literature appropriate to the regional context. Of the three potential methods for measuring neighbourhood change, a blended approach that describes neighbourhood change using individual indicators, as well as measuring change using the social status index is proposed as the preferred method.

Using a blended approach would break the analysis into two parts. First, changes in individual indicators identified from the literature such as race, age, household income, and employment status, were compared for areas of "high walkability" and "low walkability" against control CTs (regional averages). Differences between how each category has changed over the time period were discussed. For instance, it may be found that changes to certain indicators of change are more correlated with changes in walkability than others. The purpose of describing these changes across individual indicators rather than an index, is that these discrepancies (if any) would be obscured in an index. While these findings about relationship between individual indicators may not be able to fit into a regression model or show holistic change on their own, they could inform future research on the topic.

The second method of measuring neighbourhood change uses the social status index to changes in walkability. This is a simple method for measuring neighbourhood change (defined as gentrification) that has been used previously for measuring change in Vancouver, and the index while only comprising of two variables has been shown to correlate with other variables of change like income and rent (Ley, 1996). While this method does potentially oversimplify "neighourhood change" as gentrification, the method should be sufficient to differentiate change through displacement from in situ neighbourhood upgrading, whereas a method like measuring change in median household income wouldn't. Further, comparing changes against regional and city

averages tend to be an (imprecise) method for understanding if some of the changes in social status are related to demographic shifts rather than gentrification and displacement.

As described in the literature, multiple overlapping processes of urban change and displacement can be taking place in a neighbourhood at any one time. Combining these two methods is to use the social status index as the primary measure of neighbourhood change but support this analysis with a discussion of changes occurring in other indicators of urban change that may not be captured by the social status. The intention of this is to discuss other changes and processes that may be occurring that could inform future research on changes in walkability, such as demographic shifts occurring across the region, without necessarily modifying the social status index. For both portions of the analysis, the CTs of tracts of varying walkability were compared to control tracts, which were the metropolitan region measured as a whole, as the index would not reflect gentrification if the census tract difference was equal to the regions overall change. Both sections can also be controlled for proximity to rapid transit stations as well as distance to downtown cores using GIS.

12.8. Analysis

For analysis, both the baseline walkability of neighbourhoods at the start of the study period (2006) and changes in walkability from 2006 to 2016 are compared against indicators of neighbourhood change and the Social Status Index. Changes in walkability are measured using a modified version of the Frank et al. (2010) Walkability Index. Neighbourhoods have been operationalized as Census Tracts (CTs). There are 410 CTs in the Greater Vancouver Area in the 2006 Census, and 478 in the 2016 Census. CTs were matched between census years using the Canadian Longitudinal Census Tract Database (Allen & Taylor, 2018).

Histograms of the baseline walkability of the CTs and change in their walkability index scores from 2006 to 2016 are shown in Figure 12-2 and Figure 12-3 respectively. Both datasets are generally normally distributed but there are some outliers on the high end in the baseline Walkability Index scores.

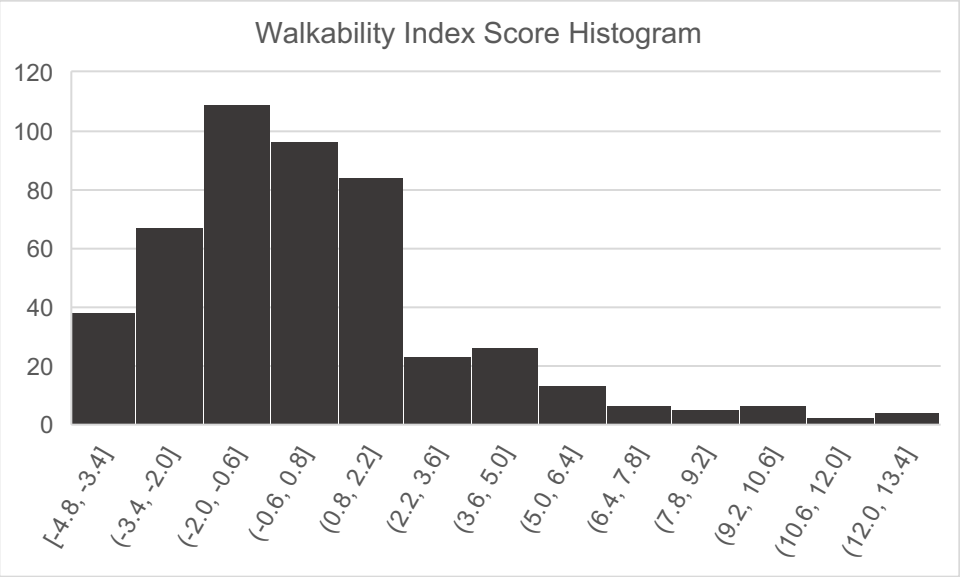


Figure 12-2: Walkability Index Score of Census Tracts (2006) Histogram

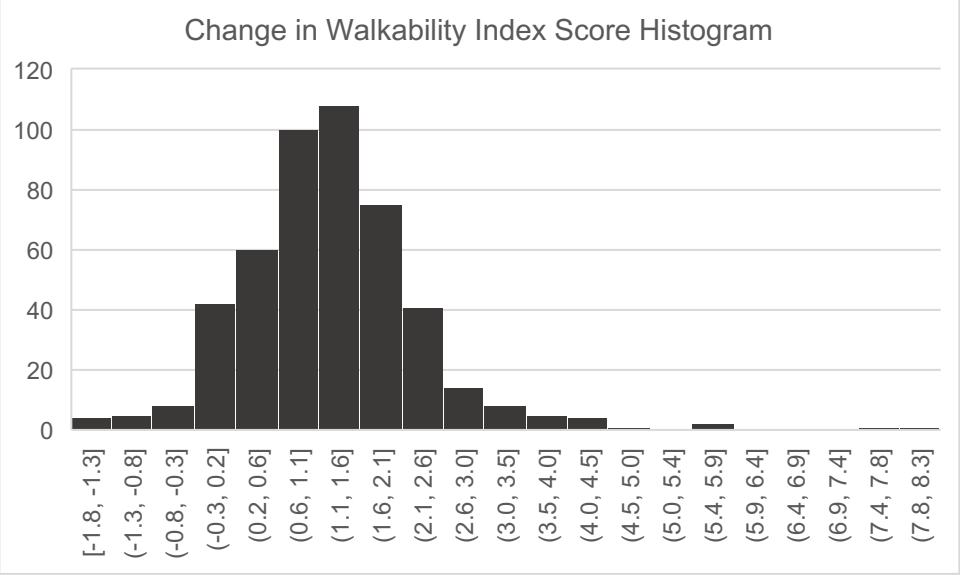


Figure 12-3: Change in Walkability Index Scores (2006 - 2016)

What was the baseline walkability of the study area in 2006?

Before measuring changes in walkability or gentrification, the baseline walkability of neighbourhoods and municipalities was established to understand the relative starting points, defined as the 2006 walkability index scores, of each area.

In Figure 12-4 the 2006 walkability index scores have been aggregated at the census tract level and divided into quintiles to illustrate the regional variation in baseline walkability. As expected, the City of Vancouver (understood to be the urban center of the region) has the highest concentration of walkable neighbourhoods, radiating outwards from its downtown core. Walkable neighbourhoods are also concentrated in the downtown core of the City of New Westminster (the oldest city in the region), the City of North Vancouver, and the downtown core of the City of Surrey.

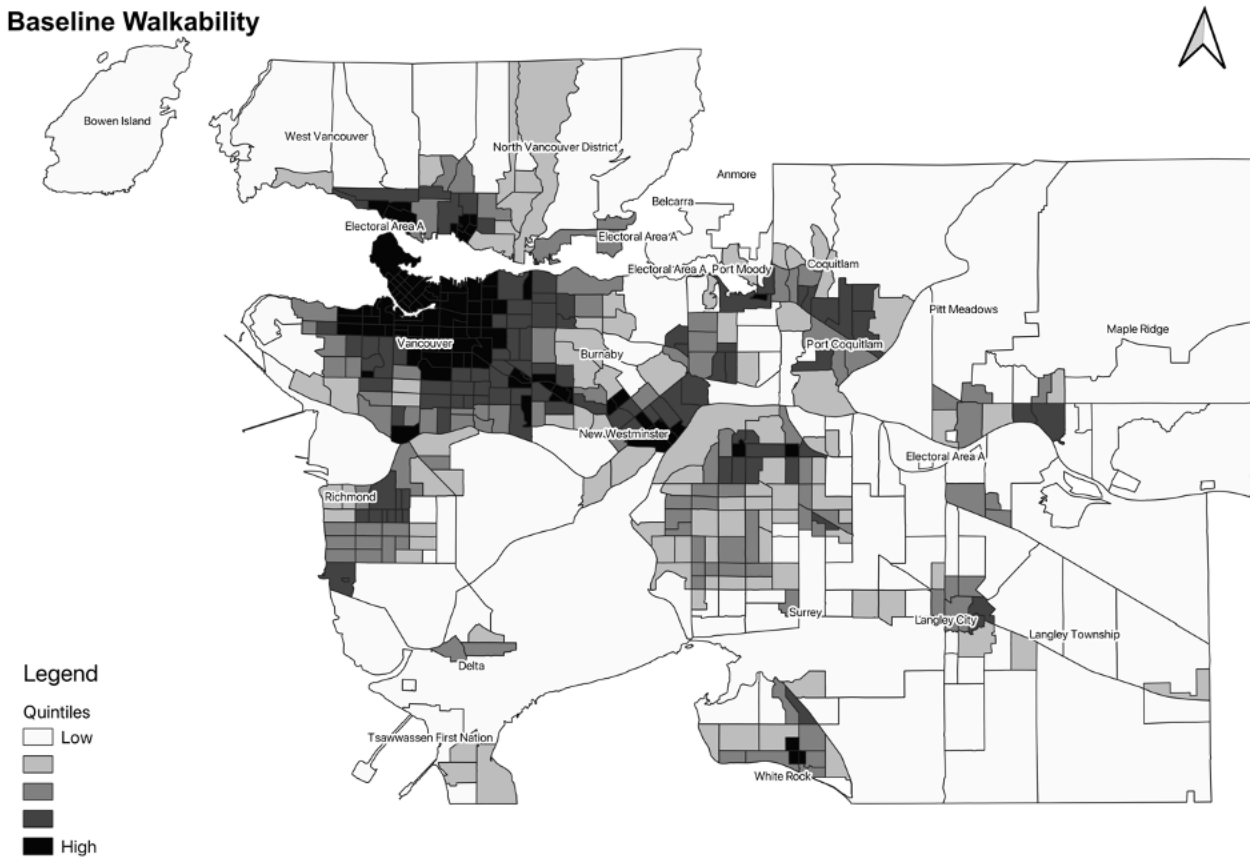


Figure 12-4: Distribution of Baseline Walkability of Metro Vancouver Census Tracts.

Baseline walkability index scores have also been aggregated at the municipal level to understand how each city measures against each other at the beginning of the study period. The actual index scores of the 25 Municipalities, Electoral Areas, and Treaty First Nations are shown in Table 12-1. When aggregated at the municipal level, the most walkable municipalities (and nations) in Metro Vancouver are the City of Vancouver, Capilano 5 (the Capilano 5 First Nations Reserve is located at the south-eastern boundary

of West Vancouver), followed by The City of New Westminster and the City of North Vancouver. The least walkable locations are Pitt Meadows, Bowen Island, Belcarra, and the Musqueam First Nation Reserve No. 4 (located east of Canoe Passage near Westham Island). It is important to note that walkability index scores are normalized, so the scores of each municipality are described relative to each other.

Table 12-1: Baseline (2006) Walkability Index Scores of Metro Vancouver Municipalities

	Municipality	Base Walkability (2006)
1	Vancouver (C)	+1.1
2	Capilano 5 (R)	+0.9
3	New Westminster (C)	-0.1
4	North Vancouver (C)	-0.2
5	White Rock (C)	-0.7
6	Port Coquitlam (C)	-1.0
7	Tsawwassen (R)	-1.8
8	Burnaby (C)	-1.9
9	Langley (C)	-1.9
10	Richmond (C)	-3.2
11	Coquitlam (C)	-3.4
12	Lions Bay (VL)	-3.5
13	Surrey (C)	-3.5
14	Port Moody (C)	-3.5
15	West Vancouver (DM)	-4.1
16	North Vancouver (DM)	-4.1
17	Greater Vancouver A (RDA)	-4.2
18	Delta (DM)	-4.3
19	Anmore (VL)	-4.5
20	Maple Ridge (DM)	-4.5
21	Langley (DM)	-4.7
22	Pitt Meadows (DM)	-4.8
23	Bowen Island (IM)	-4.9
24	Belcarra (VL)	-5.1
25	Musqueam 4 (R)	-5.5

How did walkability change by municipality during the study period?

Using the modified Walkability Index, the 2006 Walkability Index Scores of each CT have been subtracted from the 2016 Walkability Index Scores, to see how walkability has changed in the region during the study period. The difference in each CT between the time periods has been calculated and divided into quintiles to illustrate the greatest and least differences in the region

As shown in Figure 12-5, the areas that saw the greatest increases in walkability (black) are dispersed throughout the region and do not show to be consistently concentrated in

areas with baseline walkability. While downtown City of Vancouver did see relatively high increases in walkability, other areas surrounding the downtown core that had high baseline walkability were stable during the study period. In more suburban and rural areas, the City of Langley, White Rock, and Surrey were all municipalities with low baseline walkability but were shown to have concentrations of neighbourhoods with high increases in walkability.

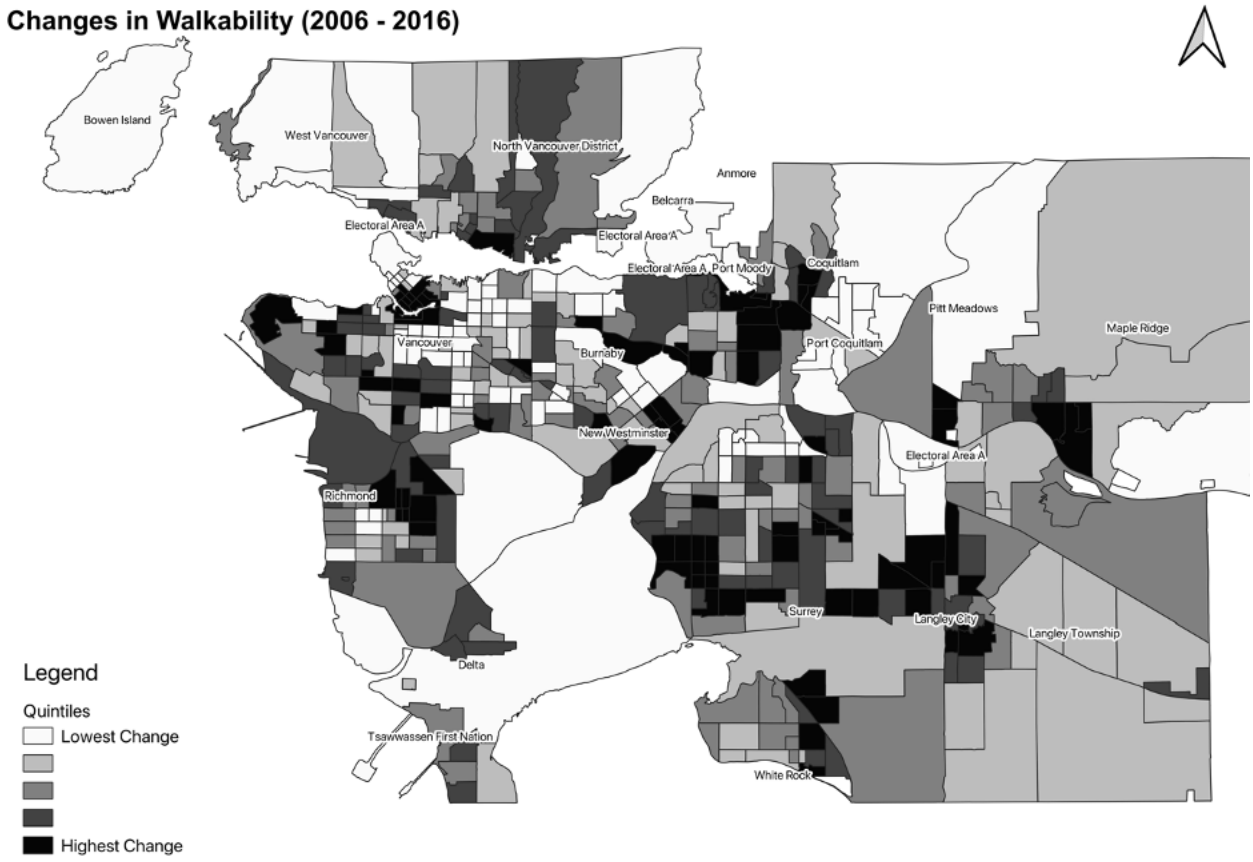


Figure 12-5: Distribution of Changes in Walkability of Metro Vancouver CTs (2006-2016).

Changes in walkability have also been aggregated at the municipal level to understand how each City, Nation and Electoral Area changed relative to each other during the study period. Shown in Table 12-2 the District of North Vancouver that had the highest relative increases in walkability, followed by the City of Langley, and the Capilano 5 First Nation Reserve. Despite being the most walkable municipality in the base year, the City of Vancouver ranked 11th in increases in walkability index score and only slightly higher than the regional average. Tsawwassen and Port Coquitlam both saw decreases in walkability index scores, likely due to low-density development in those municipalities during the study period.

Table 12-2: Change in Walkability of Metro Vancouver Municipalities (2006-2016)

Municipality	Base Walkability (2006)	Walkability 2016	Change in Walkability (2006-2016)
1 North Vancouver (DM)	-4.1	-1.6	**+2.6**
2 Langley (C)	-1.9	+0.1	**+2.1**
3 Capilano 5 (R)	+0.9	+2.8	**+1.9**
4 New Westminster (C)	-0.1	+1.5	**+1.6**
5 North Vancouver (C)	-0.2	+1.4	**+1.5**
6 Surrey (C)	-3.5	-2.2	**+1.3**
7 White Rock (C)	-0.7	+0.6	**+1.3**
8 Richmond (C)	-3.2	-2.0	**+1.2**
9 Port Moody (C)	-3.5	-2.4	**+1.2**
10 Coquitlam (C)	-3.4	-2.3	**+1.1**
11 Vancouver (C)	+1.1	+2.2	**+1.1**
12 Burnaby (C)	-1.9	-0.9	**+1.0**
13 Langley (DM)	-4.7	-3.8	**+0.9**
14 Maple Ridge (DM)	-4.5	-3.6	**+0.9**
15 Greater Vancouver A (RDA)	-4.2	-3.4	**+0.9**
16 Pitt Meadows (DM)	-4.8	-3.9	**+0.8**
17 Musqueam 4 (R)	-5.5	-4.7	**+0.8**
18 Delta (DM)	-4.3	-3.5	**+0.8**
19 West Vancouver (DM)	-4.1	-3.4	**+0.7**
20 Anmore (VL)	-4.5	-4.0	**+0.5**
21 Bowen Island (IM)	-4.9	-4.5	**+0.4**
22 Lions Bay (VL)	-3.5	-3.2	**+0.3**
23 Belcarra (VL)	-5.1	-4.9	**+0.2**
24 Tsawwassen (R)	-1.8	-2.0	**-0.2**
25 Port Coquitlam (C)	-1.0	-1.8	**-0.8**

While Table 12-2 ranked each municipality based on relative walkability index scores at the start of the study period (baseline walkability), Figure 12-6 shows how the changes in each score impacted the relative rank of each location by the end of the study period. Rankings of the top five locations were consistent between 2006 and 2016, with the exception of the Capilano 5 First Nation Reserve which surpassed the City of Vancouver as the most walkable in the region. Walkability Index ranking of other locations remained relatively consistent, with the exception of the District of North Vancouver which went from the 16th to 8th most walkable.

Anecdotally, the Capilano 5 Reserve (shown in Figure 12-7) has been the site of major commercial and residential development during the study period. Because the land area is small relative to other municipalities surrounding it, new development had a higher contribution to relative rank than development of similar scale would have in larger municipalities.

.

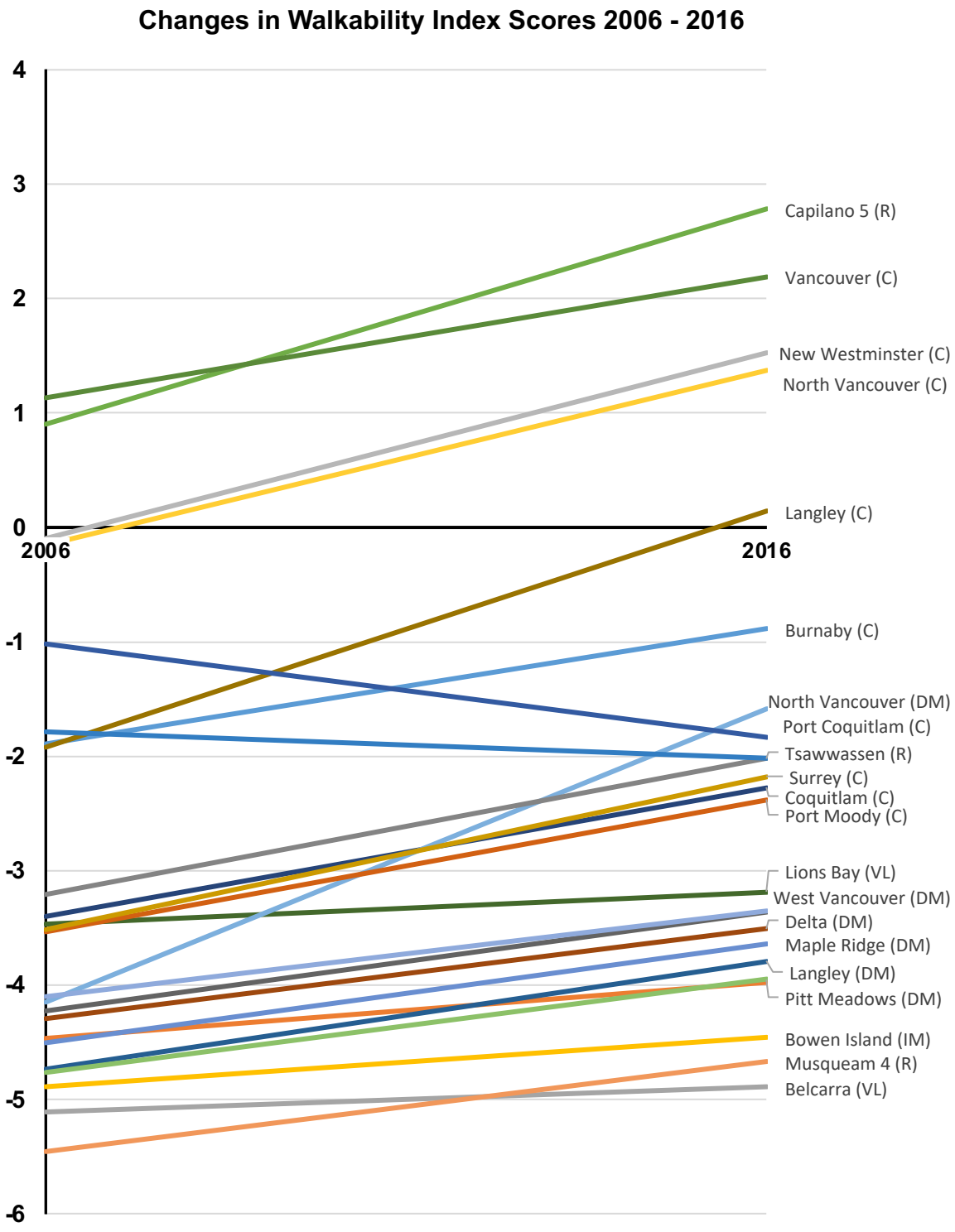


Figure 12-6: Changes in Walkability Index Scores 2006 – 2016

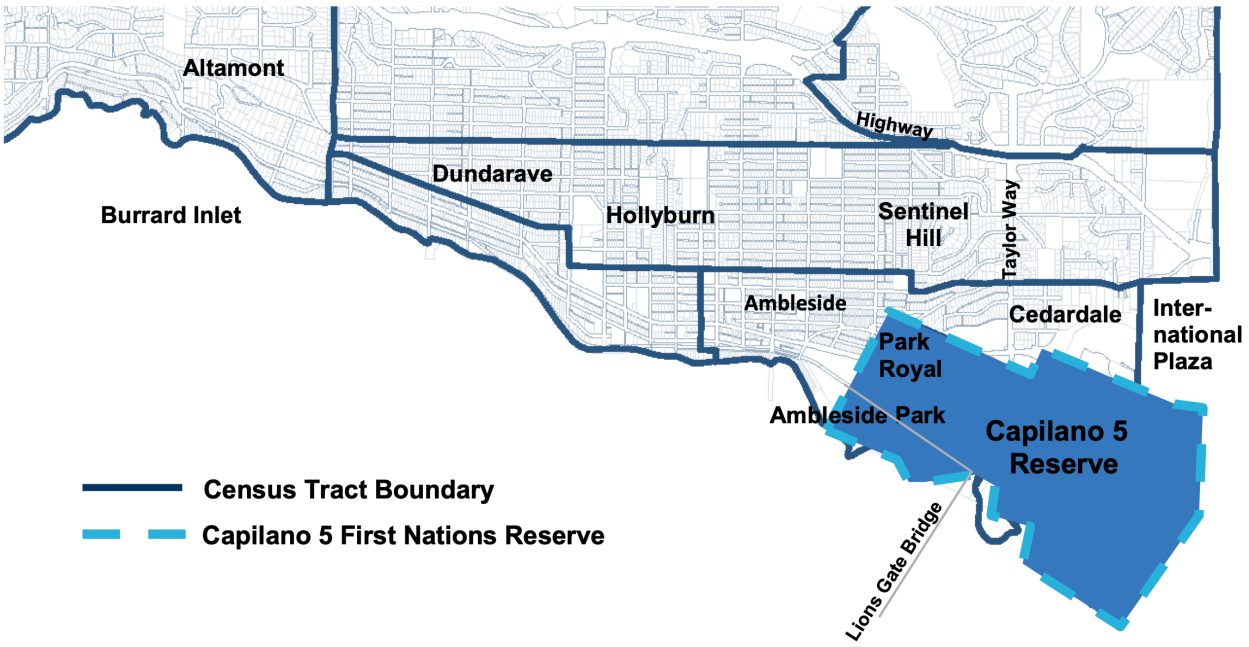


Figure 12-7: Capilano 5 Reserve had the highest Walkability Index score in Metro Vancouver in 2016 (Image Source: District of West Vancouver Planning Department)

12.1. Detailed Review of Change in The Walkability Index: 2006 to 2016

The walkability index is the composite of the four component measures added together. To conceptualize how these four variables have interacted and changed from 2006 to 2016, a walkability index normalizing these measures across the study period was created. This index was created through calculating z-scores for each component variable which represent the distribution of each measure across the 10-year study period. The grand mean and grand standard deviation of each component measure were calculated in the normalization process. Each measure was then added to create a walkability index which can represent changes over time through the delta between each index score.

Each component measure z-score was calculated as:

$$Component\ Measure\ z\ score = \frac{x - grand\ mean}{grand\ standard\ deviation}$$

The longitudinal walkability index was then calculated using the same formula as the original walkability index:

$$Longitudinal\ Walkability = zNRD + zCFAR + 2 * zIDens + zLUM$$

Where:

Longitudinal Walkability = Walkability Index, calculated using the grand mean and standard deviation

zNRD = Net Residential Density z-score

zCFAR= Commercial Floor Area Ratio z-score

zIDens = Intersection Density z-score

zLUM = Land Use Mix z-score

Calculating the walkability index in this way allows us to see how the change in each area has kept pace with the rest of the region. Each value contained in the walkability index exists across a distribution with 0 as the average. Much of the region has had relatively stable walkability from 2006 – 2016. Figure 12-8 shows that 60% of the region has remained in the same walkability quintile, while 40% of the region has shifted over the 10 year period.

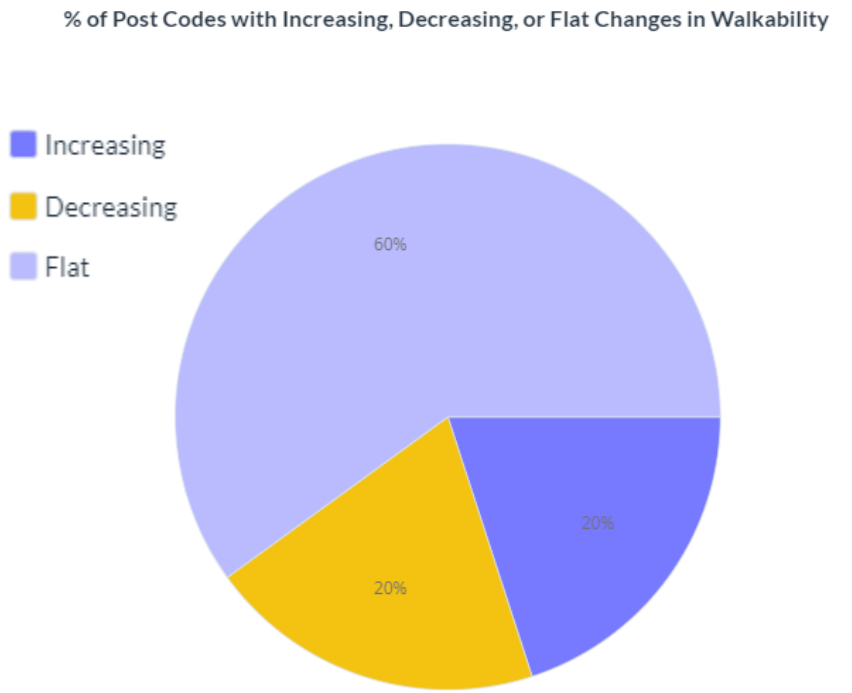


Figure 12-8: Distribution of Changes in Walkability 2006-2016.

The Sankey diagram (Figure 12-9) and subsequent maps shown below further explore these changes across Metro Vancouver.

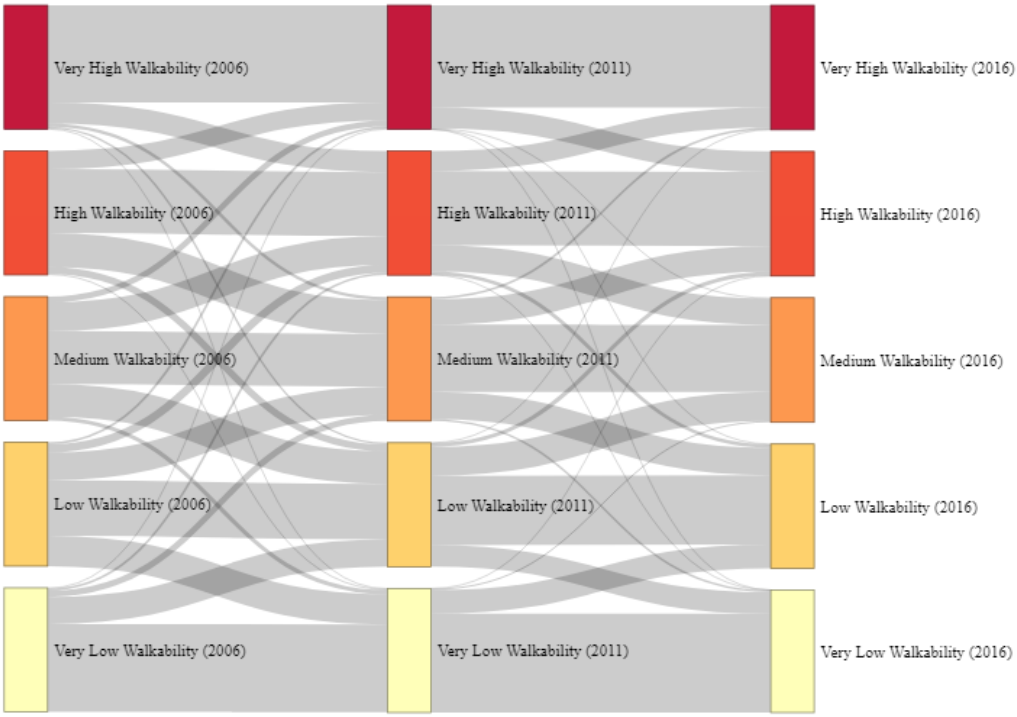


Figure 12-9 Sankey Diagram of Changes in Walkability 2006 - 2011- 2016

The Sankey diagram shows that for most places, walkability does not change significantly. However, some places shift up or down between 1 quintile. From 2006-2016, the index shows the burgeoning urban areas of the metro region increasing walkability the most. Surrey, Langley, Maple Ridge, and Port Moody are a few with the most notable changes. Looking within the study period, from 2006-2011 and 2011-2016 it is shown when the most change in areas across Metro Vancouver occurred. The increases in walkability remained consistent across the time period for many suburban areas, while areas such as the City of Vancouver and the City of North Vancouver experienced the largest changes relative to the region from 2011-2016. This pattern reflects policy initiatives in the region such as the densification of the Cambie corridor following the construction of the Canada Line and transit-oriented development in Port Moody following the completion of the Evergreen Line Skytrain extension. The longitudinal changes in the walkability index are visualized from 2006-2011, 2011-2016, and 2006-2016, in Figure 12-10, Figure 12-11,and Figure 12-12 shown below.

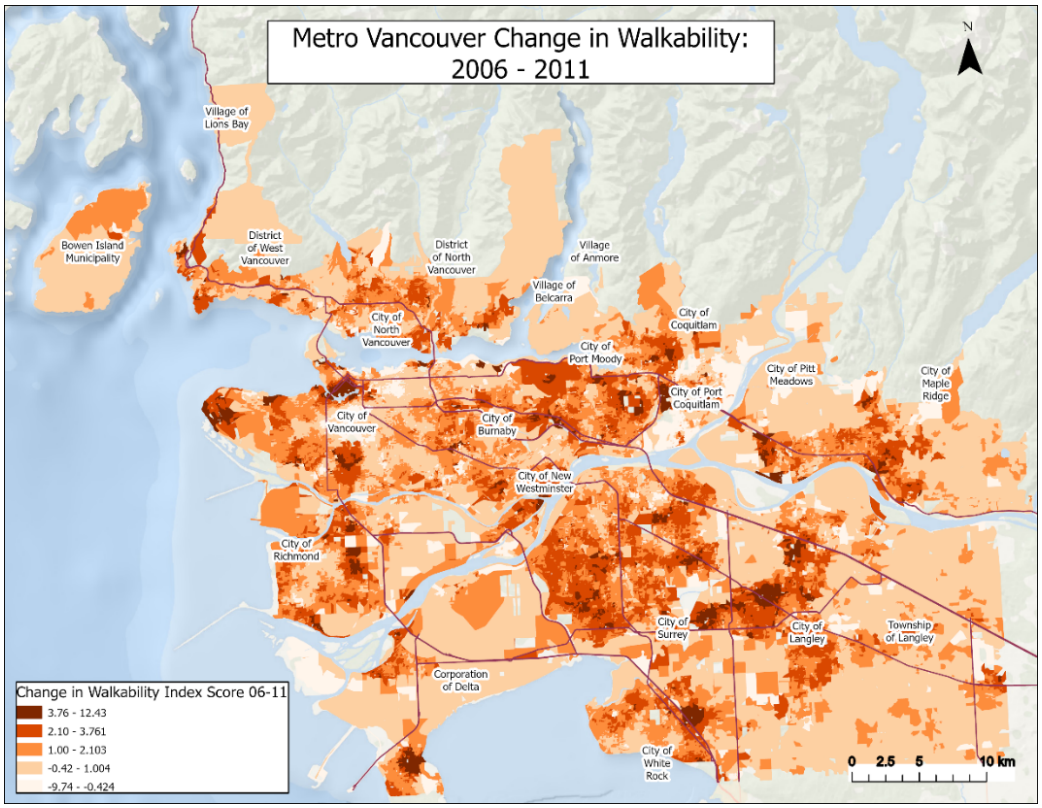


Figure 12-10 Metro Vancouver Change in Walkability Index Score 2006 - 2011

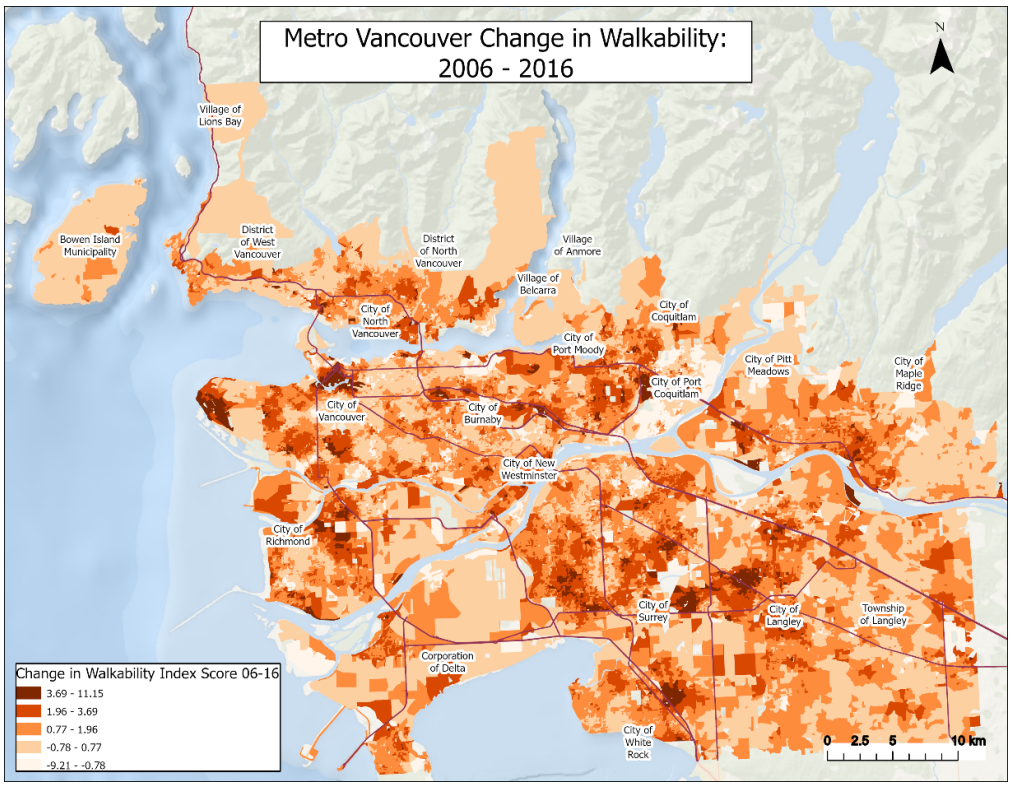


Figure 12-11 Metro Vancouver Change in Walkability Index Score 2006 - 2016

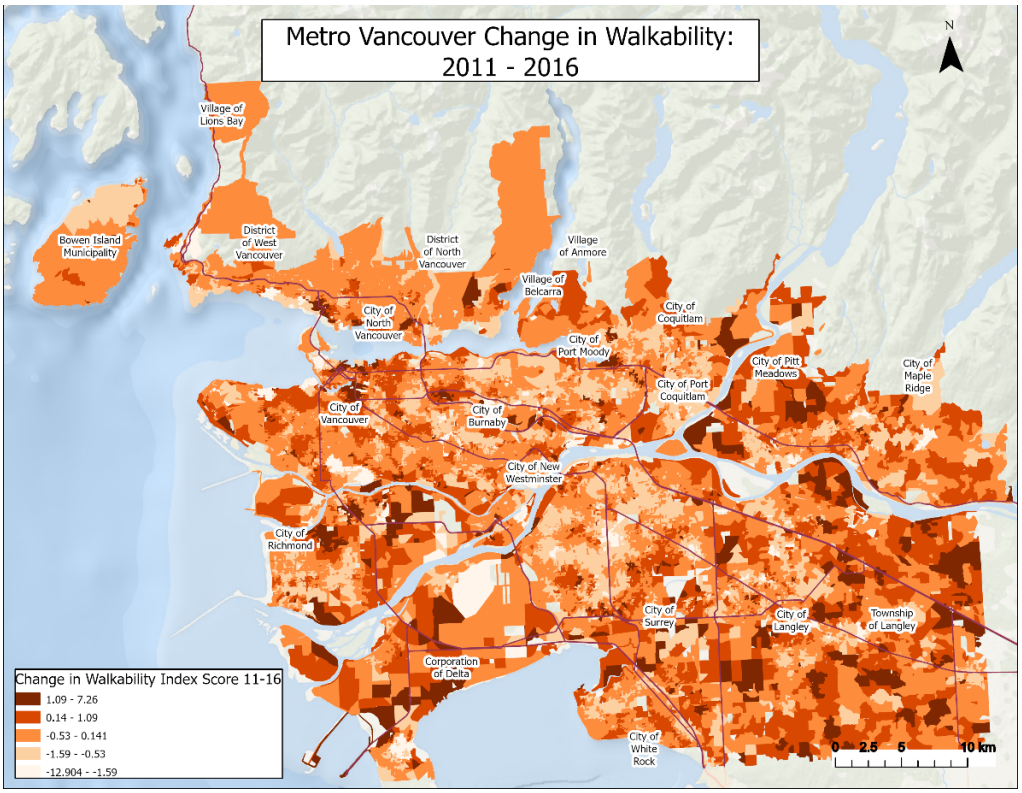


Figure 12-12 Metro Vancouver Change in Walkability Index Score 2011 – 2016

12.1.1. Intersection Density

The road network defines how we navigate the GVRD, what is accessible, and where development is happening. Figure 12-13 illustrates intersection density. The road network in many areas of Metro Vancouver is well-established, gridded and many decades old. However, changes in land use patterns, especially in outlying suburban areas, have spurred changes reducing connectivity in the network structure. Major developments can require new roads to access housing, amenities, and the rest of the region. This is reflected in the changes in intersection density over the 10 years between 2006 and 2016 which have gone from a regional average of 45 intersections per kilometre in 2006 to 65 in 2016.

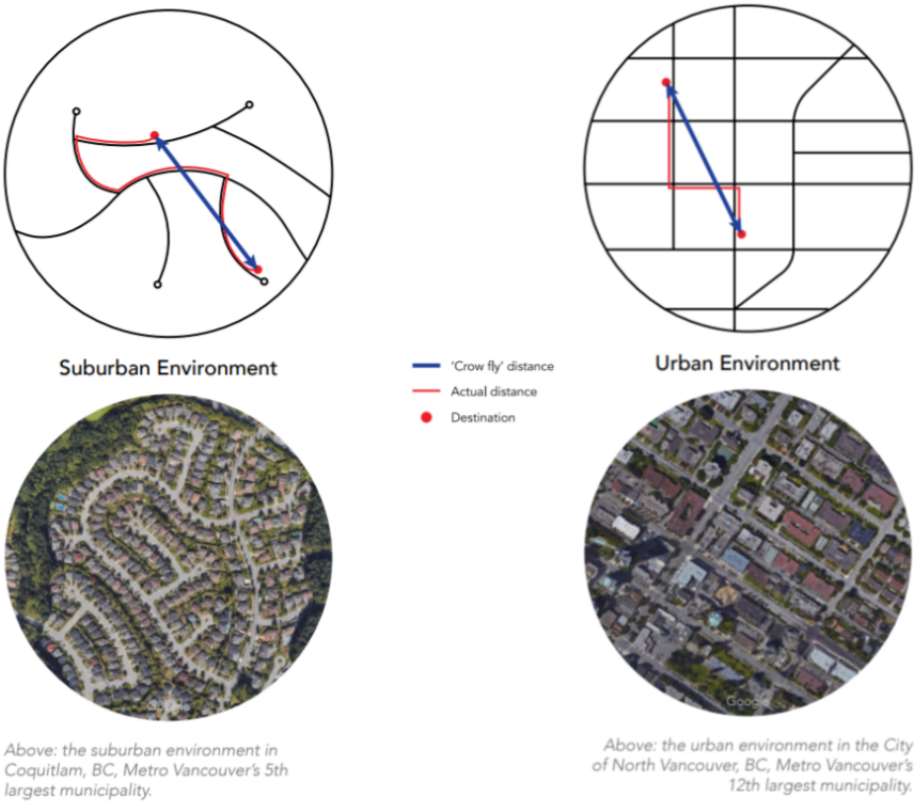


Figure 12-13 Description of Intersection Density

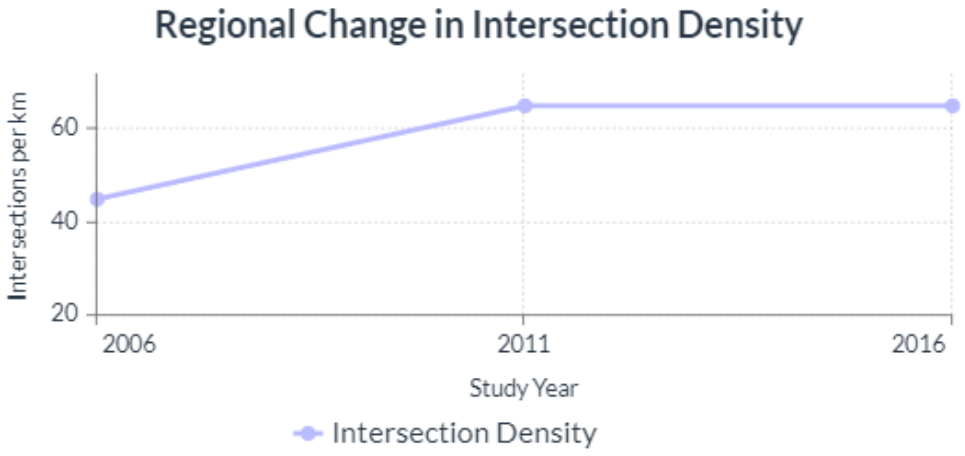


Figure 12-14: Intersection Density 2006-2016

Intersection density (Figure 12-14) is beginning to show a plateauing trend which may be attributed to stagnating greenfield development and new road building in the region. Many of the areas experiencing major development across the region such as Olympic Village

and the Cambie corridor are infill or densification projects that require relatively limited changes to the road network. These areas already have a high road connectivity.

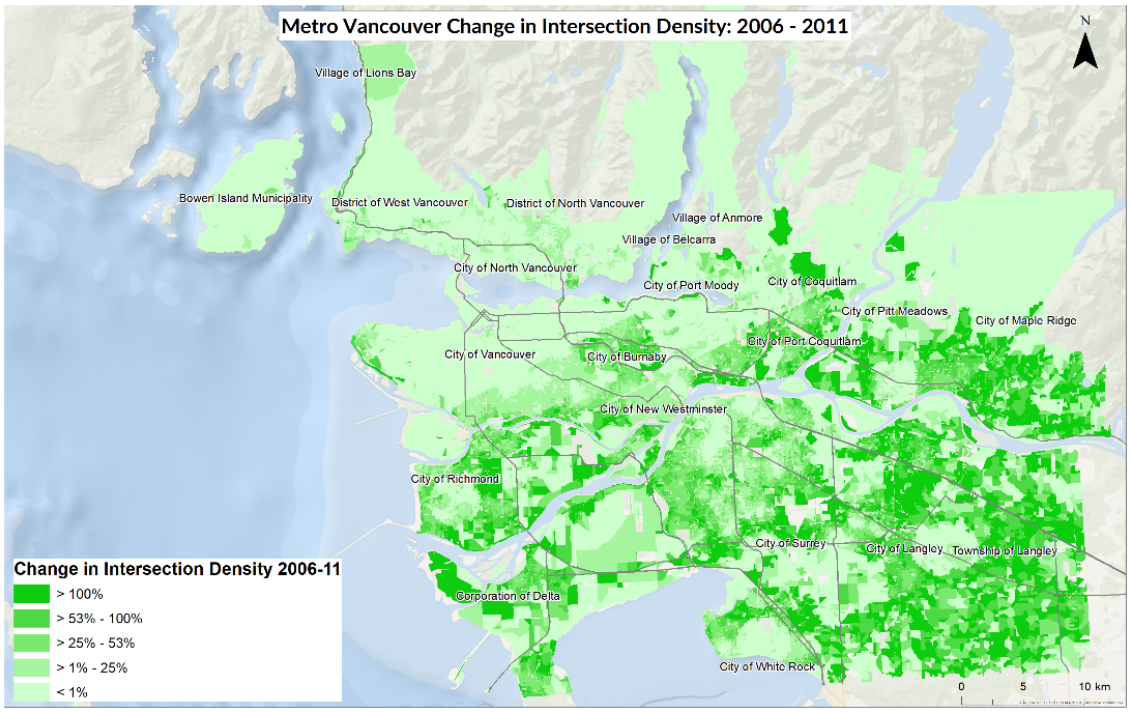


Figure 12-15: Change in Intersection Density 2006-2011

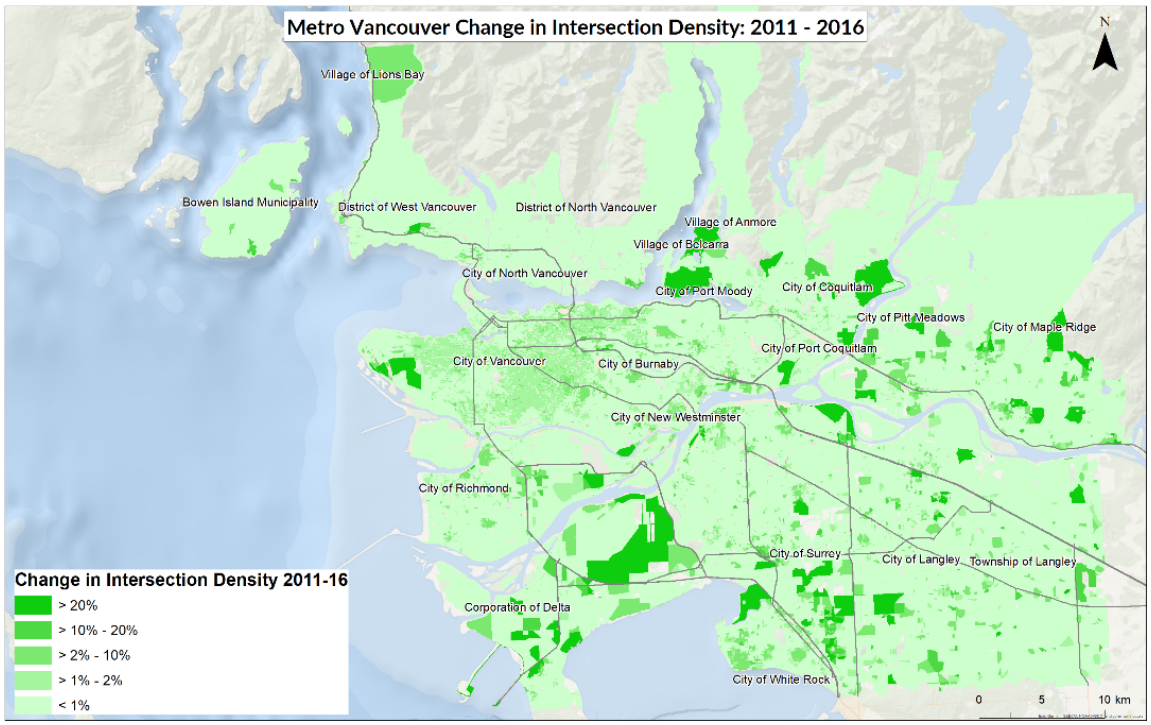


Figure 12-16: Change in Intersection Density 2011-2016

Many of the significant changes in intersection density across Metro Vancouver between 2006 to 2011 are in suburban areas of the region (Figure 12-15). Then from 2011-2016 the map shows that there is far less change across the region, especially in the suburban areas (Figure 12-16). Looking at the differing rates of intersection density change across the member jurisdictions, we can see that the suburban areas have experienced higher increases. Improved intersection density in rural areas may indicate suburban subdivisions which may have low connectivity even if increasing over time. It is also important to remember that some areas of the region, especially those designated for agricultural lands, are not intended for urban development.

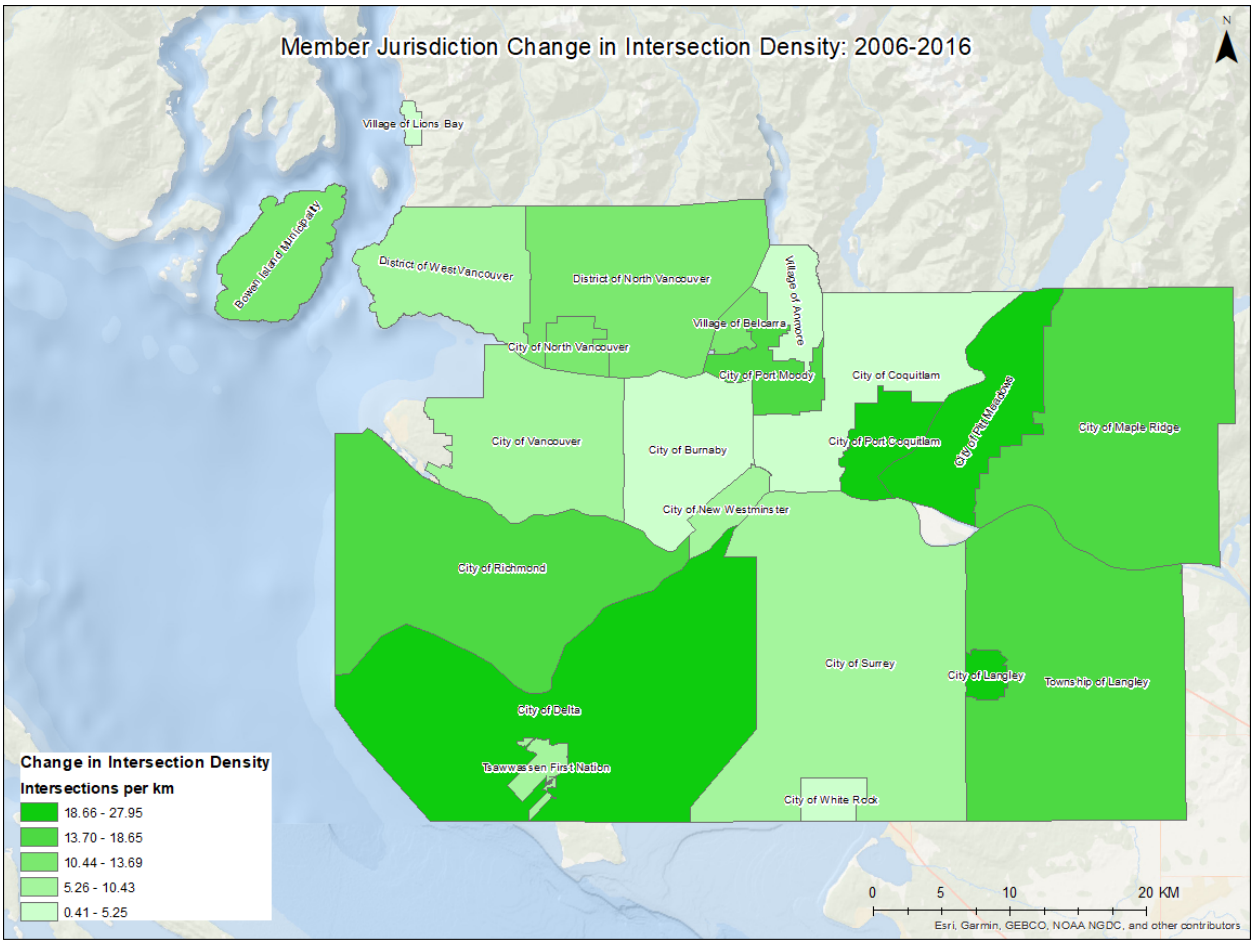
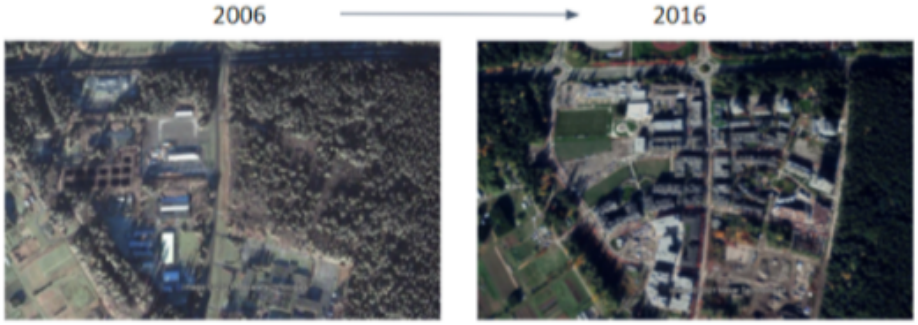


Figure 12-17 Member Jurisdiction Change in Intersection Density: 2006-2016

Changes in intersection density have been most notable where greenfield development has occurred. Shown below are examples of where intersection density has increased between 2006 and 2016.

Wesbrook Village, UBC :
North (top of photo)



Wesbrook Village at the south end of the UBC Main Campus has seen a dramatic increase in intersection density spurred by new development of residential and commercial buildings. Similar increases in intersection density have occurred with the development of suburban residential neighbourhoods at the foot of Burke Mountain in the Tri-Cities.



12.1.1. Net Residential Density

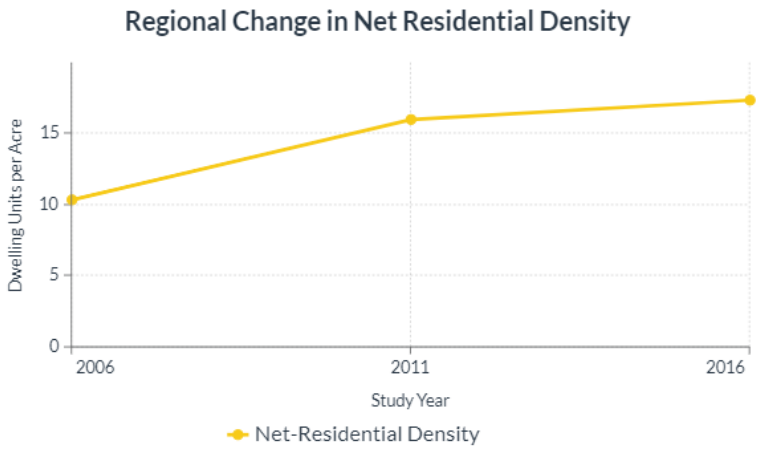
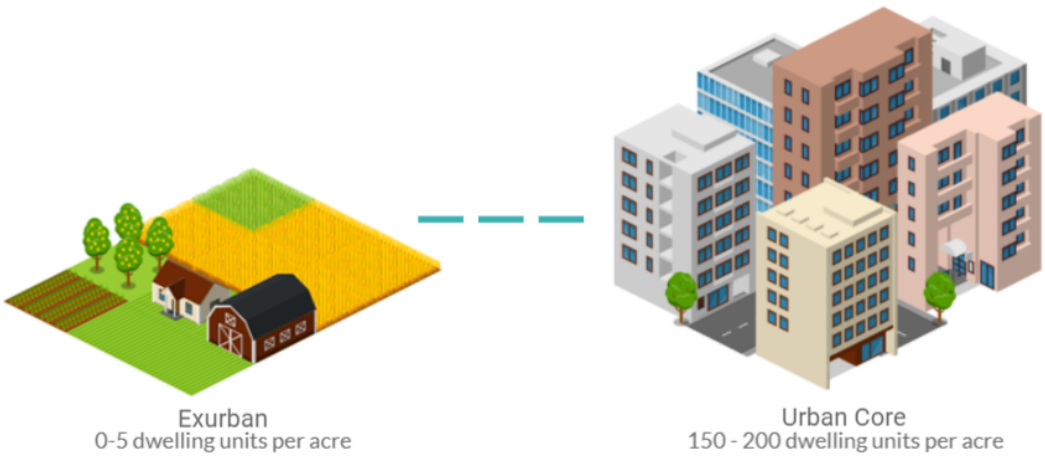


Figure 12-18: Net Residential Density 2006-2016

Residential compactness is one of the hallmarks of urban areas. Dense urban forms allow for more agglomeration of goods and services while facilitating social interaction and well-connected transportation networks.



Net residential density has continued on an upward trajectory from 2006-2016. This can be attributed to increasing density in the urban areas of Metro Vancouver and residential development in the suburbs. Places such as the City of North Vancouver, Port Moody, the UBC Main Campus, Richmond, and Vancouver show some of the highest increases in net residential density from 2006 – 2016 (Figure 12-19 and Figure 12-20).

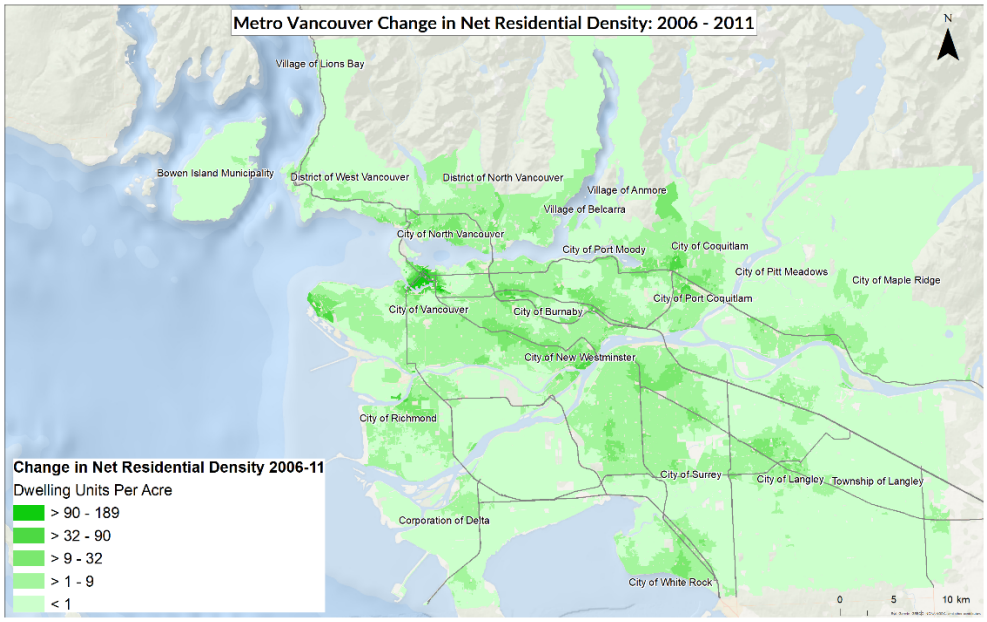


Figure 12-19: Change in Net Residential Density 2006-2011

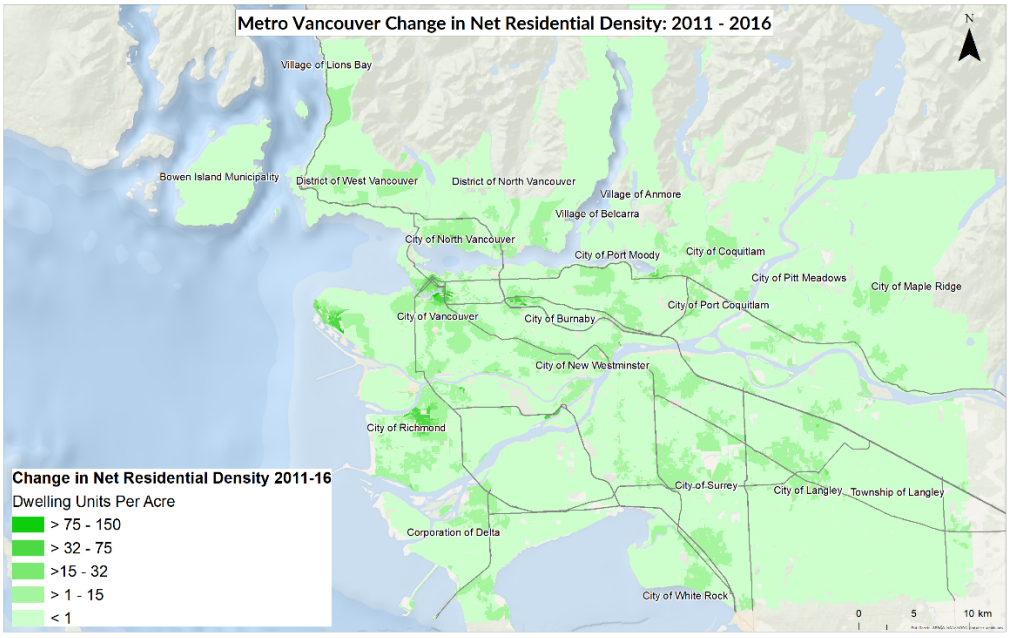


Figure 12-20: Change in Net Residential Density 2011-2016

Across the Member Jurisdictions of Metro Vancouver, Vancouver, the City of North Vancouver, Port Coquitlam, and New Westminster have experienced the largest changes in net residential density.

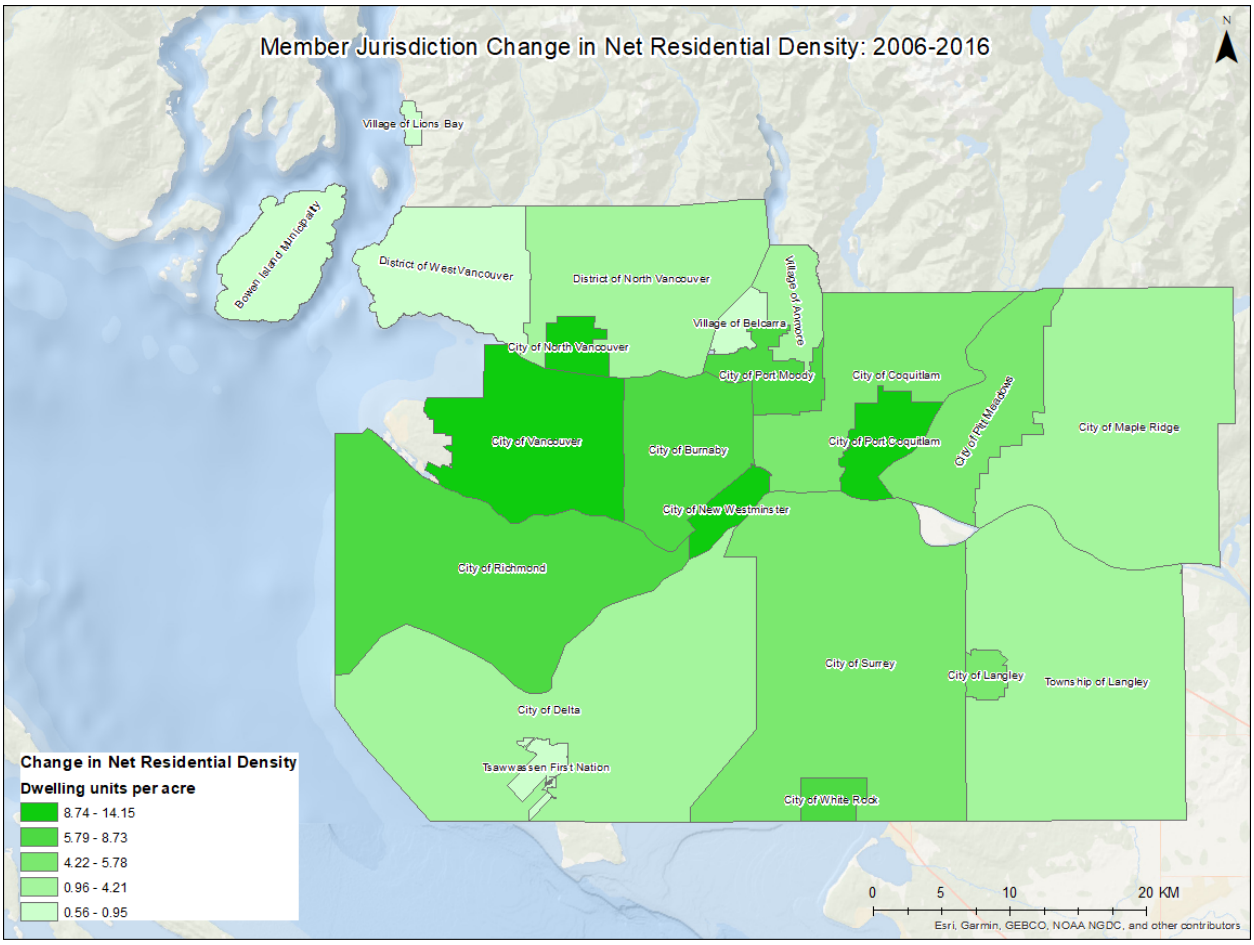


Figure 12-21 Member Jurisdiction Change in Net Residential Density: 2006 - 2016

Examples of dramatic changes in net residential density between 2006 and 2016 are present in Olympic Village in Vancouver and Wesbrook Village at the South end of the UBC campus.

Olympic Village, Vancouver:
WB @ Manitoba & 1st

2006 → 2016



30 Dwelling Units per Acre



150 Dwelling Units per Acre

Olympic Village experienced a major change in land use from a largely industrial and vacant area to a predominantly residential neighbourhood with a commercial center.

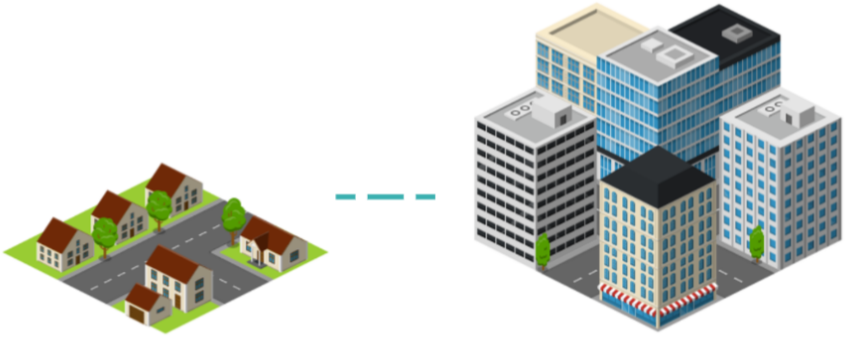
Wesbrook Village transformed from a greenfield site to a bustling commercial and residential community which added much-needed housing to the UBC Main Campus area.

Wesbrook Village, UBC:
EB @ Wesbrook Village



12.1.2. Commercial Floor Area (FAR)

Commercial floor rea ratio (FAR) of a neighbourhood describes the intensity of commercial development. Neighbourhoods with high commercial FAR are generally more urban, have reduced parking and are typically orientated towards more neighbourhood retail allowing residents to easily access goods and amenities.



Regionally, commercial FAR has stayed at a consistent level on average. From 2006 to 2016 it is showing a levelling off trend which could be attributed to widespread increases across the metro region from before 2006 and through to 2011. This indicates that much of the land use that is commercial in the region had been zoned to this use early in the development of the region. From 2006 – 2011 the region experienced the highest rates of change for each component measure, in many of the same areas, which could indicate a period of development in which commercial, residential, and road network development were completed in tandem.

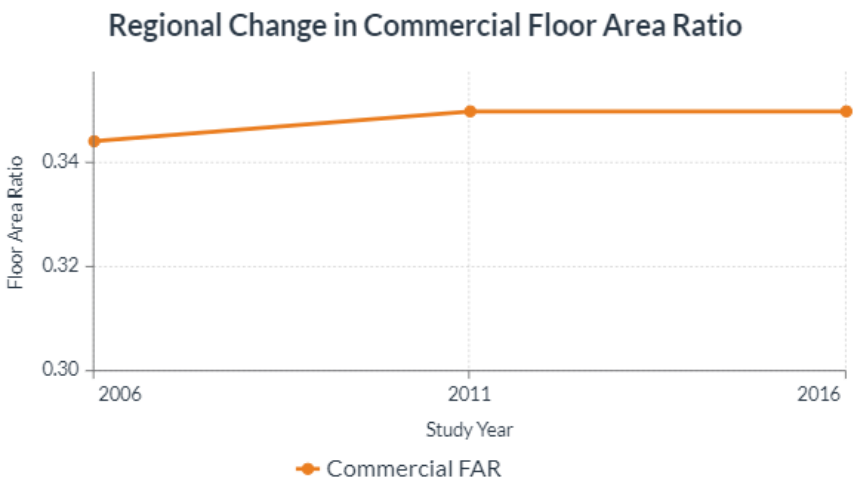


Figure 12-22: Commercial FAR 2006-2016

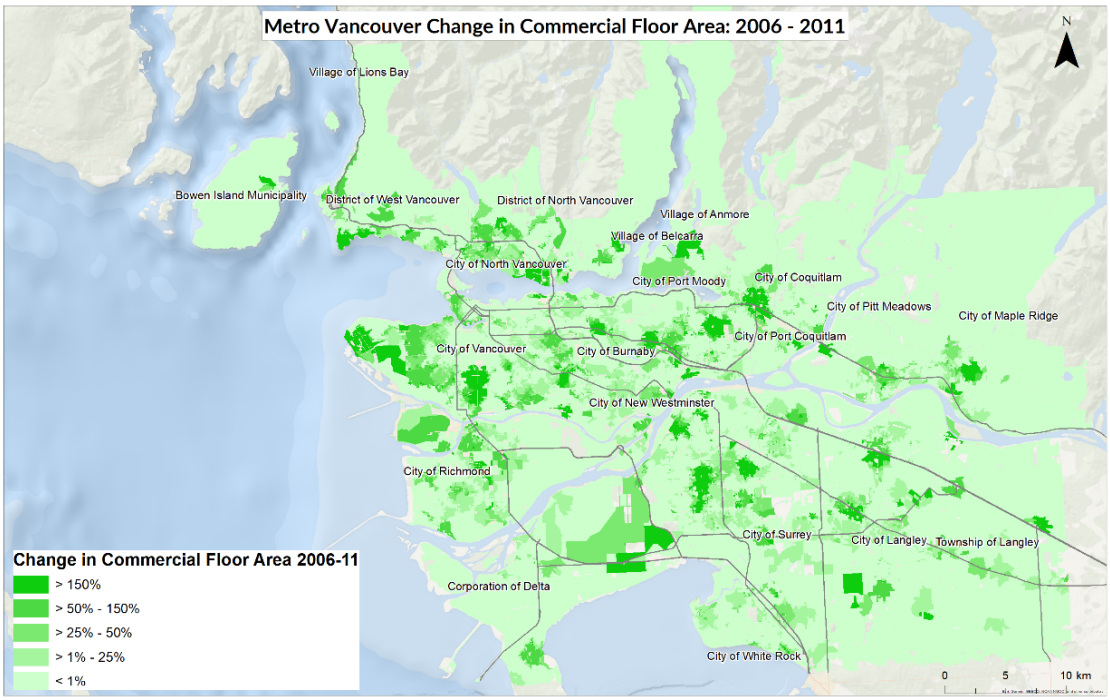


Figure 12-23: Change in Commercial FAR 2006-2011

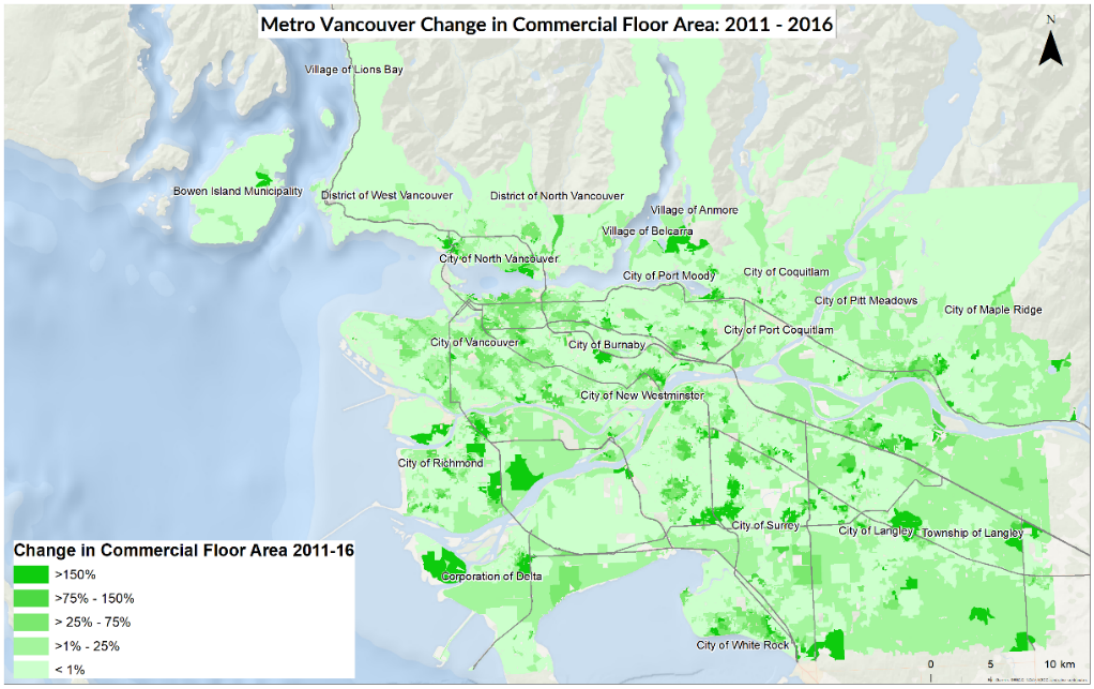


Figure 12-24: Change in Commercial FAR 2011-2016

From 2011-2016, the highest rates of changes in commercial FAR were no longer in the most urban areas of Metro Vancouver. Many of the largest changes were experienced in concentrated areas in Surrey, the City of Langley, Tsawwassen, and the City of North Vancouver. This is reflected when looking at the differing levels of change in the Member Jurisdictions of Metro Vancouver.

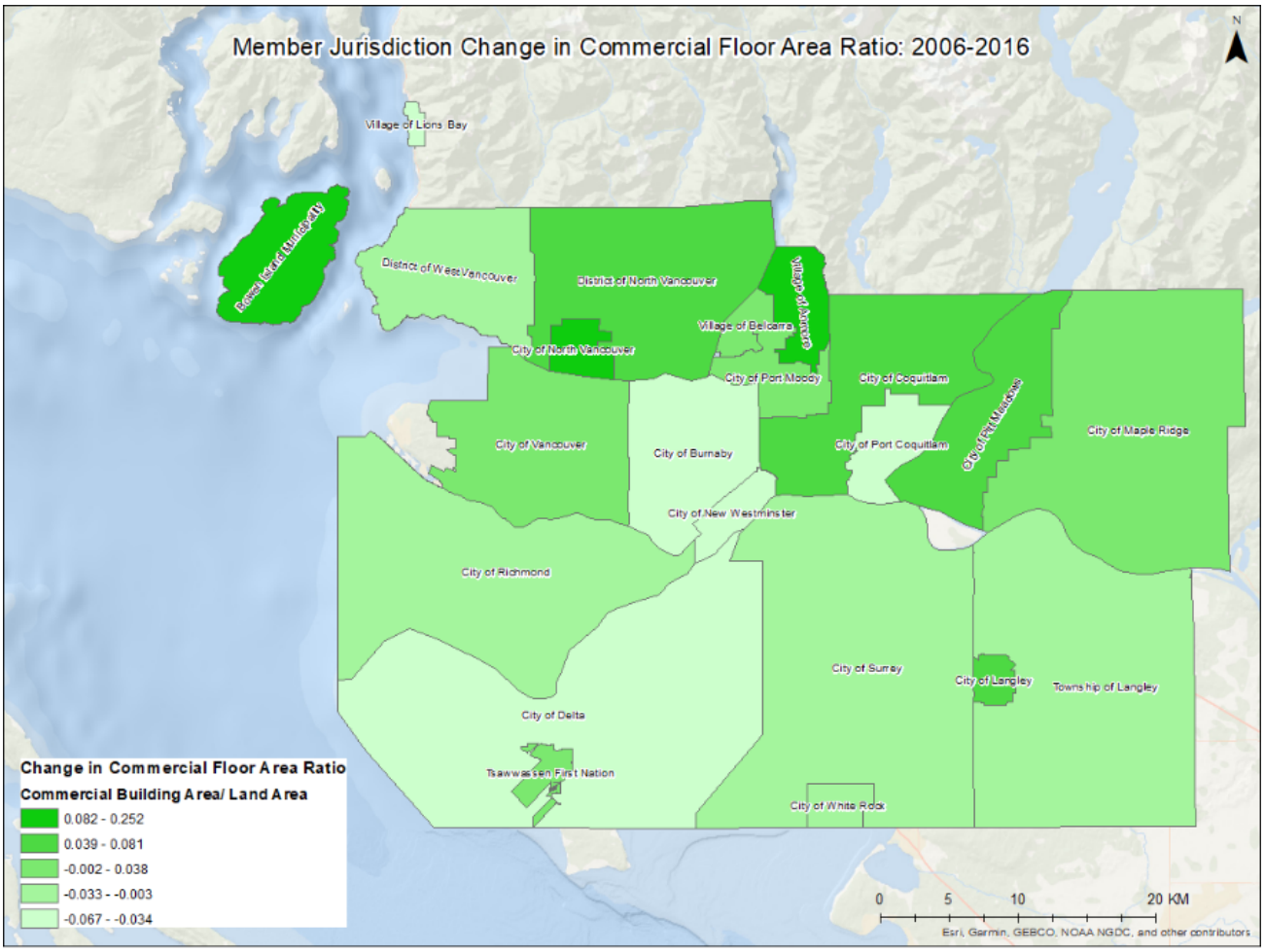


Figure 12-25 Member Jurisdiction Change in Commercial Floor Area Ratio: 2006 - 2016

Areas where significant increases in commercial FAR changed the landscape were, for example, found with the redevelopment of South Dunbar in Vancouver and Park Royal in West Vancouver.

Park Royal, West Vancouver:
EB @ Marine Drive



0.43 Commercial FAR

1.6 Commercial FAR

Dunbar, Vancouver:
SB @ Dunbar St.

2006 → 2016



0.54 Commercial FAR



1.4 Commercial FAR

12.1.3. Land Use Mix

Think of some of your favorite places to visit and walk around. Many of the neighbourhoods you thought of probably have a variety of businesses, amenities, and residences. This is what land use mix measures. Land Use Mix shows the evenness of square footage distribution across residential, commercial (including retail and services), entertainment, and office development within a neighbourhood buffer.



Suburban
0 - 0.12 Land Use Mix



Mixed-use Community
0.62 - 0.96 Land Use Mix

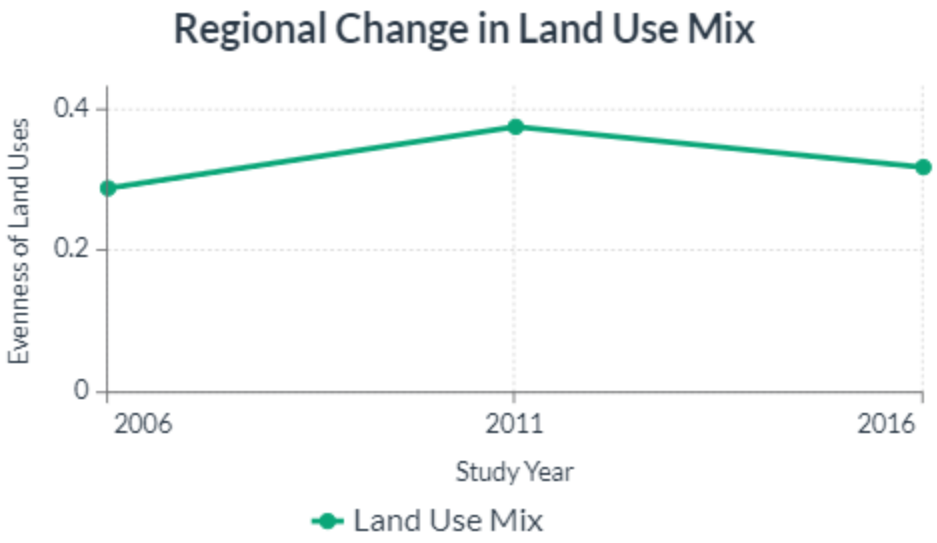


Figure 12-26: Land Use Mix 2006-2016

From 2006 to 2011 the changes in land use mix show that development across the region in these land use types became more balanced. This indicates that within a neighbourhood, new development included retail, residential, office, and entertainment land uses more equally. This can be seen in the trajectory of change in the land use mix measure as well as the consistent upward trend of commercial FAR and net residential density from 2006-2011. The graph above shows that this is the case across the region and the map below shows that there were high changes in land use mix across Metro Vancouver and specifically in smaller urban and suburban areas.

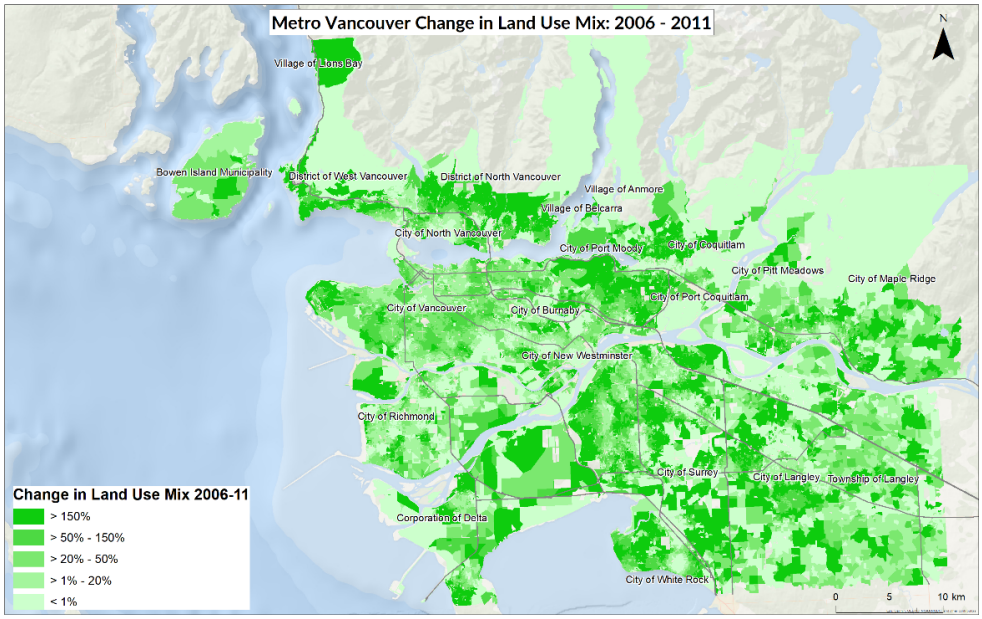


Figure 12-27: Change in Land Use Mix 2006-2011

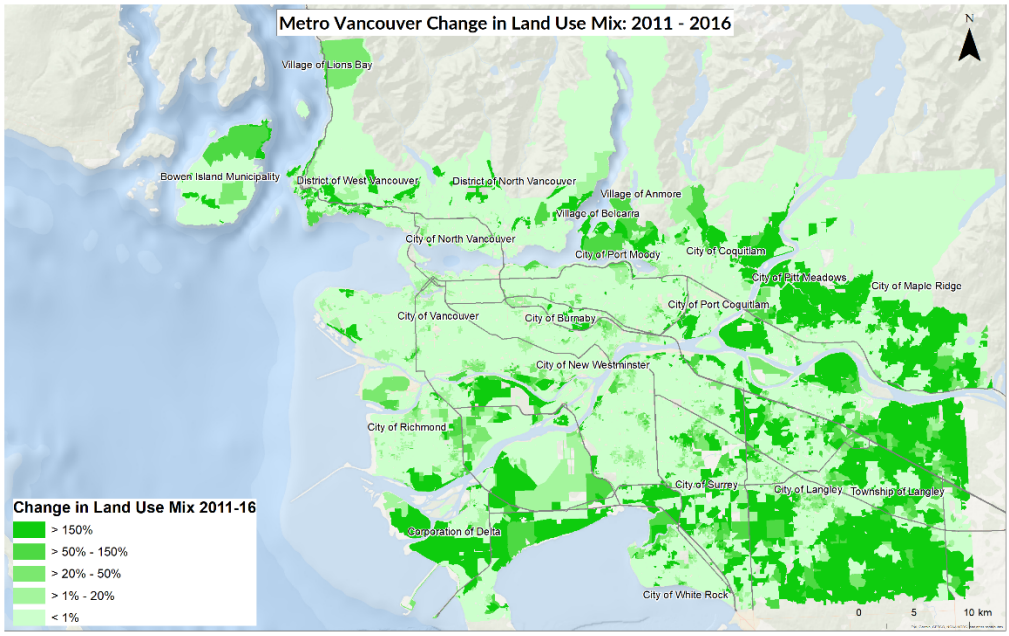


Figure 12-28: Change in Land Use Mix 2011-2016

Figure 12-28 shows that changes in land use mix from 2011 – 2016 have shifted into the southern and easternmost suburban areas where greenfield development of communities is still possible. Elsewhere in the region, changes in net residential density have kept a modest pace while commercial FAR has begun to plateau. This explains the downward trajectory of land use mix from 2011-2016 as the intensification of one land use type over

another result in a less even distribution within a neighbourhood buffer. Further, denser urban forms such as apartment buildings with ground-level retail and residences above can result in lower land use mix scores due to the increases in residential density.

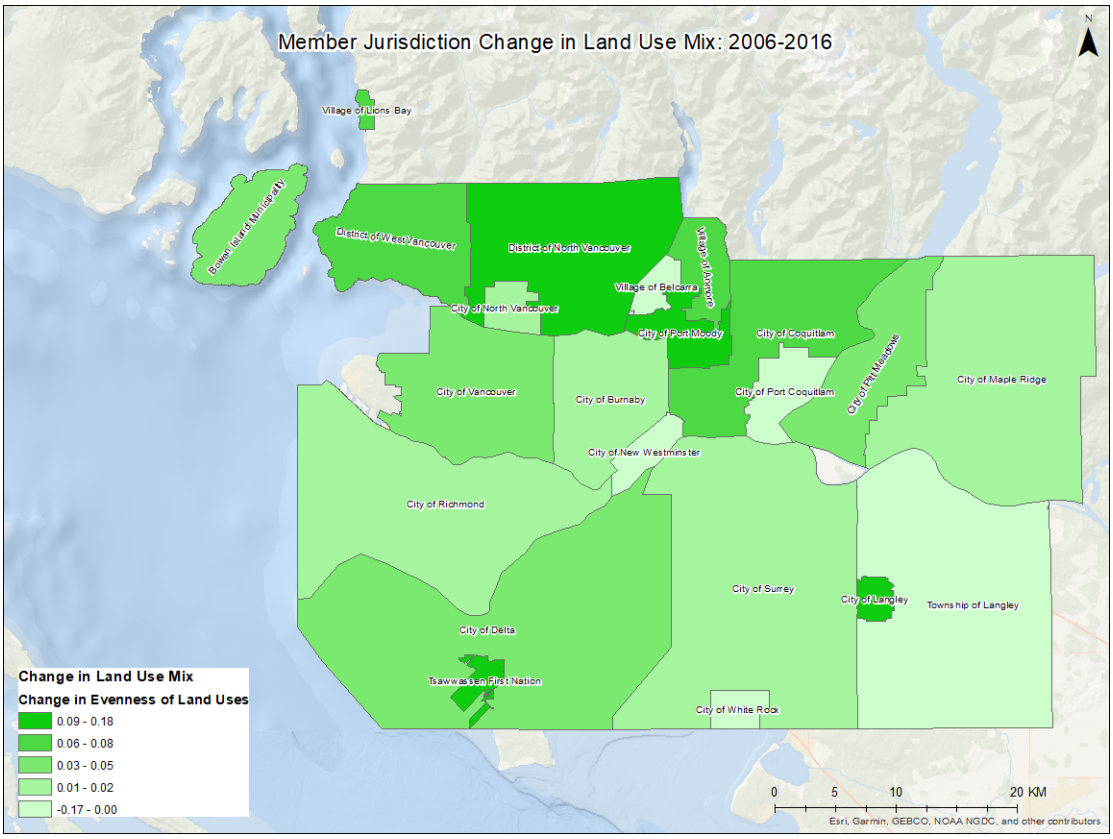


Figure 12-29 Member Jurisdiction Change in Land Use Mix: 2006 - 2016

In the region, many of the Member Jurisdictions that experienced positive changes in land use mix were smaller cities and districts such as Port Moody, Langley, and the District of North Vancouver. Site specific examples where significant changes in land use mix occurred can be found in Vancouver in the Kerrisdale neighbourhood and the District of North Vancouver in Northwoods Village.

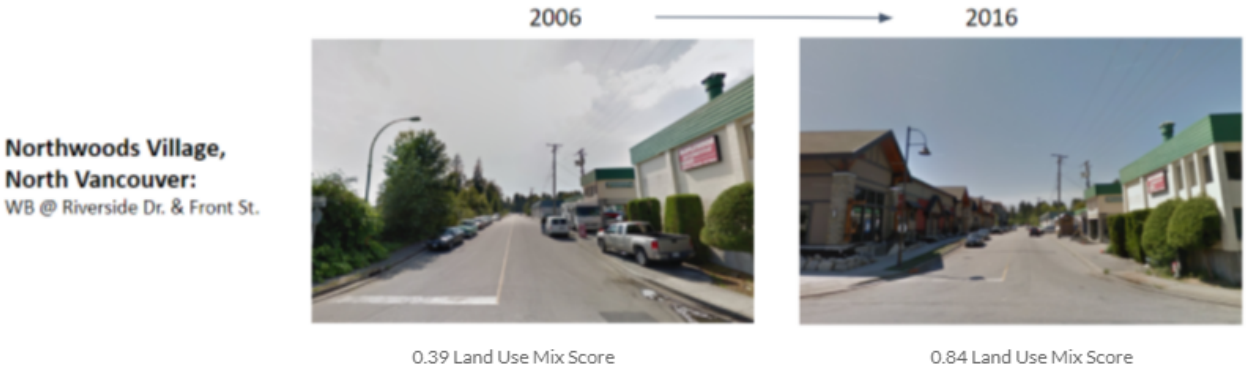
Kerrisdale, Vancouver:
WB @ Cypress & 57th



0.18 Land Use Mix Score

0.37 Land Use Mix Score

On the corner of 57th and Cypress in the neighbourhood of Kerrisdale, we can see an example of how an increase in land use mix contributed to a more even distribution of land use. The corner was upgraded through the renovation of the existing businesses and the addition of apartments on top. This happened to a greater degree in the Northwoods Village area in the District of North Vancouver.



The area surrounding Northwoods Village is an example of a medium to low-density residential and industrial area that saw an increase in land use mix and a move towards a more even distribution of land use types with increased construction in both areas.

12.1. Regional Accessibility

The Walkability Index and Change in Walkability Index describe neighbourhood level local accessibility but do not address accessing amenities beyond a 15–20-minute walk. A model describing Regional Accessibility is required to analyze how disparate areas of the region are connected. Using Generalized Transit Feed Specification (GTFS) data from TransLink average travel times for auto and transit at peak AM and mid-day times were determined for the region for 2011 and 2016. These travel times are based on a variety of regional destinations and include Metro Vancouver Regional Growth Strategy destinations, those determined by the Health and Community Design Lab (HCDL), and Metro Vancouver and UBC destinations combined. The additional destinations added by the HCDL were determined based on their importance to regional transportation using criteria such as volume and proximity to regional centers. An example of this is the Commercial Drive Station transportation hub which is one of the most heavily used transit corridors in the region[32]. The destinations are outlined in the tables below.

[32] TransLink. (n.d.). 2019 TSPR - Rail Summaries [Interactive]. Tableau Public. Retrieved August 12, 2021, from https://public.tableau.com/app/profile/translink/viz/2019TSPR-RailSummaries/TableofContents

Figure 12-30 Metro Vancouver Regional Growth Strategy Destinations

#	Destination Name	Municipality	Type
1	Commercial Dr. Station	Vancouver	Transportation Hub
2	Central Broadway	Vancouver	Transportation Hub
3	UBC	UEL	Educational
4	YVR	Richmond	Transportation Hub
5	Clearbrook	Abbotsford	Regional City Centre
6	Cottonwood Centre	Chilliwack	Municipal Town Centre
7	Mission City	Mission	Municipal Town Centre

Figure 12-31 Health and Community Design Lab Determined Destinations

#	Destination Name	Municipality	Type
1	Downtown Vancouver	Vancouver	Metropolitan Core
2	Surrey Centre	Surrey	Suburban Metro Core
3	Oakridge	Vancouver	Municipal Town Centre
4	Metrotown	Burnaby	Regional City Centre
5	Columbia Skytrain	New Westminster	Regional City Centre
6	Richmond Brighouse	Richmond	Regional City Centre
7	Lonsdale Quay	North Vancouver	Regional City Centre
8	Brentwood Town Centre	Burnaby	Municipal Town Centre
9	Lougheed Town Centre	Burnaby	Municipal Town Centre
10	Coquitlam Town Centre	Coquitlam	Regional City Centre
11	Edmonds	Burnaby	Municipal Town Centre
12	Newton	Surrey	Municipal Town Centre
13	Guildford Town Centre	Surrey	Municipal Town Centre
14	Willowbrook Centre	Langley City	Regional City Centre
15	Downtown Port Moody	Port Moody	Municipal Town Centre
16	Downtown Port Coquitlam	Port Coquitlam	Municipal Town Centre
17	Downtown Maple Ridge	Maple Ridge	Regional City Centre
18	Fleetwood	Surrey	Municipal Town Centre
19	Downtown Pitt Meadows	Pitt Meadows	Municipal Town Centre
20	Ambleside	West Vancouver	Municipal Town Centre
21	Lynn Valley Centre	DNV	Municipal Town Centre
22	Semiahmoo Centre	White Rock	Municipal Town Centre
23	Cloverdale	Surrey	Municipal Town Centre
24	Aldergrove Centre Mall	Township of Langley	Municipal Town Centre
25	Ladner	Delta	Municipal Town Centre
26	Willoughby	Township of Langley	Municipal Town Centre

To calculate the travel times for each postal code, travel times acquired from the GTFS data were linked to each postal code based on the traffic analysis zone it falls within. The travel times for each destination were then aggregated and divided by the total number

of destinations to arrive at mean AM and mid-day travel times for auto and transit. The resulting travel times for all Metro Vancouver and Health and Community Design Lab destinations are visualized in maps below.

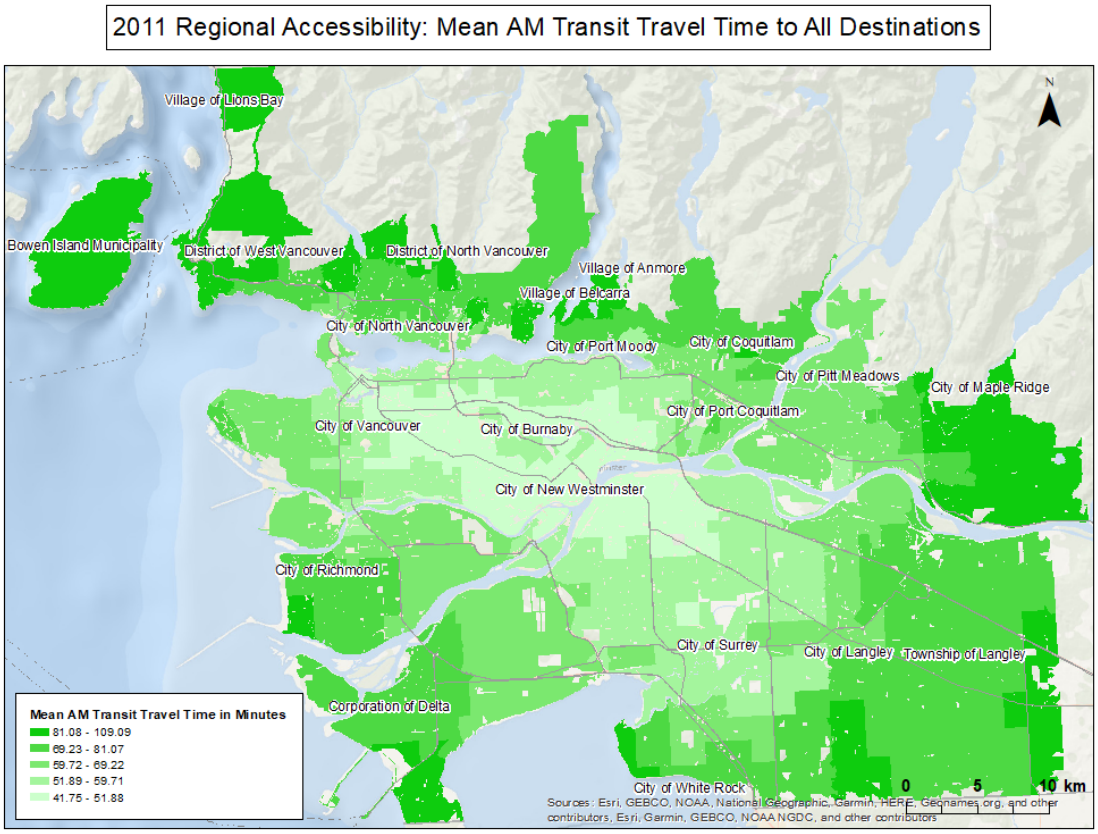


Figure 12-32 Map of 2011 Mean AM Transit Travel Time

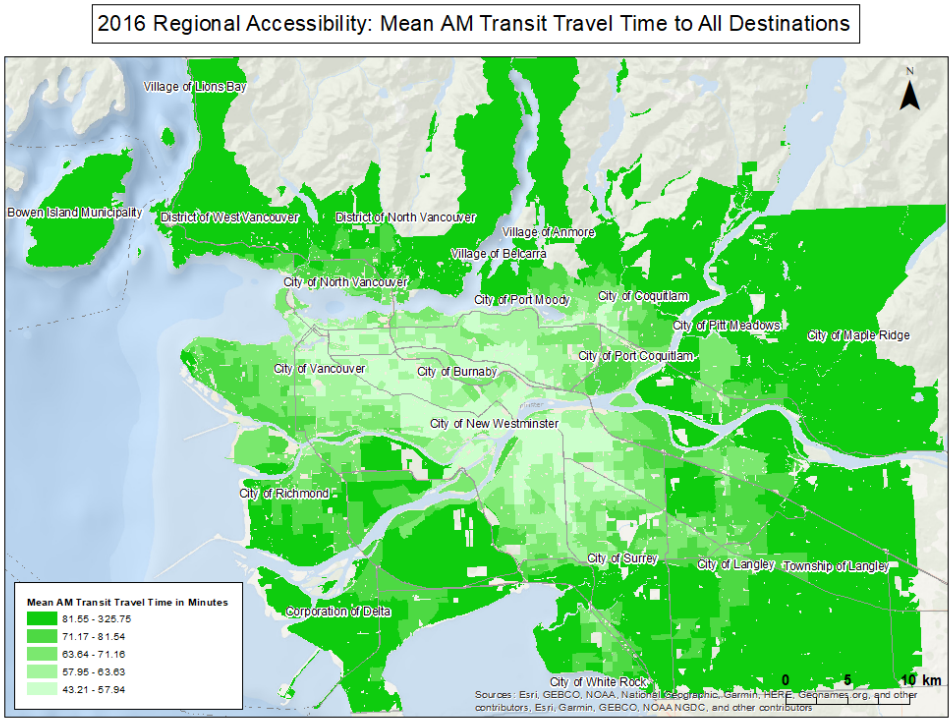


Figure 12-33: Map of 2016 Mean AM Transit Travel Time

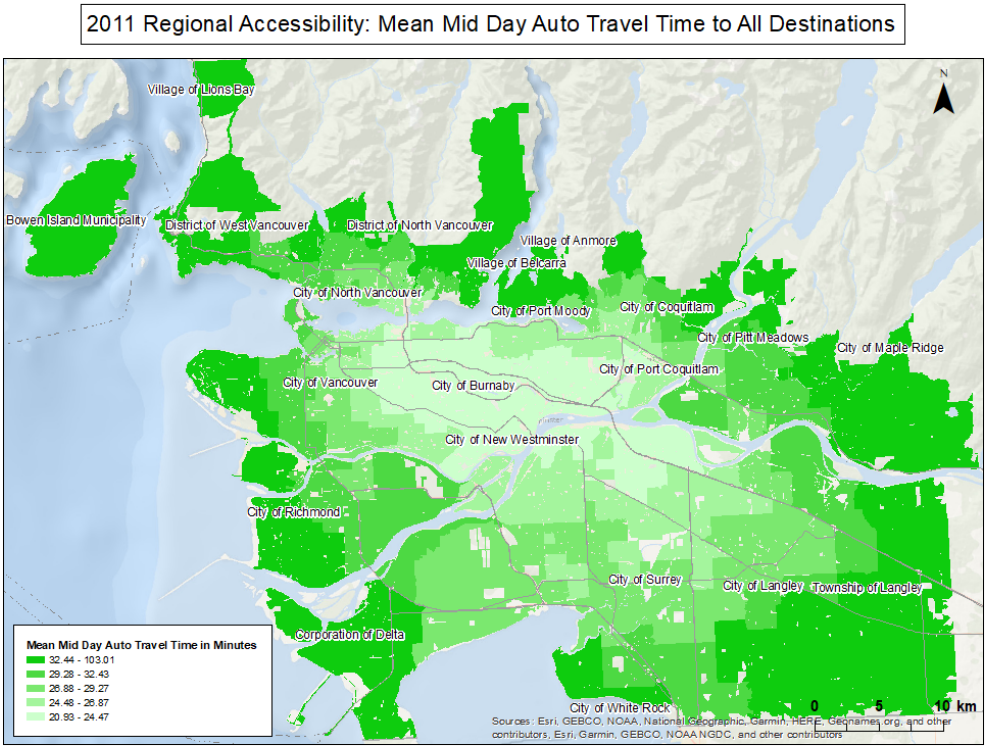


Figure 12-34: Map of 2011 Mean Mid-Day Auto Transit Travel Time

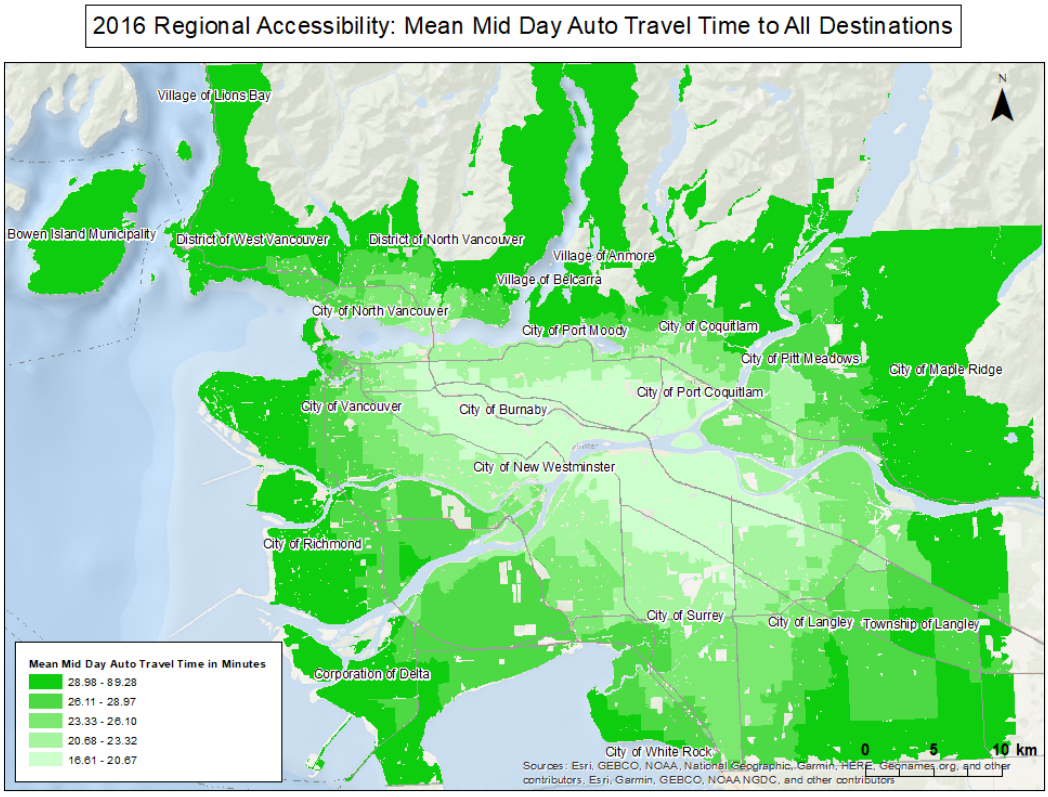


Figure 12-35: Map of 2016 Mean Mid-Day Auto Transit Travel Time

The transit travel time maps consistently show the lowest travel times for transit where transportation is easily accessible. This is apparent on the downtown peninsula of Vancouver, East Vancouver at Commercial Dr. Station, in New Westminster, and areas of Port Moody and Coquitlam where transit is concentrated. Transit travel time increases in car dependent areas with poor transportation connection. This is shown in suburban areas such as Anmore, Belcarra, Maple Ridge, and Lions Bay where transportation investment has historically been low. Auto travel times exhibit similar patterns regionally due to most destinations being closer to the downtown core of Vancouver. Some suburban areas exhibit travel times like those found closer to the downtown core of Vancouver due to transportation design differences. Many suburban areas were built as car dependent enclaves with well-connected highways, while areas within the City of Vancouver have transitioned to more transit and active transportation friendly modes of travel. As transportation policies evolve in the region, we would expect to see transit travel times decrease allowing greener more equitable travel across Metro Vancouver.

12.2. Walkability Summary

The analysis of changes in the component variables which comprise the walkability index allows policy decision makers to examine how changes in the built environment over time shape each neighbourhood and the collective region. These changes show, at the postal code level, the development trajectory of Metro Vancouver with policy relevant measures. When neighbourhood walkability is improved, the culmination of these changes has been shown to be a factor in living healthier more environmentally friendly lifestyles.

12.3. Neighbourhood Change in Metro Vancouver

From 2006 to 2016, some neighbourhoods in Metro Vancouver have undergone extensive change. These changes are reflected in the component variables of net residential density, commercial floor area ratio, land use mix, intersection density, and the walkability index. These neighbourhoods have not only undergone a physical change in the built environment. Along with the processes of densification and upgrading that change the built environment, shifting demographic patterns have occurred resulting in the attraction of new residents and the departure of others. This section describes how changes in walkability and demographic characteristics have interacted from 2006 – 2016. The neighbourhoods in focus are a selection of those that had the highest change in walkability over the study period. Willingdon Heights in Burnaby, Brighouse in Richmond, Morgan Heights in Surrey, and Olympic Village in Vancouver are highlighted in these case studies (Figure 12-36).

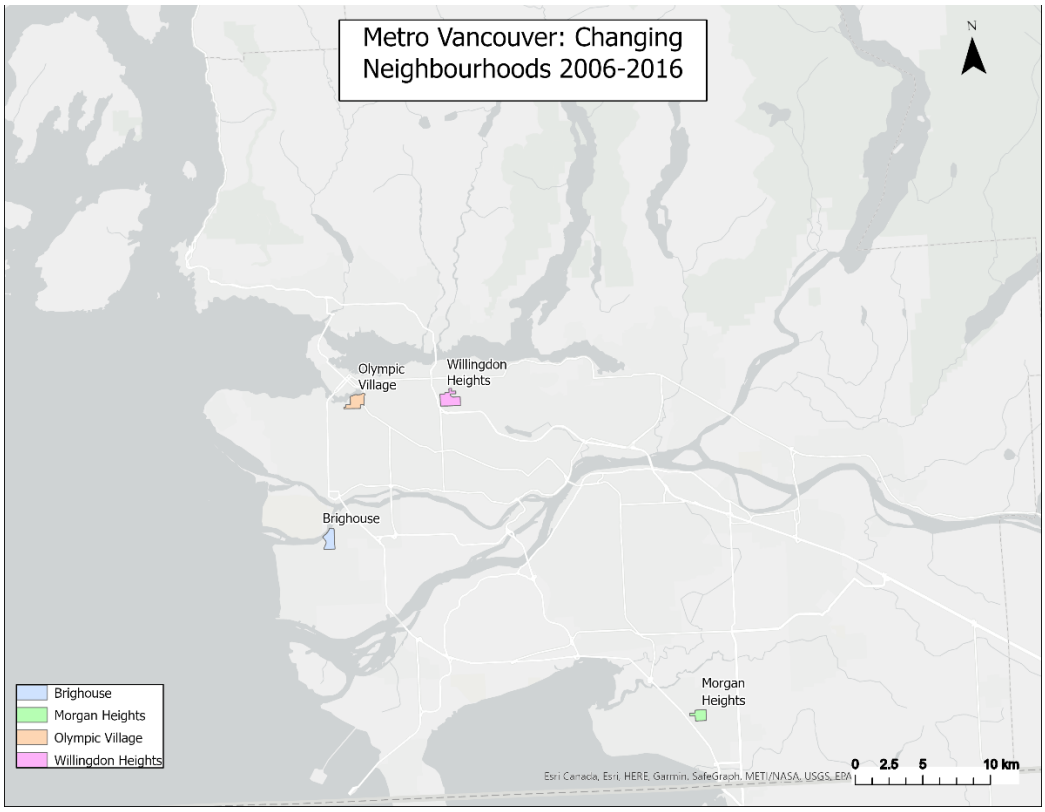
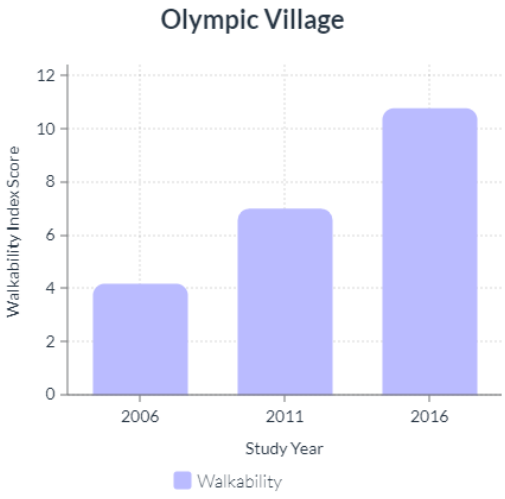


Figure 12-36 Map of Case Study Neighbourhoods

12.3.1. Olympic Village, Vancouver

Olympic Village was constructed for the 2010 Winter Olympics held in Vancouver. It was a major development project that converted largely industrial lands into dense residential



apartment buildings with retail at the bottom. From 2006 to 2016 the walkability index and demographic variables reflect this conversion from a mainly industrial area to a mixed-use residential and retail neighbourhood (Figure 12-37).

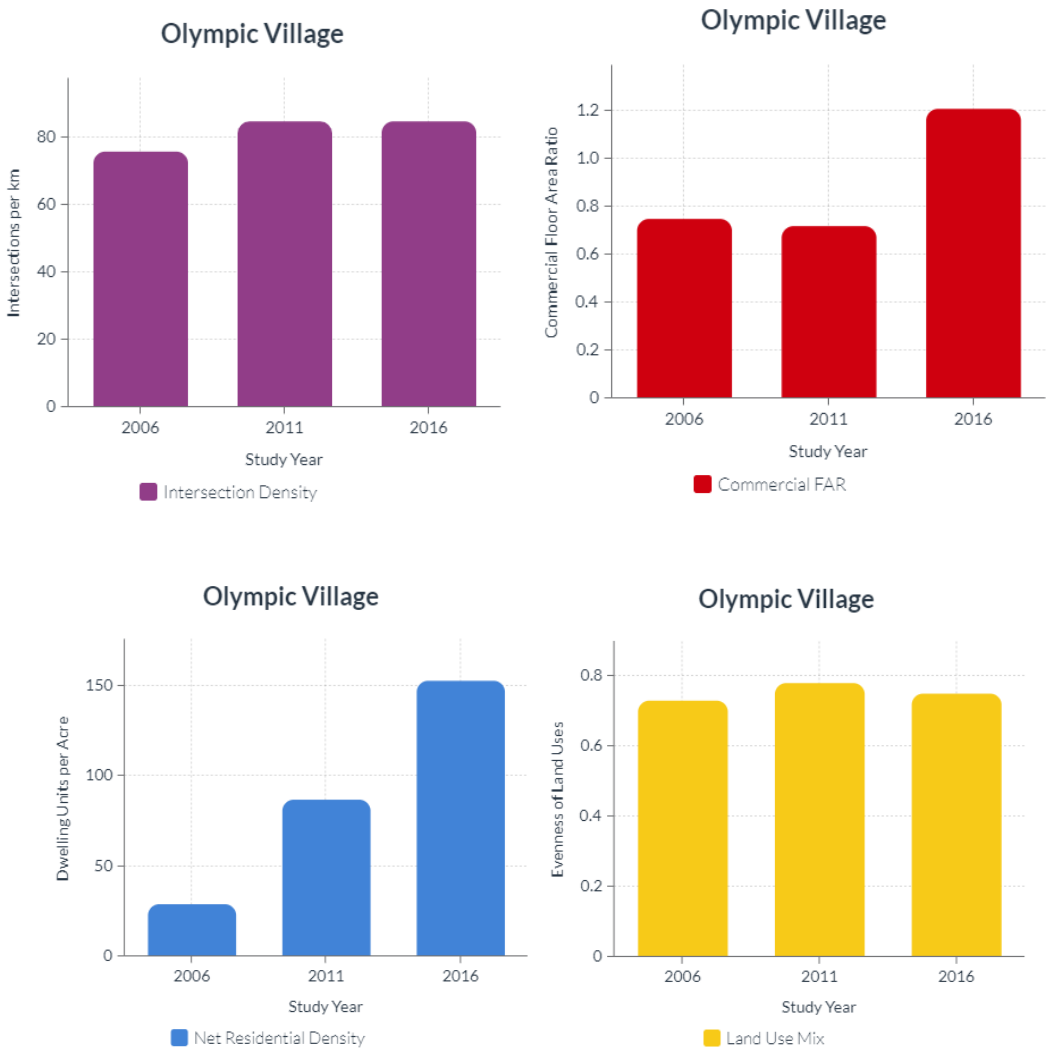


Figure 12-37 Walkability Profile of Olympic Village

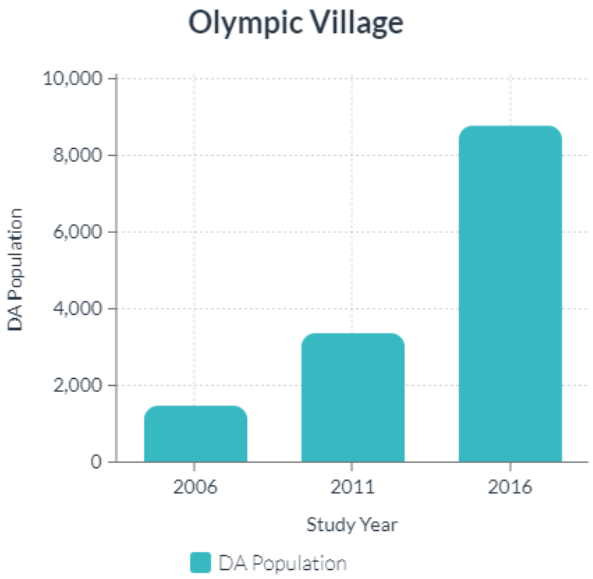
From the changes in the walkability index and the component variables, we can see many of the measures increasing resulting in significant changes in the built environment. Through the construction of apartment buildings with retail on the ground floor of many, net residential density and commercial FAR have skyrocketed from 2006 to 2016. There was a dip in commercial FAR in 2011 as the conversion from industrial to mixed-use lands occurred. When Olympic Village was first constructed many of the retail spaces remained vacant for many years.

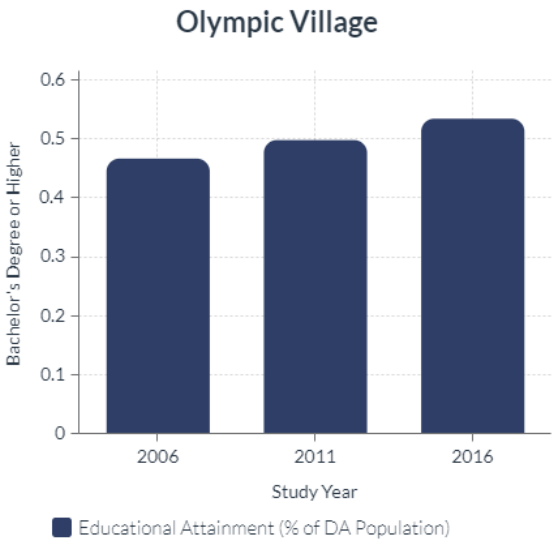
As residential buildings have been added in the years since Olympic Village's initial construction in 2011, the land use mix has decreased slightly from the intensification of 1 of the 6 land uses used to calculate the measure. The changes in the component measures have interacted to increase walkability in Olympic Village, nearly tripling the index score from 4.2 to 10.8 in 10 years.

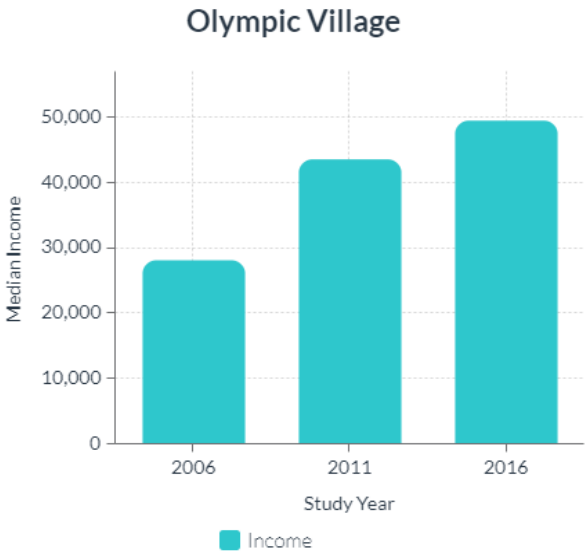


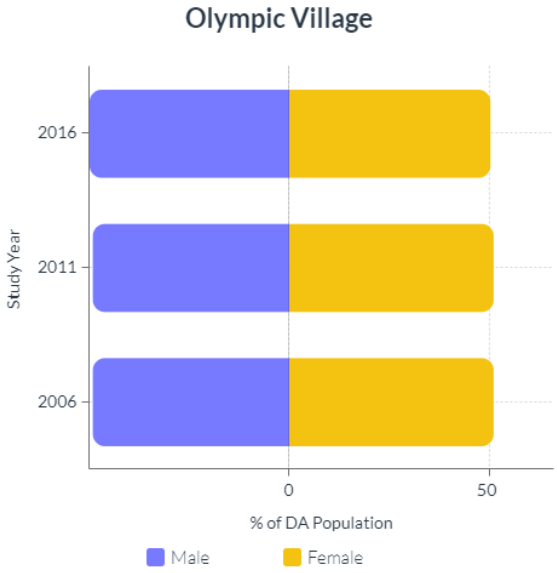
Figure 12-38 Olympic Village Changes from 2006 (left) to 2016 (right)

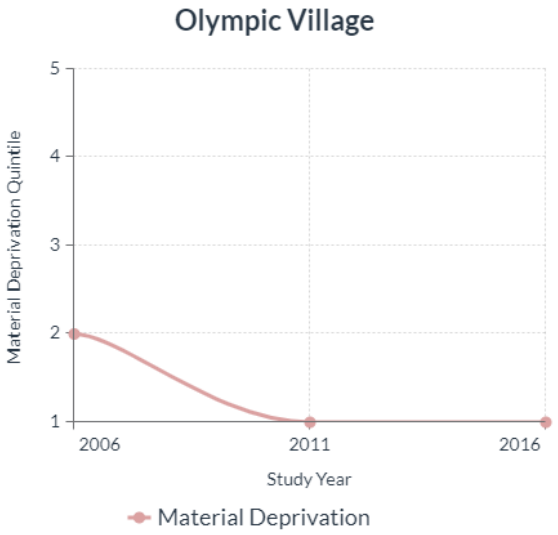
In the photos above (Figure 12-38) you can see the dramatic change in the landscape that has occurred in Olympic Village. The changes shown above have also affected the demographic profile of the area. The graphs presented below outline these shifts in demographics. Over the study period, Olympic Village has continued to become wealthier and more populated. Median annual income rose from $27,000 to $50,000, educational attainment based on those with a Bachelor's degree or higher increase, and the median age of those living in the area was stable at around 35 years old. The changes in these variables indicate that wealthier and younger people have continued to move into the area from 2006 to 2016.

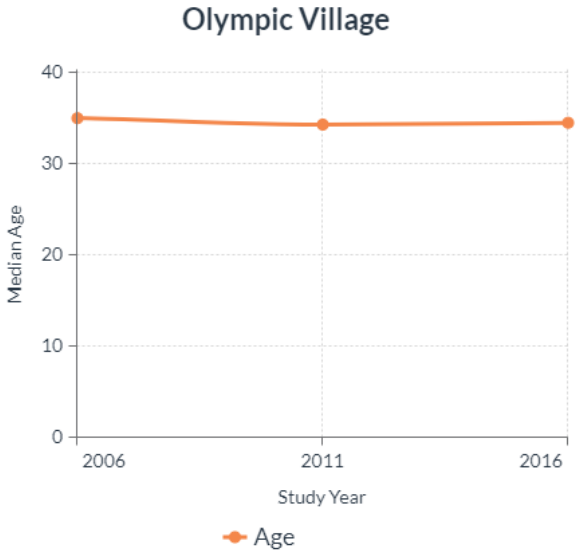

Olympic Village
10,000
8,000
6,000
4,000
2,000
0
DA Population
2006
2011
2016
Study Year
DA Population


Olympic Village
0.6
0.5
0.4
0.3
0.2
0.1
0
Bachelor's Degree or Higher
2006
2011
2016
Study Year
Educational Attainment (% of DA Population)









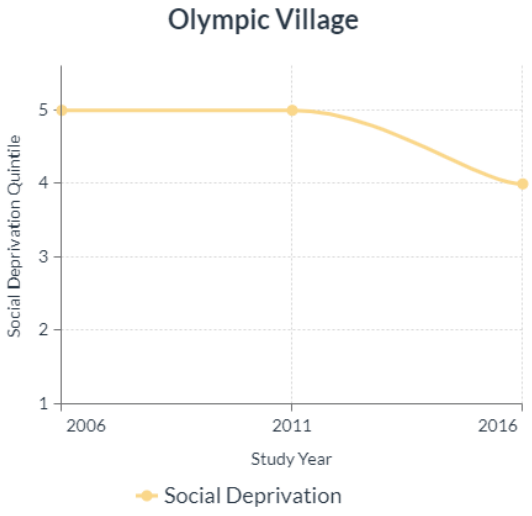


Figure 12-39 Demographic Profile of Olympic Village

12.3.2. Willingdon Heights, Burnaby

Located to the east of the City of Vancouver in Burnaby, Willingdon Heights is a neighbourhood named after Willingdon Avenue. The neighbhourhood is well connected to North Burnaby and Metrotown to the south through Kingsway and Willingdon Avenue. It is located close to Brentwood Mall and is connected by transit through the Millenium Line Skytrain at Brentwood Station and several TransLink bus routes.

From 2006 to 2016, areas of Willingdon Heights experienced significant development and densifcatoin throught the constuction of mixed use residential apartment buildings with commercial space on the ground floor. This saw the conversion of industrial, retail, and single family residential land uses converted into much denser urban forms. This is shown through the walkability index and the component measures.

During 2006 to 2016 the neighbourhood experienced a nearly 8-fold increase in net residential density. This was fueld by the densifcation and conversoin of low density land uses into tall residential towers. Further, with ground level retail in many of the residential towers the ratio of commercial lands to commercial floor area remained consistent, even though retail was converted into predominantly residential land use. This contributed to an increasing land use mix over the 10 year period as the neighbourhood developed into a walkable mixed use community. The area changed from an neighbourhood that was below aveage in walkability in 2006 to one that almost 3 times as walkable as the Metro Vancouver average in 2016. The walkability index score changed from -0.12 in 2006 to 2.8 in 2016. During that period regional accessibility, the ease at which resources can be reached within Metro Vancouver, has remained consistent weighted at 45 minutes of travel time to reach all regional destinations.



Figure 12-40 Walkability Profile of Willingdon Heights

This contributed to an increasing land use mix over the 10 year period as the neighbourhood developed into a walkable mixed use community. The area changed from an neighbourhood that was below aveage in walkability in 2006 to one that almost 3 times as walkable as the Metro Vancouver average in 2016. The walkability index score changed from -0.12 in 2006 to 2.8 in 2016. During that period regional accessibility has remained consistent weighted at 45 minutes of travel time to reach all regional destinations.



Figure 12-41 Changes in Willingdon Heights from 2006 (left) to 2016 (right)

The pictures (Figure 12-41and Figure 12-42) included show the dramatic change in the landscape from the construction of dense residential towers. The transformation of the built environment of Willingdon has also changed who lives in the neighbourhood. With rising housing costs in the City of Vancouver, many younger people are looking towards well connected neighbourhoods like Willingdon Heights that are just outside of the city.

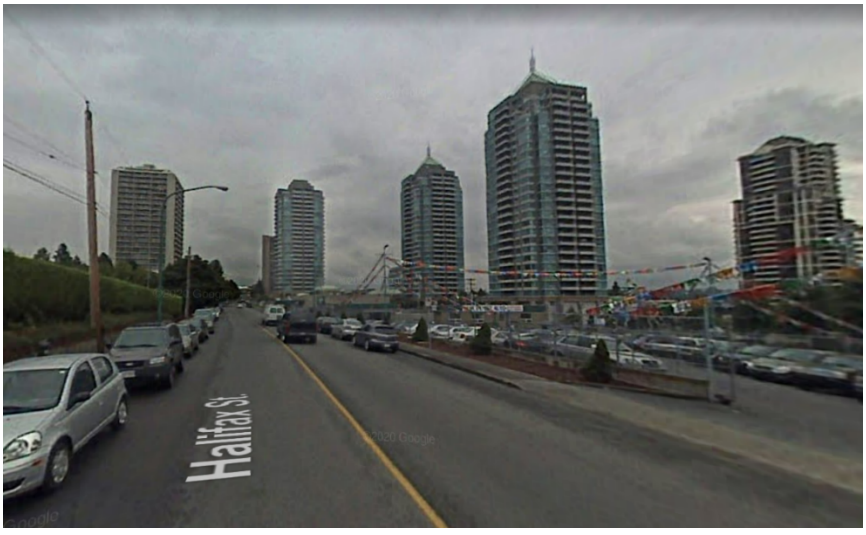
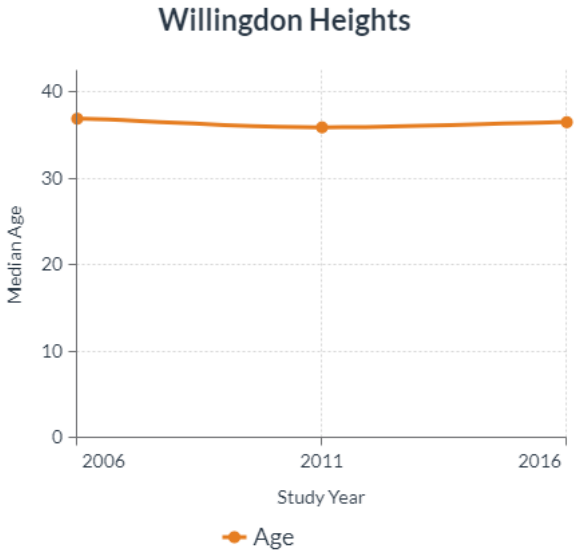




Figure 12-42 Changes in Willingdon Heights from 2006 (top) to 2016 (bottom)

The demographic profile of Willingdon Heights has shifted to be denser, younger, more highly educated, and wealthier as a whole. From 2006 to 2016 the population more than doubled from 2,500 to 5,600. The new people in the neighbourhood tended to be younger as the median age in the area has remained steady at around 36 years old, over the 10 year period. These younger residents buying and renting new apartments had incomes 25% higher than those in 2006. The median income in Willingdon in 2006 was $38,000 and had risen to 47,000 by 2016. The graphs below outline these changes in further detail:



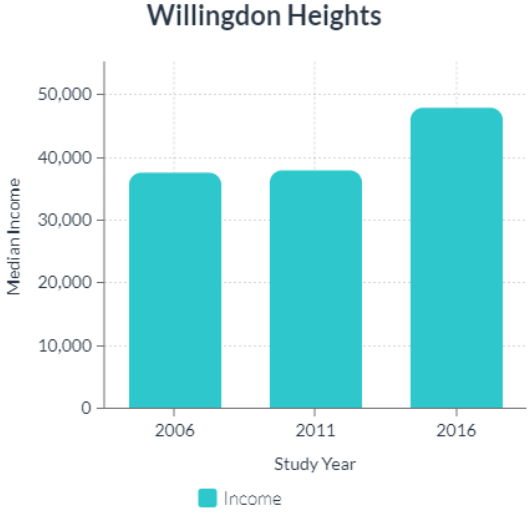
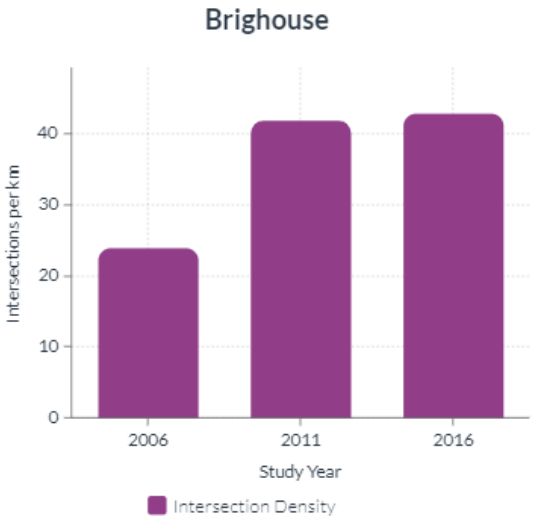


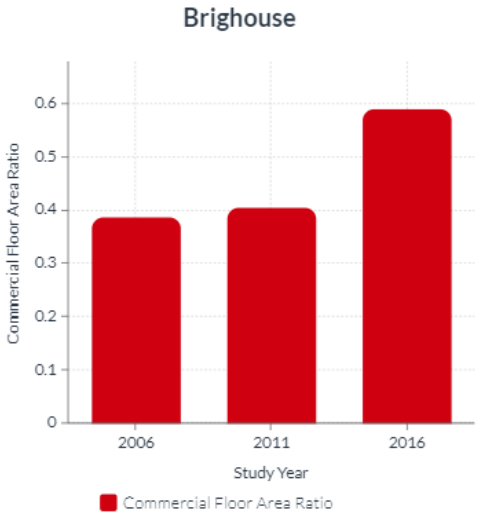


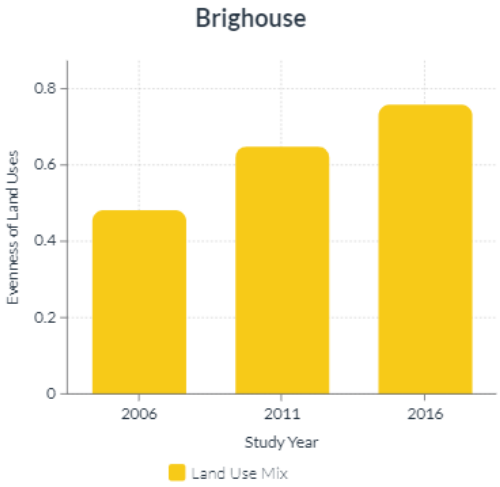
Figure 12-43 Demographic Profile of Willingdon Heights

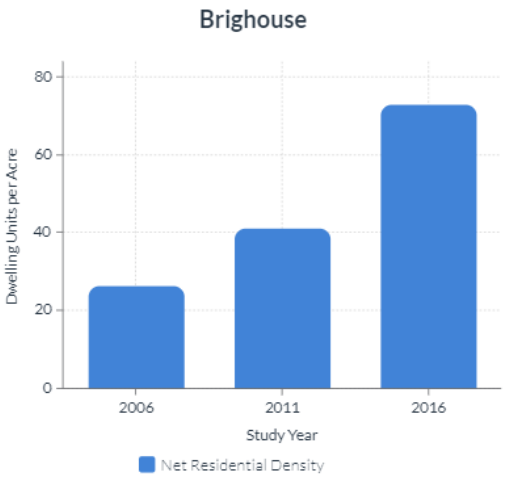
12.3.3. Brighouse, Richmond

Brighouse is a neighbourhood in Richmond which has seen significant development since the turn of millenium. The neighbourhood makes up the majority of the urban core in Richmond and has been the center of densification and development in Richmond since the introduction of the Canada Line to Brighouse station in 2010. The major changes experienced in the Brighouse neighbourhood are reflected in changes in the walkability index, the component measures, and demographic variables.









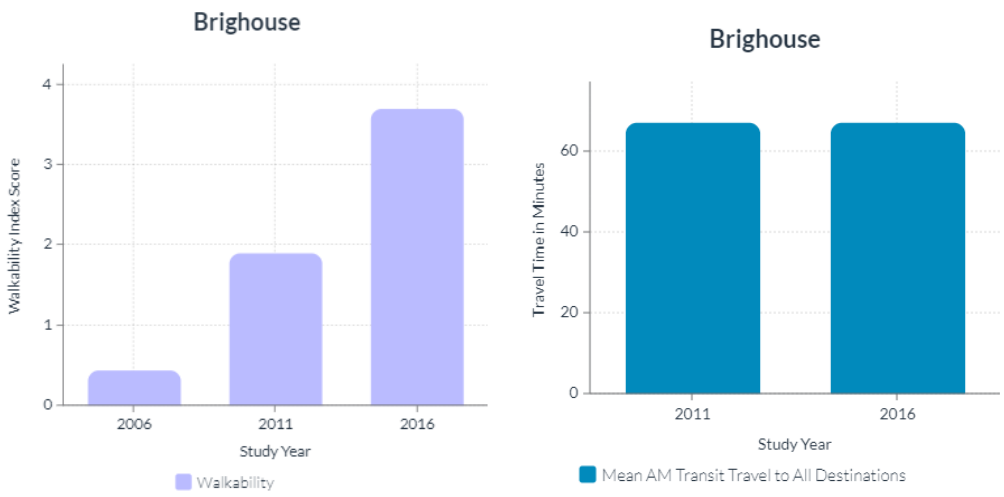


Figure 12-44 Walkability Profile of Brighouse

Brighouse has developed and increased in all component measures of walkability from 2006 to 2016. Each measure saw similar magnitudes of increase throught the period. With the construction of new retail and commercial buildings throughout the neighbourhood, new roads were required to make the new density accessible. During this time intersection density increased from just over 20 intersections per kilometre to 42. The construction of many mid-rise residential towers with commercial podiums in the area catapulted the commercial floor area ratio from 0.39 to 0.59 and the net residential density from 22 to 73 dwelling units per acre. The mixes of land use constructed in the burgeoning area drove an increase in land use mix from 0.48 to 0.76, creating a community with ample residential and commercial spaces. Below are real examples for the development of the neighbourhood. They showcase transit oriented development along the Canada Line and residential buildings with commercial podiums.



Figure 12-45 Changes in Brighouse from 2006 (left) to 2016 (right)



Figure 12-46 Changes in Brighouse from 2006 (left) to 2016 (right)

The changes in the built environment over this time attracted new people to Brighouse. The population of the neighbourhood swelled from 760 in 2006 to 4,000 in 2016. The folks that came to the area in this time were different than those that called the area home before the arrival of the Canada Line and scores of residential apartment buildings.

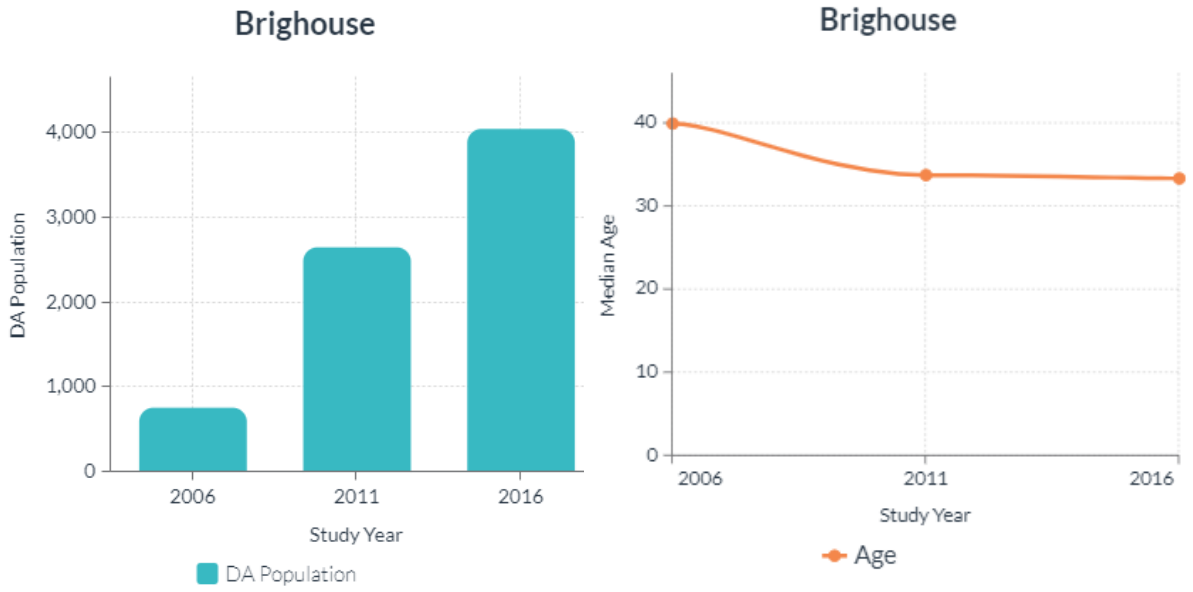




Figure 12-47 Demographic Profile of Brighouse

The trends the demographic variables exhibit is that of younger and wealthier people moving into the Brighouse neighbourhood. From 2006 to 2016 the median age in the area dropped from 40 to 33.4. At the same time, the median income rose from $19,000 to $28,553 and education remained consistent. This trend has been shown in both Olympic Village and Willingdon Heights in which the new housing in each neighbourhood tends to attract younger and wealthier individuals, perhaps escaping the increasingly unaffordable housing prices in the City of Vancouver.

Interestingly, social deprivation increased to a more deprived quintile and material deprivation remained constant over the 10-year period. The change in social deprivation to a more deprived quintile could be due to more individuals living alone. Material deprivation likely remained constant due to the interaction between income and educational attainment that occurred from 2006 to 2016. While income rose more throughout the early part of the decade than in the latter half, education took a big dip in 2011 and returned to a similar level in 2016.

12.3.4. Morgan Heights, Surrey

Morgan Heights is a newly developing suburban community in South Surrey located east of White Rock. Once a predominantly low-density single-family and rural neighbourhood, Morgan Heights has been densifying through the construction of town homes and low to mid rise apartment buildings. These changes have occurred both through largely greenfield development, but the neighbourhood has also experienced some infill development. The addition in residential buildings adds much needed density to an area that from 2006-2011 developed to be well served by amenities. Morgan Heights has schools and retail within walking distance to much of the housing in the neighbourhood. The changes in the built environment can be shown through the walkability index component measures and the overall change in walkability from 2006 to 2016.



Figure 12-48 Walkability Profile of Morgan Heights

As shown through the component measures there was an intense period of development from 2006 to 2011 in which new roads and commercial destinations were built to accommodate the incoming residential density and increased population. This is shown through the increases in intersection density and commercial FAR from 2006-2011. The development resulted in a more even land use mix in 2011 going from 0.041 to 0.59 in 5 years. From 2006 to 2016 there is a large period of residential development reflected in the increase in net residential density. The earlier part of the decade saw an increase from 0.35 dwelling units per acre to 7.25 with the latter half going up to 16.7. Land use mix changed along with these developments in the built environment and settled from 0.59 in 2011 to 0.52 in 2016 after the increase in residential density. The interaction of the changes in the component variables lead to a significant increase in walkability from 2006 to 2011 and continued increases to 2016.

Morgan Heights went from a highly unwalkable neighbourhood that was almost 5 times less walkable than average to an area that is over 2 times more walkable than the regional average. While the neighbourhood is still largely car dependant when accessing the rest of the region, with little transit infrastructure investment as reflected in the stagnant transit travel times, the local accessibility to amenities and housing is high. Some of these changes are ground-truthed in pictures captured by Google street view below:



Figure 12-49 Changes in Morgan Heights from 2006 (left) to 2016 (right)

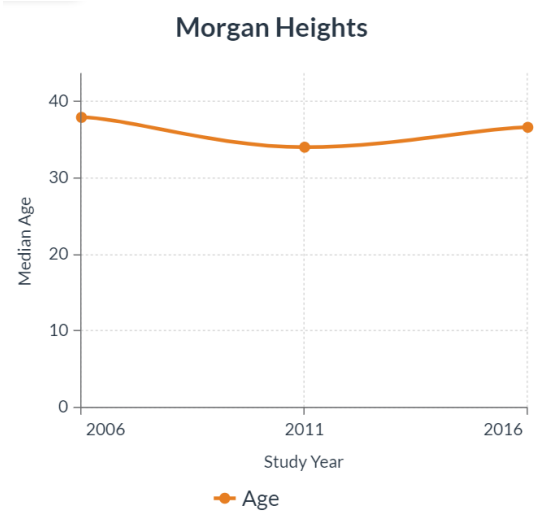


Figure 12-50 Changes in Morgan Heights from 2006 (left) to 2016 (right)

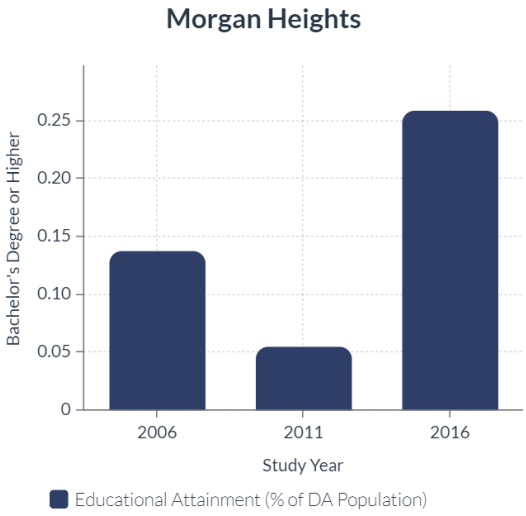
The images show increases in net residential density from the construction of large blocks of townhouses. The new housing developed in the neighbourhood attracted individuals that changed the demographic profile of Morgan Heights.

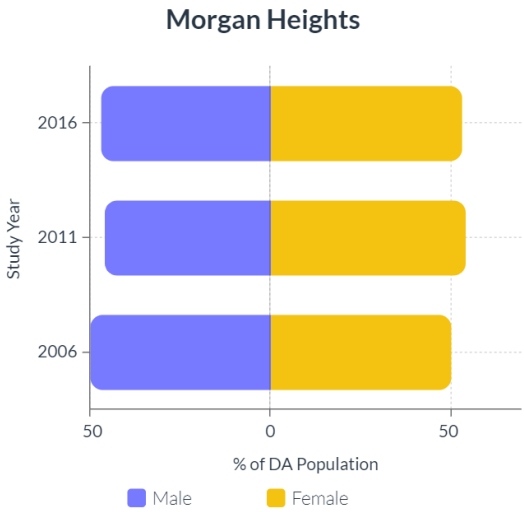
The explosion in population from 2006 to 2016 brought in over 4,000 new residents to Morgan Heights. The difference in median age from 2006 to 2011 signaled the addition of younger and wealthier people to the area. During this time the median age dropped from 38 to 34.1, while median income rose from $36,000 to $55,000. From 2011 to 2016 the population of Morgan Heights continued to increase significantly bringing in a more educated, but largely similar resident with the median age increasing to 36.7 and the median income rising to $57,000. Morgan Heights seems to have become a walkable oasis is suburbia for young families to move to with a proximate school and walkable retail amenities.

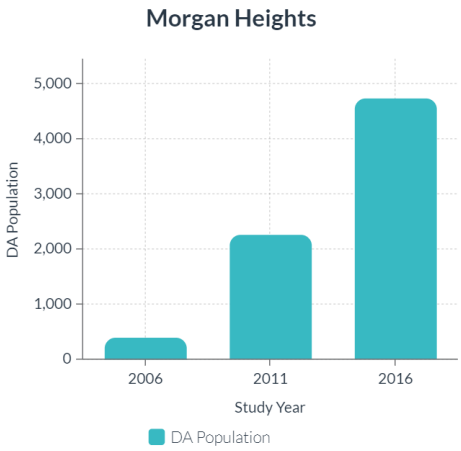
Over the 10 year period in Morgan Heights there were fluctuations in social and material deprivation. The average social deprivation throughout the neighbourhood moved from the lowest quintile to the highest indicating the most socially deprived over the study period. This could be due to more lone parent, divorced, or single individuals moving into the area. Material deprivation exhibited the opposite trend moving from one of the most deprived quintiles to the least. This can likely be attributed to higher levels of education, income, and employment moving into the area with the increase in greenfield development and net residential density.

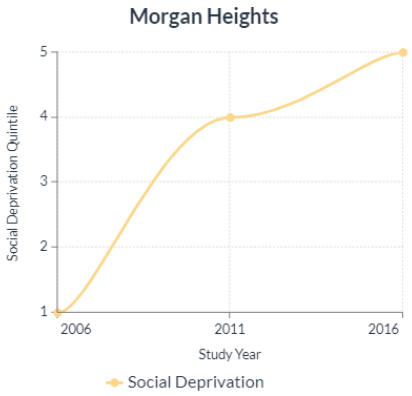





Morgan Heights
Bachelor's Degree or Higher
0.25
0.20
0.15
0.10
0.05
0
2006
2011
2016
Study Year
Educational Attainment (% of DA Population)


Morgan Heights
Study Year
2016
2011
2006
50
0
50
% of DA Population
Male
Female


Morgan Heights
DA Population
5,000
4,000
3,000
2,000
1,000
0
2006
2011
2016
Study Year
DA Population


Morgan Heights
Social Deprivation Quintile
5
4
3
2
1
2006
2011
2016
Study Year
Social Deprivation

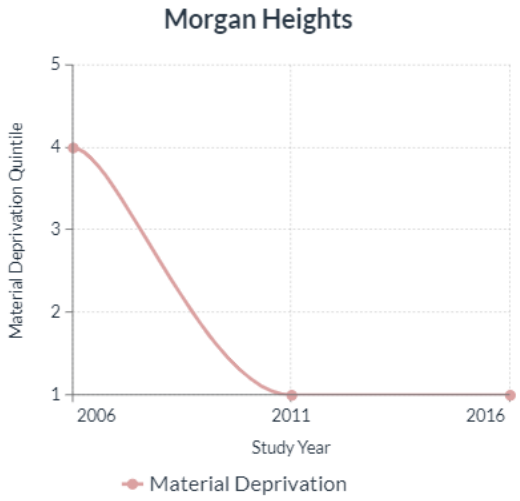


Figure 12-51 Demographic Profile of Morgan Heights

How have patterns of gentrification varied across the region during the study period?

In this section, gentrification patterns across the region from 2006 to 2016 were measuring using both David Ley's Social Status Index as well as individual indicators of change identified through the literature review.

Measuring gentrification using the Social Status Index

First, the Social Status Index for each CT have been calculated and divided into quintiles to illustrate what areas are showing the highest and lowest relative rates of gentrification in the region from 2006 to 2016 (Figure 12-52). Visually inspecting the map, high gentrification neighbourhoods are concentrated on the east side of the City of Vancouver, the City of North Vancouver, and the City of New Westminster. However, there are also more suburban and rural areas showing high relative rates of gentrification, such as Bowen Island and neighbourhoods in Surrey, Maple Ridge, and Pitt Meadows.

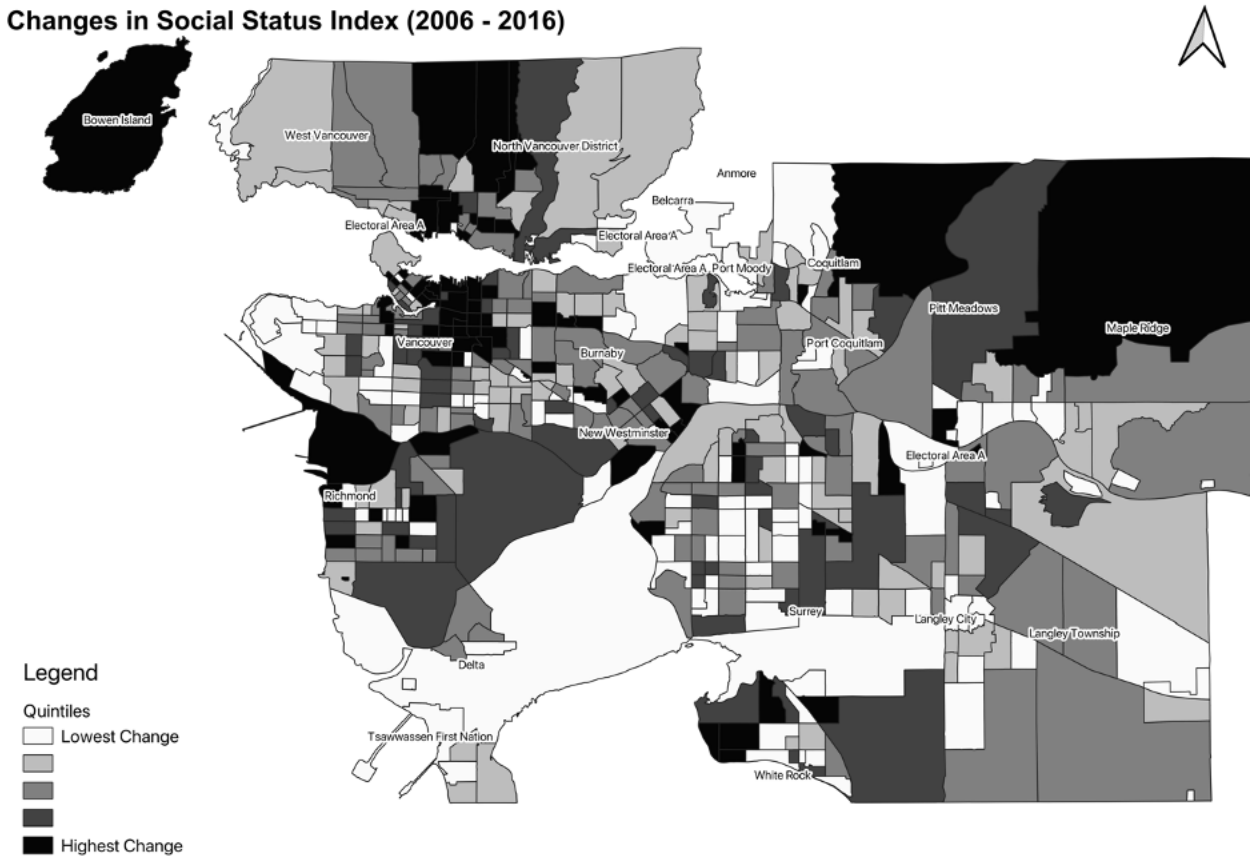


Figure 12-52: Changes in Social Status in Metropolitan Vancouver CTs, 2006 – 2016

Social Status Index scores have also been aggregated at the municipal level to see how each municipality, First Nation and Electoral Area changed relative to each other during the study period. Shown in Table 12-3, it is the rural municipalities of Bowen Island and Pitt Meadows that stand out with the highest increases in social status, which is interesting as both municipalities are relatively small, rural communities far from the urban core. In fact, all other municipalities but one are within +/- 3% of the regional average (**+6%**) change to social status index score. The one exception was the City of Langley, which actually saw a decrease in social status between 2006 and 2016. This is also interesting, as the City of Langley was one of the municipalities with the greatest relative increase in walkability during the study period (Table 12-3).

Table 12-3: Change in Social Status Index in Metropolitan Vancouver by Location, 2006 - 2016

Municipality	% Change in Managerial Profession	% Change in Post Secondary Education	Gentrification Index
Bowen Island	+8	+9	+17
Pitt Meadows	+2	+11	+13
North Vancouver City	+1	+9	+9
Electoral Area A	+3	+6	+9
Vancouver	+1	+7	+8
New Westminster	+0	+8	+8
Port Moody	-1	+8	+7
North Vancouver District	+0	+7	+7
Burnaby	+0	+6	+7
Richmond	-0	+6	+6
Metropolitan Vancouver Region	+0	+6	+6
Maple Ridge	+1	+5	+6
Coquitlam	-0	+6	+6
Surrey	-0	+6	+6
West Vancouver	-1	+6	+5
Langley Township	+1	+5	+5
Port Coquitlam	-1	+5	+4
Delta	-0	+4	+4
Langley City	-2	-1	-3

Exploring the relationship between walkability and neighbourhood change

Regional variations in walkability and neighbourhood change were described in the previous section, and the following section explores the relationships between the two urban processes. To do this, changes in social status index scores as well as individual indicators of neighbourhood change are compared across neighbourhoods that have (1) high and low walkability index scores at the start of the study period, and (2) high and low *changes* in walkability index scores across the study time period.

Baseline Walkability and Social Status Index

In Figure 12-53 the baseline walkability index scores from Table 12-1 have been compared against the Social Status Index scores from Table 12-3 to see where gentrification is occurring relative to the walkability of each neighbourhood. Neighbourhoods have been ranked and divided into deciles based on their 2006 Walkability Index scores and Social Status Index scores, with the corresponding ranges representing “high walkability”, “low walkability”, “high neighbourhood change” and “low neighbourhood change”. To create separation between low and high change neighbourhoods, the fourth, fifth and sixth deciles were omitted from analysis.

Red neighbourhoods are those with high baseline walkability and high increases in social status. On visual inspection, high-high neighbourhoods are concentrated around the City of Vancouver downtown core and the neighbourhoods immediately east of the downtown core. There are also some concentrations of high-high neighbourhoods in North Vancouver and the City of New Westminster where high-high neighbourhoods are also concentrated.

Orange neighbourhoods are those with high baseline walkability and low relative rates of gentrification. These neighbourhoods are primarily located in the City of Vancouver. There is some concentration of these neighbourhoods in the district of West Vancouver, which could be explained as these are historically affluent neighbourhoods and changes in social status likely happened in decades prior to the beginning of the study period. The concentration in the south-east of Vancouver does not have an immediately obvious explanation and is interesting because it is fairly close to two major urban centers (City of Vancouver and City of New Westminster) and is in an area well served by transit (the Expo SkyTrain Line).

Green neighbourhoods are those with low walkability and high increases in social status. These low-high neighbourhoods are generally on the urban periphery. This suggests is that there might be similar patterns of gentrification occurring in the most urban (and walkable) neighbourhoods as well as the most rural (least walkable) in the region; however, patterns of gentrification occurring in high and low walkability neighbourhoods are examined further in the following section.

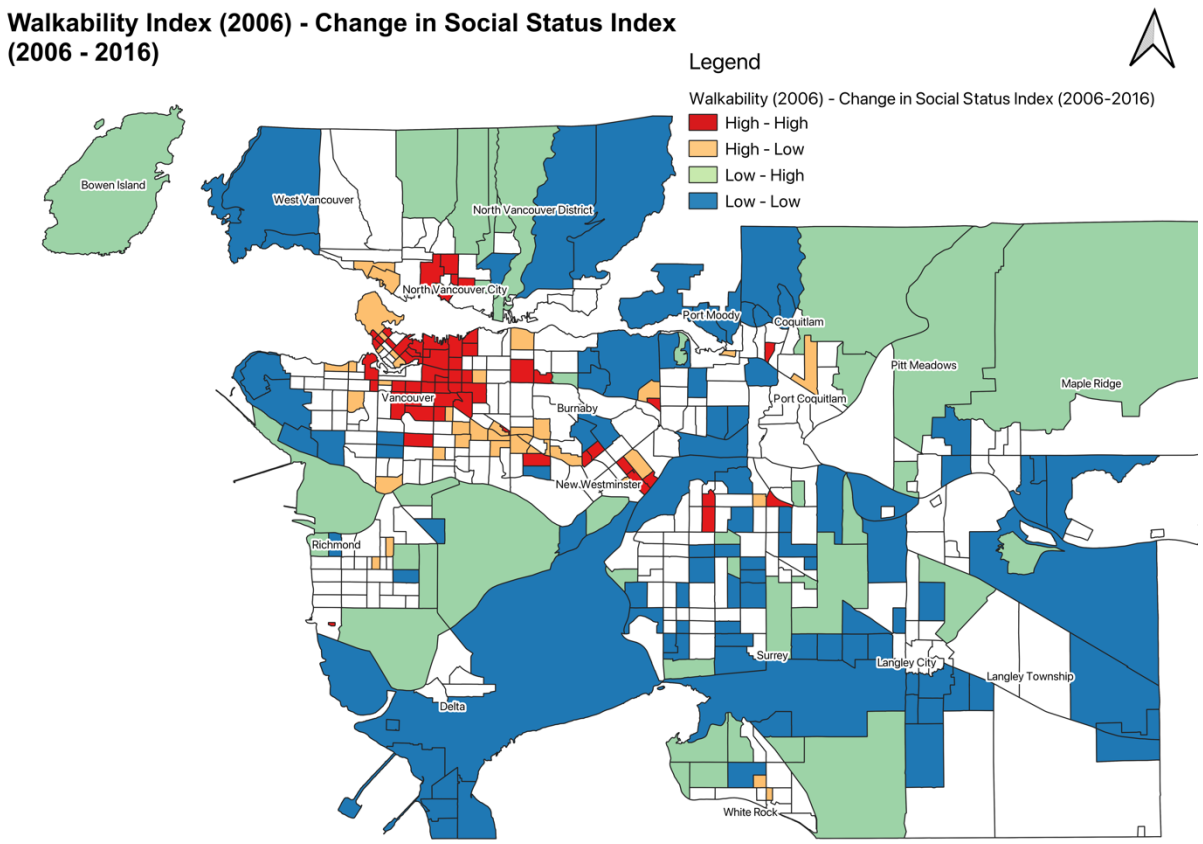


Figure 12-53: Distribution of Baseline Walkability Index Score (2006) and Social Status Index Changes (2006-2016)

Baseline Walkability and Changes in Individual Indicators of Gentrification

To understand if there are certain indicators of neighbourhood change that are more closely related with walkability than others, changes in individual measures have also been calculated for neighbourhoods of high and low baseline walkability in Table 12-4. Walkability index scores have been categorized using deciles, with high walkability defined as having a walkability index score in the top three deciles, and low walkability as having a score in the bottom three.

The findings in Table 12-4 do suggest that some social, economic, and demographic indicators are more associated with high/low walkability than others. For instance, during the study period, high walkability neighbourhoods had a greater increase in the proportion persons aged 25-25 years (+11%), while changes in low walkability neighbourhoods were consistent with regional averages (+7%). High walkability neighbourhoods had less of an increase in population 65 years and older than the regional average (+15% vs +22%), and low walkability neighbourhoods had a higher proportion than the regional average (+29%). The proportion of immigrants decreased in high walkability neighbourhoods (-3%), despite the regional proportion of immigrant population growing by +3%. For employment indicators, high walkability neighbourhoods saw much higher increases in

proportion of some occupations (such as management and health occupations) and low walkability and the region, and less of an increase than the region in others (education, government service and social science occupations). The two indicators that comprise the Social Status Index were also included in individual indicators. Interestingly, proportion of managerial employment has a stronger relationship with walkability than education, which was nearly consistent across high, low and control neighbourhoods.

What these findings suggest is that some indicators of change do likely have a stronger relationship with walkability than others, across the individual indicators as well as the two that comprise the social status index. What can be drawn from these findings is that selecting different indicators of change (and gentrification) would lead to different results. For instance, while education is a very common indicator of gentrification across the literature, there is no strong differentiation in education rates across high and low walkability neighbourhoods in this comparative analysis. If education was swapped with a different indicator that is positively associated with neighbourhood change in the social status index, perhaps the results would not show similar gentrification patterns in urban and rural settings.

Table 12-4: Changes in Individual Indicators of Neighbourhood Change for Neighbourhoods with High and Low Walkability Index Scores

	2006 - 2016		
Population Indicators	**Metro Vancouver (Control)**	**High Walkability CTs**	**Low Walkability CTs**
% Change total pop	+17	+16	+24
% Change pop. 25 - 34 years	+8	+11	+7
% Change pop. 65+ years	+22	+15	+29
% Change Pop. Immigrants	+3	-3	+9
Employment Indicators			
% Change management occupations	+4	+12	+1
% Change business, finance and administration occupations	-12	-9	-14
% Change natural and applied sciences and related occupations	+3	+2	+6
% Change health occupations	+16	+23	+15
% Change education, government service, social science occupations	+30	+23	+37
% Change art, culture, recreation, sport occupations	+12	+16	+6
% Change sales and service occupations	-2	-3	-2
% Change trades, transport, equipment occupations	-3	-12	+0
% Change agriculture and primary industry occupations	-25	-14	-33
% Change processing, manufacturing, utilities occupations	-27	-40	-19
Socioeconomic Indicators			
% Change population 15 years and older university educated	+24	+27	+25

Differences in gentrification in high and low walkability neighbourhoods

What is clear from the analysis of individual indicators of neighbourhood change is that gentrification (defined using the Social Status Index) is that some form of gentrification

occurring in both urban and suburban/rural areas of Metro Vancouver, and the index suggested higher rates of gentrification were occurring in rural settings (such as Bowen Island and Pitt Meadows). It is important to emphasize that while the findings suggest that gentrification is occurring in both high and low walkability settings, the David Ley Social Status Index is just one measure of gentrification. Many processes of gentrification can be occurring at any one time to different degrees in one place, and these cannot be captured or described using a two-indicator index of change.

PCA has been used to create principal components from the common indicators of gentrification in Table 12-4 to understand associations differ between individual indicators in high and low walkability areas. The purpose of this exercise is to see how gentrification as a process may be occurring differently in high and low walkability places (despite both high and low walkability places scoring high on the social status index).

Comparing the biplots of high gentrification and high walkability (high-high) and high gentrification/low walkability (high-low) neighbourhoods in Figure 12-54 can show how the principal components and relationships between variables differ in high and low walkability areas. Despite both high and low walkability neighbourhoods considered gentrifying, relationships between changes in individual measures are inconsistent between the two settings. For instance, the biplots show increases in immigrant population to be negatively associated with gentrification high walkability neighbourhoods, but positively associated with gentrification in low walkability neighbourhoods. Increases in arts, culture, recreation, and sports occupations are positively associated with gentrification in high walkability neighbourhoods, but negatively associated with gentrification in low walkability neighbourhoods. The loading factors of the first principal component of both high and low walkability neighbourhoods experiencing high rates of gentrification are compared in Table 12-5.

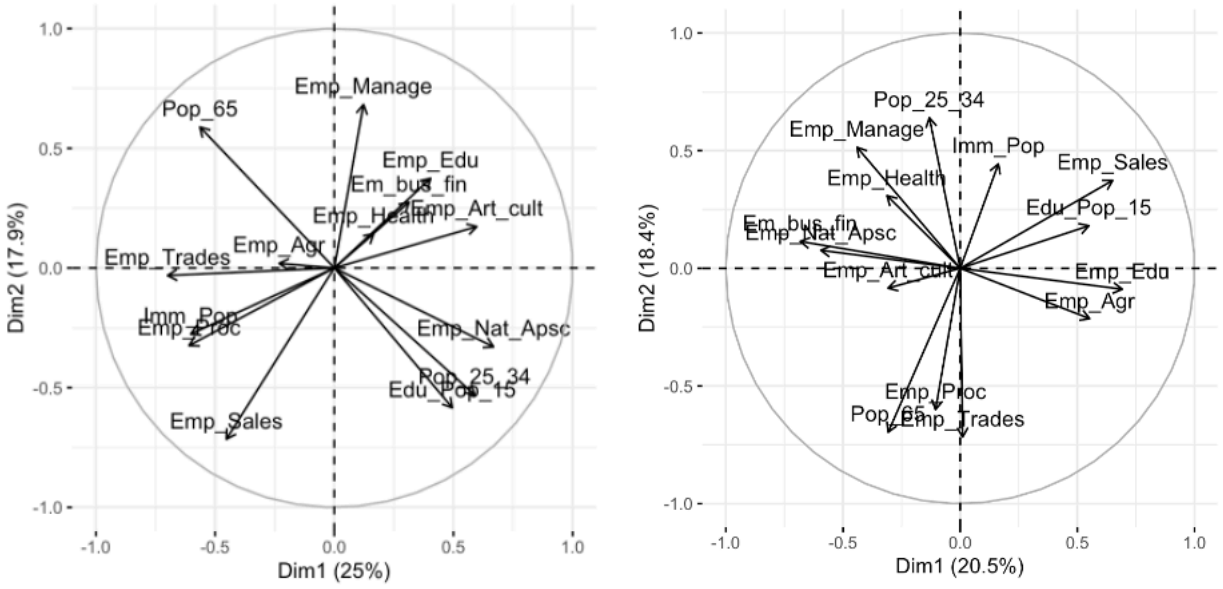


Figure 12-54: Principal Component Loading Matrix of High-High CTs (Left) and High-Low CTs (Right)

Table 12-5: Loading Factors of First Principal Component of High-High and High-Low CTs

	Principal Component 1 Factor Loadings	
Indicators	High Gentrification, High Walkability CTs	High Gentrification, Low Walkability CTs
% Change pop. 25 - 34 years	0.31	-0.08
% Change pop. 65+ years	-0.30	-0.18
% Change Pop. Immigrants	-0.32	0.10
% Change management occupations	0.07	-0.26
% Change business, finance and administration occupations	0.17	-0.40
% Change natural and applied sciences and related occupations	0.36	-0.35
% Change health occupations	0.09	-0.18
% Change education, government service, social science occupations	0.22	0.41
% Change art, culture, recreation, sport occupations	0.32	-0.18
% Change sales and service occupations	-0.24	0.38
% Change trades, transport, equipment occupations	-0.37	0.01
% Change agriculture and primary industry occupations	-0.12	0.33
% Change processing, manufacturing, utilities occupations	-0.33	-0.06
% Change population 15 years and older university educated	0.26	0.32

How are changes in walkability associated with neighbourhood change?

The paper also tried to explore the relationship between changes in neighbourhood walkability and neighbourhood change by comparing the changes in the walkability index scores Table 12-2 and changes in both the social status index (Figure 12-52) and individual indicators (Table 12-4**).** In summary, a relationship could not be found between the two processes using the visual and comparative analysis methods.

Another potential limitation for identifying relationships between changes in walkability and neighbourhood change is the temporal scope. This exercise compares two processes of change over the same (relatively short) time period. What this does not consider is that one process may lag behind the other, with built form changing first and neighbourhood change taking place in later time periods (or even vice vera). A further analysis could try comparing changes in walkability between an initial time point, such as 2006 to 2011, to gentrification trends at a later time point, to see if the processes are occurring during different periods.

12.4. Discussion

When comparing common indicators of neighbourhood change over the study period to the walkability of the neighbourhoods at baseline, there are some distinct patterns. The findings in Table 12-4 suggest that younger people tend to live in more walkable neighbourhoods, while a disproportionate percentage of immigrants and seniors live in neighbourhoods with the lowest walkability. Visually comparing the walkability of neighbourhoods to changes in social status index over the study period (Figure 12-52**)**, neighbourhoods that are highly walkable at the start of the analysis period also saw higher increases in social status. However, many suburban and rural areas with low walkability also saw increases in social status index scores. The highest changes to social status index scores were found to be in two of the most rural municipalities in the region, Bowen Island and Pitt Meadows.

When comparing changes in neighbourhood walkability and other aspects of neighbourhood change, patterns are less distinct. Comparing changes in individual indicators of neighbourhood change in neighbourhoods with high and low changes in walkability, results for both categories are nearly identical to regional patterns. Visually inspecting the distribution of neighbourhoods with high and low changes in walkability and social status index, neighbourhoods that had high instances of both (red) were dispersed throughout the region, while neighbourhoods with low changes in walkability but high changes in social status (green) were concentrated around urban centers, despite some of them having high baseline walkability (City of Vancouver) and others low (Pitt Meadows and Maple Ridge). Other regions saw high changes in walkability but low changes in social status. For example, the City of Langley saw the second highest increase in walkability index score during the study period (see Table 12-2), but it was the only city to have a negative change in social status index score (Table 12-3**)**.

The analysis results suggest there is a stronger relationship between baseline walkability of a neighbourhood and gentrification than changes in walkability and gentrification. The findings of this analysis did not find a strong relationship between changes in walkability and other aspects of neighbourhood change, however, there may be a relationship that could be found through other analysis methods and more granular data, such as regression modelling. Using visual inspection methods and calculating changes at relatively coarse level (CTs and Municipalities) is a way to identify preliminary trends and patterns, but data at the DA level along with more rigorous ways of measuring spatial correlation could be an area of further research. Measuring data at the dissemination area was initially considered as it would be a more granular analysis and may be easier to interpret a relationship between neighbourhood change and walkability (which is measured at the census block level), but there were several issues with data suppression for some of the variables at this scale. If another method for measuring neighbourhood change other than the social status index or individual indicators, analysis at the DA level could reveal some spatial patterns not apparent at the CT level.

Gentrification can often be understood as multiple overlapping processes taking place over both the short and long term. One limitation of this analysis is that it considers both processes of urban physical change (walkability) and neighbourhood change

(gentrification) over the same time period, where this may not be the case. One process may be taking place before the other, and some may be taking place over a much longer period than the 10 years analyzed.

12.5. Conclusion

The purpose of this paper is to explore the relationship between walkability and neighbourhood social change. Using longitudinal walkability data and Metropolitan Vancouver as a case study, this project sought to investigate how walkability has changed in Metro Vancouver between the study period (2006-2016), how socioeconomic and sociodemographic characteristics of neighbourhoods have changed during the same time period, and what the relationship is between the two.

At the start of the analysis period (2006), walkable neighbourhoods were generally concentrated within the City of Vancouver near the downtown core, with walkability decreasing radially from there. While the City of the Vancouver was the most walkable municipality in 2006, it was more suburban and rural areas that saw the greatest increases in walkability during the study period, and the Capilano 5 First Nation Reserve surpassed Vancouver as the most walkable in the region by 2016, largely spurred by high density development.

The findings of analysis did find a relationship between walkability and certain indicators of neighbourhood change, such as younger persons tending to live in more walkable neighbourhoods and a disproportionate number of immigrants living in low walkability neighbourhoods in the region. The greatest increases in social status index scores were also concentrated in high walkability neighbourhoods, and with the greatest changes concentrated near urban cores. However, there were also several low walkability neighbourhoods that stood out with the highest increase in social status index scores during the study period. On closer investigation, it was found that while high relative rates of gentrification (defined by the social status index) were taking place in high and low walkability neighbourhoods, there were stark differences in the processes and their associated social, economic and demographic shifts. For instance, gentrification was more associated with young persons (25-35 years) in high walkability areas, but older persons (65+) in low walkability neighbourhoods. These findings suggest that there is opportunity to examine the relationship between walkability and various individual indicators of neighbourhood change, possibly developing a better method than the social status index to differentiate between urban and rural processes.

A relationship between changes in walkability and neighbourhood change was harder to discern. Neighbourhoods that experienced high (and low) rates of each phenomena were dispersed throughout the region, and reviewing changes in individual indicators didn't show much differentiation between neighbourhoods with high or low changes in walkability.

12.5.1. Limitations and Future Research

This exercise was exploratory, relying on visual analysis and data aggregated at a relatively coarse level (census tracts and municipality) to draw conclusions. The temporal scope of the study was relatively short (10 years), and future research that measures longitudinal change over a longer duration and multiple (3+) time points might yield important findings.

With regards to measuring change in walkability, this analysis was a first attempt that made assumptions about the preferred method. Further research could involve testing and validating various methods to measure change in walkability against actual travel behavior.

One of the most important findings of this analysis was that findings on gentrification and the conclusions that drawn were largely dictated by how it is defined. It is important to carefully consider the conclusions that can be drawn from findings, and how they might be limited by the methods used to analyze the phenomenon. This study found that some indicators of change were more closely associated with walkability than others, and further research could investigate the various processes of urban change occurring in high and low walkability neighbourhoods and see how gentrification patterns differ in these contexts.

While a relationship between change in walkability and neighbourhood change wasn't found using these analysis methods, using more granular data and quantitative analysis methods such as regression modelling would be the next step in identifying patterns in neighbourhood change and walkability change. Further research could also include investigating the relationship between the individual measures that make up the walkability index (intersection density, net residential density, retail floor area, land-use mix), to understand if certain measures are more or less associated with gentrification patterns through a correlation matrix.

Evaluating the influence of built environment changes on neighbourhood social trajectories can help us understand why some neighbourhoods experience change while others remain stable, and potentially help identify predictors of future processes of gentrification. Further research could also include investigating policy or contextual reasons that some walkable neighbourhoods are rapidly gentrifying in Vancouver, while some have remained relatively stable.

Quantified research can indicate general trends in the way that the social and the built form are connected. This paper demonstrates how longitudinal walkability data can be used to understand regional variations in macro-level neighbourhood walkability over time, which is important for regional authorities like Metro Vancouver that are committed to growth plans that emphasize walkable communities but have no jurisdiction over land use decisions. While walkability indices do not capture many important measures of walkability like road safety and vibrancy, using them to measure how large areas are changing over time could be used to understand how municipal development patterns are

tracking towards broader regional policy goals, and investigate the social implications of those policy goals.

Walkability is an essential resource for many persons with mobility issues or those who do not have access to a car. The findings of this paper suggest that walkable neighbourhoods are a resource that is not equally accessible by all residents, that people who might need walkable environments the most might have unequal access to them. In addition to being a spatial justice issue, gentrification of highly walkable areas may diminish the benefits of walkable neighbourhoods if the persons moving into them have the means and desire to continue to travel by car, while those who benefit the most from walkable neighbourhoods become increasingly unable to afford to live in them and must instead relocate to the car-dependent suburbs.

Understanding how social and physical aspects of the built environment influence each other is important, especially in a region facing an enduring affordability crisis. The Metro Vancouver region and many of its member municipalities are emphasizing walkable neighbourhoods on their urban planning agendas as a means of meeting congestion and air quality targets, and densification is essential in accommodating the additional 1 million new residents the region it is expected to welcome over the next three decades. As the Metro Vancouver region continues to invest in walkable communities, it is important to consider whether the strategies deployed to operationalize the region's policy goals are serving the regions diverse populations and how changes in built and social neighbourhood trajectories are connected.

13. Appendix C: Community Design Characteristics – Greenspace: How Does Neighbourhood Walkability Relate to Greenspace Exposure, Park Access, and Social and Material Deprivation?

13.1.1. Introduction

Neighbourhood factors do not act independently; rather, they all affect one another collectively impacting residents. There is extensive literature examining the impacts of the built and natural environment on engaging in health behaviours and human health outcomes. Along with other environmental exposures, neighbourhood walkability, and greenspace exposure and access have been linked to many health behaviours and health outcomes (Frank et al., 2010; Glazier et al., 2014; Kardan et al., 2015; Markevych et al., 2017; Twohig-Bennett & Jones, 2018). Several pathways have been proposed to explain the positive impact of access and exposure to greenspace, such as mitigation of harmful exposures (e.g., noise, air pollution and heat), providing increased restoration, and by increasing health promoting behaviours (e.g., social interaction and physical activity) (Markevych et al., 2017). The predominant pathway by which neighbourhood walkability is theorized to improve human health and wellbeing, is through increasing physical activity and reducing sedentary time (Frank et al., 2007). Adjusting for socioeconomic factors in this analysis is important since those effects can modify health outcomes in relation to greenspace accessibility.

Several previous studies have looked at both neigbourhood walkability and greenspace exposure. In general, neighbourhoods which are highly walkable tend to have a lower overall exposure to greenspace (typically measured by NDVI). This pattern may be due, at least in part, by the fact that the characteristics of a walkability area (e.g., sidewalk network, intersection density and building density – for residential units, commercial land uses and land use mix) require land to be developed, and therefore often reduce the maximum amount of vegetation possible in the area. On the other hand, park count (e.g., the number of parks which are present and/or accessible in an area) tends to be the greenspace metric which more closely relates to walkability (Shuvo et al., 2021).

There are also a number of mutual confounding factors which complicate the relationship between green and walkable neighbourhoods and health, specifically neighbourhood self-selection and household socio-economic status (SES). Individuals who place a greater importance on engaging in outdoor activities, such as leisure and transport walking, may forgo other housing criteria to live in walkable areas with greater access to greenspace (Dendup et al., 2019; Heinen et al., 2018). In addition, residential areas with desirable amenities, such as access to greenspace and increased walkability tend to be associated with higher housing costs. Therefore, it is vital to acknowledge and attempt to consider household SES, as this may otherwise distort the apparent relationship between positive neighbourhood characteristics and improved individual health outcomes (Adler & Ostrove, 1999).

Previous work has examined both the relationship between neigbourhood level deprivation and health, and the spatial relationship of built and natural environment (specifically walkability and NDVI) in high and low material deprivation neighbourhoods. However, to date, less work has looked at how other greenspace metrics relate to walkability, and how these neighbourhood characteristics are associated with both social and material deprivation in Metro Vancouver.

13.1.2. Material and Social Deprivation Index

Local area deprivation was measured using the 2016 Material and Social Deprivation Index (MSDI) using data collected from the Canadian National Household Survey (NHS). The NHS replaced the long form census in 2011, to collect more comprehensive data on Canadian citizens and has been sent to 30% of Canadian household every 5 years to correspond with the short form census. This index uses a total of 6 measures to quantify the material and social deprivation at the dissemination area geographic level. Social deprivation is comprised of three measures of the population aged 15 and older: the proportion of individuals living alone, proportion of lone parent families, and proportion of separated, divorced, or widowed individuals. Material deprivation is also comprised of three measures: average income, the proportion of individuals without a high school diploma, and the proportion of employed individuals (Institut National de Sante Publique du Quebec, 2017).

13.1.3. Statistical Analysis

To measure correlations, each greenspace metric, walkability, and social and material deprivation variables outlined above were joined by unique 6-digit postal code. The values were then compared at the 400m and 1000m distances for both the circular and network buffers. Correlation matrices were created, for the 400m and 1000m circular and network buffers, using the "Hmisc" package (Harrell Jr, 2021). To display the series of relationships heatmap visualizations were created using the "corrplot" package (Wei & Simko, 2021). All analysis were preformed using R version 3.6.1 (R Core Team, 2019).

13.2. Results

13.2.1. Comparison of Walkability and Greenspace Metrics

The same general patterns emerged at both the 1000m and 400m buffers sizes (apart from the relationship between park count and walkability), but with stronger relationships found in the 1000m buffers compared to 400m. Walkability was negatively associated (from weak to moderate) with postal-code level proportion of total green land cover type (400m r = -0.43; 1000m r = -0.55; p < .01), NDVI (400m r = -0.21; 1000m r = -0.47, p < .01), and tree canopy (400m r = -0.27; 1000m r = -0.33, p < .01) . The relationship between park count and walkability shifted from weakly negative (400m r = -0.04, p < .01) to weakly positive (1000m r = 0.07, p < .01).

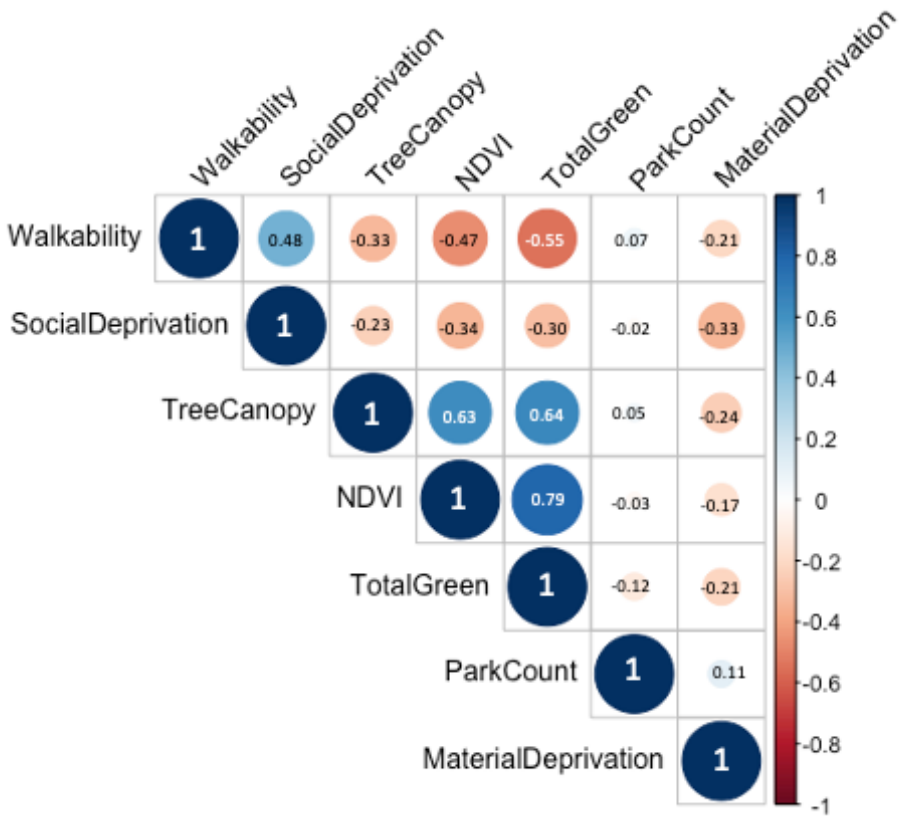


Figure 13-1: Pearson correlation coefficients between walkability and greenspace metrics for 1000m network buffers

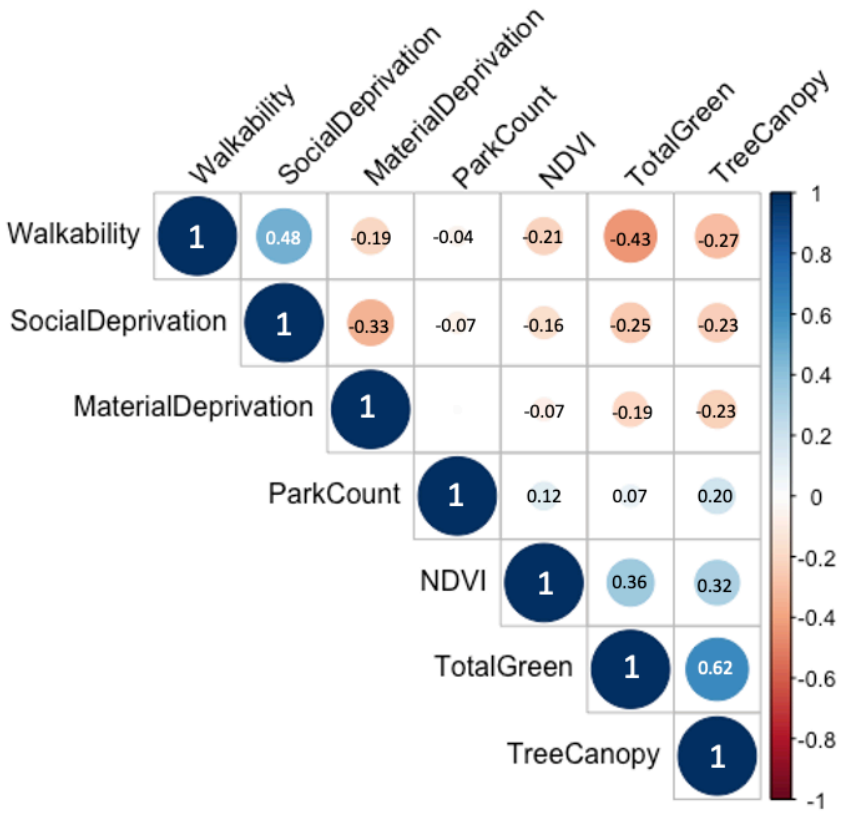


Figure 13-2: Pearson correlation coefficients between walkability and greenspace relationships for 400m network buffers

13.2.2. Neighbourhood Social and Material Deprivation, Walkability and Tree Canopy

Social and material deprivation were negatively correlated (1000m r = -0.33; 400m r = -0.33, p < .01). Walkability was positively associated with social deprivation (1000m r = 0.48; 400m r = 0.48, p < .01), while walkability has a weak inverse relationship with material deprivation (1000m r = -0.21, p < .01). Tree canopy was negatively related to both social (1000m r = -0.23, 400m r = -0.23, p < .01) and material deprivation (1000m r = -0.24, 400m r = -0.23, p < .01).

13.3. Discussion

Park count was weakly associated with walkability, with this negative association (r = -0.04, p < .01) at the 400m buffer distance, shifting to a positive relationship at the 1000m buffer distance (r = 0.07, p < .01). All other measures of greenspace (total green land cover, NDVI and tree canopy cover) were negatively associated with walkability. In this study area, social and material deprivation were moderately negatively associated, which supports previous research suggesting that these two measures should be considered separately rather than as a composite "deprivation" index (Pampalon et al., 2012). Walkability was positively correlated with social deprivation, indicating that neighbourhoods with greater social deprivation tended to be more walkable in this study area. All greenspace metrics were negatively correlated with both social and material deprivation (except for no statistically significant relationship between park count and material deprivation at the 400m distance, and a weak positive correlation between these two variables at the 1000m distance), indicating that in general neighbourhoods with more social and material deprivation also tended to have less greenspace. The relationship between park count and social and material deprivation was weak, indicating that the number of parks in an neighbourhood was not strongly related to the level of deprivation. Yet, these more deprived areas may be less green overall.

These findings are consistent with previous works, which found that overall greenspace and walkability tend to have a moderate negative relationship. Previous work has found that neighbourhoods with the highest NDVI values tended to be more car-dependent, whereas the most walkable neighbourhoods have lower average NDVI (Shuvo et al., 2021). Similar relationships (-0.6) between walkability and NDVI were seen previously in Vancouver, and negative correlations (-0.2 to -0.6) have been reported in other US cities (San Diego and Seattle) and in other Canadian cities (Clark et al., 2017; Marquet et al., 2020; Shuvo et al., 2021).

The use of multiple greenspace metrics to determine associations between walkability and greenspace in this paper is novel, as typically only NDVI and/or park count have been used. In addition, this work compares four commonly used greenspace metrics, a walkability index, and social and material deprivation calculated from data collected in either 2014 or 2016, reducing temporal mismatch which may otherwise influence the association between these measures.

Due to the scope of this analysis, no health outcome data has been included, which would allow for a richer analysis of how these neighbourhood built and natural environment and local area social and material deprivation related to health outcomes. Additionally, longitudinal data on these neighbourhood features would allow for analysis of whether changes to the built and natural environment (e.g., additional greenspace or improved walkability) would in turn impact the local area social and material deprivation. This current descriptive cross-sectional analysis only suggests relationships between these variables.

A larger limitation inherent in the study of neighbourhood characteristics and health, is the potentially confounding effect of individual income or wealth. Although local area or

individual income, or other measures of material deprivation or affluence, can be controlled, it is virtually impossible to disentangle these variables from other desirable built and natural environment features which tend to be represented in wealthier neighbourhoods. Individuals with higher incomes or more wealth, are more able to self-select their residential neighbourhood, based upon factors other than just housing costs.

13.4. Implications

Future work should consider how postal-code level walkability, greenspace exposure and deprivation relate to health outcomes. Additionally, these measures can be tracked longitudinally to better understand potential causal relationships. The finding that areas with greater social and material deprivation tend to be associated with lower greenspace, indicate that these areas may benefit from investments in additional greenspaces. The identification of neighbourhoods with higher material deprivation, low walkability, and low greenspace, should be prioritized by urban planners and decision makers as possible locations for additional greenspace allocation. In already developed areas where adding large park spaces or dramatically altering the build environment may be impossible to quickly implement, more micro-scale pedestrian and green infrastructure investments may be more feasible. In areas with greater material deprivation and limited greenspace, it may also be important to consider the potential impacts on land values associated with incorporating additional greenspaces, and to attempt to reduce any displacement of existing residents. Future work may also strive to better understand the role of smaller scale greenspace investments and the associated impacts of resident health, which may support decision makers in determining how to best allocate greenspace throughout a city or region.

14. Appendix D: Health Impacts - Full Article - Longitudinal Associations Between Walkability and Incident Obesity, Hypertension, and Type 2 Diabetes Among Adults in Vancouver, Canada

14.1. Background

Obesity and related diseases continue to adversely impact health and economic indicators across low, middle, and high income countries (Shekar & Popkin, 2020; World Health Organization (WHO), 2016). The prevalence of obesity worldwide has tripled in the last 50 years and is responsible for nearly 3 million premature deaths annually (World Health Organization (WHO), n.d.). Overweight and obesity are linked to increased risk of numerous chronic conditions including type 2 diabetes mellitus (T2DM) and high blood pressure (HBP), which are leading causes of cardiovascular disease and premature mortality globally (Leon & Maddox, 2015; Mills et al., 2020).

Insufficient physical activity (PA) is one of the primary causes of these preventable diseases (*Facts about Physical Activity*| *CDC*, n.d.) and the prevalence of adults who do not meet physical activity guidelines remain low despite concerted global public health efforts (World Health Organization (WHO), 2022). The World Health Organization's Global Action Plan on Physical Activity recommends policies and infrastructure to encourage active (i.e. non-motorized vehicle) modes of travel for everyday trips, which has been highlighted as one of the best investments to meaningfully increase population-level PA (Giles-Corti et al., 2016; Global Advocacy for Physical Activity (GAPA) the Advocacy Council of the International Society for Physical Activity and Health (ISPAH), 2011; World Health Organization (WHO), 2018, 2022).

Living in walkable environments has been linked to significantly higher levels of PA and active travel across multiple age groups (Carlson et al., 2017; Cerin et al., 2017; L. Frank et al., 2016; Grasser et al., 2012; J. Sallis et al., 2016). Research has shown several macro-level, built environment features support walkability including, having a mix of land uses in close proximity (i.e. destination diversity), greater residential density, retail floor area ratio, and a highly connected road network (L. D. Frank et al., 2005; Saelens & Handy, 2008). Among adults, there is growing evidence linking GIS-measured walkability to lower prevalence of obesity and metabolic disorders. Several recent reviews show generally consistent inverse relationships between walkability and body weight or obesity, hypertension and diabetes (S. Barbosa et al., 2019; Chandrabose, Cerin, et al., 2019; L. D. Frank et al., 2022; Jones et al., 2021; J. Sallis et al., 2016; Tarlov et al., 2020a), though

findings have been mixed. Obesity is by far the most studied of these outcomes and most research to date has been cross-sectional. Longitudinal studies have commonly utilized a single baseline walkability measure with repeated health measures over time. This paper aims to contribute to our understanding of temporal relationships between longitudinal, objectively measured walkability and reported health outcomes.

Using data from an observational, longitudinal cohort in Canada, this study investigated associations between change in objectively-measured walkability and incident obesity, HBP, and T2DM. We hypothesized that walkability would be inversely related to odds of becoming obese or starting treatment for HBP or T2DM at follow up. In secondary analyses, we additionally studied whether relationships differed across demographic characteristics, including sex, age, and income.

14.2. Methods

14.2.1. Analytic sample

The current study used data from the British Columbia Generations Project (BCGP), the largest health study in British Columbia. Details have been published elsewhere but, in brief, BCGP prospectively follows a cohort of nearly 30,000 adults from 35 to 69 years of age (Dhalla et al., 2019). This analysis includes data only from participants residing in the Metro Vancouver and Fraser Valley Regional Districts to maximize potential change in walkability over time (n=12,181). Between 2009 and 2013, participants were recruited to complete baseline questionnaires on health, lifestyle factors and medical histories and roughly half of the full sample had physiological measures collected in person at an assessment center. From 2016 to 2019, participants were invited to complete follow-up surveys on health and lifestyle factors, with approximately three-quarters of the original sample contributing data. The Behavioral Research Ethics Board of the University of British Columbia approved this study (H17-00648).

14.2.2. Exposure variable

GIS-based walkability index: Participant-level walkability was assessed using a validated composite index which includes four built environment features: land use mix ((LUM) diversity of destinations), intersection density ((IDENS) street connectivity), net residential density ((NRD) housing density), and commercial floor-to-area ratio ((CFAR) ratio of floor area to lot size) (L. D. Frank et al., 2010a). A walkability score was created for each postal code which, on average, covers roughly 19 Canadian households and has been shown to provide acceptable positional accuracy, especially in urban areas (Khan et al., 2018; Pinault et al., 2020). The index was applied to a 1km road network buffer from participants' postal code centroid. Participants provided their residential history since childhood. An average of each walkability component feature was calculated for participants' residential locations from 2000-2006 (baseline) and 2012-2016 (follow up). We created the baseline and follow up walkability indices by calculating z-scores for each of the 4 components (LUM, IDENS, NRD, CFAR) using 2006 mean and standard deviations for the Vancouver population center to exclude rural hinterlands (*Statistics Canada*, n.d.). Standardizing to baseline regional walkability provides a measure of how

individuals' walkability compares to the region and how it has changed over time. Change in walkability was the sum of zCFAR + zLUM + zIDENS + zNRD at follow up minus the sum in baseline. We additionally quintiled the change in walkability score to explore the relationship between walkability and the outcomes of interest in more depth.

14.2.3. Outcome Variables

Obesity: At baseline, a subset of participants (n=8,100) had height and weight measured at an assessment center, otherwise, self-reported height and weight from the health questionnaire were used (n=3,696). At follow up, all data were self-reported. BMI was calculated as the weight in kilograms divided by the height in metres squared and a binary obesity variable was created (BMI ≥30 or BMI <30). Incident obesity was defined as shifting from not obese at baseline to obese at follow up.

Hypertension: At both baseline and follow up, participants were considered to have prevalent hypertension if they reported currently being treated for high blood pressure or hypertension. Those not treated for hypertension at baseline and treated at follow up were considered to have incident hypertension.

Diabetes: At baseline, participants were considered to have type 2 diabetes if they reported being currently under treatment for diabetes and having been diagnosed with type 2 diabetes. At follow up, participants reported whether they were currently under treatment for type 2 diabetes. Incident T2DM was defined as a change from not being treated at baseline to currently being treated for at follow up.

14.2.4. Covariates

Participant demographics were collected through the health and lifestyle questionnaire and included age, male/female sex. Racial and ethnic descent was classified as "White or European", "Some other descent", or "Unknown". Baseline income was dichotomized into "≤74,999" or "≥$75,999", to approximate above or below median income in the Vancouver area during baseline data collection. We also adjusted models for the length of time (in years) between the baseline and follow up assessment.

14.2.5. Statistical analysis

Descriptive statistics compared baseline participant characteristics across change in walkability quintiles using ANOVA for continuous and χ^2 for categorical variables. We used mixed effects regression models to assess associations between change in walkability (as a continuous variable) with binary incident obesity, T2DM, and HBP status, in separate models. We also modeled change in obesity status by quintiled change in

walkability. Mixed model analyses allow for missing observations in studies with repeated measures, avoiding bias associated with complete case analysis (Gabrio et al., 2022). To account for non-independence of repeated measures, we included participant ID as a random effect. We assessed clustering by Forward Sortation Area (the geographical unit designated by the first 3 digits in Canadian postal codes) and found it accounted for less than 1% of total variance so did not include it in models. All models adjusted for sex, age, racial/ethnic descent, baseline income, and length of time between assessments. We conducted a sensitivity analysis including only those with self-reported height and weight data at both assessments to test the robustness of results. We additionally explored associations within individual subgroups, including sex (female/male), age (above/below 60 years), and baseline income (above/below $75,000). All analyses were conducted in Stata Version 16.1 (StataCorp, College Station, TX).

14.3. Results

14.3.1. Descriptive statistics

We included those participants with walkability data at both time points (N=9,932). The time between study assessments ranged from 2.7 to 9.3 years, with a mean 5.5 years. At baseline, participants were on average 55 years of age, and nearly 70% were female. The majority (80%) were White or of European descent, and roughly 60% had an income over $75,000 CAD. Approximately 16% of the sample were obese, and 12% and 2% were being treated for hypertension and T2DM at baseline, respectively. There were differences in age, length of follow up and education level across change in walkability quintiles, though no obvious pattern was discernible. We did not observe any differences in baseline obesity, HBP or T2DM across change in walkability groups. As expected, those living in the most walkable neighourhoods at baseline had the least change in walkability between study assessments.

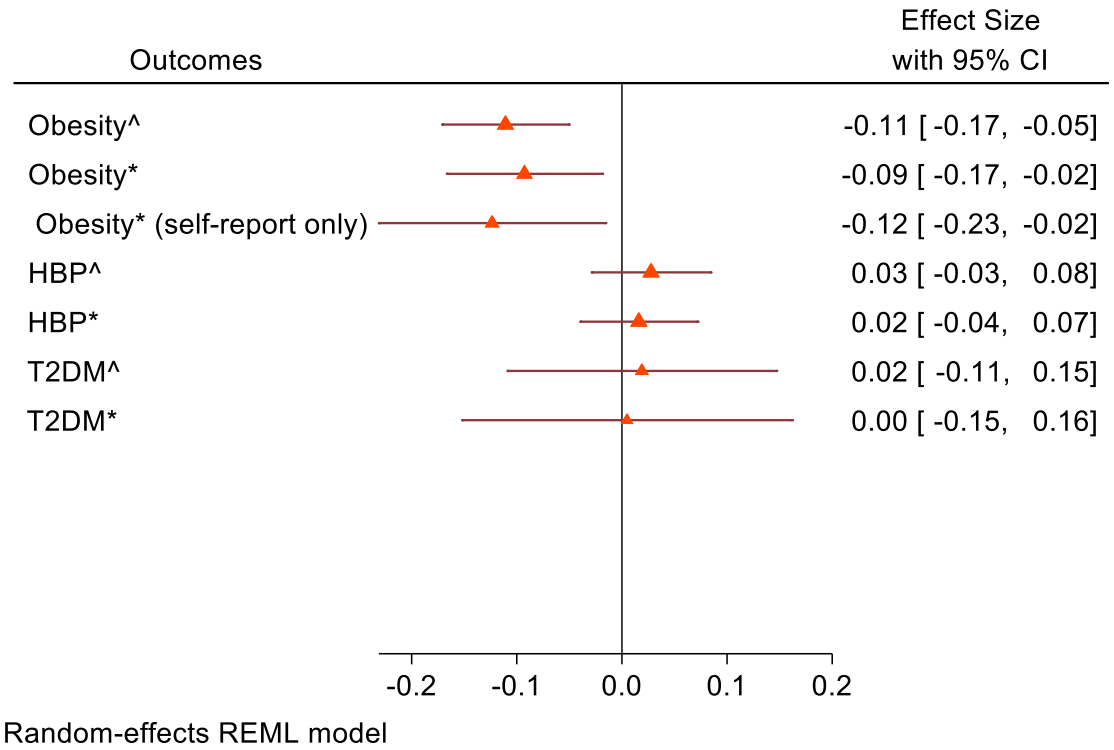
Table. 1 Baseline characteristics of the study sample by change in walkability quintiles

Baseline Descriptives	Total Sample	Change in walkability index from 2006 to 2016 (quintiles)					p-value
	N=9,932	Q1 n=1,987	Q2 n=1,986	Q3 n=1,987	Q4 n=1,986	Q5 n=1,986	
	n(%) or mean(SD)						
Length of follow up (years)	5.5 (1.2)	5.66 (1.27)	5.51 (1.19)	5.52 (1.18)	5.43 (1.20)	5.61 (1.23)	**0.00**
Age (years)	55.0 (9.0)	52.2 (9.5)	55.00 (8.8)	56.30 (8.6)	56.20 (8.4)	55.40 (8.9)	**0.00**
Female	8,456 (69.4)	1,373 (69.1)	1,362 (68.6)	1,389 (69.9)	1,371 (69,0)	1,381 (69.5)	0.92
White/European descent	7,902 (79.6)	1,597 (80.4)	1,542 (77.6)	1,595 (80.3)	1,604 (80.8)	1,564 (78.8)	0.04
Bachelor's degree or above	4,821 (48.8)	1,053(53.3)	962 (48.7)	945 (47.8)	890 (45.1)	971 (49.1)	**0.00**
Income >=$75,000	5,631 (60.9)	1,165 (61.7)	1,153 (62.8)	1,095 (59.6)	1,124 (61.4)	1,094 (58.9)	0.09
Obese (BMI ≥30)	1,530 (15.9)	307 (16.0)	283 (14.7)	315 (16.4)	322 (16.8)	303 (15.7)	0.45
Currently treated for hypertension	436 (12.2)	84 (10.4)	81 (11.8)	87 (13.0)	83 (13.2)	101 (13.1)	0.40
Currently treated for diabetes	74 (2.1)	17 (2.1)	10 (1.5)	10 (1.5)	14 (2.2)	23 (3.0)	0.24
Baseline walkability index (z-scores)	0.8 (3.2)	3.1 (3.3)	0.6 (2.8)	0.1 (2.8)	-0.10 (2.7)	0.1 (3.1)	**0.00**

14.3.2. Model Results

Odds ratios and confidence intervals for all models are presented in Table 2, whereas the figures show the effect size and 95% CIs. Change in walkability was inversely associated with incident obesity in both unadjusted and adjusted models (Figure 1). In adjusted analyses, a 1-unit increase in the walkability change score was associated with an 9% reduction in odds of becoming obese (OR=0.91, 95% CI 0.85, 0.98). In those with self-reported height and weight data only, there was a slightly larger decrease in odds of incident obesity (OR 0.88, 95% CI 0.79,0.98). Change in walkability was not associated with incident HBP or T2DM in unadjusted or adjusted models.

Figure 1. Incident obesity, HBP and T2DM

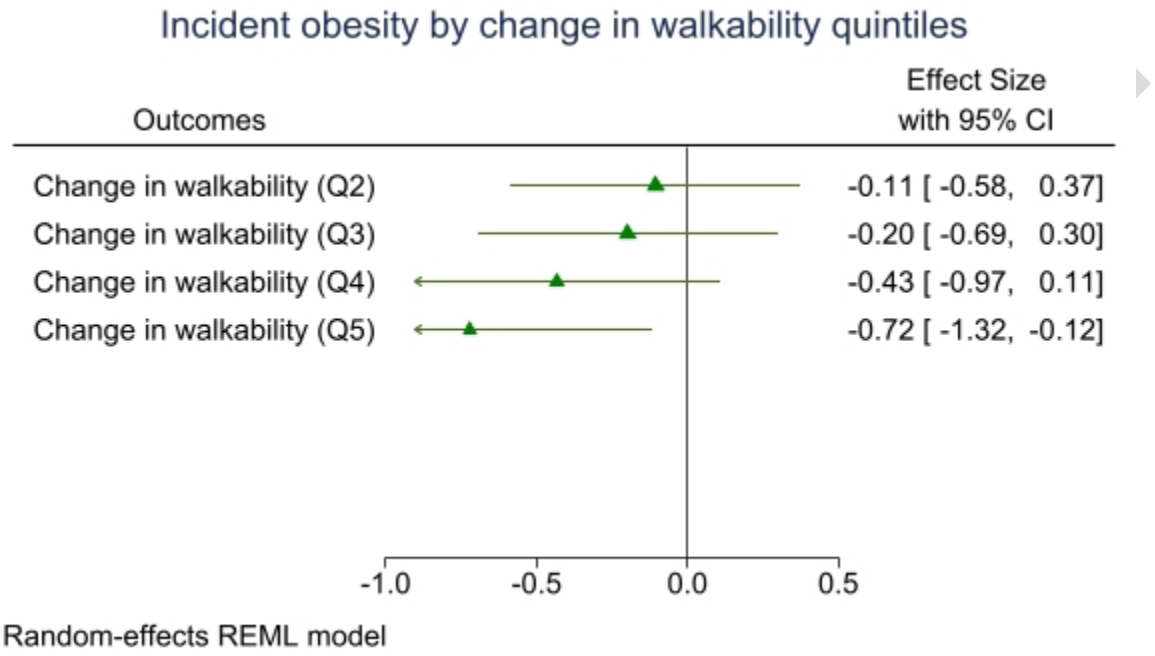


^Unadjusted models

*Adjusted for sex, age, racial/ethnic descent, baseline income, and length of time between assessments.

Figure 2 shows the association between change in walkability quintiles and incident obesity. Compared to quintile 1, those in quintile 5 had a 51% reduction in odds of becoming obese (OR=0.49, 95% CI 0.27, 0.88). Confidence intervals overlapped the null value for other quintiles, though the reduction in odds of incident obesity suggested a graded inverse association with greater change in walkability.

Figure 2. Incident obesity by change in walkability quintiles

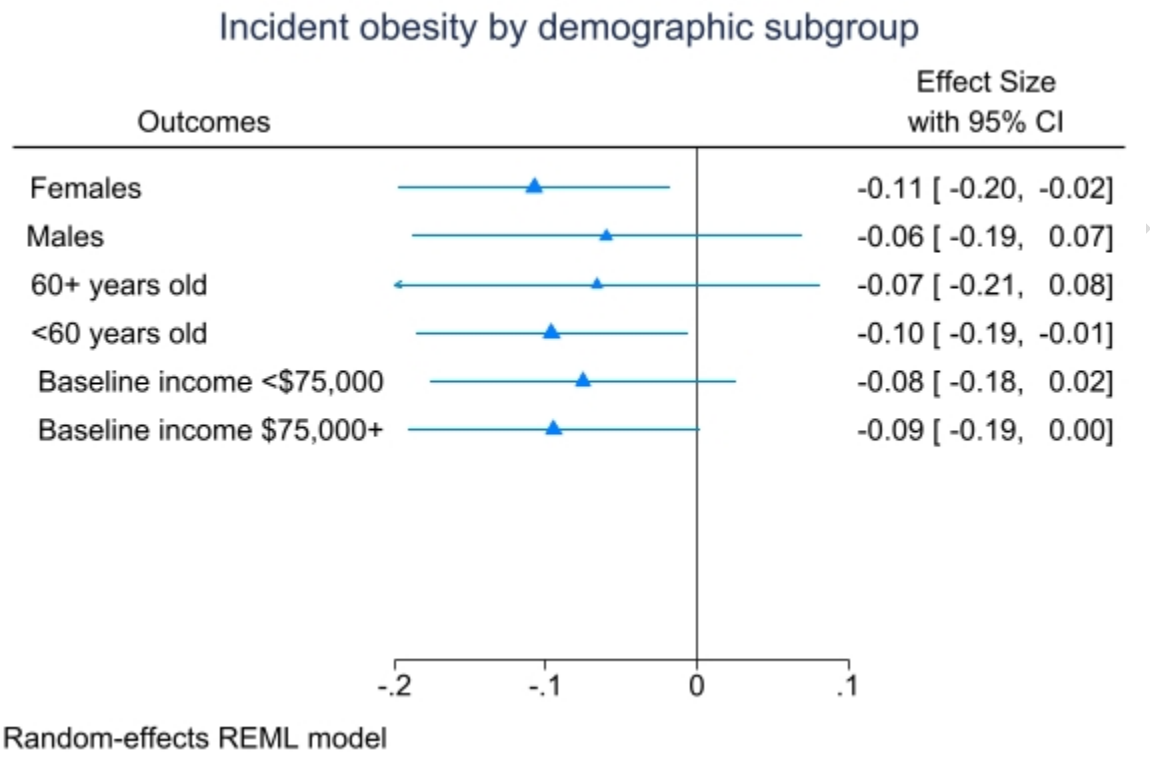


All models adjusted for sex, age, racial/ethnic descent, baseline income, and length of time between assessments.

Change in walkability was associated with an 10% reduction in the odds of becoming obese in females (OR=0.90, 95% CI 0.82,0.98) , while results among males were imprecise (Figure 3). A similar reduction in odds of obesity at follow up was observed among those who were less than 60 years old at baseline (OR=0.91, 95% CI 0.83,0.99), while this relationship was imprecise in older adults. Results by income were imprecise

though suggestive that higher household income was associated with a slightly greater reduction in odds of obesity (OR=0.91, 95% CI 0.83, 1.0) compared to the lower income group.

Figure 3. Incident obesity by demographic subgroups



All models adjusted for sex, age, racial/ethnic descent, baseline income, and length of time between assessments.

Table 2. Odds ratios, p-values, and 95% confidence intervals for models

	Odds Ratio	p-value	95% CI	95% CI
Becoming obese[+]	**0.895**	**0.000**	**0.843**	**0.951**
Becoming obese*	**0.911**	**0.014**	**0.847**	**0.981**
Becoming obese (self-report only)*	0.884	0.025	0.794	0.984
Treated for HBP[+]	1.028		0.972	1.088
Treated for HBP*	1.016	0.571	0.961	1.074
Treated for T2 Diabetes[+]	1.019	0.771	0.897	1.158
Treated for T2 Diabetes*	**1.005**	0.952	0.859	1.175
Incident obesity by change in walkability quintiles				
Quintile 2	0.899	0.663	0.558	1.449
Quintile 3	0.820	0.431	0.500	1.344
Quintile 4	0.649	0.115	0.379	1.111
Quintile 5	**0.486**	**0.018**	**0.268**	**0.884**
Incident obesity by age				
60 and over	0.936	0.377	0.809	1.084
Under 60	**0.908**	**0.035**	**0.830**	**0.993**
Incident obesity by sex				
Female	**0.898**	**0.019**	**0.821**	**0.982**
Male	0.942	0.360	0.828	1.071
Incident obesity by income				
Baseline income <$75,000	0.927	0.141	0.839	1.025
Baseline income $75,000+	**0.910**	**0.052**	**0.827**	**1.001**

DRAFT

14.4. Discussion

We found change in walkability was associated with reduced odds of incident obesity in both unadjusted and adjusted models. The inverse relationship was strongest among

women, adults 60 years and younger, and those with higher incomes. The odds of becoming obese decreased with greater change in walkability over time. While estimates were imprecise except for comparisons between the largest and smallest change in walkability quintiles, the pattern was suggestive of an inverse, dose response relationship with obesity. We did not observe a relationship between walkability and incident HBP or T2DM. The follow up period may have been insufficient to observe changes in these longer-term, chronic disease outcomes. Much of the research on walkability and health outcomes has been cross-sectional or utilized a single baseline measure of walkability with repeated health outcomes (Chandrabose, Rachele, et al., 2019a; Lai et al., 2023). The current study expands the longitudinal evidence supporting urban design as an effective approach to reducing the significant public health burden of obesity and obesity-related conditions.

Our longitudinal analyses builds on a prior cross-sectional study of this BCGP cohort which found those living in the most walkable neighourhoods had significantly lower odds of obesity compared to those living in the least walkable neighourhoods (L. D. Frank et al., 2022). Research evidence generally supports an inverse relationship between GIS walkability factors and indices with obesity (S. Barbosa et al., 2019; Chandrabose, Rachele, et al., 2019b; Fazeli Dehkordi et al., 2022; Zhang et al., 2023), though inconsistencies have been documented (Grasser et al., 2013; Mackenbach et al., 2014). Studies are largely cross-sectional (J. P. D. A. S. Barbosa et al., 2019; Mackenbach et al., 2014) or rely on a single walkability measure (Chandrabose, Rachele, et al., 2019a). Neither the CARDIA nor SOF studies, both of which used longitudinal measures of walkability, found associations with BMI or obesity risk (Braun et al., 2016; Michael et al., 2013). An analysis of participants who relocated in the MESA study reported a small decrease in BMI among those moving to a more walkable neighourhood (as measured by Walk Score), though no relationships with BMI categories (Hirsch et al., 2014). Tarlov et al., had similar findings to ours with an inverse relationship between walkability and weight outcomes in younger age groups (Tarlov et al., 2020b). However, King et al. found living in more walkable neighourhoods to be associated with lower BMI in older adults over the age of 65 (King et al., 2011b). Other health and mobility factors are likely to play a role in physical activity and weight status in older adults that may explain mixed results with walkability in this age group. There is an established inverse association between income and body weight and some evidence that income may modify the impact of walkability on weight outcomes (T. J. Kim & Von Dem Knesebeck, 2018; J. F. Sallis et al., 2009). The longitudinal REGARDS study found duration weighted Walk Score was associated with lower odds of obesity though they didn't find significant interaction by

DRAFT

neighourhood socioeconomic status (I. M. Lang et al., 2022). This difference could be due to use of census versus individually reported income data used in the present study.

Our null findings for hypertension and T2DM deviate from most prior research. Reductions in odds of T2DM of from 12% to 20% have been reported (DenBraver et al., 2018; Dendup et al., 2018; Zhang et al., 2023). A large population study of adults in Sweden reported greater walkability decreased risk of objectively measured T2DM after 4 years of follow up, though associations were no longer significant after adjustment for individual factors as done in the current study (Sundquist et al., 2015). A meta-analysis of studies with longitudinal, objectively measured outcomes found strong evidence of a relationship between walkability and decreased incidence of T2DM and HBP (Chandrabose, Rachele, et al., 2019a). Of note, the strength of the relationship with these outcomes was attenuated when using objective, GIS measures of walkability, rather than perceived environmental measures. A systematic review by Lai et al., found protective effects of walkability and objectively measured blood pressure outcomes in cross-sectional studies, though the results were mixed in studies with longitudinal design (Lai et al., 2023). Our study differs from those reported by Braun et al. where increased walkability after residential relocation was associated with reductions in systolic blood pressure, though not with BMI (Braun et al., 2016). Participants in this study were younger, on average, than the current study and it may be that younger groups may be more susceptible to change from environmental factors and have less medication-controlled conditions. Similar to our findings, analyses of older adults in the MESA study found relationships between walkability and weight in the expected direction, but not with other cardiometabolic risk factors, including blood pressure.

14.4.1. Strengths and Limitations

This study had a large sample size and participants' residential history allowing for longitudinal assessment of GIS-based walkability indicators with an average of 6 years between baseline and follow up assessments. Our walkability index averaged 6 years of residential location data at each time point, thus should give an accurate estimate of participants' walkability exposure. We utilized a street network buffer to define walkability, which is preferable to radial buffers utilized in many studies (REF). The association of walkability with obesity but not with T2DM or HBP may indicate the follow up time was insufficient to detect these longer-term outcomes, though our time in study was similar to

DRAFT

studies reporting significant associations. We did not have follow up physical activity data so were unable to assess the impact of walkability on this mediating variable. We were not able to control for residential self-selection, which may be related to both the exposure and outcomes studied (L. D. Frank et al., 2007). A further limitation with this study was the use of self-reported data for health outcomes which could result in misclassification. While self-report is a reasonable indicator among those under treatment for these conditions, some in the population may be undiagnosed (Burvill et al., 2022; Ng et al., 2013). Studies with both objective and self-reported outcomes have found protective results with HBP and T2DM. While the longitudinal walkability data are useful in exploring causal relationships with health outcomes, interpretation is challenging. Our exposure measure was somewhat imprecise in that a similar lack of change would apply equally to those who remained in highly walkable or unwalkable neighourhoods.

14.5. Conclusions

This study provides longitudinal evidence on the benefits of neighourhood walkability on reduced incidence of obesity in urban dwelling adults. Our findings do not support relationships with downstream health outcomes, though results may be limited by self-reported blood pressure and diabetes data and insufficient follow up. Longer monitoring would help elucidate this relationship and the length of exposure required to modify risk. As obesity remains a significant public health concern, policies and investments to support walkable communities are justified.

14.6. References

(2023), R. C. T. (2019). R: A language and environment for statistical computing. *R Foundation for Statistical Computing, Vienna, Austria*.

Ace Charters Vancouver. (2023). *Vancouver Shuttle & Charter Service*. Ace Charters Vancouver. https://www.acechartersvancouver.com/

Agbai, C. O. (2021). Shifting neighborhoods, shifting health: A longitudinal analysis of gentrification and health in Los Angeles County. *Social Science Research*, *100*, 102603. https://doi.org/10.1016/j.ssresearch.2021.102603

Allen, J., & Taylor, Z. (2018). A new tool for neighbourhood change research: The Canadian Longitudinal Census Tract Database, 1971-2016: Canadian Longitudinal Tract Database. *The Canadian Geographer / Le Géographe Canadien*, *62*(4), 575–588. https://doi.org/10.1111/cag.12467

DRAFT

Al-Rijleh, M.-K., Alam, A., Foti, R., Gurian, P. L., Spatari, S., & Hatzopoulou, M. (2018). Strategies to achieve deep reductions in metropolitan transportation GHG emissions: The case of Philadelphia. *Transportation Planning and Technology*, *41*(8), 797–815. https://doi.org/10.1080/03081060.2018.1526879

Alshehri, Y. M. (2016). Performance-Based Funding: History, Origins, Outcomes, and Obstacles. *Journal of Higher Education Theory & Practice*, *16*(4).

Antweiler, W., & Gulati, S. (2015). Scrapping for clean air: Emissions savings from the BC SCRAP-IT program. *Journal of Environmental Economics and Management*, *71*, 198–214. https://doi.org/10.1016/j.jeem.2015.03.002

Aquabus. (2022). *Aquabus Granville Island False Creek Ferry*. Aquabus. https://theaquabus.com/

Astell-Burt, T., Navakatikyan, M., Eckermann, S., Hackett, M., & Feng, X. (2022). Is urban green space associated with lower mental healthcare expenditure? *Social Science & Medicine*, *292*, 114503.

Atkinson, R., Wulff, M. G., & Australian Housing and Urban Research Institute. (2009). *Gentrification and displacement: A review of approaches and findings in the literature*. The Institute.

Australia Department of Education. (2020). *Mission based Compacts* [Text]. Department of Education, Skills and Employment; scheme=AGLSTERMS.AglsAgent; corporateName=Department of Education, Skills and Employment; address=50 Marcus Clarke St, Canberra City, ACT 2601; contact=+61 1300 566 046. https://www.dese.gov.au/higher-education-funding/mission-based-compacts

Azarafshar, R., & Vermeulen, W. N. (2020). Electric vehicle incentive policies in Canadian provinces. *Energy Economics*, *91*, 104902. https://doi.org/10.1016/j.eneco.2020.104902

Bailey, N., van Gent, W. P. C., & Musterd, S. (2017). Remaking Urban Segregation: Processes of Income Sorting and Neighbourhood Change. *Population, Space and Place*, *23*(3), e2013. https://doi.org/10.1002/psp.2013

Baker, D. C., Sipe, N. G., & Gleeson, B. J. (2006). Performance-Based Planning: Perspectives from the United States, Australia, and New Zealand. *Journal of Planning Education and Research*, *25*(4), 396–409. https://doi.org/10.1177/0739456X05283450

Barbosa, J. P. D. A. S., Guerra, P. H., Santos, C. de O., Nunes, A. P. de O. B., Turrell, G., & Florindo, A. A. (2019). Walkability, overweight, and obesity in adults: A systematic review of observational studies. *International Journal of Environmental Research and Public Health*, *16*(17). https://doi.org/10.3390/ijerph16173135

DRAFT

Barbosa, S., Guerra, P. H., Santos, C. D. O., Paula, A., Barbosa, D. O., & Turrell, G. (2019). Walkability , Overweight , and Obesity in Adults: A Systematic Review of Observational Studies. *International Journal of Environmental Research and Public Health*, *16*(3135).

Barker, D., Cassidy, J., & Chen, W. (2018). *Paying for Results: Reforming How the Public Sector Funds Social Services*. Bank of America. https://investinresults.org/chapter/paying-results.html

Barla, P., Miranda-Moreno, L. F., & Lee-Gosselin, M. (2011a). Urban travel CO2 emissions and land use: A case study for Quebec City. *Transportation Research Part D: Transport and Environment*, *16*(6), 423–428. https://doi.org/10.1016/j.trd.2011.03.005

Barla, P., Miranda-Moreno, L. F., & Lee-Gosselin, M. (2011b). Urban travel CO2 emissions and land use: A case study for Quebec City. *Transportation Research Part D: Transport and Environment*, *16*(6), 423–428. https://doi.org/10.1016/j.trd.2011.03.005

Barton, M. (2016). An exploration of the importance of the strategy used to identify gentrification. *Urban Studies*, *53*(1), 92–111. https://doi.org/10.1177/0042098014561723

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, *67*(1). https://doi.org/10.18637/jss.v067.i01

BC Ferries. (2022). *Our Fleet*. https://www.bcferries.com/on-the-ferry/our-fleet

B.C. Ministry of Energy, Mines and Petroleum Resources. (2017). *Using GHGenius in B.C.* (Renewable and Low Carbon Fuel Requirements Regulation Information Bulletin RLCF-010). https://www2.gov.bc.ca/assets/gov/farming-natural-resources-and-industry/electricity-alternative-energy/transportation/renewable-low-carbon-fuels/rlcf010_-_using_ghgenius_for_bc.pdf

B.C. Ministry of Environment and Climate Change Strategy. (2017). *Community energy and emissions inventory (CEEI)*. Province of British Columbia. https://www2.gov.bc.ca/gov/content/environment/climate-change/data/ceei

B.C. Ministry of Environment and Climate Change Strategy. (2019). *B.C. Methodological Guidance for Quantifying Greenhouse Gas Emissions*. https://www2.gov.bc.ca/assets/gov/environment/climate-change/cng/methodology/2018-pso-methodology.pdf

B.C. Ministry of Environment and Climate Change Strategy. (2021). *CleanBC Roadmap to 2030*.

DRAFT

BC Ministry of Environment and Climate Change Strategy. (2022). *B.C. Best Practices Methodology for Quantifying Greenhouse Gas Emissions*.

B.C. Ministry of Environment and Climate Change Strategy. (2022). *Electricity emission intensity factors for grid-connected entities—Province of British Columbia*. Province of British Columbia. https://www2.gov.bc.ca/gov/content/environment/climate-change/industry/reporting/quantify/electricity

BCGP. (2019). *Across Generations: BC Generations Project Newsletter, Winter 2019/20*.

Bel, G., & Rosell, J. (2017). The impact of socioeconomic characteristics on CO2 emissions associated with urban mobility: Inequality across individuals. *Energy Economics*, *64*, 251–261. https://doi.org/10.1016/j.eneco.2017.04.002

Berjisian, E., & Bigazzi, A. (2022). Evaluation of methods to distinguish trips from activities in walking and cycling GPS data. *Transportation Research Part C: Emerging Technologies*, *137*, 103588. https://doi.org/10.1016/j.trc.2022.103588

Beyer, K. M. M., Kaltenbach, A., Szabo, A., Bogar, S., Nieto, F. J., & Malecki, K. M. (2014). Exposure to neighborhood green space and mental health: Evidence from the survey of the health of Wisconsin. *International Journal of Environmental Research and Public Health*, *11*(3), 3453–3472.

Bigazzi, A. (2019). Comparison of marginal and average emission factors for passenger transportation modes. *Applied Energy*, *242*, 1460–1466. https://doi.org/10.1016/j.apenergy.2019.03.172

Bigazzi, A. (2020). Marginal emission factors for public transit: Effects of urban scale and density. *Transportation Research Part D: Transport and Environment*, *88*, 102585. https://doi.org/10.1016/j.trd.2020.102585

Bigazzi, A. Y., & Hassanpour, A. (2022). *Human-electric hybrid vehicles: Implications of new non-auto mobility options for street design and policy in the Vancouver region* (p. 105) [Final Report]. Prepared for TransLink. https://reactlab.civil.ubc.ca/human-electric-hybrid-vehicles/

Bird, E. L., Ige, J. O., Pilkington, P., Pinto, A., Petrokofsky, C., & Burgess-Allen, J. (2018). Built and natural environment planning principles for promoting health: An umbrella review. *BMC Public Health*, *18*(1), 1–13.

Blanco-Davis, E., Castillo, F. del, & Zhou, P. (2014). Fouling release coating application as an environmentally efficient retrofit: A case study of a ferry-type ship. *The International Journal of Life Cycle Assessment*, *19*(10), Article 10. https://doi.org/10.1007/s11367-014-0780-8

DRAFT

Bleyen, P., Klimovský, D., Bouckaert, G., & Reichard, C. (2017). Linking budgeting to results? Evidence about performance budgets in European municipalities based on a comparative analytical model. *Public Management Review*, *19*(7), 932–953. https://doi.org/10.1080/14719037.2016.1243837

Bloom, D. E., Cafiero, E., Jané-Llopis, E., Abrahams-Gessel, S., Bloom, L. R., Fathima, S., Feigl, A. B., Gaziano, T., Hamandi, A., & Mowafi, M. (2012). *The global economic burden of noncommunicable diseases*. Program on the Global Demography of Aging.

Brand, C., & Preston, J. M. (2010). '60-20 emission'—The unequal distribution of greenhouse gas emissions from personal, non-business travel in the UK. *Transport Policy*, *17*(1), 9–19. https://doi.org/10.1016/j.tranpol.2009.09.001

Brander, M., & Ascui, F. (2015). The Attributional-Consequential Distinction and Its Applicability to Corporate Carbon Accounting. In S. Schaltegger, D. Zvezdov, I. Alvarez Etxeberria, M. Csutora, & E. Günther (Eds.), *Corporate Carbon and Climate Accounting* (pp. 99–120). Springer International Publishing. https://doi.org/10.1007/978-3-319-27718-9_5

Brander, M., Gillenwater, M., & Ascui, F. (2018). Creative accounting: A critical perspective on the market-based method for reporting purchased electricity (scope 2) emissions. *Energy Policy*, *112*, 29–33. https://doi.org/10.1016/j.enpol.2017.09.051

Bratman, G. N., Hamilton, J. P., Hahn, K. S., Daily, G. C., & Gross, J. J. (2015). Nature experience reduces rumination and subgenual prefrontal cortex activation. *Proceedings of the National Academy of Sciences*, *112*(28), 8567–8572.

Braun, L., Rodriguez, D., Song, Y., Meyer, K., Lewis, C., Reis, J., & Gordon-Larsen, P. (2016). Changes in walking, body mass index, and cardiometabolic risk factors following residential relocation: Longitudinal results from the CARDIA study. *J Transp Health.*, *3*(4), 426–439. https://doi.org/10.1016/j.jth.2016.08.006

Brown, M., Eldridge, M., & Bieretz, B. (2019). *Performance-Based Strategies: Defining Terms and Comparing Common Strategies* (p. 5). Urban Institute.

Brown, N. M. (2019). *Millennium Challenge Corporation: Overview and Issues* (p. 36). Congressional Research Service.

Bureau of Transportation Statistics, U.S. Department of Transportation. (n.d.). *National Transportation Statistics*. Retrieved December 20, 2017, from http://www.bts.gov/publications/national_transportation_statistics/

Burvill, A. J., Murray, K., Knuiman, M. W., & Hung, J. (2022). Comparing self-reported and measured hypertension and hypercholesterolaemia at standard and more

DRAFT

stringent diagnostic thresholds: The cross-sectional 2010–2015 Busselton Healthy Ageing study. *Clinical Hypertension*, *28*(1), 1–10. https://doi.org/10.1186/s40885-022-00199-1

Buzar, S., Ogden, P., Hall, R., Haase, A., Kabisch, S., & Steinfiihrer, A. (2007). Splintering Urban Populations: Emergent Landscapes of Reurbanisation in Four European Cities. *Urban Studies*, *44*(4), 651–677. https://doi.org/10.1080/00420980601185544

Camhi, S. M., Troped, P. J., Garvey, M., Hayman, L. L., Must, A., Lichtenstein, A. H., & Crouter, S. E. (2019). Associations between Walk Score and objective measures of physical activity in urban overweight and obese women. *PLoS One*, *14*(3), e0214092.

CANUE. (n.d.). *The Canadian Urban Environmental Health Research Consortium: Understanding urban living and human health*.

Carlson, J. A., Saelens, B. E., Kerr, J., Schipperijn, J., Conway, T. L., Frank, L. D., Chapman, J. E., Glanz, K., Cain, K. L., & Sallis, J. F. (2017). Association between neighborhood walkability and GPSmeasured walking, bicycling and vehicle time in adolescents. *Health & Place*, *32*, 1–7. https://doi.org/10.1016/j.healthplace.2014.12.008.Association

Carranza, G., Do Nascimiento, M., Fanals, J., Febrer, J., & Valderrama, C. (2022). Life cycle assessment and economic analysis of the electric motorcycle in the city of Barcelona and the impact on air pollution. *Science of The Total Environment*, *821*, 153419. https://doi.org/10.1016/j.scitotenv.2022.153419

Cerin, E., Nathan, A., Van Cauwenberg, J., Barnett, D. W., & Barnett, A. (2017). The neighbourhood physical environment and active travel in older adults: A systematic review and meta-analysis on behalf of the Council on Environment and Physical Activity (CEPA) – Older Adults working group. *International Journal of Behavioral Nutrition and Physical Activity*, *14*(15). https://doi.org/10.1186/s12966-017-0471-5

Cerqueira, E. D. V., Motte-Baumvol, B., Chevallier, L. B., & Bonin, O. (2020). Does working from home reduce CO2 emissions? An analysis of travel patterns as dictated by workplaces. *Transportation Research Part D: Transport and Environment*, *83*, 102338. https://doi.org/10.1016/j.trd.2020.102338

Chan, S., Miranda-Moreno, L., Alam, A., & Hatzopoulou, M. (2013). Assessing the impact of bus technology on greenhouse gas emissions along a major corridor: A lifecycle analysis. *World Transit Research*. https://www.worldtransitresearch.info/research/4746

DRAFT

Chandrabose, M., Cerin, E., Mavoa, S., Dunstan, D., Carver, A., Turrell, G., Owen, N., Giles-Corti, B., & Sugiyama, T. (2019). Neighborhood walkability and 12-year changes in cardio-metabolic risk: The mediating role of physical activity. *The International Journal of Behavioral Nutrition and Physical Activity*, *16*(1), 86. https://doi.org/10.1186/s12966-019-0849-7

Chandrabose, M., Rachele, J. N., Gunn, L., Kavanagh, A., Owen, N., Turrell, G., Giles-Corti, B., & Sugiyama, T. (2019a). Built environment and cardio-metabolic health: Systematic review and meta-analysis of longitudinal studies. *Obesity Reviews*, *20*(1), 41–54. https://doi.org/10.1111/obr.12759

Chandrabose, M., Rachele, J. N., Gunn, L., Kavanagh, A., Owen, N., Turrell, G., Giles-Corti, B., & Sugiyama, T. (2019b). Built environment and cardio-metabolic health: Systematic review and meta-analysis of longitudinal studies. *Obesity Reviews*, *20*(1), 41–54. https://doi.org/10.1111/obr.12759

Chester, M., & Horvath, A. (2009). *Life-cycle Energy and Emissions Inventories for Motorcycles, Diesel Automobiles, School Buses, Electric Buses, Chicago Rail, and New York City Rail*. https://escholarship.org/uc/item/6z37f2jr

Chester, M. V. (2008). *Life-cycle Environmental Inventory of Passenger Transportation in the United States*. https://escholarship.org/uc/item/7n29n303

Choi, K., & Zhang, M. (2017). The net effects of the built environment on household vehicle emissions: A case study of Austin, TX. *Transportation Research Part D: Transport and Environment*, *50*, 254–268. https://doi.org/10.1016/j.trd.2016.10.036

Clark, C., Menifield, C. E., & Stewart, L. M. (2018). Policy Diffusion and Performance-based Budgeting. *International Journal of Public Administration*, *41*(7), 528–534. https://doi.org/10.1080/01900692.2016.1278384

Condon, P. M., & Dow, K. (2011). *Transportation for Sustainable Communities: A cost and impact comparison between alternative transportation modes*.

Conway, M. W., & Stewart, A. F. (2019). Getting Charlie off the MTA: A multiobjective optimization method to account for cost constraints in public transit accessibility metrics. *International Journal of Geographical Information Science*, *33*(9), 1759–1787. https://doi.org/10.1080/13658816.2019.1605075

Cooney, G., Hawkins, T. R., & Marriott, J. (2013). Life Cycle Assessment of Diesel and Electric Public Transportation Buses. *Journal of Industrial Ecology*, *17*(5), 689–699. https://doi.org/10.1111/jiec.12024

Corradi, O., McCormick, G., Richardson, H., & Hinkle, T. (2021). *A vision for how ambitious organizations can accurately measure electricity emissions to take*

DRAFT

genuine action. Tomorrow and Watt Time. https://www.watttime.org/app/uploads/2021/08/GHG-Frameworks-WhitePaper-Tomorrow-WattTime-202108.pdf

Cottagiri, S. A., Villeneuve, P. J., Raina, P., Griffith, L. E., Rainham, D., Dales, R., Peters, C. E., Ross, N. A., & Crouse, D. L. (2022). Increased urban greenness associated with improved mental health among middle-aged and older adults of the Canadian Longitudinal Study on Aging (CLSA). *Environmental Research*, *206*, 112587.

Cox, B. L., & Mutel, C. L. (2018). The environmental and cost performance of current and future motorcycles. *Applied Energy*, *212*, 1013–1024. https://doi.org/10.1016/j.apenergy.2017.12.100

Cramer, J., & Krueger, A. B. (2016). Disruptive Change in the Taxi Business: The Case of Uber. *American Economic Review*, *106*(5), 177–182. https://doi.org/10.1257/aer.p20161002

Croissant, Y., & Millo, G. (2008). Panel Data Econometrics in R: The plm Package. *Journal of Statistical Software*, *27*. https://doi.org/10.18637/jss.v027.i02

Csárdi, G., Nepusz, T., Müller, K., Horvát, S., Traag, V., Zanini, F., & Noom, D. (2023). *igraph for R: R interface of the igraph library for graph theory and network analysis* [Computer software]. Zenodo. https://doi.org/10.5281/zenodo.8046777

Darwish, A. M., Zagow, M., & Elkafoury, A. (2023). Impact of land use, travel behavior, and socio-economic characteristics on carbon emissions in cool-climate cities, USA. *Environmental Science and Pollution Research*, *30*(39), 91108–91124. https://doi.org/10.1007/s11356-023-28487-9

DC Water. (2016). *DC Water, Goldman Sachs and Calvert Foundation pioneer environmental impact bond; | DCWater.com*. https://www.dcwater.com/whats-going-on/news/dc-water-goldman-sachs-and-calvert-foundation-pioneer-environmental-impact-bond

De Boer, H., Jongbloed, B., Benneworth, P., Cremonini, L., Kolster, R., Kottmann, A., Lemmens-Krug, K., & Vossensteyn, H. (2015). Performance-based funding and performance agreements in fourteen higher education systems. *Center for Higher Education Policy Studies*.

de Bortoli, A. (2021). Environmental performance of shared micromobility and personal alternatives using integrated modal LCA. *Transportation Research Part D: Transport and Environment*, *93*, 102743. https://doi.org/10.1016/j.trd.2021.102743

Del Pero, F., Delogu, M., Pierini, M., & Bonaffini, D. (2015). Life Cycle Assessment of a heavy metro train. *Journal of Cleaner Production*, *87*, 787–799. https://doi.org/10.1016/j.jclepro.2014.10.023

DRAFT

DenBraver, N. R., Lakerveld, J., Rutters, F., Schoonmade, L. J., Brug, J., & Beulens, J. W. J. (2018). Built environmental characteristics and diabetes: A systematic review and meta-analysis. *BMC Medicine*, *16*(1). https://doi.org/10.1186/s12916-017-0997-z

Dendup, T., Feng, X., Clingan, S., & Astell-Burt, T. (2018). Environmental risk factors for developing type 2 diabetes mellitus: A systematic review. *International Journal of Environmental Research and Public Health*, *15*(1). https://doi.org/10.3390/ijerph15010078

Des Rosiers, F., Thériault, M., Biba, G., & Vandersmissen, M.-H. (2017). Greenhouse gas emissions and urban form: Linking households' socio-economic status with housing and transportation choices. *Environment and Planning B: Urban Analytics and City Science*, *44*(5), 964–985. https://doi.org/10.1177/0265813516656862

Dey, S., Caulfield, B., & Ghosh, B. (2019). Modelling uncertainty of vehicular emissions inventory: A case study of Ireland. *Journal of Cleaner Production*, *213*, 1115–1126. https://doi.org/10.1016/j.jclepro.2018.12.125

Dhalla, A., McDonald, T. E., Gallagher, R. P., Spinelli, J. J., Brooks-Wilson, A. R., Lee, T. K., Lai, C., Borugian, M. J., Woods, R. R., Le, N. D., & Dummer, T. J. B. (2019). Cohort profile: The British Columbia Generations Project (BCGP). *International Journal of Epidemiology*, *48*(2), 377–378k. https://doi.org/10.1093/ije/dyy160

DMTISpatial. CanMap® GIS Data for GIS Mapping Software—DMTI Spatial. (n.d.). https://www.dmtispatial.com/canmap/

Environment and Climate Change Canada. (2020). *Historical Data—Climate*. https://climate.weather.gc.ca/historical_data/search_historic_data_e.html

Environment and Climate Change Canada. (2021). *Greenhouse gas sources and sinks in Canada*. Government of Canada. https://www.canada.ca/en/environment-climate-change/services/climate-change/greenhouse-gas-emissions/inventory.html

Environment and Climate Change Canada. (2022). *Canada's air pollutant emissions inventory report 2022*. https://publications.gc.ca/site/eng/9.869731/publication.html

Facts about Physical Activity| CDC. (n.d.). Retrieved April 8, 2017, from https://www.cdc.gov/physicalactivity/data/facts.htm

Fan, V. Y., Duran, D., Silverman, R., & Glassman, A. (2013). Performance-based financing at the Global Fund to Fight AIDS, Tuberculosis and Malaria: An analysis of grant ratings and funding, 2003–12. *The Lancet Global Health*, *1*(3), e161–e168.

DRAFT

Fan, Y., Das, K. V, & Chen, Q. (2011). Neighborhood green, social support, physical activity, and stress: Assessing the cumulative impact. *Health & Place*, *17*(6), 1202–1211.

Fazeli Dehkordi, Z. S., Khatami, S. M., & Ranjbar, E. (2022). The Associations Between Urban Form and Major Non-communicable Diseases: A Systematic Review. *Journal of Urban Health*, *99*(5), 941–958. https://doi.org/10.1007/s11524-022-00652-4

Fong, K. C., Hart, J. E., & James, P. (2018). A review of epidemiologic studies on greenness and health: Updated literature through 2017. *Current Environmental Health Reports*, *5*, 77–87.

Frank, L. D., Adhikari, B., White, K. R., Dummer, T., Sandhu, J., Demlow, E., Hu, Y., Hong, A., & Van den Bosch, M. (2022). Chronic disease and where you live: Built and natural environment relationships with physical activity, obesity, and diabetes. *Environment International*, *158*, 106959. https://doi.org/10.1016/J.ENVINT.2021.106959

Frank, L. D., Iroz-Elardo, N., MacLeod, K. E., & Hong, A. (2019). Pathways from built environment to health: A conceptual framework linking behavior and exposure-based impacts. *Journal of Transport & Health*, *12*, 319–335.

Frank, L. D., Jr, B. S., & Bachman, W. (2000). *Linking land use with household vehicle emissions in the central puget sound: Methodological framework and ®ndings*.

Frank, L. D., Saelens, B. E., Powell, K. E., & Chapman, J. E. (2007). Stepping towards causation: Do built environments or neighborhood and travel preferences explain physical activity, driving, and obesity? *Social Science and Medicine*, *65*(9), 1898–1914. https://doi.org/10.1016/j.socscimed.2007.05.053

Frank, L. D., Sallis, J. F., Saelens, B. E., Leary, L., Cain, K., Conway, T. L., & Hess, P. M. (2010a). The development of a walkability index: Application to the Neighborhood Quality of Life Study. *British Journal of Sports Medicine*, *44*(13), 924–933. https://doi.org/10.1136/bjsm.2009.058701

Frank, L. D., Sallis, J. F., Saelens, B. E., Leary, L., Cain, K., Conway, T. L., & Hess, P. M. (2010b). The development of a walkability index: Application to the Neighborhood Quality of Life Study. *British Journal of Sports Medicine*, *44*(13), 924–933. https://doi.org/10.1136/bjsm.2009.058701

Frank, L. D., Schmid, T. L., Sallis, J. F., Chapman, J., & Saelens, B. E. (2005). Linking objectively measured physical activity with objectively measured urban form: Findings from SMARTRAQ. *American Journal of Preventive Medicine*, *28*(2), 117–125. https://doi.org/10.1016/J.AMEPRE.2004.11.001

DRAFT

Frank, L. D., Stone, B., & Bachman, W. (2000). Linking land use with household vehicle emissions in the central puget sound: Methodological framework and findings. *Transportation Research Part D: Transport and Environment*, *5*(3), 173–196. https://doi.org/10.1016/S1361-9209(99)00032-2

Frank, L., Giles-Corti, B., & Ewing, R. (2016). *The influence of the built environment on transport and health*. https://doi.org/10.1016/j.jth.2016.11.004

Freeman, L. (2005). Displacement or Succession?: Residential Mobility in Gentrifying Neighborhoods. *Urban Affairs Review*, *40*(4), 463–491. https://doi.org/10.1177/1078087404273341

Freeman, L., & Braconi, F. (2004). Gentrification and Displacement New York City in the 1990s. *Journal of the American Planning Association*, *70*(1), 39–52. https://doi.org/10.1080/01944360408976337

Frey, H. C. (2007). *Quantification of Uncertainty in Emission Factors and Inventories*. Environmental Protection Agency,; Google Scholar.

Gabrio, A., Plumpton, C., Banerjee, S., & Leurent, B. (2022). Linear mixed models to handle missing at random data in trial-based economic evaluations. *Health Economics (United Kingdom)*, *31*(6), 1276–1287. https://doi.org/10.1002/hec.4510

Gariepy, G., Blair, A., Kestens, Y., & Schmitz, N. (2014). Neighbourhood characteristics and 10-year risk of depression in Canadian adults with and without a chronic illness. *Health & Place*, *30*, 279–286.

GBD Mental Disorders Collaborators. Global, regional, and national burden of 12 mental disorders in 204 countries and territories, 1990–2019: A systematic analysis for the Global Burden of Disease Study 2019. (2022). *The Lancet Psychiatry*, *9*(2), 137–150.

Generaal, E., Timmermans, E. J., Dekkers, J. E. C., Smit, J. H., & Penninx, B. W. J. H. (2019). Not urbanization level but socioeconomic, physical and social neighbourhood characteristics are associated with presence and severity of depressive and anxiety disorders. *Psychological Medicine*, *49*(1), 149–161.

Ghafghazi, G., & Hatzopoulou, M. (2014). Simulating the environmental effects of isolated and area-wide traffic calming schemes using traffic simulation and microscopic emission modeling. *Transportation*, *41*(3), 633–649. https://doi.org/10.1007/s11116-014-9513-x

Giles-Corti, B., Vernez-Moudon, A., Reis, R., Turrell, G., Dannenberg, A. L., Badland, H., Foster, S., Lowe, M., Sallis, J. F., Stevenson, M., & Owen, N. (2016). City planning and population health: A global challenge. *The Lancet*. https://doi.org/10.1016/S0140-6736(16)30066-6

DRAFT

Glass, R. (1964). Aspects of change. *The Gentrification Debates: A Reader*, 19–30.
Global Advocacy for Physical Activity (GAPA) the Advocacy Council of the International Society for Physical Activity and Health (ISPAH). (2011). *NCD Prevention: Investments that Work for Physical Activity*. https://doi.org/10.1093/bmb/ldq037
Gold, J., Mendelsohn, M., & Mowat Centre for Policy Innovation. (2014). *Better Outcomes for Public Services: Achieving Social Impact Through Outcomes-Based Funding*. Mowat Center. http://www.deslibris.ca/ID/243716
Google. (2022). *Google Search*. https://www.google.com/
GPRBA. (2021). *Results-Based Financing | The Global Partnership for Results-Based Approaches*. https://www.gprba.org/results-based-financing
Grant, M., Bird, C., & Marno, P. (2012). Health inequalities and determinants in the physical urban environment: Evidence briefing. *WHO Collaborating Centre for Healthy Urban Environments: Bristol, UK*.
Grasser, G., Van Dyck, D., Titze, S., & Stronegger, W. (2012). Objectively measured walkability and active transport and weight-related outcomes in adults: A systematic review. *International Journal of Public Health*, *58*, 615–625.
Grasser, G., Van Dyck, D., Titze, S., & Stronegger, W. (2013). Objectively measured walkability and active transport and weight-related outcomes in adults: A systematic review. *Int J Public Health*, *58*(4), 615–625. https://doi.org/10.1007/s00038-012-0435-0
Grigsby, W. (1986). *The Dynamics of Neighborhood Change and Decline.*
Grittner, A. M. (2013). *Results-based financing: Evidence from performance-based financing in the health sector*. Dt. Inst. für Entwicklungspolitik.
Groenewegen, P. P., Van den Berg, A. E., De Vries, S., & Verheij, R. A. (2006). Vitamin G: effects of green space on health, well-being, and social safety. *BMC Public Health*, *6*(1), 1–9.
Gulcimen, S., Aydogan, E. K., & Uzal, N. (2021). Life cycle sustainability assessment of a light rail transit system: Integration of environmental, economic, and social impacts. *Integrated Environmental Assessment and Management*, *17*(5), 1070–1082. https://doi.org/10.1002/ieam.4428
Hackworth, J., & Smith, N. (2001). The changing state of gentrification. *Tijdschrift Voor Economische En Sociale Geografie*, *92*(4), 464–477.
Hammel, D. J., & Wyly, E. K. (1996). A MODEL FOR IDENTIFYING GENTRIFIED AREAS WITH CENSUS DATA. *Urban Geography*, *17*(3), 248–268. https://doi.org/10.2747/0272-3638.17.3.248

DRAFT

Hamnett, C. (1994). Social polarisation in global cities: Theory and evidence. *Urban Studies*, *31*(3), 401–424.
Harnisch, T. L. (2011). *Performance-based Funding: A Re-Emerging Strategy in Public Higher Education Financing*. 12.
Hartig, T. (2008). Green space, psychological restoration, and health inequality. *The Lancet*, *372*(9650), 1614–1615.
Hartig, T., Mitchell, R., De Vries, S., & Frumkin, H. (2014). Nature and health. *Annual Review of Public Health*, *35*, 207–228.
Harvard Kennedy School Government Performance Lab. (2017). *Social Impact Bonds 101*. https://govlab.hks.harvard.edu/files/govlabs/files/sibs_101_gpl_2017.pdf
Hassanpour, A., & Bigazzi, A. (2023). What is on the Bicycle Paths? A Detailed Vehicle Taxonomy with Mode Share Data for Off-Street Paths in Metropolitan Vancouver, Canada. *Transportation Research Record*, *2677*(11), 258–271. https://doi.org/10.1177/03611981231165017
Hawkins, R., Bieretz, B., & Brown, M. (2019, June 24). *Incentivizing Results: Contracting for Outcomes in Social Service Delivery*. Urban Institute. https://www.urban.org/research/publication/incentivizing-results-contracting-outcomes-social-service-delivery
Hedman, L. (2011). *Residential mobility and neighbourhood effects: A holistic approach*. Acta Universitatis Upsaliensis.
Helbich, M., Poppe, R., Oberski, D., van Emmichoven, M. Z., & Schram, R. (2021). Can't see the wood for the trees? An assessment of street view-and satellite-derived greenness measures in relation to mental health. *Landscape and Urban Planning*, *214*, 104181.
Hirsch, J. A., Roux, A. V. D., Moore, K. A., Evenson, K. R., & Rodriguez, D. A. (2014). Change in walking and body mass index following residential relocation: The multi-ethnic study of atherosclerosis. *American Journal of Public Health*, *104*(3), 49–56. https://doi.org/10.2105/AJPH.2013.301773
Hirschfeld, R. M. A., & Weissman, M. M. (2002). Risk factors for major depression and bipolar disorder. *Neuropsychopharmacology: The Fifth Generation of Progress*, 1017–1025.
Hochstenbach, C., & van Gent, W. P. (2015). An anatomy of gentrification processes: Variegating causes of neighbourhood change. *Environment and Planning A: Economy and Space*, *47*(7), 1480–1501. https://doi.org/10.1177/0308518X15595771

DRAFT

Hystad, P., Payette, Y., Noisel, N., & Boileau, C. (2019). Green space associations with mental health and cognitive function: Results from the Quebec CARTaGENE cohort. *Environmental Epidemiology*, *3*(1).

Insurance Corporation of British Columbia (ICBC). (2020). *British Columbia Vehicle Population Data* [dataset]. https://public.tableau.com/views/VehiclePopulationIntroPage/VehiclePopulationData?%3Adisplay_static_image=y&%3AbootstrapWhenNotified=true&%3Aembed=true&%3Alanguage=en-US&:embed=y&:showVizHome=n&:apiID=host0#navType=0&navSrc=Parse

Ipsos. (2018). *2017 Regional Trip Diary Technical Report*. TransLink.

Istrate, I., Iribarren, D., Dufour, J., Ortiz Cebolla, R., Arrigoni, A., Moretto, P., & Dolci, F. (2022). *Quantifying Emissions in the European Maritime Sector: A Review on Life Cycle Assessments of Maritime Systems Combined With an Analysis of the THETIS-MRV Portal* (JRC128870). https://trid.trb.org/view/1948241

Jacobs, P., Dewa, C. S., Lesage, A., Vasiliadis, H.-M., Escober, C., Mulvale, G., & Yim, R. (2010). *The cost of mental health and substance abuse services in Canada: A report to the Mental Health Commission of Canada*. Institute of Health Economics.

Janus, H., Klingebiel, S., & Paulo, S. (2015). Beyond Aid: A Conceptual Perspective on the Transformation of Development Cooperation. *Journal of International Development*, *27*(2), 155–169.

Johnson, D., & Zajonc, T. (2006). *Can Foreign Aid Create an Incentive for Good Governance? Evidence from the Millennium Challenge Corporation* [SSRN Scholarly Paper]. Social Science Research Network. https://doi.org/10.2139/ssrn.896293

Jones, A. C., Chaudhary, N. S., Patki, A., Howard, V. J., Howard, G., Colabianchi, N., Judd, S. E., & Irvin, M. R. (2021). Neighborhood Walkability as a Predictor of Incident Hypertension in a National Cohort Study. *Frontiers in Public Health*, *9*(February), 1–7. https://doi.org/10.3389/fpubh.2021.611895

Jongbloed, B., & De Boer, H. (2020). *Performance Agreements in Denmark, Ontario and the Netherlands*. University of Twente. https://doi.org/10.1787/735e1f44-en

Julien, D., Richard, L., Gauvin, L., & Kestens, Y. (2012). Neighborhood characteristics and depressive mood among older adults: An integrative review. *International Psychogeriatrics*, *24*(8), 1207–1225.

Kahn, M. E. (1998). A household level environmental Kuznets curve. *Economics Letters*, *59*(2), 269–273. https://doi.org/10.1016/S0165-1765(98)00035-4

DRAFT

Kannangara, M., Bensebaa, F., & Vasudev, M. (2021). An adaptable life cycle greenhouse gas emissions assessment framework for electric, hybrid, fuel cell and conventional vehicles: Effect of electricity mix, mileage, battery capacity and battery chemistry in the context of Canada. *Journal of Cleaner Production*, *317*, 128394. https://doi.org/10.1016/j.jclepro.2021.128394

Kaplan, R., & Kaplan, S. (1989). *The experience of nature: A psychological perspective*. Cambridge university press.

Keats, M. R., Cui, Y., DeClercq, V., Grandy, S. A., Sweeney, E., & Dummer, T. J. B. (2020). Associations between neighborhood walkability, physical activity, and chronic disease in Nova Scotian adults: An Atlantic PATH cohort study. *International Journal of Environmental Research and Public Health*, *17*(22), 8643.

Kessler, R. C., Aguilar-Gaxiola, S., Alonso, J., Chatterji, S., Lee, S., Ormel, J., Üstün, T. B., & Wang, P. S. (2009). The global burden of mental disorders: An update from the WHO World Mental Health (WMH) surveys. *Epidemiology and Psychiatric Sciences*, *18*(1), 23–33.

Khan, S., Pinault, L., Tjepkema, M., & Wilkins, R. (2018). Positional accuracy of geocoding from residential postal codes versus full street addresses. *Health Reports*, *29*(2), 3–9.

Kim, E. J., Kim, J., & Kim, H. (2020). Does Environmental Walkability Matter? The Role of Walkable Environment in Active Commuting. *International Journal of Environmental Research and Public Health*, *17*(4), 1261. https://doi.org/10.3390/ijerph17041261

Kim, T. J., & Von Dem Knesebeck, O. (2018). Income and obesity: What is the direction of the relationship? A systematic review and meta-analysis. *BMJ Open*, *8*(1). https://doi.org/10.1136/bmjopen-2017-019862

King, A. C., Sallis, J. F., Frank, L. D., Saelens, B. E., Cain, K., Conway, T. L., Chapman, J. E., Ahn, D. K., & Kerr, J. (2011a). Aging in neighborhoods differing in walkability and income: Associations with physical activity and obesity in older adults. *Social Science & Medicine (1982)*, *73*(10), 1525–1533. https://doi.org/10.1016/j.socscimed.2011.08.032

King, A. C., Sallis, J. F., Frank, L. D., Saelens, B. E., Cain, K., Conway, T. L., Chapman, J. E., Ahn, D. K., & Kerr, J. (2011b). Aging in neighborhoods differing in walkability and income: Associations with physical activity and obesity in older adults. *Social Science & Medicine*, *73*(10), 1525–1533. https://doi.org/10.1016/J.SOCSCIMED.2011.08.032

DRAFT

Klompmaker, J. O., Hoek, G., Bloemsma, L. D., Wijga, A. H., van den Brink, C., Brunekreef, B., Lebret, E., Gehring, U., & Janssen, N. A. H. (2019). Associations of combined exposures to surrounding green, air pollution and traffic noise on mental health. *Environment International*, *129*, 525–537.

Ko, J., Park, D., Lim, H., & Hwang, I. C. (2011). Who produces the most CO2 emissions for trips in the Seoul metropolis area? *Transportation Research Part D: Transport and Environment*, *16*(5), 358–364. https://doi.org/10.1016/j.trd.2011.02.001

Koohsari, M. J., McCormack, G. R., Nakaya, T., Shibata, A., Ishii, K., Yasunaga, A., Hanibuchi, T., & Oka, K. (2019). Urban design and Japanese older adults' depressive symptoms. *Cities*, *87*, 166–173.

Koohsari, M. J., Owen, N., Cole, R., Mavoa, S., Oka, K., Hanibuchi, T., & Sugiyama, T. (2017). Built environmental factors and adults' travel behaviors: Role of street layout and local destinations. *Preventive Medicine*, *96*, 124–128. https://doi.org/10.1016/j.ypmed.2016.12.021

Koohsari, M. J., Yasunaga, A., McCormack, G. R., Shibata, A., Ishii, K., Nakaya, T., Hanibuchi, T., Nagai, Y., & Oka, K. (2023). Depression among middle-aged adults in Japan: The role of the built environment design. *Landscape and Urban Planning*, *231*, 104651.

Koren, H. S., & Butler, C. D. (2006). The interconnection between the built environment ecology and health. *Environmental Security and Environmental Management: The Role of Risk Assessment*, 111–125.

Kotval-K, Z., & Vojnovic, I. (2015). The socio-economics of travel behavior and environmental burdens: A Detroit, Michigan regional context. *Transportation Research Part D: Transport and Environment*, *41*, 477–491. https://doi.org/10.1016/j.trd.2015.10.017

Krols, J., Aerts, R., Vanlessen, N., Dewaelheyns, V., Dujardin, S., & Somers, B. (2022). Residential green space, gardening, and subjective well-being: A cross-sectional study of garden owners in northern Belgium. *Landscape and Urban Planning*, *223*, 104414.

Lai, K. Y., Webster, C., Gallacher, J. E., & Sarkar, C. (2023). Associations of Urban Built Environment with Cardiovascular Risks and Mortality: A Systematic Review. In *Journal of Urban Health* (Vol. 100, Issue 4). Springer US. https://doi.org/10.1007/s11524-023-00764-5

Lajunen, A., & Lipman, T. (2016). Lifecycle cost assessment and carbon dioxide emissions of diesel, natural gas, hybrid electric, fuel cell hybrid and electric transit buses. *Energy*, *106*, 329–342. https://doi.org/10.1016/j.energy.2016.03.075

DRAFT

Lang, D. W. (2016). *Incentive Funding Meets Incentive-Based Budgeting: Can They Coexist? 46*(4), 22.

Lang, I. M., Antonakos, C. L., Judd, S. E., & Colabianchi, N. (2022). A longitudinal examination of objective neighborhood walkability, body mass index, and waist circumference: The REasons for Geographic And Racial Differences in Stroke study. *International Journal of Behavioral Nutrition and Physical Activity*, *19*(1), 1–15. https://doi.org/10.1186/s12966-022-01247-7

Le Hong, Z., & Zimmerman, N. (2021). Air quality and greenhouse gas implications of autonomous vehicles in Vancouver, Canada. *Transportation Research Part D: Transport and Environment*, *90*, 102676. https://doi.org/10.1016/j.trd.2020.102676

Lederer, J., Ott, C., Brunner, P. H., & Ossberger, M. (2016). The life cycle energy demand and greenhouse gas emissions of high-capacity urban transport systems: A case study from Vienna's subway line U2. *International Journal of Sustainable Transportation*, *10*(2), 120–130. https://doi.org/10.1080/15568318.2013.869704

Lee, S., & Lee, B. (2020). Comparing the impacts of local land use and urban spatial structure on household VMT and GHG emissions. *Journal of Transport Geography*, *84*, 102694. https://doi.org/10.1016/j.jtrangeo.2020.102694

Lees, L. (2000). A reappraisal of gentrification: Towards a 'geography of gentrification.' *Progress in Human Geography*, *24*(3), 389–408.

Leon, B. M., & Maddox, T. M. (2015). Diabetes and cardiovascular disease: Epidemiology , biological mechanisms , treatment recommendations and future research. *World Journal of Diabetes*, *6*(13), 1246–1258. https://doi.org/10.4239/wjd.v6.i13.1246

Lesage, A., Vasiliadis, H. M., Gagné, M. A., Dudgeon, S., Kasman, N., & Hay, C. (2012). *Prevalence of mental illnesses and related service utilization in Canada: An analysis of the Canadian Community Health Survey. Mississauga, ON: Canadian Collaborative Mental Health Initiative; 2006*.

Levelton Engineering Ltd. (2002). *Marine Vessel Air Emissions in B.C. and Washington State outside the GVRD and FVRD for the Year 2000*. Greater Vancouver Regional District. https://georgiastrait.org/wp-content/uploads/2015/03/MarineVesselEmission2000Outside.pdf

Ley, D. (1986). Alternative Explanations for Inner-City Gentrification: A Canadian Assessment. *Annals of the Association of American Geographers*, *76*(4), 521–535. https://doi.org/10.1111/j.1467-8306.1986.tb00134.x

Ley, D. (2003). Artists, Aestheticisation and the Field of Gentrification. *Urban Studies*, *40*(12), 2527–2544. https://doi.org/10.1080/0042098032000136192

DRAFT

Ley, D., & Dobson, C. (2008). Are There Limits to Gentrification? The Contexts of Impeded Gentrification in Vancouver. *Urban Studies*, *45*(12), 2471–2498. https://doi.org/10.1177/0042098008097103

Li, T., Qi, G.-J., & Stern, R. (2022). Taxi Utilization Rate Maximization by Dynamic Demand Prediction: A Case Study in the City of Chicago. *Transportation Research Record*, *2676*(4), 367–379. https://doi.org/10.1177/03611981211059769

Li, T., Wu, X., Ban, X., & Wang, Y. (2020, August). *"Centralized" Taxi Services in Big Metropolitan Areas: Evidenced by Chicago Data*. International Conference on Transportation and Development 2020American Society of Civil Engineers. https://trid.trb.org/view/1735651

Liao, B., E. W. Van Den Berg, P., Van Wesemael, P. J. V., & A. Arentze, T. (2020). How Does Walkability Change Behavior? A Comparison between Different Age Groups in the Netherlands. *International Journal of Environmental Research and Public Health*, *17*(2), 540. https://doi.org/10.3390/ijerph17020540

Lim, G. Y., Tam, W. W., Lu, Y., Ho, C. S., Zhang, M. W., & Ho, R. C. (2018). Prevalence of depression in the community from 30 countries between 1994 and 2014. *Scientific Reports*, *8*(1), 2861.

Liu, Y., Wang, R., Xiao, Y., Huang, B., Chen, H., & Li, Z. (2019). Exploring the linkage between greenness exposure and depression among Chinese people: Mediating roles of physical activity, stress and social cohesion and moderating role of urbanicity. *Health & Place*, *58*, 102168.

Logtenberg, R., Pawley, J., & Saxifrage, B. (2018). *Comparing Fuel and Maintenance Costs of Electric and Gas Powered Vehicles in Canada*. 2 Degrees Institute.

Ma, J., Heppenstall, A., Harland, K., & Mitchell, G. (2014). Synthesising carbon emission for mega-cities: A static spatial microsimulation of transport CO2 from urban travel in Beijing. *Computers, Environment and Urban Systems*, *45*, 78–88. https://doi.org/10.1016/j.compenvurbsys.2014.02.006

Maas, J., Verheij, R. A., de Vries, S., Spreeuwenberg, P., Schellevis, F. G., & Groenewegen, P. P. (2009). Morbidity is related to a green living environment. *Journal of Epidemiology & Community Health*, *63*(12), 967–973.

Maas, J., Verheij, R. A., Spreeuwenberg, P., & Groenewegen, P. P. (2008). Physical activity as a possible mechanism behind the relationship between green space and health: A multilevel analysis. *BMC Public Health*, *8*, 1–13.

Mackenbach, J. D., Rutter, H., Compernolle, S., Glonti, K., Oppert, J. M., Charreire, H., De Bourdeaudhuij, I., Brug, J., Nijpels, G., & Lakerveld, J. (2014). Obesogenic environments: A systematic review of the association between the physical

DRAFT

environment and adult weight status, the SPOTLIGHT project. *BMC Public Health*, *14*(1). https://doi.org/10.1186/1471-2458-14-233

Mahmud, M. A. P., Huda, N., Farjana, S. H., & Lang, C. (2019). Comparative Life Cycle Environmental Impact Analysis of Lithium-Ion (LiIo) and Nickel-Metal Hydride (NiMH) Batteries. *Batteries*, *5*(1), Article 1. https://doi.org/10.3390/batteries5010022

Mair, C., Roux, A. V. D., & Galea, S. (2008). Are neighbourhood characteristics associated with depressive symptoms? A review of evidence. *Journal of Epidemiology & Community Health*, *62*(11), 940–946.

Majeau-Bettez, G., Hawkins, T. R., & Strømman, A. H. (2011). Life Cycle Environmental Assessment of Lithium-Ion and Nickel Metal Hydride Batteries for Plug-In Hybrid and Battery Electric Vehicles. *Environmental Science & Technology*, *45*(10), 4548–4554. https://doi.org/10.1021/es103607c

Marcuse, P. (1985). Gentrification, abandonment, and displacement: Connections, causes, and policy responses in New York City. *Wash. UJ Urb. & Contemp. L.*, *28*, 195.

Martin, E., & Shaheen, S. (2016). *Impacts of car2go on Vehicle Ownership, Modal Shift, Vehicle Miles Traveled, and Greenhouse Gas Emissions: An Analysis of Five North American Cities*. Transportation Sustainability Research Center. https://tsrc.berkeley.edu/publications/impacts-car2go-vehicle-ownership-modal-shift-vehicle-miles-traveled-and-greenhouse-gas

Martínez, J., Pearson, M., & Sørensen, B. H. (2012). *Evaluation of the Health Results Innovation Trust Fund*. Norad Evaluation Department.

McCormack, G. R., & Shiell, A. (2011). In search of causality: A systematic review of the relationship between the built environment and physical activity among adults. *International Journal of Behavioral Nutrition and Physical Activity*, *8*, 1–11.

McElhanney. (2018). *2017 Vancouver Panel Survey*. City of Vancouver. https://vancouver.ca/files/cov/2017-transportation-panel-survey-final-draft-20180516.pdf

McKinnish, T., Walsh, R., & White, T. K. (2010). Who Gentrifies Low-Income Neighborhoods? *Journal of Urban Economics*, *67*(2), 180–193. https://doi.org/10.1016/j.jue.2009.08.003

Meegan, R., & Mitchell, A. (2001). "It's not community round here, it's neighbourhood": Neighbourhood change and cohesion in urban regeneration policies. *Urban Studies*, *38*(12), 2167–2194.

DRAFT

Mehta, U., Wilt, G. E., Okereke, O. I., Coull, B., James, P., Laden, F., Iyer, H. S., Deville, N. V, & Hart, J. E. (2022). Interactions between multiple environmental factors and associations with generalized anxiety disorder in Nurses' Health Study II. *ISEE Conference Abstracts*, *2022*(1).

Metro Vancouver. (2014). *The Metro Vancouver Car Share Study: Technical Report*. https://learn.sharedusemobilitycenter.org/overview/the-metro-vancouver-car-share-study-technical-report-british-columbia-canada-2014/

Metro Vancouver. (2018). *2015 Lower Fraser Valley Air Emissions Inventory and Forecast* [Final Report]. https://metrovancouver.org/services/air-quality-climate-change/Documents/lower-fraser-valley-air-emissions-inventory-forecast-2015.pdf#search=2015%20emission%20inventory

Metro Vancouver. (2020). *Regional Land Use Designation*. http://www.metrovancouver.org:80/metro2040/land-use-designation/Pages/default.aspx

Miao, K. (2012). *Performance-Based Funding of Higher Education* (p. 12). Center for American Progress.

Michael, Y., Gold, R., Perrin, N., & Hillier, T. (2013). Built environment and change in body mass index in older women. *Health Place.*, *22*(July), 7–10. https://doi.org/10.1016/j.healthplace.2013.02.001

Mills, K. T., Stefanescu, A., & He, J. (2020). The global epidemiology of hypertension. *Nature Reviews Nephrology*, *16*(April). https://doi.org/10.1038/s41581-019-0244-2

Mio, A., Fermeglia, M., & Favi, C. (2022). A critical review and normalization of the life cycle assessment outcomes in the naval sector. Articles description. *Journal of Cleaner Production*, *370*, 133476. https://doi.org/10.1016/j.jclepro.2022.133476

Mitchell, R. J., Richardson, E. A., Shortt, N. K., & Pearce, J. R. (2015). Neighborhood environments and socioeconomic inequalities in mental well-being. *American Journal of Preventive Medicine*, *49*(1), 80–84.

Mitchell, R., & Popham, F. (2007). Greenspace, urbanity and health: Relationships in England. *Journal of Epidemiology & Community Health*, *61*(8), 681–683.

Mitchell, R., & Popham, F. (2008). Effect of exposure to natural environment on health inequalities: An observational population study. *The Lancet*, *372*(9650), 1655–1660.

Moreira, T. C. L., Polize, J. L., Brito, M., da Silva Filho, D. F., Chiavegato Filho, A. D. P., Viana, M. C., Andrade, L. H., & Mauad, T. (2022). Assessing the impact of urban environment and green infrastructure on mental health: Results from the São

DRAFT

Paulo Megacity Mental Health Survey. *Journal of Exposure Science & Environmental Epidemiology*, *32*(2), 205–212.
Musgrove, P. (2011). *Financial and Other Rewards for Good Performance or Results: A Guided Tour of Concepts and Terms and a Short Glossary* (p. 12). World Bank.
Mytton, O. T., Townsend, N., Rutter, H., & Foster, C. (2012). Green space and physical activity: An observational study using Health Survey for England data. *Health & Place*, *18*(5), 1034–1041.
Natural Resources Canada. (2010). *Canadian Vehicle Survey 2008 Update Report*. Governement of Canada. https://oee.nrcan.gc.ca/publications/statistics/cvs08/summary.cfm?attr=0
Natural Resources Canada. (2022). *Fuel consumption ratings*. https://open.canada.ca/data/en/dataset/98f1a129-f628-4ce4-b24d-6f16bf24dd64
Newman, K., & Wyly, E. K. (2006). The Right to Stay Put, Revisited: Gentrification and Resistance to Displacement in New York City. *Urban Studies*, *43*(1), 23–57. https://doi.org/10.1080/00420980500388710
Ng, E., Vanderloo, S. E., Geiss, L., & Johnson, J. A. (2013). Concordance between self-report and a survey-based algorithm for classification of type 1 and type 2 diabetes using the 2011 population-based survey on living with chronic diseases in canada (slcdc)-diabetes component. *Canadian Journal of Diabetes*, *37*(4), 249–253. https://doi.org/10.1016/j.jcjd.2013.05.007
Nordelöf, A., Romare, M., & Tivander, J. (2019). Life cycle assessment of city buses powered by electricity, hydrogenated vegetable oil or diesel. *Transportation Research Part D: Transport and Environment*, *75*, 211–222. https://doi.org/10.1016/j.trd.2019.08.019
Núñez-González, S., Delgado-Ron, J. A., Gault, C., Lara-Vinueza, A., Calle-Celi, D., Porreca, R., & Simancas-Racines, D. (2020). Overview of “systematic reviews” of the built environment’s effects on mental health. *Journal of Environmental and Public Health*, *2020*.
OECD. (2020). *Resourcing Higher Education: Challenges, Choices and Consequences*. OECD. https://doi.org/10.1787/735e1f44-en
Ontario. (2018, May 9). *College and university Strategic Mandate Agreements*. Ontario.Ca. https://www.ontario.ca/page/all-college-and-university-strategic-mandate-agreements
Ortuzar, J., & Willumsen, L. (2011). *Modelling Transport* (4th ed.). Wiley.

DRAFT

Oxman, A. D., Lewin, S., Lavis, J. N., & Fretheim, A. (2009). Support Tools for Evidence-Informed Health Policymaking (stp) 15: Engaging the Public in Evidence-Informed Policymaking. *Health Research Policy and Systems*, *7*(1), 1–9.

Pacific Climate Impacts Consortium. (2020). *BC Station Data Portal*. https://pacificclimate.org/data/bc-station-data-portal-notice

Pardy, A. (2018). *Densification of Vancouver's neighbourhoods: Energy use, emissions, and affordability* [Simon Fraser University]. https://summit.sfu.ca/item/18772

Pearson, C., Janz, T., & Ali, J. (2013a). *Mental and substance use disorders in Canada*. Statistics Canada Ottawa, ON.

Pearson, C., Janz, T., & Ali, J. (2013b). *Mental and substance use disorders in Canada*. Statistics Canada Ottawa, ON.

Pearson, M., Johnson, M., & Ellison, R. (2010). *Review of major Results Based Aid (RBA) and Results Based Financing (RBF) schemes* (p. 98). DFID Human Development Resource Centre.

Perakis, R., & Savedoff, W. (2015). Does results-based aid change anything? Pecuniary interests, attention, accountability and discretion in four case studies. *CGD Policy Paper*, *52*.

Perakis, R., & Savedoff, W. D. (2014). An Introduction to Cash on Delivery Aid for Funders. *Note. Washington, DC: CGD*.

Pereira, R. H. M., Saraiva, M., Herszenhut, D., Braga, C. K. V., & Conway, M. W. (2021). r5r: Rapid Realistic Routing on Multimodal Transport Networks with R^5 in R. *Findings*. https://doi.org/10.32866/001c.21262

Perrino, T., Lombard, J., Rundek, T., Wang, K., Dong, C., Gutierrez, C. M., Toro, M., Byrne, M. M., Nardi, M. I., Kardys, J., Szapocznik, J., & Brown, S. C. (2019). Neighbourhood greenness and depression among older adults. *Br J Psychiatry*, *215*(2), 476–480. https://doi.org/10.1192/bjp.2019.129

Pinault, L., Khan, S., & Tjepkema, M. (2020). Accuracy of matching residential postal codes to census geography. *Health Reports*, *31*(3), 3–13. https://doi.org/10.25318/82-003-x202000300001-eng

Poister, T. H., Aristigueta, M. P., & Hall, J. L. (2014). *Managing and Measuring Performance in Public and Nonprofit Organizations: An Integrated Approach*. John Wiley & Sons, Incorporated. http://ebookcentral.proquest.com/lib/utoronto/detail.action?docID=1776337

Pommier, R., Grimaud, G., Prinçaud, M., Perry, N., & Sonnemann, G. (2016). Comparative environmental life cycle assessment of materials in wooden boat

DRAFT

ecodesign. *International Journal of Life Cycle Assessment*, *21*(2), 265–275. https://doi.org/10.1007/s11367-015-1009-1

Pourahmadiyan, A., Ahmadi, P., & Kjeang, E. (2021). Dynamic simulation and life cycle greenhouse gas impact assessment of CNG, LNG, and diesel-powered transit buses in British Columbia, Canada. *Transportation Research Part D: Transport and Environment*, *92*, 102724. https://doi.org/10.1016/j.trd.2021.102724

Pun, V. C., Manjourides, J., & Suh, H. H. (2018). Association of neighborhood greenness with self-perceived stress, depression and anxiety symptoms in older US adults. *Environmental Health*, *17*, 1–11.

R Core Team. (2019). *R: A language and environment for statistical computing* (3.3.0) [Computer software]. R Foundation for Statistical Computing. http://www.R-project.org/

Ramos, H., Kaida, L., Singh, D., Pritchard, P., & Wijesingha, R. (2021). The power of a simple index of neighbourhood change: Challenging the perception that there is no such thing as simplicity in creating indexes. *The Canadian Geographer / Le Géographe Canadien*, *n/a*(n/a). https://doi.org/10.1111/cag.12711

RAND. (2016). *Evaluating the World's First Social Impact Bond*. https://www.rand.org/randeurope/research/projects/social-impact-bonds.html

Reichert, A., Holz-Rau, C., & Scheiner, J. (2016). GHG emissions in daily travel and long-distance travel in Germany – Social and spatial correlates. *Transportation Research Part D: Transport and Environment*, *49*, 25–43. https://doi.org/10.1016/j.trd.2016.08.029

Renalds, A., Smith, T. H., & Hale, P. J. (2010). A systematic review of built environment and health. *Family and Community Health*, 68–78.

Requia, W. J., Higgins, C. D., Adams, M. D., Mohamed, M., & Koutrakis, P. (2018). The health impacts of weekday traffic: A health risk assessment of PM2.5 emissions during congested periods. *Environment International*, *111*, 164–176. https://doi.org/10.1016/j.envint.2017.11.025

Rickwood, P., Glazebrook, G., & Searle, G. (2008). Urban Structure and Energy—A Review. *Urban Policy and Research*, *26*(1), 57–81. https://doi.org/10.1080/08111140701629886

Rodriguez, D., Suardi, Mario, Ham, Marcel, Mimmi, Luisa, & Goksu, Amanda. (2014). *Applying Results-Based Financing in Water Investments*. The Global Partnership on Output-Based Aid. https://openknowledge.worldbank.org/handle/10986/16997

Roe, J. J., Thompson, C. W., Aspinall, P. A., Brewer, M. J., Duff, E. I., Miller, D., Mitchell, R., & Clow, A. (2013). Green space and stress: Evidence from cortisol measures

DRAFT

in deprived urban communities. *International Journal of Environmental Research and Public Health*, *10*(9), 4086–4103.
Rose, D. (1984). Rethinking Gentrification: Beyond the Uneven Development of Marxist Urban Theory. *Environment and Planning D: Society and Space*, *2*(1), 47–74. https://doi.org/10.1068/d020047
Rothschild, S. (2019). *An Exploratory Statistical Analysis of Gentrification and Neighborhood Change in Seattle*. 42.
Saarloos, D., Alfonso, H., Giles-Corti, B., Middleton, N., & Almeida, O. P. (2011). The built environment and depression in later life: The health in men study. *The American Journal of Geriatric Psychiatry*, *19*(5), 461–470.
Saelens, B. E., & Handy, S. L. (2008). Built environment correlates of walking: A review. *Medicine and Science in Sports and Exercise*, *40*(7 Suppl), S550-66. https://doi.org/10.1249/MSS.0b013e31817c67a4
Saleh, M., & Hatzopoulou, M. (2020). Greenhouse gas emissions attributed to empty kilometers in automated vehicles. *Transportation Research Part D: Transport and Environment*, *88*, 102567. https://doi.org/10.1016/j.trd.2020.102567
Sallis, J., Cerin, E., Conway, T., Adams, M., Frank, L., Pratt, M., Salvo, D., Schipperijn, J., Smith, G., Cain, K., Davey, R., Kerr, J., Lai, P., Mitas, J., Reis, R., Sarmiento, O., Schofield, G., Troelsen, J., Van Dyck, D., … Owen, N. (2016). Physical activity in relation to urban environments in 14 cities worldwide: A cross-sectional study. *The Lancet*, *387*(10034), 2207–2217. https://doi.org/10.1016/S0140-6736(15)01284-2
Sallis, J. F., Floyd, M. F., Rodríguez, D. A., & Saelens, B. E. (2012). Role of built environments in physical activity, obesity, and cardiovascular disease. *Circulation*, *125*(5), 729–737.
Sallis, J. F., Saelens, B. E., Frank, L. D., Conway, T. L., Slymen, D. J., Cain, K. L., Chapman, J. E., & Kerr, J. (2009). Neighborhood built environment and income: Examining multiple health outcomes. *Social Science and Medicine*, *68*(7), 1285–1293. https://doi.org/10.1016/j.socscimed.2009.01.017
Salmi, J., & Hauptman, A. M. (2006). *Innovations in Tertiary Education Financing:* (p. 98).
San Francisco County Transportation Authority. (2017). *TNCs Today: A Profile of San Francisco Transportation Network Company Activity* [Final Report]. https://www.sfcta.org/sites/default/files/2019-02/TNCs_Today_112917_0.pdf
Sayers, J. (2001). The world health report 2001—Mental health: New understanding, new hope. *Bulletin of the World Health Organization*, *79*(11), 1085.

DRAFT

Schmidt, J. H., & Watson, J. (2014). *Eco Island Ferry: Comparative LCA of island ferry with carbon fibre composite based and steel based structures*. 2.-0 LCA consultants.
Scottish Funding Council. (2020). *Outcome Agreements*. http://www.sfc.ac.uk/funding/outcome-agreements/outcome-agreements.aspx
Shekar, M., & Popkin, B. M. (2020). *Obesity Health and Economic Consequences of an Impending Global Challenge*.
Shekarrizfard, M., Minet, L., Miller, E., Yusuf, B., Weichenthal, S., & Hatzopoulou, M. (2020). Influence of travel behaviour and daily mobility on exposure to traffic-related air pollution. *Environmental Research*, *184*, 109326. https://doi.org/10.1016/j.envres.2020.109326
Shen, Y. (2014). Community building and mental health in mid-life and older life: Evidence from China. *Social Science & Medicine*, *107*, 209–216.
Sider, T., Alam, A., Zukari, M., Dugum, H., Goldstein, N., Eluru, N., & Hatzopoulou, M. (2013). Land-use and socio-economics as determinants of traffic emissions and individual exposure to air pollution. *Journal of Transport Geography*, *33*, 230–239. https://doi.org/10.1016/j.jtrangeo.2013.08.006
Siqueira Junior, J. de A., Lopes, A. A. dos S., Godtsfriedt, C. E. S., Justina, M. D. Della, Paiva, K. M. de, d'Orsi, E., & Rech, C. R. (2022). Neighbourhood walkability and mental health in older adults: A cross-sectional analysis from EpiFloripa Aging Study. *Frontiers in Aging*, *3*, 915292.
Slater, T. (2011). Gentrification of the city. *The New Blackwell Companion to the City*, *1*.
Smetanin, P., Stiff, D., Briante, C., Adair, C. E., Ahmad, S., & Khan, M. (2011). *The life and economic impact of major mental illnesses in Canada: 2011 to 2014. Toronto, ON: RiskAnalytica on behalf of Mental Health Commission of Canada*.
Social Finance. (2016). Connecticut Family Stability. *Social Finance*. https://socialfinance.org/project/connecticut-family-stability/
Spreafico, C., & Russo, D. (2020). Exploiting the Scientific Literature for Performing Life Cycle Assessment about Transportation. *Sustainability*, *12*(18), Article 18. https://doi.org/10.3390/su12187548
(S&T) Squared Consultants Inc. (2022). *GHGenius*. https://www.ghgenius.ca/index.php
Statistics Canada. (n.d.). https://www150.statcan.gc.ca/n1/en/catalogue/92-166-X
Statistics Canada. (2010). *Canadian Vehicle Survey* (Catalogue no. 53-223-X). http://www.statcan.gc.ca/pub/53-223-x/2009000/userinfo-usagerinfo-eng.htm
Statistics Canada. Canadian Community Health Survey, 2019: Mental HealthStatistics. Canada Catalogue no. 11–001-X. (2020). In *The Daily*.

DRAFT

StatsCan. (n.d.). *Canada's national statistical agency—Statistics Canada*. https://www.statcan.gc.ca/eng/start

Steemers, K. (2003). Energy and the city: Density, buildings and transport. *Energy and Buildings*.

Sugiyama, T., Leslie, E., Giles-Corti, B., & Owen, N. (2008). Associations of neighbourhood greenness with physical and mental health: Do walking, social coherence and local social interaction explain the relationships? *Journal of Epidemiology & Community Health*, *62*(5), e9–e9.

Sun, S., & Ertz, M. (2021). Environmental impact of mutualized mobility: Evidence from a life cycle perspective. *The Science of the Total Environment*, *772*, 145014. https://doi.org/10.1016/j.scitotenv.2021.145014

Sundquist, K., Eriksson, U., Mezuk, B., & Ohlsson, H. (2015). Neighborhood walkability, deprivation and incidence of type 2 diabetes: A population-based study on 512,061 Swedish adults. *Health Place*, *0*, 24–30. https://doi.org/10.1016/j.healthplace.2014.10.011

Tarlov, E., Silva, A., Wing, C., Slater, S., Matthews, S. A., Jones, K. K., & Zenk, S. N. (2020a). Neighborhood Walkability and BMI Change: A National Study of Veterans in Large Urban Areas. *Obesity*, *28*(1), 46–54. https://doi.org/10.1002/oby.22611

Tarlov, E., Silva, A., Wing, C., Slater, S., Matthews, S. A., Jones, K. K., & Zenk, S. N. (2020b). Neighborhood Walkability and Body Mass Index Change: A National Study of Veterans in Large Urban Areas. *Obesity (Silver Spring, Md.)*, *28*(1), 46. https://doi.org/10.1002/OBY.22611

Temkin, K., & Rohe, W. (1996). Neighborhood Change and Urban Policy. *Journal of Planning Education and Research*, *15*(3), 159–170. https://doi.org/10.1177/0739456X9601500301

Thielman, J., Rosella, L., Copes, R., Lebenbaum, M., & Manson, H. (2015). Neighborhood walkability: Differential associations with self-reported transport walking and leisure-time physical activity in Canadian towns and cities of all sizes. *Preventive Medicine*, *77*, 174–180. https://doi.org/10.1016/j.ypmed.2015.05.011

Thomassen, M. A., Dalgaard, R., Heijungs, R., & de Boer, I. (2008). Attributional and consequential LCA of milk production. *The International Journal of Life Cycle Assessment*, *13*(4), 339–349. https://doi.org/10.1007/s11367-008-0007-y

Timmermans, E. J., Visser, M., Wagtendonk, A. J., Noordzij, J. M., & Lakerveld, J. (2021). Associations of changes in neighbourhood walkability with changes in walking activity in older adults: A fixed effects analysis. *BMC Public Health*, *21*(1), 1323. https://doi.org/10.1186/s12889-021-11368-6

DRAFT

Toftager, M., Ekholm, O., Schipperijn, J., Stigsdotter, U., Bentsen, P., Grønbæk, M., Randrup, T. B., & Kamper-Jørgensen, F. (2011). Distance to green space and physical activity: A Danish national representative survey. *Journal of Physical Activity and Health*, *8*(6), 741–749.

TransLink. (2013a). *2011 Metro Vancouver Regional Screenline Survey* (p. 64) [Final Report]. TransLink. https://www.translink.ca/-/media/translink/documents/about-translink/customer-service/trip-diary/2011-screenline-survey-report.pdf

TransLink. (2013b). *2011 Metro Vancouver Regional Trip Diary—Analysis Report*. http://www.translink.ca/-/media/Documents/customer_info/translink_listens/customer_surveys/trip_diaries/2011%20Metro%20Vancouver%20Regional%20Trip%20Diary%20%20Analysis%20Report.pdf

TransLink. (2018). *Greater Vancouver Regional Travel Model Phase 3* [Development and Validation Report].

TransLink. (2019). *Transit Service Performance Review* [Final Report]. https://www.translink.ca/plans-and-projects/strategies-plans-and-guidelines/managing-the-transit-network#transit-network-review

TransLink. (2020a). *2021 Business Plan Operating and Capital Budget Summary*. https://www.translink.ca/resources/translink/about%20translink/corporate%20reports/business_plan/2021%20business%20plan%20operating%20and%20capital%20budget%20summary

TransLink. (2020b). *Low Carbon Fleet Transition Plan* [Final Report]. https://www.translink.ca/-/media/translink/documents/about-translink/policies/translink_low_carbon_fleet_transition_plan_2020_02_24.pdf

TransLink. (2022a). *TransLink GTFS - Open Mobility Data* [dataset]. https://transitfeeds.com/p/translink-vancouver/29?p=29

TransLink. (2022b). *Transport 2050* [Regional Transportation Strategy].

Transport Canada. (2020). *Transportation in Canada 2020*. https://tc.canada.ca/sites/default/files/2021-07/transportation_canada_2020_overview_report.pdf

Transport Canada. (2021). *Canadian Vehicle Specifications (CVS)*. https://open.canada.ca/data/en/dataset/913f8940-036a-45f2-a5f2-19bde76c1252

Twardzik, E., Judd, S., Bennett, A., Hooker, S., Howard, V., Hutto, B., Clarke, P., & Colabianchi, N. (2019). Walk Score and objectively measured physical activity within a national cohort. *J Epidemiol Community Health*, *73*(6), 549–556.

DRAFT

United Nations (UN). World Urbanization Prospects 2018. (2018). United Nations. https://www.un.org/development/desa/pd/news/world-urbanization-prospects-2018

U.S. Department of Energy & U.S. Environmental Protection Agency. (2022). *FuelEconomy.Gov*. https://www.fueleconomy.gov/feg/download.shtml

U.S. Environmental Protection Agency. (2016). *MOVES: MOtor Vehicle Emission Simulator* (Version MOVES2014) [Computer software]. https://www.epa.gov/moves/moves-onroad-technical-reports#moves2014

U.S. Environmental Protection Agency. (2019, February 22). *Can I model emissions from Electric, Fuel-Cell, and Hybrid Vehicles and Equipment in MOVES?* [Overviews and Factsheets]. https://www.epa.gov/moves/can-i-model-emissions-electric-fuel-cell-and-hybrid-vehicles-and-equipment-moves

U.S. Environmental Protection Agency. (2022a). *2022 EPA Automotive Trends Report* [Data and Tools]. www.epa.gov/automotive-trends/explore-automotive-trends-data

U.S. Environmental Protection Agency. (2022b). *MOVES Onroad Technical Reports* [Reports and Assessments]. https://www.epa.gov/moves/moves-onroad-technical-reports

Van den Berg, A. E., Maas, J., Verheij, R. A., & Groenewegen, P. P. (2010). Green space as a buffer between stressful life events and health. *Social Science & Medicine*, *70*(8), 1203–1210.

Vancouver Bus Charters. (2021). *Vancouver Bus Charters*. https://vancouverbuscharters.com/#

Vancouver School Bus Charters Inc. (2022). *Vancouver School Bus Charters—Fleet*. https://www.vancouverschoolbus.com/fleet/

Venigalla, M., Dixit, S., & Pulugurtha, S. (2018). A methodology to derive land use specific auto-trip emission footprints from household travel survey data. *Urban, Planning and Transport Research*, *6*(1), 111–128. https://doi.org/10.1080/21650020.2018.1555055

Vivid Economics. (2013). *Results-Based Financing in the Energy Sector: An Analytical Guide* [Text/HTML]. World Bank. https://documents.worldbank.org/en/publication/documents-reports/documentdetail/847181468344642825/Results-based-financing-in-the-energy-sector-an-analytical-guide

DRAFT

Walks, R. A., & Maaranen, R. (2008). Gentrification, Social Mix, and Social Polarization: Testing the Linkages in Large Canadian Cities. *Urban Geography*, *29*(4), 293–326. https://doi.org/10.2747/0272-3638.29.4.293

Wang, A., Stogios, C., Gai, Y., Vaughan, J., Ozonder, G., Lee, S., Posen, I. D., Miller, E. J., & Hatzopoulou, M. (2018). Automated, electric, or both? Investigating the effects of transportation and technology scenarios on metropolitan greenhouse gas emissions. *Sustainable Cities and Society*, *40*, 524–533. https://doi.org/10.1016/j.scs.2018.05.004

Wang, A., Weichenthal, S., Lloyd, M., Hong, K., Saxe, S., & Hatzopoulou, M. (2023). Personal Mobility Choices and Disparities in Carbon Emissions. *Environmental Science & Technology*, *57*(23), 8548–8558. https://doi.org/10.1021/acs.est.2c06993

Wang, R., Liu, Y., Xue, D., & Helbich, M. (2019). Depressive symptoms among Chinese residents: How are the natural, built, and social environments correlated? *BMC Public Health*, *19*(1), 1–8.

Wang, S., Yu, J., & Okubo, K. (2021). Life cycle assessment on the reuse and recycling of the nickel-metal hydride battery: Fleet-based study on hybrid vehicle batteries from Japan. *Journal of Industrial Ecology*, *25*(5), 1236–1249. https://doi.org/10.1111/jiec.13126

Warnecke, C., Röser, F., Hänsel, G., & Höhne, N. (2015). *Connecting the dots: Results-based financing in climate policy*. New Climate Institute.

Weather Underground. (2022). *Vancouver, Canada Weather Conditions*. https://www.wunderground.com/weather/ca/vancouver

Weier, J., & Herring, D. (n.d.). *Measuring vegetation (NDVI & EVI)[Internet]. 2000 [cited 2013 Dec 30]*.

Where Matters: Health & Economic Benefits Study. (n.d.).

(WHO), W. H. O. (2022). *Mental health*. https://www.who.int/news-room/fact-sheets/detail/mental-health-strengthening-our-response

WHO (World Health Organization). (2017). Other common mental disorders: Global health estimates. *Geneva: World Health Organization*, *24*.

WHO (World Health Organization). (2018). *mhGAP operations manual- Mental Health Gap Action Programme*.

Wilson, J., Spinney, J., Millward, H., Scott, D., Hayden, A., & Tyedmers, P. (2013). Blame the exurbs, not the suburbs: Exploring the distribution of greenhouse gas emissions within a city region. *Energy Policy*, *62*, 1329–1335. https://doi.org/10.1016/j.enpol.2013.07.012

DRAFT

World Health Organization (WHO). (n.d.). *Obesity*.
World Health Organization (WHO). (2016). *GLOBAL REPORT ON DIABETES*.
World Health Organization (WHO). (2018). *Global Action Plan on Physical Activity 2018-2030*.
World Health Organization (WHO). (2022). *Global status report on physical activity 2022*.
World Health Organization (WHO). Mental health action plan 2013–2020. (2013).
World Resources Institute (WRI). (2014). *Policy and Action Standard | Greenhouse Gas Protocol*. https://ghgprotocol.org/policy-and-action-standard
World Resources Institute (WRI). (2015). *Scope 2 Guidance | Greenhouse Gas Protocol*. https://ghgprotocol.org/scope_2_guidance
Wu, X., Tao, T., Cao, J., Fan, Y., & Ramaswami, A. (2019). Examining threshold effects of built environment elements on travel-related carbon-dioxide emissions. *Transportation Research Part D: Transport and Environment*, *75*, 1–12. https://doi.org/10.1016/j.trd.2019.08.018
Wyly, E. K., & Hammel, D. J. (1998). Modeling the Context and Contingency of Gentrification. *Journal of Urban Affairs*, *20*(3), 303–326. https://doi.org/10.1111/j.1467-9906.1998.tb00424.x
Xiao, Z., Lenzer Jr., J. H., & Chai, Y. (2017). Examining the Uneven Distribution of Household Travel Carbon Emissions Within and Across Neighborhoods: The Case of Beijing. *Journal of Regional Science*, *57*(3), 487–506. https://doi.org/10.1111/jors.12278
Xu, J., Saleh, M., Wang, A., Tu, R., & Hatzopoulou, M. (2019). Embedding local driving behaviour in regional emission models to increase the robustness of on-road emission inventories. *Transportation Research Part D: Transport and Environment*, *73*, 1–14. https://doi.org/10.1016/j.trd.2019.05.011
Xu, L., Cui, S., Tang, J., Yan, X., Huang, W., & Lv, H. (2018). Investigating the comparative roles of multi-source factors influencing urban residents' transportation greenhouse gas emissions. *Science of The Total Environment*, *644*, 1336–1345. https://doi.org/10.1016/j.scitotenv.2018.07.072
Yang, L., Wang, Y., Han, S., & Liu, Y. (2019). Urban transport carbon dioxide (CO2) emissions by commuters in rapidly developing Cities: The comparative study of Beijing and Xi'an in China. *Transportation Research Part D: Transport and Environment*, *68*, 65–83. https://doi.org/10.1016/j.trd.2017.04.026
Zeileis, A., & Hothorn, T. (2002). Diagnostic Checking in Regression Relationships (lmtest). *R News*, *3*(2), 7–10.

DRAFT

Zhang, Y., Liu, N., Li, Y., Long, Y., Baumgartner, J., Adamkiewicz, G., Bhalla, K., Rodriguez, J., & Gemmell, E. (2023). Neighborhood infrastructure-related risk factors and non-communicable diseases: A systematic meta-review. *Environmental Health: A Global Access Science Source*, *22*(1), 1–15. https://doi.org/10.1186/s12940-022-00955-8

Zhao, E., Walker, P. D., & Surawski, N. C. (2022). Emissions life cycle assessment of diesel, hybrid and electric buses. *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, *236*(6). https://trid.trb.org/view/1937361

Zlatinov, A., & Gillette, R. (2018). *Implementation of California's AB1837 Pay for Success Initiative and Opportunities for Expanded Impact* (p. 4). Harvard Kennedy School.

Zwiers, M., Kleinhans, R., & Van Ham, M. (2017). The Path-Dependency of Low-Income Neighbourhood Trajectories: An Approach for Analysing Neighbourhood Change. *Applied Spatial Analysis and Policy*, *10*(3), 363–380. https://doi.org/10.1007/s12061-016-9189-z

DRAFT

15. Appendix E: Health Impacts - Full Article - Multifaceted Impacts of Green Space and Walkability on Mental Health: Depression and Anxiety in Focus

15.1. Background

Mental health refers to the overall state of an individual's well-being and their capacity to positively impact the community, while effectively managing the everyday challenges of stress ((WHO), 2022). The term "mental health conditions" encompasses mental disorders, psychosocial disabilities, and other mental states characterized by considerable distress, impaired functioning, or a potential risk of self-harm (Perrino et al., 2019). Mental disorders have a significant impact on the global burden of disease, affecting communities and people of all ages in both high and low-income countries (WHO (World Health Organization), 2018).

15.1.1. Problem statement:

The World Health Organization (WHO) states that one out of every four individuals will encounter a mental health issue at some stage during their lifetime (Sayers, 2001). During 2019, approximately 970 million individuals, which accounts for 1 in every 8 people worldwide, were experiencing a mental disorder, with anxiety and depressive disorders being the most prevalent conditions (Núñez-González et al., 2020). Mental health is a matter of concern for a substantial number of Canadians as well, as it is estimated that 1 in 5 Canadians will experience some sort of mental health condition during their lifetime (Lesage et al., 2012) and the prevalence of Canadian individuals living with mental illness is expected to rise by 31% in the next three decades (Smetanin et al., 2011).

Mental disorders not only compromise individual well-being but also have substantial socio-economic repercussions, including increased healthcare costs and loss of productivity (Kessler et al., 2009; WHO (World Health Organization), 2017). Research

DRAFT

indicates that mental illness ranks among the most expensive health conditions in Canada (Smetanin et al., 2011). Approximately $14.3 billion of public funds were allocated to mental health services and supports in 2007-2008, constituting 7.2% of the overall government health expenditure (Jacobs et al., 2010). The global cost of mental disorders was estimated to be 2.5 trillion USD in 2010, and these costs could rise to six trillion USD by 2030 (Bloom et al., 2012).

Depression stands as a significant public health issue affecting 344 million individuals globally in 2019 ("GBD Mental Disorders Collaborators. Global, Regional, and National Burden of 12 Mental Disorders in 204 Countries and Territories, 1990–2019: A Systematic Analysis for the Global Burden of Disease Study 2019," 2022). Based on the 2012 Canadian Community Health Survey (CCHS), approximately 4.7% of Canadians aged 15 and above exhibited symptoms consistent with a diagnosis of major depression (C. Pearson et al., 2013a). The research indicates that depression is estimated to affect approximately 10.8% of the global population throughout their lifetime (Lim et al., 2018). While it is estimated that about 11.3% of Canadians experienced a major depressive episode at some point in their lives (C. Pearson et al., 2013b).

Depression is identified by symptoms such as a loss of interest or enjoyment in activities, decreased energy levels, and depressed mood (World Health Organization, 2017) (2). Depression differs from normal mood fluctuations and daily emotional responses. During a depressive episode, individuals experience persistent feelings of sadness, irritability, or emptiness, along with reduced interest in activities, lasting for most of the day, nearly every day, for at least two weeks. Additional symptoms include difficulty concentrating, overwhelming guilt or low self-esteem, a sense of hopelessness about the future, thoughts of death or suicide, disrupted sleep, appetite changes, and persistent fatigue (Perrino et al., 2019).

Anxiety disorders stand as the second most common mental disorders globally, affecting approximately 301 million individuals in 2019 (Núñez-González et al., 2020). These disorders are characterized by intense feelings of fear and worry, accompanied by associated behavioral disturbances. The severity of these symptoms is significant enough to cause either notable distress or substantial impairment in daily functioning (Perrino et al., 2019). In the Canadian context, the prevalence of diagnosed mood and anxiety disorders has shown a notable increase. In 2019, it was estimated that about 4.4 million Canadians, or 14% of those aged 12 and older residing in the provinces, had a diagnosed mood or anxiety disorder. This shows an increase from 3.7 million individuals, or 12%, in

DRAFT

2015. Importantly, this rise has been particularly significant among young adults aged 18 to 34, where the prevalence increased from 13% in 2015 to 17% in 2019 (“Statistics Canada. Canadian Community Health Survey, 2019: Mental HealthStatistics. Canada Catalogue No. 11–001-X,” 2020).

Mental health is influenced by a multifaceted interplay of factors, extending beyond individual characteristics to encompass a range of health determinants. These include elements at the individual, family, community, and structural levels, all of which can either bolster or compromise mental well-being (Perrino et al., 2019; Shen, 2014; *World Health Organization (WHO). Mental Health Action Plan 2013–2020*, 2013). Hirschfeld and Weismann (2002) identified several risk factors for depression, such as being female, having medical illnesses, experiencing early-life trauma, and facing adverse life events. These risk factors encompass various individual-level attributes, underscoring the significance of investigating environmental risk factors as well in understanding this major public health concern (Hirschfeld & Weissman, 2002).

The built environment encompasses the human-made infrastructure and arrangement, which includes urban green spaces, road and pedestrian networks, as well as residential and commercial establishments (J. F. Sallis et al., 2012). It plays a role in influencing health through factors such as dietary choices, physical activity, circadian rhythm, hormonal changes, air pollution, and other environmental exposures (Bird et al., 2018; L. D. Frank et al., 2019; Koren & Butler, 2006). One review revealed that higher population density, greater land-use mix, and increased availability of retail goods were associated with higher depressive symptoms, while walking-friendly neighourhoods were linked to lower depressive symptoms in adults 65 years old or above (Julien et al., 2012). On the other hand, another review found that measures of the built environment showed more consistent associations with depression compared to socio-economic factors (Mair et al., 2008). Renalds and colleagues further argued that the built environment could be a fundamental asset in promoting general health and wellness (Renalds et al., 2010).

Among the various built environment factors, walkability has been hypothesized to have a considerable impact on mental health outcomes (Sugiyama et al., 2008). Walkability refers to the convenience and attractiveness of walking in a given environment, often assessed through a Walkability Index that includes parameters such as street connectivity, density, and land-use mix (L. D. Frank et al., 2019). Walkability indices have been found to be linked with physical activity (Camhi et al., 2019; Twardzik et al., 2019).

Nevertheless, there have been limited studies examining the relationship between walkability and depression or anxiety, and the results have been inconclusive.

Multiple research studies have indicated that besides built environment, components of natural environment such as green spaces have the potential to enhance overall well-being (Grant et al., 2012), self-assessed health status (Maas et al., 2008; R. Mitchell & Popham, 2007), promote increased physical activity levels (Mytton et al., 2012; Toftager et al., 2011), reduce morbidity, and increase life expectancy (Maas et al., 2009). Moreover, access to green areas has been associated with greater satisfaction regarding housing, jobs, and life perspectives (Kaplan & Kaplan, 1989). Furthermore, access to green areas is a factor that has been gaining attention for its potential impact on mental health and well-being too (Beyer et al., 2014; Hartig, 2008; R. J. Mitchell et al., 2015). Studies have linked environmental greenness to reduced symptoms of depression, stress, and anxiety in adult populations (Beyer et al., 2014; Groenewegen et al., 2006; Roe et al., 2013). The underlying mechanisms for these effects include attention restoration, reduced rumination, stress reduction, increased physical activity, and improved social contact and support (Bratman et al., 2015; Y. Fan et al., 2011; Roe et al., 2013; Van den Berg et al., 2010). Notably, Mitchell et al. proposed that greater exposure to green spaces could mitigate the negative impacts of income disparities on mental health and mortality, suggesting a viable strategy for tackling health inequalities (R. J. Mitchell et al., 2015; R. Mitchell & Popham, 2008).

The association of built and natural environment with mental health remains an underexplored domain. While some studies have found a positive correlation between increased walkability or green space and reduced levels of depression and anxiety (Beyer et al., 2014; Hartig et al., 2014), the relationships are often not straightforward, and the mechanisms underlying these associations are not fully understood (McCormack & Shiell, 2011). The findings from this study could guide urban planning efforts to focus on the mental health of residents. Given the ongoing global shift towards city living (*United Nations (UN). World Urbanization Prospects 2018*, 2018), using evidence-based strategies to improve mental well-being through changes in the environment is both relevant and crucial.

The primary objective of this study is to investigate the relationship between key elements of the urban environment—specifically, walkability and green space—and clinically

DRAFT

diagnosed depression and anxiety. Complementing this, the secondary objective aims to delve into the underlying mechanisms that drive these associations. To accomplish this, we explore how varying levels of walkability and green space correlate with specific symptoms characteristic of depression (e.g., little interest or pleasure in doing things, sleep disturbances) and anxiety (e.g., nervousness, restlessness).

15.2. Methods

15.2.1. Data sources:

The study integrated data from three sources: BC Generations Project (BCGP) (BCGP, 2019), the Canadian Urban Environmental Health Research Consortium (CANUE) (CANUE, n.d.), and the Where Matters: Health & Economic Benefits Study (*Where Matters: Health & Economic Benefits Study*, n.d.). This analysis involve secondary data analysis of the mental health variables from BC Generations Project (BCGP) (BCGP, 2019), along with environmental measures associated with these cohorts from The Canadian Urban Environmental Health Research Consortium (CANUE) (CANUE, n.d.) and the Where Matters project (*Where Matters: Health & Economic Benefits Study*, n.d.).

15.2.2. Green space assessment:

The normalized difference vegetation index (NDVI) is a widely used measure to assess the the health and density of vegetation in an area, and it is derived from satellite imagery. In plants, chlorophyll efficiently absorbs visible light (0.4–0.7 μm) for photosynthesis, while leaves reflect near-infrared light (0.7–1.1 μm). NDVI is calculated by taking the ratio of the difference between reflectance values of near-infrared wavelength and red wavelength of light to the sum of these two measures (Weier & Herring, n.d.). NDVI values fall within the range of -1 to 1, where higher positive values indicate a denser and healthier presence of vegetation (Fong et al., 2018). The NDVI for the residential neighbourhood is derived from the CANUE dataset. The categories applied for NDVI as a categorical variable is obtained from NDVI quintiles. The NDVI levels used are as follow: very low – 1st quintile (0.22,0.316], low – 2nd quintile (0.316,0.39], medium - 3rd quintile (0.316,0.39], high - 4th quintile (0.39,0.48], very high - 5th quintile (0.48,0.81].

DRAFT

15.2.3. Walkability assessment:

The Where Matters Study (*Where Matters: Health & Economic Benefits Study*, n.d.) constructed a walkability index for the Greater Vancouver region in British Columbia, utilizing postal codes. This index was developed by integrating data from different sources, including Statistics Canada (StatsCan, n.d.) and CanMap (*DMTISpatial. CanMap® GIS Data for GIS Mapping Software - DMTI Spatial.*, n.d.), and it is specifically linked to the BCGP cohort, focusing on residential postal codes. In comparison to the CANUE walkability index, the Where Matters index incorporates extra factors to evaluate walkability and has been established for the years 2006, 2011, and 2016, utilizing the following measures:

a) Residential Density: The number of residential units per acre within a neighourhood.

b) Commercial Density: The area designated for commercial use within a neighourhood.

c) Land use mix: A measure of the different purposes of land use in a neighourhood. A higher value indicates even distribution between purposes of land use such as residential, commercial, entertainment, and office development.

d) Street Connectivity: The number of street intersections in a neighourhood. A larger number of intersections would lead to increased connectivity and movement.

The walkability index used in the current study is the sample standardized walkability index. The categories applied for walkability index as a categorical variable is obtained from walkability index quintiles. The walkability index levels used in the analysis are as follow: very low – 1st quintile [-6.1,-1.86], low – 2nd quintile (-1.86,-0.363], medium - 3rd quintile (-0.363,1.25], high - 4th quintile (1.25,3.03], very high - 5th quintile (3.03,13.8].

Depression and anxiety were evaluated separately as both continuous variables and categorical variables, utilizing a cutoff score of 10 to distinguish between different levels.

Descriptive statistics was used to summarize the characteristics of the study sample, including demographics and relevant variables. Univariate descriptive analysis was conducted to assess the distribution of variables of interest, which includes exposure variables (i.e., NDVI and walkability index), outcome variables (i.e., depression and anxiety), and covariates (i.e., income, education, marital status, health perception,

DRAFT

alcohol, smoking, sleep duration, activity category). Continuous variables were analyzed to reveal means, standard deviations, and interquartile ranges, while categorical variables were presented in terms of frequencies.

The study employed bivariate analysis to examine the relationships between exposure and outcome variables, as well as the associations between covariates and both exposure and outcome variables. The selection of appropriate statistical tests, such as the chi-square test, independent samples t-test, or Pearson's correlation, were determined based on the characteristics of the variables under investigation. Complete case analysis was utilized for the statistical analysis. All statistical computations were performed using R version 4.2.2 ((2023), 2019) with a significance level set at $p < 0.05$ for all tests.

We employed generalized linear models for our multivariable analysis. We examined the relationship between green space and depression, as well as anxiety, and also looked at how walkability correlates with these mental health conditions. Logistic regression was used for analyzing relationships with categorical mental health outcomes, while linear regression was applied for continuous mental health scores. This included overall scores as well as individual components of depression and anxiety questionnaires.

as which controls for confounders and risk factors. First, the logistic regression assumptions was checked for separately for each relationship and further considerations made to address possible issues. Second, an unadjusted model was fitted to analyze the relationship of interest. Currently the following potential adjustment variables or risk factors for the outcome variables are identified based on the literature: age, sex, education level, occupation, income, physical activity, sleep pattern, dietary intake, smoking habits, and alcohol intake. Thus, the hypothesized adjustment variables were included in the DAG and the minimal adjustment set was identified. The variables to be adjusted for in the model were selected by backward selection using the Akaike Information Criteria (AIC). Afterwards, a logistic model was fitted and adjusted for the detected adjustment variables and the unadjusted and adjusted odds ratio with 95% confidence intervals were reported. Additionally, the model’s goodness of fit was assessed by Area Under the Curve (AUC) from Receiver Operating Characteristics (ROC). A sensitivity analysis was performed to compare the participants with complete data and participants with missing values.

DRAFT

15.3. Results

The characteristics of participants stratified by depression is presented in Table 1. The initial sample collected in this study was 9,238. After removing the participants with missing data, a total of 5,085 participants with complete information were considered for the analysis, of which 213 (4.1%) were categorized as depressed, and 4872 (95.8%) as depressed. The mean age of the overall sample was 60.72 years (SD = 9.08).

The distribution of various sociodemographic, behavioral, and environmental factors was examined between the two groups. The sample was predominantly female, with 67.5% females and 32.5% males. There were no significant gender differences between the two groups in terms of depression ($p = 0.081$). However, marital status showed a significant difference; a higher percentage of depressed individuals were single or separated (32.9%) compared to non-depressed participants (24.8%; $p = 0.010$).

Regarding educational attainment, a higher percentage of depressed participants had education level of equal or below bachelor's degree compared to non-depressed participants (84.5% vs. 77.3%) while non-depressed participants had higher percentage of graduate studies (22.7% vs. 15.5). In terms of income distribution, a significantly higher percentage of depressed participants (27.7%) were in the lowest income bracket compared to non-depressed participants (17.3% vs. 17.3%; $p < 0.001$).

Health perception also differed significantly between the groups. Interestingly, a higher percentage of depressed participants compared to the non-depressed group rated their health excellent (6.6% vs. 1.0%), very good (17.4% vs. 5.0%), good (43.2% vs. 25.3%), and fair (28.6% vs. 45.0%) ($p < 0.001$). Moreover, 37.1% of depressed participants had history of depression compared to 5.0% of non-depressed participants. In terms of alcohol consumption, depressed individuals were more likely to be never drinker (8.9% vs. 5.0%) and former drinker (10.8% vs. 4.6%). In terms of smoking status, depressed participants were more likely to be former (39.4% vs. 36.4%) or current smoker (7.0% vs. 2.6%) compared to non-depressed participants.

Significant differences were also found in sleep duration and physical activity levels. Over half of (52.6%) depressed participants reported getting insufficient sleep (less than 7 hours per day), compared to 27.5% in the non-depressed group. Depressed participants were also less active, with 20.2% falling into the lowest activity category, compared to 11.3% for non-depressed individuals ($p < 0.001$).

DRAFT

The characteristics of participants stratified by anxiety is also presented in Table 1. The mean age differed between the two groups, with participants with anxiety being younger (58.08 ± 9.64 years) compared to participants without anxiety (60.84 ± 9.04 years). Gender distribution also varied significantly between the groups, with a higher percentage of females in anxiety group (76.3%) compared to females without anxiety (67.1%), p = 0.005. Marital status, education, and income did not show significant differences between the two groups.

Similar to depressed participants, participants in anxiety group had better health perceptions than those in non-anxiety group, as evidenced by significant differences across the health perception excellent, very good and good categories (p < 0.001). History of depression was significantly more common in participants with anxiety (32.5%) compared to participants without anxiety (5.1%), p < 0.001. Alcohol consumption and smoking habits were also significantly different between the groups, with a lower number of current drinkers (82.5% vs. 90.3%) and higher number of current smokers (6.1% vs. 2.6%) observed in participants with anxiety.

Sleep duration differed dramatically between the groups, with 52.2% of anxiety group sleeping less than 7 hours per day compared to only 27.5% in non-anxiety group, p < 0.001.

A higher percentage of anxiety group reported lower activity levels (18.0%) compared to non-anxiety group (11.4%), and this was statistically significant (p = 0.009).

Table 1- Characteristics of the study participants (n=5085)

	Level	Overall	Depression			Anxiety		
			No	Yes	p-value	No	Yes	p-value
N (%)		5085	4872 (95.8)	213 (4.1)		4857 (95.5)	228 (4.5)	

DRAFT

Age (mean (SD))		60.72 (9.08)	60.81 (9.06)	58.58 (9.31)	**<0.001**	60.84 (9.04)	58.08 (9.64)	**<0.001**
Sex (%)	Male	1651 (32.5)	1594 (32.7)	57 (26.8)	0.081	1597 (32.9)	54 (23.7)	**0.005**
	Female	3434 (67.5)	3278 (67.3)	156 (73.2)		3260 (67.1)	174 (76.3)	
Marital_status (%)	Single or separated	1277 (25.1)	1207 (24.8)	70 (32.9)	**0.010**	1213 (25.0)	64 (28.1)	0.329
	Married or living with partner	3808 (74.9)	3665 (75.2)	143 (67.1)		3644 (75.0)	164 (71.9)	
Education (%)	Less than college	683 (13.4)	648 (13.3)	35 (16.4)	**0.035**	645 (13.3)	38 (16.7)	0.138
	College or bachelor's degree	3265 (64.2)	3120 (64.0)	145 (68.1)		3116 (64.2)	149 (65.4)	
	Master's degree or higher	1137 (22.4)	1104 (22.7)	33 (15.5)		1096 (22.6)	41 (18.0)	
Income (%)	< 50K	901 (17.7)	842 (17.3)	59 (27.7)	**<0.001**	851 (17.5)	50 (21.9)	0.223
	(50k - 70k]	951 (18.7)	914 (18.8)	37 (17.4)		912 (18.8)	39 (17.1)	
	(75k-100k]	945 (18.6)	902 (18.5)	43 (20.2)		898 (18.5)	47 (20.6)	
	>= 100k	2288 (45.0)	2214 (45.4)	74 (34.7)		2196 (45.2)	92 (40.4)	
Health_Perception (%)	Excellent	64 (1.3)	50 (1.0)	14 (6.6)	**<0.001**	55 (1.1)	9 (3.9)	**<0.001**
	Very good	281 (5.5)	244 (5.0)	37 (17.4)		248 (5.1)	33 (14.5)	
	Good	1325 (26.1)	1233 (25.3)	92 (43.2)		1236 (25.4)	89 (39.0)	

DRAFT

	Fair	2253 (44.3)	2192 (45.0)	61 (28.6)		2181 (44.9)	72 (31.6)	
	Poor	1162 (22.9)	1153 (23.7)	9 (4.2)		1137 (23.4)	25 (11.0)	
History of major depression (%)	No	4763 (93.7)	4629 (95.0)	134 (62.9)	**<0.001**	4609 (94.9)	154 (67.5)	**<0.001**
	Yes	322 (6.3)	243 (5.0)	79 (37.1)		248 (5.1)	74 (32.5)	
Alcohol (%)	Never	262 (5.2)	243 (5.0)	19 (8.9)	**<0.001**	243 (5.0)	19 (8.3)	**<0.001**
	Former	249 (4.9)	226 (4.6)	23 (10.8)		228 (4.7)	21 (9.2)	
	Current	4574 (90.0)	4403 (90.4)	171 (80.3)		4386 (90.3)	188 (82.5)	
Smoking (%)	Never	3087 (60.7)	2973 (61.0)	114 (53.5)	**<0.001**	2955 (60.8)	132 (57.9)	**0.006**
	Former	1858 (36.5)	1774 (36.4)	84 (39.4)		1776 (36.6)	82 (36.0)	
	Current	140 (2.8)	125 (2.6)	15 (7.0)		126 (2.6)	14 (6.1)	
Sleep_hr (%)	<= 7 hours	1454 (28.6)	1342 (27.5)	112 (52.6)	**<0.001**	1335 (27.5)	119 (52.2)	**<0.001**
	7 - 9 hours	3570 (70.2)	3480 (71.4)	90 (42.3)		3470 (71.4)	100 (43.9)	
	>= 9 hours	61 (1.2)	50 (1.0)	11 (5.2)		52 (1.1)	9 (3.9)	
Race (%)	White	4289 (84.3)	4111 (84.4)	178 (83.6)	0.824	4101 (84.4)	188 (82.5)	0.477
	Others	796 (15.7)	761 (15.6)	35 (16.4)		756 (15.6)	40 (17.5)	

DRAFT

Activity_category (%)	Low Activity	595 (11.7)	552 (11.3)	43 (20.2)	**<0.001**	554 (11.4)	41 (18.0)	**0.009**
	Moderate Activity	2410 (47.4)	2318 (47.6)	92 (43.2)		2306 (47.5)	104 (45.6)	
	High Activity	2080 (40.9)	2002 (41.1)	78 (36.6)		1997 (41.1)	83 (36.4)	
Walkability index (mean (SD))	N/A	0.72 (3.00)	0.71 (2.99)	1.02 (3.10)	0.141	0.70 (2.99)	1.13 (3.17)	**0.034**
Walkability index quartiles (%)	[-6.1,-1.86]	1053 (20.7)	1013 (20.8)	40 (18.8)	0.419	1015 (20.9)	38 (16.7)	0.179
	(-1.86,-0.363)	989 (19.4)	950 (19.5)	39 (18.3)		944 (19.4)	45 (19.7)	
	(-0.363,1.25)	1023 (20.1)	987 (20.3)	36 (16.9)		977 (20.1)	46 (20.2)	
	(1.25,3.03]	1016 (20.0)	967 (19.8)	49 (23.0)		975 (20.1)	41 (18.0)	
	(3.03,13.8]	1004 (19.7)	955 (19.6)	49 (23.0)		946 (19.5)	58 (25.4)	
NDVI (mean (SD))	N/A	0.35 (0.15)	0.35 (0.15)	0.34 (0.14)	0.374	0.35 (0.15)	0.33 (0.15)	**0.018**
NDVI quartiles (%)	[-0.17, 0.22]	1060 (20.8%)	1017 (20.9%)	43 (20.2%)	0.314	1003 (20.7)	57 (25.0)	0.262
	(0.22, 0.316]	955 (18.8%)	913 (18.7%)	42 (19.7%)		907 (18.7)	48 (21.1)	
	(0.316, 0.39]	1042 (20.5%)	997 (20.5%)	45 (21.1%)		1000 (20.6)	42 (18.4)	
	(0.39, 0.48]	1086 (21.4%)	1032 (21.2%)	54 (25.4%)		1038 (21.4)	48 (21.1)	
	(0.48, 0.81]	942 (18.5%)	913 (18.7%)	29 (13.6%)		909 (18.7)	33 (14.5)	

DRAFT

Table 2.a presents the unadjusted, minimally adjusted, and fully adjusted logistic regression models assessing the association between walkability index levels and the likelihood of depression as categorical variable (n=5085). No significant associations were observed between various levels of walkability and the occurrence of depression in either the unadjusted or adjusted models.

Table 2.b provides the linear regression models evaluating the impact of walkability index levels on the total score of depression among the complete cases (n=5085). The unadjusted model showed a significant association between high walkability and increased total score of depression ($\beta = 0.31$, $p=0.02$) as well as very high walkability ($\beta = 0.45$, $p < 0.001$). However, these associations were not maintained after adjustments for confounding variables in both minimally and fully adjusted models.

Table 2.c presents the linear regression models evaluating the relationship between different levels of walkability and component scores of depression in unadjusted, minimally adjusted, and fully adjusted analyses. In the unadjusted analysis, significant associations were observed for 'High' and 'Very High' walkability levels across multiple depression components. For example, 'High' walkability was significantly associated with interest ($\beta = 0.06$, $p < 0.01$), feeling depressed ($\beta = 0.05$, $p = 0.03$), confidence ($\beta = 0.06$, $p < 0.01$), ability to concentrate ($\beta = 0.04$, $p = 0.04$), and suicidal thoughts ($\beta = 0.02$, $p = 0.03$). 'Very High' walkability showed similar significant associations with interest, feeling depressed, confidence, and ability to concentrate ($p < 0.001$ for all). In the minimally adjusted model, only 'Low' walkability showed a significant association with ability to concentrate ($\beta = 0.05$, $p = 0.02$). 'Very High' walkability remained significant in multiple components including interest ($\beta = 0.05$, $p = 0.02$), feeling depressed ($\beta = 0.05$, $p = 0.02$), confidence ($\beta = 0.05$, $p = 0.04$), and ability to concentrate ($\beta = 0.05$, $p = 0.01$). In the fully adjusted model, no significant associations were observed between walkability levels and any of the depression components.

Table 3.a presents the univariable and multivariable logistic regression analyses exploring the association between the walkability index and anxiety condition using complete cases (n=5085). In the unadjusted model, compared to areas with very low walkability, areas with very high walkability showed a statistically significant increased

DRAFT

odds of anxiety with an odds ratio (OR) of 1.74 (95% CI: 1.16–2.64). This association remained significant in both the minimally adjusted model (OR=1.35, 95% CI: 1.00–1.84) and the fully adjusted model (OR=1.43, 95% CI: 1.03–1.98), suggesting that people living in areas with very high walkability had increased odds of experiencing anxiety, even after adjusting for demographic, lifestyle, and health-related variables.

Table 3.b demonstrates the linear regression analyses on the relationship between walkability index and the total score of anxiety. The unadjusted and fully adjusted models revealed that individuals in areas with very high walkability had a statistically significant increase in the total anxiety score (β=0.46, $p<0.001$; β=0.36, $p<0.01$, respectively). This trend remained even after adjusting for confounding variables, indicating a strong positive association between high walkability and anxiety scores.

Table 3.c displays the results from the linear regression analyses exploring the relationship between walkability index and individual components of anxiety. For areas with very high walkability, the unadjusted analysis showed a statistically significant positive association across multiple components, such as 'Nervous' (β=0.11, $p<0.0001$), 'Worrying1' (β=0.08, $p<0.001$), and 'Afraid' (β=0.05, $p=0.01$). This relationship generally held in the minimally and fully adjusted models, particularly for the components 'Nervous' and 'Worrying1' ($p<0.01$).

Table 4.a presents the results from logistic regression analyses examining the association between green space (as measured by NDVI) and depression condition. In the unadjusted model, compared to the reference category of "very low" NDVI, those living in areas with "very high" NDVI showed a reduced odds ratio (OR) of 0.72 (95% CI: 0.47 – 1.10). However, this association was not statistically significant. After adjusting for age, sex, and income in the minimally adjusted model, the OR changed to 0.82 (95% CI: 0.60 – 1.12), still not reaching statistical significance. Finally, in the fully adjusted model, which controlled for additional variables like education, health perception, history of depression, alcohol consumption, smoking, and sleep duration, the OR for the "very high" NDVI category was 0.97 (95% CI: 0.62 – 1.51), indicating no significant relationship between high levels of green space and depression condition.

Table 4.b demonstrates the results from linear regression analyses. In the unadjusted model, a "very high" NDVI was significantly associated with a lower total depression score ($\beta = -0.39$, $p < 0.01$). However, the significance disappeared when adjusting for covariates

DRAFT

in both the minimally and fully adjusted models (β = -0.05, p = 0.64 in the fully adjusted model).

Table 4.c shows the linear regression outcomes for individual components of depression. In the unadjusted model, higher NDVI was significantly associated with lower scores in multiple components, including feeling "depressed" (β = -0.05, p < 0.01), "tired" (β = -0.05, p = 0.08), and "eating" (β = -0.05, p = 0.04). After adjusting for covariates in the minimally and fully adjusted models, most of these significant associations were attenuated, and only a few remained significant, such as an increase in "sleeping" scores (β = 0.08, p = 0.02) and a decrease in "concentrate" scores (β = -0.05, p = 0.01) in the "very high" NDVI category in the fully adjusted model.

In Table 5.a, logistic regression models assessed the association between varying levels of green space (NDVI) and the likelihood of experiencing an anxiety condition. In the unadjusted model, medium (OR: 0.62, 95% CI: 0.41–0.92) and very high (OR: 0.60, 95% CI: 0.39–0.90) levels of NDVI were significantly associated with lower odds of anxiety. However, this association attenuated after adjusting in the minimally adjusted model and further variables in the fully adjusted model (age, sex, income, education, health perception, alcohol, smoking, and sleep duration). In the fully adjusted model, none of the NDVI categories were significantly associated with anxiety (e.g., Medium NDVI OR: 0.92, 95% CI: 0.68–1.23).

Table 5.b presented linear regression models to quantify the association between NDVI and the total anxiety score. In the unadjusted model, higher levels of green space tended to be associated with lower total anxiety scores, although the results were not statistically significant (e.g., High NDVI β: -0.16, p-value: 0.20). This non-significant trend persisted in the minimally and fully adjusted models (e.g., High NDVI in fully adjusted model β: -0.03, p-value: 0.81).

Table 5.c showed the relationship between NDVI and individual components of anxiety. In the unadjusted model, the "Very high" level of NDVI was significantly associated with lower scores in the "Relax" component (β: -0.06, p-value: 0.01). This relationship remained significant in the minimally adjusted model (β: -0.05, p-value: 0.03) but lost significance in the fully adjusted model (β: -0.05, p-value: 0.07). No other significant associations were found between NDVI levels and individual components of anxiety in any of the models.

DRAFT

Table 2.a – Unadjusted, minimally adjusted and fully adjusted logistic regression models using complete cases (n=5085) for the relationship between walkability index and depression condition

Outcome: Depression (No / Yes)			
	Unadjusted model	**Minimally adjusted model[a]**	**Fully adjusted model[b]**
Independent variable	**OR (95%CI)**	**OR (95%CI)**	**OR (95%CI)**
Walkability index			
Very low	Ref	Ref	Ref
Low	1.08 (0.70 – 1.67)	1.11 (0.81 - 1.54)	0.97 (0.61 – 1.53)
Medium	1.07 (0.69 – 1.65)	1.08 (0.78 - 1.49)	0.94 (0.59 – 1.49)
High	1.42 (0.95 – 2.15)	1.23 (0.90 - 1.69)	1.17 (0.76 – 1.83)
Very high	1.37 (0.91 – 2.08)	1.17 (0.86 - 1.61)	1.05 (0.67 – 1.63)

[a] Minimally adjusted model is adjusted for age, sex, and income

[b] Fully adjusted model is adjusted for age, sex, income, education, health perception, history of depression, alcohol, smoking, and sleep duration

Table 2.b - Univariable and multivariable linear regression using complete cases (n=5085) for the relationship between walkability index and the total score of depression

Outcome: Depression total score						
	Unadjusted model		**Minimally adjusted model[a]**		**Fully adjusted model[b]**	
Independent variable	**β**	**p-value**	**β**	**p-value**	**β**	**p-value**
Walkability index						
Very low	Ref		Ref		Ref	
Low	0.12	0.36	0.06	0.68	0.06	0.60
Medium	0.20	0.13	0.06	0.65	-0.01	0.94

DRAFT

High	**0.31**	**0.02 ***	0.16	0.25	0.10	0.41
Very high	**0.45**	**<0.001 ***	0.25	0.06	0.14	0.24

[a] Minimally adjusted model is adjusted for age, sex, and income

[b] Fully adjusted model is adjusted for age, sex, income, education, health perception, history of depression, alcohol, smoking, and sleep duration

Table 2.c – Unadjusted, minimally adjusted and fully adjusted linear regression using complete cases (n=5085) for the relationship between walkability index and the scores of depression components separately.

Outcome: Depression component scores									
	Unadjusted analysis								
	interest	**depressed**	**sleeping**	**tired**	**eating**	**confidence**	**concentrate**	**move**	**suicidal**
	β (p-value)	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**
Walkability index									
Very low	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Low	0.04 (1.68)	0.02 (0.24)	-0.02 (0.49)	0.01 (0.83)	0.01 (0.62)	0.01 (0.56)	0.04 (0.05)	0.01 (0.77)	0.00 (0.93)
Medium	0.03 (0.13)	0.01 (0.49)	0.01 (.81)	0.03 (0.23)	0.02 (0.51)	0.03 (0.17)	**0.04 (0.03*)**	0.02 (0.14)	0.00 (0.72)
High	**0.06 (<0.01*)**	**0.05 (0.03*)**	0.02 (0.56)	0.02 (0.50)	0.01 (0.59)	**0.06 (<0.01*)**	**0.04 (0.04*)**	0.02 (0.08)	0.02 (0.03)
Very high	**0.08 (<0.001*)**	**0.08 (<0.001*)**	0.02 (0.47)	**0.06 (0.05)**	0.04 (0.15)	**0.08 (<0.001*)**	**0.07 (<0.001*)**	0.00 (0.77)	0.02 (0.10)

DRAFT

	Minimally adjusted analysis[a]								
	interest	**depressed**	**sleeping**	**tired**	**eating**	**confidence**	**concentrate**	**move**	**suicidal**
	β (p-value)	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**
Walkability index									
Very low	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Low	0.02 (0.28)	0.01 (0.63)	-0.02 (0.45)	-0.01 (0.87)	-0.01 (0.76)	0.00 (0.87)	**0.05 (0.02)**	0.01 (0.68)	0.00 (0.98)
Medium	0.01 (0.67)	-0.01 (0.81)	-0.01 (0.82)	0.00 (0.88)	-0.01 (0.81)	0.01 (0.56)	0.03 (0.11)	0.01 (0.32)	0.00 (0.69)
High	0.03 (0.17)	0.02 (0.37)	0.01 (0.70)	0.00 (0.93)	-0.01 (0.72)	0.04 (0.07)	0.03 (0.19)	0.01 (0.30)	0.02 (0.10)
Very high	**0.05 (0.02)**	**0.05 (0.02)**	0.01 (0.84)	0.03 (0.30)	0.01 (0.53)	**0.05 (0.04)**	**0.05 (0.01)**	-0.01 (0.51)	0.00 (0.65)

	Fully adjusted analysis[b]								
	interest	**depressed**	**sleeping**	**tired**	**eating**	**confidence**	**concentrate**	**move**	**suicidal**
	β (p-value)	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**
Walkability index									
Very low	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Low	0.03 (0.18)	0.01 (0.67)	-0.01 (0.83)	0.01 (0.70)	-0.01 (0.54)	-0.01 (0.55)	0.03 (0.17)	0.00 (0.96)	0.01 (0.15)
Medium	0.00 (0.98)	0.00 (0.96)	0.00 (0.95)	0.00 (0.95)	-0.03 (0.24)	0.00 (0.9)	0.01 (0.64)	0.00 (0.89)	0.01 (0.54)
High	0.03 (0.22)	0.02 (0.32)	0.03 (0.42)	0.00 (0.91)	-0.02 (0.45)	0.02 (0.28)	0.00 (0.84)	0.00 (0.58)	0.01 (0.16)
Very high	0.04 (0.12)	0.03 (0.13)	0.04 (0.24)	0.03 (0.40)	-0.02 (0.56)	0.02 (0.43)	0.01 (0.57)	-0.01 (0.63)	0.00 (0.64)

DRAFT

[a] Minimally adjusted model is adjusted for age, sex, and income

[b] Fully adjusted model is adjusted for age, sex, income, education, health perception, history of depression, alcohol, smoking, and sleep duration

Table 3.a - Univariable and multivariable logistic regression using complete cases (n=5085) for the relationship between walkability index and anxiety condition

Outcome: Anxiety (Yes – No)			
	Unadjusted model	**Minimally adjusted model[a]**	**Fully adjusted model[b]**
Independent variable	**OR (95%CI)**	**OR (95%CI)**	**OR (95%CI)**
Walkability index			
Very low	Ref	Ref	Ref
Low	1.28 (0.83 – 1.98)	1.18 (0.86 – 1.62)	1.22 (0.88 – 1.70)
Medium	1.32 (0.86 – 2.04)	1.02 (0.74 – 1.42)	1.03 (0.73 – 1.45)
High	1.12 (0.72 – 1.75)	0.96 (0.70 – 1.34)	1.02 (0.72 – 1.43)
Very high	**1.74 (1.16 – 2.64)**	**1.35 (1.00 – 1.84)**	**1.43 (1.03 – 1.98)**

[a] Minimally adjusted model is adjusted for age, sex, and income

[b] Fully adjusted model is adjusted for age, sex, income, education, health perception, alcohol, smoking, and sleep duration

DRAFT

Table 3.b - Univariable and multivariable linear regression using complete cases (n=5085) for the relationship between walkability index and the total score of anxiety

Outcome: Anxiety total score						
	Unadjusted model		**Minimally adjusted model[a]**		**Fully adjusted model[b]**	
Independent variable	**β**	**p-value**	**β**	**p-value**	**β**	**p-value**
Walkability index						
Very low	Ref		Ref		Ref	
Low	0.16	0.23	0.10	0.47	0.10	0.43
Medium	0.04	0.76	0.14	0.53	-0.12	0.37
High	0.12	0.36	-0.01	0.95	-0.01	0.92
Very high	**0.46**	**<0.001**	**0.39**	**<0.01**	**0.36**	**<0.01**

[a] Minimally adjusted model is adjusted for age, sex, and income

[b] Fully adjusted model is adjusted for age, sex, income, education, health perception, alcohol, smoking, and sleep duration

Table 3.c – Unadjusted, minimally adjusted and fully adjusted linear regression using complete cases (n=5085) for the relationship between walkability index and the scores of anxiety components separately.

Outcome: Anxiety component scores

DRAFT

	Unadjusted analysis						
	Nervous	**Worrying1**	**Worrying2**	**Relax**	**Restless**	**Annoyed**	**Afraid**
	β (p-value)	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**
Walkability index							
Very low	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Low	0.02 (0.51)	0.03 (0.21)	0.02 (0.52)	0.03 (0.21)	0.01 (0.71)	0.03 (0.19)	0.02 (0.25)
Medium	0.00 (0.89)	0.00 (0.86)	-0.02 (0.45)	0.02 (0.41)	0.01 (0.52)	0.02 (0.49)	0.02 (0.33)
High	0.03 (0.34)	0.02 (0.36)	0.00 (0.90)	0.03 (0.19)	0.00 (0.89)	0.02 (0.32)	0.03 (0.21)
Very high	**0.11 (<0.0001)**	**0.08 (<0.001)**	**0.06 (0.02)**	**0.09 (<0.001)**	0.03 (0.18)	**0.06 (0.01)**	0.05 (0.01)

	Minimally adjusted analysis[a]						
	Nervous	**Worrying1**	**Worrying2**	**Relax**	**Restless**	**Annoyed**	**Afraid**
	β (p-value)	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**
Walkability index							
Very low	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Low	0.00 (0.95)	0.02 (0.38)	0.00 (0.98)	0.02 (0.36)	0.00 (0.81)	0.03 (0.27)	0.02 (0.37)
Medium	-0.02 (0.38)	-0.01 (0.57)	-0.05 (0.09)	0.01 (0.82)	0.00 (0.88)	0.00 (0.89)	0.00 (0.87)
High	0.01 (0.77)	0.00 (0.96)	-0.02 (0.42)	0.02 (0.45)	-0.02 (0.36)	0.00 (0.86)	0.00 (0.84)
Very high	**0.1 (<0.001)**	**0.07 (0.01)**	0.05 (0.09)	**0.08 (<0.01)**	0.02 (0.36)	**0.05 (0.05)**	0.04 (0.09)

	Fully adjusted analysis[b]						
	Nervous	**Worrying1**	**Worrying2**	**Relax**	**Restless**	**Annoyed**	**Afraid**
	β (p-value)	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**

DRAFT

Walkability index							
Very low	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Low	0.01 (0.71)	0.02 (0.33)	0.00 (0.89)	0.03 (0.31)	0.01 (0.75)	0.02 (0.31)	0.02 (0.43)
Medium	-0.02 (0.39)	-0.02 (0.38)	**-0.54 (0.04)**	0.00 (0.86)	-0.01 (0.79)	-0.01 (0.82)	0.00 (0.97)
High	0.01 (0.79)	0.00 (0.95)	-0.03 (0.33)	0.02 (0.53)	-0.02 (0.36)	0.00 (0.89)	0.01 (0.76)
Very high	**0.09 (<0.001)**	**0.07 (0.01)**	0.04 (0.12)	**0.07 (<0.01)**	0.02 (0.36)	**0.05 (0.04)**	0.03 (0.18)

[a] Minimally adjusted model is adjusted for age, sex, and income

[b] Fully adjusted model is adjusted for age, sex, income, education, health perception, alcohol, smoking, and sleep duration

Table 4.a - Univariable and multivariable logistic regression using complete cases (n=5085) for the relationship between green space (NDVI) and depression condition

Outcome: Depression (Yes – No)			
	Unadjusted model	**Minimally adjusted model[a]**	**Fully adjusted model[b]**
Independent variable	**OR (95%CI)**	**OR (95%CI)**	**OR (95%CI)**
NDVI			
Very low	Ref	Ref	Ref
Low	0.89 (0.60 – 1.33)	0.93 (0.69 – 1.24)	1.05 (0.68 – 1.60)
Medium	0.86 (0.58 – 1.28)	1.06 (0.80 – 1.40)	1.11 (0.74 – 1.68)
High	0.97 (0.66 – 1.44)	1.03 (0.78 – 1.37)	1.10 (0.73 – 1.67)
Very high	0.72 (0.47 – 1.10)	0.82 (0.60 – 1.12)	0.97 (0.62 – 1.51)

[a] Minimally adjusted model is adjusted for age, sex, and income

[b] Fully adjusted model is adjusted for age, sex, income, education, health perception, history of depression, alcohol, smoking, and sleep duration

DRAFT

Table 4.b - Univariable and multivariable linear regression using complete cases (n=5085) for the relationship between green space (NDVI) and the total score of depression

Outcome: Depression total score						
	Unadjusted model		**Minimally adjusted model[a]**		**Fully adjusted model[b]**	
Independent variable	**β**	**p-value**	**β**	**p-value**	**β**	**p-value**
NDVI						
Very low	Ref		Ref		Ref	
Low	-0.12	0.34	-0.06	0.65	0.09	0.42
Medium	-0.11	0.35	0.02	0.89	0.11	0.33
High	-0.19	0.122	0.01	0.94	0.10	0.40
Very high	**-0.39**	**<0.01**	-0.22	0.09	-0.05	0.64

[a] Minimally adjusted model is adjusted for age, sex, and income

[b] Fully adjusted model is adjusted for age, sex, income, education, health perception, history of depression, alcohol, smoking, and sleep duration

DRAFT

Table 4.c – Unadjusted, minimally adjusted and fully adjusted linear regression using complete cases (n=5085) for the relationship between green space (NDVI) and the scores of depression components separately.

Outcome: Depression component scores

Unadjusted analysis

	interest	**depressed**	**sleeping**	**tired**	**eating**	**confidence**	**concentrate**	**move**	**suicidal**
	β (p-value)	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**
NDVI									
Very low	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Low	-0.02 (0.33)	-0.04 (0.05)	0.02 (0.40)	0.02 (0.42)	-0.02 (0.49)	-0.03 (0.10)	-0.03 (0.16)	-0.01 (0.47)	-0.02 (0.07)
Medium	-0.02 (0.23)	-0.04 (0.05)	0.04 (0.13)	-0.02 (0.46)	-0.01 (0.54)	-0.05 (0.02)	0.00 (0.97)	0.00 (0.67)	-0.01 (0.20)
High	-0.03 (0.21)	**-0.02 (<0.01)**	0.04 (0.21)	-0.03 (0.26)	-0.01 (0.61)	**-0.05 (<0.01)**	-0.03 (0.09)	0.00 (0.77)	-0.01 (0.13)
Very high	**-0.06 (<0.01)**	**-0.05 (<0.01)**	0.00 (0.94)	-0.05 (0.08)	**-0.05 (0.04)**	**-0.02 (<0.01)**	**-0.07 (<0.001)**	**-0.03 (0.01)**	**-0.02 (0.01)**

Minimally adjusted analysis[a]

	interest	**depressed**	**sleeping**	**tired**	**eating**	**confidence**	**concentrate**	**move**	**suicidal**
	β (p-value)	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**
NDVI									
Very low	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Low	-0.01 (0.75)	-0.03 (0.09)	0.03 (0.29)	0.01 (0.65)	0.00 (0.92)	-0.02 (0.41)	-0.02 (0.21)	-0.01 (0.63)	-0.01 (0.29)
Medium	0.01 (0.68)	-0.02 (0.21)	0.04 (0.17)	-0.02 (0.55)	0.04 (0.13)	-0.02 (0.30)	0.00 (0.83)	0.01 (0.59)	-0.01 (0.20)
High	0.01 (0.75)	-0.01 (0.61)	0.06 (0.06)	0.00 (0.97)	0.01 (0.54)	-0.01 (0.48)	**-0.04 (0.04)**	0.00 (0.70)	-0.01 (0.15)

DRAFT

Very high	-0.02 (0.28)	-0.03 (0.16)	-0.01 (0.74)	-0.04 (0.15)	0.00 (0.96)	-0.04 (0.09)	**-0.05 (0.01)**	-0.01 (0.47)	-0.02 (0.05)

	Fully adjusted analysis[b]								
	interest	**depressed**	**sleeping**	**tired**	**eating**	**confidence**	**concentrate**	**move**	**suicidal**
	β (p-value)	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**
NDVI									
Very low	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Low	0.01 (0.74)	-0.01 (0.61)	0.05 (0.15)	**0.08 (<0.01)**	0.00 (0.87)	0.00 (0.91)	-0.02 (0.29)	-0.01 (0.47)	**-0.02 (0.03)**
Medium	0.01 (0.76)	-0.01 (0.59)	**0.08 (0.02)**	0.02 (0.43)	0.02 (0.48)	-0.03 (0.22)	0.01 (0.80)	-0.01 (0.56)	-0.01 (0.18)
High	0.03 (0.13)	-0.01 (0.61)	**0.07 (0.04)**	0.00 (0.99)	0.03 (0.17)	-0.01 (0.56)	-0.01 (0.77)	0.01 (0.39)	-0.01 (0.18)
Very high	0.01 (0.78)	0.02 (0.46)	**0.07 (0.03)**	0.04 (0.20)	0.02 (0.48)	-0.01 (0.72)	-0.03 (0.18)	-0.01 (0.31)	-0.02 (0.07)

[a] Minimally adjusted model is adjusted for age, sex, and income

[b] Fully adjusted model is adjusted for age, sex, income, education, health perception, history of depression, alcohol, smoking, and sleep duration

Table 5.a - Univariable and multivariable logistic regression using complete cases (n=5085) for the relationship between green space (NDVI) and anxiety condition

Outcome: Anxiety (Yes – No)			
	Unadjusted model	**Minimally adjusted model[a]**	**Fully adjusted model[b]**
Independent variable	**OR (95%CI)**	**OR (95%CI)**	**OR (95%CI)**

DRAFT

NDVI			
Very low	Ref	Ref	Ref
Low	0.88 (0.60 – 1.27)	0.93 (0.69 – 1.24)	0.96 (0.71 – 1.30)
Medium	**0.62 (0.41 – 0.92)**	0.92 (0.69 – 1.22)	0.92 (0.68 – 1.23)
High	0.71 (0.48 – 1.05)	0.85 (0.63 – 1.13)	0.81 (0.59 – 1.09)
Very high	**0.60 (0.39 – 0.90)**	0.97 (0.73 – 1.30)	0.99 (0.73 – 1.34)

[a] Minimally adjusted model is adjusted for age, sex, and income

[b] Fully adjusted model is adjusted for age, sex, income, education, health perception, alcohol, smoking, and sleep duration

Table 5.b - Univariable and multivariable linear regression using complete cases (n=5085) for the relationship between green space (NDVI) and the total score of anxiety

Outcome: Anxiety total score						
	Unadjusted model		**Minimally adjusted model[a]**		**Fully adjusted model[b]**	
Independent variable	**β**	**p-value**	**β**	**p-value**	**β**	**p-value**
NDVI						
Very low	Ref		Ref		Ref	
Low	-0.11	0.35	0.02	0.86	0.03	0.79
Medium	-0.02	0.90	-0.03	0.84	0.00	1.00
High	-0.16	0.20	-0.02	0.88	-0.03	0.81
Very high	-0.19	0.13	-0.08	0.54	-0.02	0.85

[a] Minimally adjusted model is adjusted for age, sex, and income

DRAFT

[b] Fully adjusted model is adjusted for age, sex, income, education, health perception, alcohol, smoking, and sleep duration

Table 5.c – Unadjusted, minimally adjusted and fully adjusted linear regression using complete cases (n=5085) for the relationship between green space (NDVI) and the scores of anxiety components separately.

Outcome: Anxiety component scores

Unadjusted analysis

	Nervous	Worrying1	Worrying2	Relax	Restless	Annoyed	Afraid
	β (p-value)	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**
NDVI							
Very low	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Low	-0.11 (0.35)	-0.01 (0.54)	-0.02 (0.44)	-0.04 (0.13)	0.00 (0.83)	0.02 (0.28)	**-0.05 (0.02)**
Medium	-0.02 (0.90)	-0.01 (0.66)	0.00 (0.96)	-0.01 (0.59)	0.01 (0.57)	0.02 (0.27)	-0.03 (0.14)
High	-0.16 (0.20)	-0.02 (0.37)	-0.04 (0.13)	-0.03 (0.25)	-0.02 (0.20)	-0.02 (0.49)	-0.02 (0.20)
Very high	-0.19 (0.13)	-0.02 (0.27)	-0.02 (0.38)	**-0.06 (0.01)**	-0.02 (0.17)	0.00 (0.99)	-0.03 (0.10)

Minimally adjusted analysis[a]

	Nervous	Worrying1	Worrying2	Relax	Restless	Annoyed	Afraid
	β (p-value)	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**
NDVI							
Very low	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Low	0.00 (0.94)	0.01 (0.74)	0.00 (0.94)	-0.02 (0.53)	0.01 (0.44)	0.03 (0.15)	-0.03 (0.16)
Medium	-0.01 (0.68)	0.02 (0.41)	-0.01 (0.62)	-0.01 (0.54)	0.03 (0.11)	0.01 (0.57)	-0.02 (0.28)

DRAFT

High	0.00 (0.88)	0.01 (0.77)	-0.01 (0.68)	-0.02 (0.53)	0.01 (0.74)	-0.02 (0.51)	0.00 (0.89)
Very high	0.00 (0.95)	-0.01 (0.77)	0.00 (0.85)	**-0.05 (0.03)**	-0.01 (0.51)	0.02 (0.48)	-0.02 (0.24)

	Fully adjusted analysis[b]						
	Nervous	**Worrying1**	**Worrying2**	**Relax**	**Restless**	**Annoyed**	**Afraid**
	β (p-value)	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**	**β (p-value)**
NDVI							
Very low	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Low	0.01 (0.77)	0.01 (0.63)	0.01 (0.83)	-0.02 (0.53)	0.01 (0.45)	0.03 (0.23)	-0.02 (0.22)
Medium	0.00 (0.96)	-0.01 (0.60)	-0.01 (0.78)	-0.01 (0.65)	0.03 (0.14)	0.02 (0.49)	-0.02 (0.27)
High	0.01 (0.75)	0.01 (0.80)	-0.01 (0.61)	-0.01 (0.58)	0.00 (0.89)	-0.02 (0.36)	-0.01 (0.78)
Very high	0.01 (0.67)	0.00 (0.87)	0.02 (0.48)	-0.05 (0.07)	-0.02 (0.40)	0.02 (0.37)	-0.02 (0.39)

[a] Minimally adjusted model is adjusted for age, sex, and income

[b] Fully adjusted model is adjusted for age, sex, income, education, health perception, alcohol, smoking, and sleep duration

15.4. Discussion

Our study investigated the relationship between walkability index and depression, employing three regression models—unadjusted, minimally adjusted, and fully adjusted—for both categorical and continuous outcomes of depression. In the logistic regression model we did not observe any significant association between walkability index and categorical depression measure in any of the regression models. The continuous outcome analysis, measured as the total score of depression, revealed higher walkability index was associated with a higher depression score in the unadjusted model, reaching statistical significance for high and very high levels. However, these associations

DRAFT

were considerably attenuated in both minimally adjusted and fully adjusted models. The lack of a significant association in the minimally adjusted model, which considered age, sex, and income, suggests that these factors may be confounding the relationship between walkability and depression. This is in line with previous literature that has identified age, sex, and income as significant determinants of mental health. The fully adjusted model further attenuated the relationship between walkability and depression, underscoring the possible role of other variables such as education, health perception, history of depression, alcohol, smoking, and sleep duration in influencing this association. On the other hand, the unadjusted regression model on the association between walkability index and various components of depression showed significant associations between high and very high walkability indices and multiple depression components, namely interest, depressed mood, confidence, concentration, and suicidal thoughts. However, these associations were attenuated in the minimally adjusted and fully adjusted models, suggesting that confounding variables may be playing a considerable role.

Similar to our findings, Guo et al in 2020 showed that walkability was associated with fewer depressive symptoms or continuous total depression score, but this association was not observed in categorical depression in the elderly in Hong Kong. There are some other cross-sectional studies observing an inverse relationship between walkability index and depression among older adults (Keats et al., 2020; Koohsari et al., 2019; R. Wang et al., 2019). In contrary, a cross-sectional study by Koohsari et al in 2023 showed that higher total perceived walkability was also associated with lower odds of having mild depressive symptoms in both men and women, while none of the objective built environment attributes were associated with depressive symptoms in women or men (Koohsari et al., 2023). Another recent cross-sectional study on older adults by Siqueira Junior et al, could not find any association between walkability index and depressive symptoms in either crude or adjusted models (Siqueira Junior et al., 2022).

The observed attenuation in the adjusted models and the mixed findings in the literature raises questions about the possible mechanisms by which walkability might influence depression. It's conceivable that walkability itself is not a direct predictor of depression but rather interacts with other lifestyle and demographic factors. Another explanation could be the "urban paradox," where areas with higher walkability also have higher stressors like noise and pollution, potentially affecting mental health adversely.

DRAFT

The present study aimed to explore the relationship between walkability index and anxiety measures. Both logistic and linear regression models were employed to understand these associations more comprehensively. In the unadjusted model, participants residing in areas with a "very high" walkability index were 1.74 times more likely to report experiencing anxiety compared to those living in areas with a "very low" walkability index. After controlling for age, sex, and income in the minimally adjusted model, the odds ratio decreased to 1.35, and further reduced to 1.43 in the fully adjusted model. Although the magnitude of the relationship attenuated with adjustment, the association remained statistically significant in the fully adjusted model. This suggests that while confounding variables play a role, there is a unique and positive association between high walkability and the likelihood of experiencing anxiety. Similarly, in the linear regression model examining continuous anxiety scores, a significant association was observed in the "very high" walkability index category. In the unadjusted model, living in a "very high" walkability area was associated with a higher total anxiety score. This association remained robust in both minimally adjusted and fully adjusted models, indicating that high walkability is associated with increased total anxiety scores, irrespective of the covariates adjusted for. The current study also aimed to assess the relationship between walkability indices and various components of anxiety. In the unadjusted analysis, a significant association was observed only in the "very high" walkability index category across multiple anxiety components, such as nervousness, worrying1, worrying2, relaxation, annoyance, and fearfulness. After adjusting for age, sex, and income in the minimally adjusted model, we noticed a slight attenuation but the significance was maintained for many of the anxiety components like nervousness, worrying1, and relaxation, particularly in very high walkability areas. Further adjusting for education, health perception, history of depression, alcohol, smoking, and sleep duration in the fully adjusted model did not dramatically alter the outcome, especially in the "very high" walkability index category. This suggests that walkability may indeed have a unique relationship with individual components of anxiety, independent of several other factors.

There is a research gap on the number of studies investigating the association between walkability index and anxiety measure. According to a study performed by Wang et al in 2019, street walkability was negatively associated with Geriatric Depression Scale scores (GDS 15-item) and Geriatric Anxiety Inventory scores (GAI 20-item), and the associations were stronger for disadvantaged older adults than others (R. Wang et al., 2019). In contrary, a study conducted by Mehta et al, revealed that higher walkability was associated with elevated odds of anxiety symptoms (Mehta et al., 2022). While high walkability is generally considered beneficial for physical health, our findings indicate a

DRAFT

complex relationship with emotional and mental well-being. One possible interpretation could be that very high walkability areas are often urban centers with various stressors like noise, crowding, and overstimulation, potentially contributing to multiple facets of anxiety. Understanding these relationships is crucial for healthcare professionals to make more informed recommendations and interventions for mental health in different urban settings.

This study was designed to investigate the relationship between the availability of green space, measured through the Normalized Difference Vegetation Index (NDVI), and both categorical and continuous measures of depression. In the unadjusted logistic regression model, the odds ratios (ORs) were generally below 1, suggesting a potential protective effect of green space on depression, although this was not statistically significant. For the continuous depression score, the unadjusted model found a significant association only in the "very high" NDVI category. When the model was minimally adjusted for age, sex, and income, the ORs and β-values moved closer to 1 and lost their statistical significance, indicating that these factors may partially explain the initial associations seen in the unadjusted model. The fully adjusted model, accounting for additional confounders, also did not find a statistically significant relationship between green space and depression, suggesting that the initial protective effect might be influenced by these other variables.

A cross-sectional study conducted by Klompmakera showed that NDVI 300 m was inversely associated psychological distress which is a combined measure of depressive symptoms and anxiety. However, NDVI 1000m (OR: 0.98) showed no significant association with psychological distress (Klompmaker et al., 2019). According to another study by Saarloos et al in 2011 on elderly men in Australia, higher degrees of land-use mix, specifically through retail availability, independent of other walkability factors including street connectivity and residential density was associated with higher odds of depression in elderly men in Australia (Saarloos et al., 2011). On the other hand, a study by Moreira et al in 2022 found no significant results for depression and percentage of different green spaces within districts (Moreira et al., 2022).

Our findings present a complex narrative. While the unadjusted model suggested a protective role for very high green spaces in reducing depression scores, this effect was attenuated after controlling for confounders. This could imply that the benefits of green spaces may be more complex and potentially confounded by social, economic, or lifestyle factors.

DRAFT

The current study also investigated the impact of green spaces on various components of depression employed three different regression models. In the unadjusted model, NDVI levels mostly showed negative β-values for interest, depressed mood, eating habits, confidence, and concentration; however, the results reached statistical significance only in the "very high" NDVI category for most components except for sleeping and tiredness. Notably, the variables confidence and depressed were significantly impacted even at high levels of NDVI. The minimally adjusted model, accounting for age, sex, and income, showed a dilution of the associations between NDVI levels and most depression components, with only the "concentrate" component in the "very high" NDVI showing a significant relationship ($\beta = -0.05$, $p = 0.01$). In the fully adjusted model, statistical significance was further reduced for most components. Interestingly, the sleeping component showed a significant positive relationship with medium, high and very high NDVI levels, suggesting that higher green space may not necessarily be beneficial for this specific aspect of depression.

A cross-sectional study by Cottagiri et al in 2021 showed an inverse association between self-reported clinical diagnosis of depression in relation to an increase of NDVI within a 500 m buffer of the participant's residence (Cottagiri et al., 2022). There are plenty of research showing the inverse relationship between green space and depression (Cottagiri et al., 2022; Gariepy et al., 2014; Krols et al., 2022; Liu et al., 2019; R. Wang et al., 2019). Interesting, a longitudinal study by Astell-Burt et al in Australia in 2022 revealed that a 10% increase in green space was associated with higher levels of antidepressant prescription (Astell-Burt et al., 2022). In addition, a study by Helbich et al in 2021 showed there was no statistically significant evidence that people with less urban residential greenness had higher depression or anxiety scores than those exposed to higher levels (Helbich et al., 2021).

Inconsistencies in the literature, and attenuation of initial associations in the unadjusted models in the current study when adjusted minimally and fully, underscore the complexity of the impact of green spaces on mental health. For instance, the availability of green space might help improve concentration and confidence but not necessarily sleep quality. This multifaceted impact has implications for public health interventions and urban planning.

Current study also examined the relationship between varying levels of green space and anxiety. In the unadjusted logistic regression model on green space and categorical anxiety, individuals residing in areas with medium and very high NDVI levels were less

DRAFT

likely to report anxiety. However, upon controlling for confounding factors, the strength and significance of these associations were attenuated. In both the minimally adjusted and fully adjusted models, no statistically significant relationships were observed between NDVI levels and the likelihood of experiencing anxiety. For the continuous anxiety scores, no statistically significant relationship was observed in any of the models. The β coefficients in both minimally and fully adjusted models were negligible and not statistically significant, suggesting that green space might not have a measurable impact on the overall anxiety score under the conditions studied. The current study also assessed the relationship between green space, as indicated by the and various components of anxiety. In the unadjusted analysis, living in areas with "Very High" NDVI levels seemed to be somewhat associated with lower scores in the "Relax" component and living in areas with "low" NDVI levels seemed to be somewhat associated with lower scores in the "Afraid" component. In the minimally adjusted model, the significant association for the "Relax" component remained. Interestingly, in the fully adjusted model, the "Relax" component's significant association was slightly attenuated and became marginally non-significant. All other components showed no statistically significant associations with NDVI levels.

In a 2019 study in Quebec Canada, Hystad and colleagues found that in fully controlled models, a small increase (0.1) in local green space, as measured by NDVI within a 500-metre radius, was linked to a reduced likelihood of both depression and moderate anxiety (Hystad et al., 2019). Similarly, in a study by Moreira et al in 2022, The percentage of different green spaces within districts was negatively associated with the presence of anxiety (Moreira et al., 2022). In contrast there are several studies revealing there were no significant association between green space and anxiety (Generaal et al., 2019; Helbich et al., 2021; Pun et al., 2018).

The attenuated effects observed after adjusting for potential confounders suggest that while green spaces may have a mild relaxing effect, this is not sufficiently robust to stand up against a range of socio-economic and lifestyle factors.

15.5. Conclusion

15.5.1. Limitations and Future Directions

It is crucial to acknowledge the limitations of this study. The current study has a limitation in the cross-sectional design, limiting the ability to draw causal inferences. Additionally,

DRAFT

while we adjusted for several potential confounders, unmeasured influential variables, such as social cohesion, neighourhood crime rates, and environmental pollution might still influence the observed associations.

Given these limitations, future research should prioritize longitudinal designs and incorporate a broader set of variables. Qualitative studies could also be invaluable, providing context to the statistical relationships and helping design more effective public health interventions.

15.5.2. Policy Implications

The complexities unveiled in our studies have significant implications for urban planning and healthcare policies. A one-size-fits-all approach to public health interventions based on walkability or green spaces would be insufficient. Policymakers and healthcare providers should adopt a multidimensional approach that accounts for these intricate relationships.

15.6. References

(2023), R. C. T. (2019). R: A language and environment for statistical computing. *R Foundation for Statistical Computing, Vienna, Austria*.

Ace Charters Vancouver. (2023). *Vancouver Shuttle & Charter Service*. Ace Charters Vancouver. https://www.acechartersvancouver.com/

Agbai, C. O. (2021). Shifting neighborhoods, shifting health: A longitudinal analysis of gentrification and health in Los Angeles County. *Social Science Research*, *100*, 102603. https://doi.org/10.1016/j.ssresearch.2021.102603

Allen, J., & Taylor, Z. (2018). A new tool for neighbourhood change research: The Canadian Longitudinal Census Tract Database, 1971-2016: Canadian Longitudinal Tract Database. *The Canadian Geographer / Le Géographe Canadien*, *62*(4), 575–588. https://doi.org/10.1111/cag.12467

Al-Rijleh, M.-K., Alam, A., Foti, R., Gurian, P. L., Spatari, S., & Hatzopoulou, M. (2018). Strategies to achieve deep reductions in metropolitan transportation GHG emissions: The case of Philadelphia. *Transportation Planning and Technology*, *41*(8), 797–815. https://doi.org/10.1080/03081060.2018.1526879

DRAFT

Alshehri, Y. M. (2016). Performance-Based Funding: History, Origins, Outcomes, and Obstacles. *Journal of Higher Education Theory & Practice*, *16*(4).

Antweiler, W., & Gulati, S. (2015). Scrapping for clean air: Emissions savings from the BC SCRAP-IT program. *Journal of Environmental Economics and Management*, *71*, 198–214. https://doi.org/10.1016/j.jeem.2015.03.002

Aquabus. (2022). *Aquabus Granville Island False Creek Ferry*. Aquabus. https://theaquabus.com/

Astell-Burt, T., Navakatikyan, M., Eckermann, S., Hackett, M., & Feng, X. (2022). Is urban green space associated with lower mental healthcare expenditure? *Social Science & Medicine*, *292*, 114503.

Atkinson, R., Wulff, M. G., & Australian Housing and Urban Research Institute. (2009). *Gentrification and displacement: A review of approaches and findings in the literature*. The Institute.

Australia Department of Education. (2020). *Mission based Compacts* [Text]. Department of Education, Skills and Employment; scheme=AGLSTERMS.AglsAgent; corporateName=Department of Education, Skills and Employment; address=50 Marcus Clarke St, Canberra City, ACT 2601; contact=+61 1300 566 046. https://www.dese.gov.au/higher-education-funding/mission-based-compacts

Azarafshar, R., & Vermeulen, W. N. (2020). Electric vehicle incentive policies in Canadian provinces. *Energy Economics*, *91*, 104902. https://doi.org/10.1016/j.eneco.2020.104902

Bailey, N., van Gent, W. P. C., & Musterd, S. (2017). Remaking Urban Segregation: Processes of Income Sorting and Neighbourhood Change. *Population, Space and Place*, *23*(3), e2013. https://doi.org/10.1002/psp.2013

Baker, D. C., Sipe, N. G., & Gleeson, B. J. (2006). Performance-Based Planning: Perspectives from the United States, Australia, and New Zealand. *Journal of Planning Education and Research*, *25*(4), 396–409. https://doi.org/10.1177/0739456X05283450

Barbosa, J. P. D. A. S., Guerra, P. H., Santos, C. de O., Nunes, A. P. de O. B., Turrell, G., & Florindo, A. A. (2019). Walkability, overweight, and obesity in adults: A systematic review of observational studies. *International Journal of Environmental Research and Public Health*, *16*(17). https://doi.org/10.3390/ijerph16173135

Barbosa, S., Guerra, P. H., Santos, C. D. O., Paula, A., Barbosa, D. O., & Turrell, G. (2019). Walkability , Overweight , and Obesity in Adults: A Systematic Review of Observational Studies. *International Journal of Environmental Research and Public Health*, *16*(3135).

DRAFT

Barker, D., Cassidy, J., & Chen, W. (2018). *Paying for Results: Reforming How the Public Sector Funds Social Services*. Bank of America. https://investinresults.org/chapter/paying-results.html

Barla, P., Miranda-Moreno, L. F., & Lee-Gosselin, M. (2011a). Urban travel CO2 emissions and land use: A case study for Quebec City. *Transportation Research Part D: Transport and Environment*, *16*(6), 423–428. https://doi.org/10.1016/j.trd.2011.03.005

Barla, P., Miranda-Moreno, L. F., & Lee-Gosselin, M. (2011b). Urban travel CO2 emissions and land use: A case study for Quebec City. *Transportation Research Part D: Transport and Environment*, *16*(6), 423–428. https://doi.org/10.1016/j.trd.2011.03.005

Barton, M. (2016). An exploration of the importance of the strategy used to identify gentrification. *Urban Studies*, *53*(1), 92–111. https://doi.org/10.1177/0042098014561723

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, *67*(1). https://doi.org/10.18637/jss.v067.i01

BC Ferries. (2022). *Our Fleet*. https://www.bcferries.com/on-the-ferry/our-fleet

B.C. Ministry of Energy, Mines and Petroleum Resources. (2017). *Using GHGenius in B.C.* (Renewable and Low Carbon Fuel Requirements Regulation Information Bulletin RLCF-010). https://www2.gov.bc.ca/assets/gov/farming-natural-resources-and-industry/electricity-alternative-energy/transportation/renewable-low-carbon-fuels/rlcf010_-_using_ghgenius_for_bc.pdf

B.C. Ministry of Environment and Climate Change Strategy. (2017). *Community energy and emissions inventory (CEEI)*. Province of British Columbia. https://www2.gov.bc.ca/gov/content/environment/climate-change/data/ceei

B.C. Ministry of Environment and Climate Change Strategy. (2019). *B.C. Methodological Guidance for Quantifying Greenhouse Gas Emissions*. https://www2.gov.bc.ca/assets/gov/environment/climate-change/cng/methodology/2018-pso-methodology.pdf

B.C. Ministry of Environment and Climate Change Strategy. (2021). *CleanBC Roadmap to 2030*.

BC Ministry of Environment and Climate Change Strategy. (2022). *B.C. Best Practices Methodology for Quantifying Greenhouse Gas Emissions*.

B.C. Ministry of Environment and Climate Change Strategy. (2022). *Electricity emission intensity factors for grid-connected entities—Province of British Columbia*.

DRAFT

Province of British Columbia. https://www2.gov.bc.ca/gov/content/environment/climate-change/industry/reporting/quantify/electricity

BCGP. (2019). *Across Generations: BC Generations Project Newsletter, Winter 2019/20*.

Bel, G., & Rosell, J. (2017). The impact of socioeconomic characteristics on CO2 emissions associated with urban mobility: Inequality across individuals. *Energy Economics*, *64*, 251–261. https://doi.org/10.1016/j.eneco.2017.04.002

Berjisian, E., & Bigazzi, A. (2022). Evaluation of methods to distinguish trips from activities in walking and cycling GPS data. *Transportation Research Part C: Emerging Technologies*, *137*, 103588. https://doi.org/10.1016/j.trc.2022.103588

Beyer, K. M. M., Kaltenbach, A., Szabo, A., Bogar, S., Nieto, F. J., & Malecki, K. M. (2014). Exposure to neighborhood green space and mental health: Evidence from the survey of the health of Wisconsin. *International Journal of Environmental Research and Public Health*, *11*(3), 3453–3472.

Bigazzi, A. (2019). Comparison of marginal and average emission factors for passenger transportation modes. *Applied Energy*, *242*, 1460–1466. https://doi.org/10.1016/j.apenergy.2019.03.172

Bigazzi, A. (2020). Marginal emission factors for public transit: Effects of urban scale and density. *Transportation Research Part D: Transport and Environment*, *88*, 102585. https://doi.org/10.1016/j.trd.2020.102585

Bigazzi, A. Y., & Hassanpour, A. (2022). *Human-electric hybrid vehicles: Implications of new non-auto mobility options for street design and policy in the Vancouver region* (p. 105) [Final Report]. Prepared for TransLink. https://reactlab.civil.ubc.ca/human-electric-hybrid-vehicles/

Bird, E. L., Ige, J. O., Pilkington, P., Pinto, A., Petrokofsky, C., & Burgess-Allen, J. (2018). Built and natural environment planning principles for promoting health: An umbrella review. *BMC Public Health*, *18*(1), 1–13.

Blanco-Davis, E., Castillo, F. del, & Zhou, P. (2014). Fouling release coating application as an environmentally efficient retrofit: A case study of a ferry-type ship. *The International Journal of Life Cycle Assessment*, *19*(10), Article 10. https://doi.org/10.1007/s11367-014-0780-8

Bleyen, P., Klimovský, D., Bouckaert, G., & Reichard, C. (2017). Linking budgeting to results? Evidence about performance budgets in European municipalities based on a comparative analytical model. *Public Management Review*, *19*(7), 932–953. https://doi.org/10.1080/14719037.2016.1243837

DRAFT

Bloom, D. E., Cafiero, E., Jané-Llopis, E., Abrahams-Gessel, S., Bloom, L. R., Fathima, S., Feigl, A. B., Gaziano, T., Hamandi, A., & Mowafi, M. (2012). *The global economic burden of noncommunicable diseases*. Program on the Global Demography of Aging.

Brand, C., & Preston, J. M. (2010). '60-20 emission'—The unequal distribution of greenhouse gas emissions from personal, non-business travel in the UK. *Transport Policy*, *17*(1), 9–19. https://doi.org/10.1016/j.tranpol.2009.09.001

Brander, M., & Ascui, F. (2015). The Attributional-Consequential Distinction and Its Applicability to Corporate Carbon Accounting. In S. Schaltegger, D. Zvezdov, I. Alvarez Etxeberria, M. Csutora, & E. Günther (Eds.), *Corporate Carbon and Climate Accounting* (pp. 99–120). Springer International Publishing. https://doi.org/10.1007/978-3-319-27718-9_5

Brander, M., Gillenwater, M., & Ascui, F. (2018). Creative accounting: A critical perspective on the market-based method for reporting purchased electricity (scope 2) emissions. *Energy Policy*, *112*, 29–33. https://doi.org/10.1016/j.enpol.2017.09.051

Bratman, G. N., Hamilton, J. P., Hahn, K. S., Daily, G. C., & Gross, J. J. (2015). Nature experience reduces rumination and subgenual prefrontal cortex activation. *Proceedings of the National Academy of Sciences*, *112*(28), 8567–8572.

Braun, L., Rodriguez, D., Song, Y., Meyer, K., Lewis, C., Reis, J., & Gordon-Larsen, P. (2016). Changes in walking, body mass index, and cardiometabolic risk factors following residential relocation: Longitudinal results from the CARDIA study. *J Transp Health.*, *3*(4), 426–439. https://doi.org/10.1016/j.jth.2016.08.006

Brown, M., Eldridge, M., & Bieretz, B. (2019). *Performance-Based Strategies: Defining Terms and Comparing Common Strategies* (p. 5). Urban Institute.

Brown, N. M. (2019). *Millennium Challenge Corporation: Overview and Issues* (p. 36). Congressional Research Service.

Bureau of Transportation Statistics, U.S. Department of Transportation. (n.d.). *National Transportation Statistics*. Retrieved December 20, 2017, from http://www.bts.gov/publications/national_transportation_statistics/

Burvill, A. J., Murray, K., Knuiman, M. W., & Hung, J. (2022). Comparing self-reported and measured hypertension and hypercholesterolaemia at standard and more stringent diagnostic thresholds: The cross-sectional 2010–2015 Busselton Healthy Ageing study. *Clinical Hypertension*, *28*(1), 1–10. https://doi.org/10.1186/s40885-022-00199-1

DRAFT

Buzar, S., Ogden, P., Hall, R., Haase, A., Kabisch, S., & Steinfiihrer, A. (2007). Splintering Urban Populations: Emergent Landscapes of Reurbanisation in Four European Cities. *Urban Studies*, *44*(4), 651–677. https://doi.org/10.1080/00420980601185544

Camhi, S. M., Troped, P. J., Garvey, M., Hayman, L. L., Must, A., Lichtenstein, A. H., & Crouter, S. E. (2019). Associations between Walk Score and objective measures of physical activity in urban overweight and obese women. *PLoS One*, *14*(3), e0214092.

CANUE. (n.d.). *The Canadian Urban Environmental Health Research Consortium: Understanding urban living and human health*.

Carlson, J. A., Saelens, B. E., Kerr, J., Schipperijn, J., Conway, T. L., Frank, L. D., Chapman, J. E., Glanz, K., Cain, K. L., & Sallis, J. F. (2017). Association between neighborhood walkability and GPSmeasured walking, bicycling and vehicle time in adolescents. *Health & Place*, *32*, 1–7. https://doi.org/10.1016/j.healthplace.2014.12.008.Association

Carranza, G., Do Nascimiento, M., Fanals, J., Febrer, J., & Valderrama, C. (2022). Life cycle assessment and economic analysis of the electric motorcycle in the city of Barcelona and the impact on air pollution. *Science of The Total Environment*, *821*, 153419. https://doi.org/10.1016/j.scitotenv.2022.153419

Cerin, E., Nathan, A., Van Cauwenberg, J., Barnett, D. W., & Barnett, A. (2017). The neighbourhood physical environment and active travel in older adults: A systematic review and meta-analysis on behalf of the Council on Environment and Physical Activity (CEPA) – Older Adults working group. *International Journal of Behavioral Nutrition and Physical Activity*, *14*(15). https://doi.org/10.1186/s12966-017-0471-5

Cerqueira, E. D. V., Motte-Baumvol, B., Chevallier, L. B., & Bonin, O. (2020). Does working from home reduce CO2 emissions? An analysis of travel patterns as dictated by workplaces. *Transportation Research Part D: Transport and Environment*, *83*, 102338. https://doi.org/10.1016/j.trd.2020.102338

Chan, S., Miranda-Moreno, L., Alam, A., & Hatzopoulou, M. (2013). Assessing the impact of bus technology on greenhouse gas emissions along a major corridor: A lifecycle analysis. *World Transit Research*. https://www.worldtransitresearch.info/research/4746

Chandrabose, M., Cerin, E., Mavoa, S., Dunstan, D., Carver, A., Turrell, G., Owen, N., Giles-Corti, B., & Sugiyama, T. (2019). Neighborhood walkability and 12-year changes in cardio-metabolic risk: The mediating role of physical activity. *The*

DRAFT

International Journal of Behavioral Nutrition and Physical Activity, *16*(1), 86. https://doi.org/10.1186/s12966-019-0849-7

Chandrabose, M., Rachele, J. N., Gunn, L., Kavanagh, A., Owen, N., Turrell, G., Giles-Corti, B., & Sugiyama, T. (2019a). Built environment and cardio-metabolic health: Systematic review and meta-analysis of longitudinal studies. *Obesity Reviews*, *20*(1), 41–54. https://doi.org/10.1111/obr.12759

Chandrabose, M., Rachele, J. N., Gunn, L., Kavanagh, A., Owen, N., Turrell, G., Giles-Corti, B., & Sugiyama, T. (2019b). Built environment and cardio-metabolic health: Systematic review and meta-analysis of longitudinal studies. *Obesity Reviews*, *20*(1), 41–54. https://doi.org/10.1111/obr.12759

Chester, M., & Horvath, A. (2009). *Life-cycle Energy and Emissions Inventories for Motorcycles, Diesel Automobiles, School Buses, Electric Buses, Chicago Rail, and New York City Rail*. https://escholarship.org/uc/item/6z37f2jr

Chester, M. V. (2008). *Life-cycle Environmental Inventory of Passenger Transportation in the United States*. https://escholarship.org/uc/item/7n29n303

Choi, K., & Zhang, M. (2017). The net effects of the built environment on household vehicle emissions: A case study of Austin, TX. *Transportation Research Part D: Transport and Environment*, *50*, 254–268. https://doi.org/10.1016/j.trd.2016.10.036

Clark, C., Menifield, C. E., & Stewart, L. M. (2018). Policy Diffusion and Performance-based Budgeting. *International Journal of Public Administration*, *41*(7), 528–534. https://doi.org/10.1080/01900692.2016.1278384

Condon, P. M., & Dow, K. (2011). *Transportation for Sustainable Communities: A cost and impact comparison between alternative transportation modes*.

Conway, M. W., & Stewart, A. F. (2019). Getting Charlie off the MTA: A multiobjective optimization method to account for cost constraints in public transit accessibility metrics. *International Journal of Geographical Information Science*, *33*(9), 1759–1787. https://doi.org/10.1080/13658816.2019.1605075

Cooney, G., Hawkins, T. R., & Marriott, J. (2013). Life Cycle Assessment of Diesel and Electric Public Transportation Buses. *Journal of Industrial Ecology*, *17*(5), 689–699. https://doi.org/10.1111/jiec.12024

Corradi, O., McCormick, G., Richardson, H., & Hinkle, T. (2021). *A vision for how ambitious organizations can accurately measure electricity emissions to take genuine action*. Tomorrow and Watt Time. https://www.watttime.org/app/uploads/2021/08/GHG-Frameworks-WhitePaper-Tomorrow-WattTime-202108.pdf

DRAFT

Cottagiri, S. A., Villeneuve, P. J., Raina, P., Griffith, L. E., Rainham, D., Dales, R., Peters, C. E., Ross, N. A., & Crouse, D. L. (2022). Increased urban greenness associated with improved mental health among middle-aged and older adults of the Canadian Longitudinal Study on Aging (CLSA). *Environmental Research*, *206*, 112587.

Cox, B. L., & Mutel, C. L. (2018). The environmental and cost performance of current and future motorcycles. *Applied Energy*, *212*, 1013–1024. https://doi.org/10.1016/j.apenergy.2017.12.100

Cramer, J., & Krueger, A. B. (2016). Disruptive Change in the Taxi Business: The Case of Uber. *American Economic Review*, *106*(5), 177–182. https://doi.org/10.1257/aer.p20161002

Croissant, Y., & Millo, G. (2008). Panel Data Econometrics in R: The plm Package. *Journal of Statistical Software*, *27*. https://doi.org/10.18637/jss.v027.i02

Csárdi, G., Nepusz, T., Müller, K., Horvát, S., Traag, V., Zanini, F., & Noom, D. (2023). *igraph for R: R interface of the igraph library for graph theory and network analysis* [Computer software]. Zenodo. https://doi.org/10.5281/zenodo.8046777

Darwish, A. M., Zagow, M., & Elkafoury, A. (2023). Impact of land use, travel behavior, and socio-economic characteristics on carbon emissions in cool-climate cities, USA. *Environmental Science and Pollution Research*, *30*(39), 91108–91124. https://doi.org/10.1007/s11356-023-28487-9

DC Water. (2016). *DC Water, Goldman Sachs and Calvert Foundation pioneer environmental impact bond; | DCWater.com*. https://www.dcwater.com/whats-going-on/news/dc-water-goldman-sachs-and-calvert-foundation-pioneer-environmental-impact-bond

De Boer, H., Jongbloed, B., Benneworth, P., Cremonini, L., Kolster, R., Kottmann, A., Lemmens-Krug, K., & Vossensteyn, H. (2015). Performance-based funding and performance agreements in fourteen higher education systems. *Center for Higher Education Policy Studies*.

de Bortoli, A. (2021). Environmental performance of shared micromobility and personal alternatives using integrated modal LCA. *Transportation Research Part D: Transport and Environment*, *93*, 102743. https://doi.org/10.1016/j.trd.2021.102743

Del Pero, F., Delogu, M., Pierini, M., & Bonaffini, D. (2015). Life Cycle Assessment of a heavy metro train. *Journal of Cleaner Production*, *87*, 787–799. https://doi.org/10.1016/j.jclepro.2014.10.023

DenBraver, N. R., Lakerveld, J., Rutters, F., Schoonmade, L. J., Brug, J., & Beulens, J. W. J. (2018). Built environmental characteristics and diabetes: A systematic review

DRAFT

and meta-analysis. *BMC Medicine*, *16*(1). https://doi.org/10.1186/s12916-017-0997-z

Dendup, T., Feng, X., Clingan, S., & Astell-Burt, T. (2018). Environmental risk factors for developing type 2 diabetes mellitus: A systematic review. *International Journal of Environmental Research and Public Health*, *15*(1). https://doi.org/10.3390/ijerph15010078

Des Rosiers, F., Thériault, M., Biba, G., & Vandersmissen, M.-H. (2017). Greenhouse gas emissions and urban form: Linking households' socio-economic status with housing and transportation choices. *Environment and Planning B: Urban Analytics and City Science*, *44*(5), 964–985. https://doi.org/10.1177/0265813516656862

Dey, S., Caulfield, B., & Ghosh, B. (2019). Modelling uncertainty of vehicular emissions inventory: A case study of Ireland. *Journal of Cleaner Production*, *213*, 1115–1126. https://doi.org/10.1016/j.jclepro.2018.12.125

Dhalla, A., McDonald, T. E., Gallagher, R. P., Spinelli, J. J., Brooks-Wilson, A. R., Lee, T. K., Lai, C., Borugian, M. J., Woods, R. R., Le, N. D., & Dummer, T. J. B. (2019). Cohort profile: The British Columbia Generations Project (BCGP). *International Journal of Epidemiology*, *48*(2), 377–378k. https://doi.org/10.1093/ije/dyy160

DMTISpatial. CanMap® GIS Data for GIS Mapping Software—DMTI Spatial. (n.d.). https://www.dmtispatial.com/canmap/

Environment and Climate Change Canada. (2020). *Historical Data—Climate*. https://climate.weather.gc.ca/historical_data/search_historic_data_e.html

Environment and Climate Change Canada. (2021). *Greenhouse gas sources and sinks in Canada*. Government of Canada. https://www.canada.ca/en/environment-climate-change/services/climate-change/greenhouse-gas-emissions/inventory.html

Environment and Climate Change Canada. (2022). *Canada's air pollutant emissions inventory report 2022*. https://publications.gc.ca/site/eng/9.869731/publication.html

Facts about Physical Activity| CDC. (n.d.). Retrieved April 8, 2017, from https://www.cdc.gov/physicalactivity/data/facts.htm

Fan, V. Y., Duran, D., Silverman, R., & Glassman, A. (2013). Performance-based financing at the Global Fund to Fight AIDS, Tuberculosis and Malaria: An analysis of grant ratings and funding, 2003–12. *The Lancet Global Health*, *1*(3), e161–e168.

Fan, Y., Das, K. V, & Chen, Q. (2011). Neighborhood green, social support, physical activity, and stress: Assessing the cumulative impact. *Health & Place*, *17*(6), 1202–1211.

DRAFT

Fazeli Dehkordi, Z. S., Khatami, S. M., & Ranjbar, E. (2022). The Associations Between Urban Form and Major Non-communicable Diseases: A Systematic Review. *Journal of Urban Health*, *99*(5), 941–958. https://doi.org/10.1007/s11524-022-00652-4

Fong, K. C., Hart, J. E., & James, P. (2018). A review of epidemiologic studies on greenness and health: Updated literature through 2017. *Current Environmental Health Reports*, *5*, 77–87.

Frank, L. D., Adhikari, B., White, K. R., Dummer, T., Sandhu, J., Demlow, E., Hu, Y., Hong, A., & Van den Bosch, M. (2022). Chronic disease and where you live: Built and natural environment relationships with physical activity, obesity, and diabetes. *Environment International*, *158*, 106959. https://doi.org/10.1016/J.ENVINT.2021.106959

Frank, L. D., Iroz-Elardo, N., MacLeod, K. E., & Hong, A. (2019). Pathways from built environment to health: A conceptual framework linking behavior and exposure-based impacts. *Journal of Transport & Health*, *12*, 319–335.

Frank, L. D., Jr, B. S., & Bachman, W. (2000). *Linking land use with household vehicle emissions in the central puget sound: Methodological framework and ®ndings*.

Frank, L. D., Saelens, B. E., Powell, K. E., & Chapman, J. E. (2007). Stepping towards causation: Do built environments or neighborhood and travel preferences explain physical activity, driving, and obesity? *Social Science and Medicine*, *65*(9), 1898–1914. https://doi.org/10.1016/j.socscimed.2007.05.053

Frank, L. D., Sallis, J. F., Saelens, B. E., Leary, L., Cain, K., Conway, T. L., & Hess, P. M. (2010a). The development of a walkability index: Application to the Neighborhood Quality of Life Study. *British Journal of Sports Medicine*, *44*(13), 924–933. https://doi.org/10.1136/bjsm.2009.058701

Frank, L. D., Sallis, J. F., Saelens, B. E., Leary, L., Cain, K., Conway, T. L., & Hess, P. M. (2010b). The development of a walkability index: Application to the Neighborhood Quality of Life Study. *British Journal of Sports Medicine*, *44*(13), 924–933. https://doi.org/10.1136/bjsm.2009.058701

Frank, L. D., Schmid, T. L., Sallis, J. F., Chapman, J., & Saelens, B. E. (2005). Linking objectively measured physical activity with objectively measured urban form: Findings from SMARTRAQ. *American Journal of Preventive Medicine*, *28*(2), 117–125. https://doi.org/10.1016/J.AMEPRE.2004.11.001

Frank, L. D., Stone, B., & Bachman, W. (2000). Linking land use with household vehicle emissions in the central puget sound: Methodological framework and findings.

DRAFT

Transportation Research Part D: Transport and Environment, *5*(3), 173–196. https://doi.org/10.1016/S1361-9209(99)00032-2

Frank, L., Giles-Corti, B., & Ewing, R. (2016). *The influence of the built environment on transport and health*. https://doi.org/10.1016/j.jth.2016.11.004

Freeman, L. (2005). Displacement or Succession?: Residential Mobility in Gentrifying Neighborhoods. *Urban Affairs Review*, *40*(4), 463–491. https://doi.org/10.1177/1078087404273341

Freeman, L., & Braconi, F. (2004). Gentrification and Displacement New York City in the 1990s. *Journal of the American Planning Association*, *70*(1), 39–52. https://doi.org/10.1080/01944360408976337

Frey, H. C. (2007). *Quantification of Uncertainty in Emission Factors and Inventories*. Environmental Protection Agency,; Google Scholar.

Gabrio, A., Plumpton, C., Banerjee, S., & Leurent, B. (2022). Linear mixed models to handle missing at random data in trial-based economic evaluations. *Health Economics (United Kingdom)*, *31*(6), 1276–1287. https://doi.org/10.1002/hec.4510

Gariepy, G., Blair, A., Kestens, Y., & Schmitz, N. (2014). Neighbourhood characteristics and 10-year risk of depression in Canadian adults with and without a chronic illness. *Health & Place*, *30*, 279–286.

GBD Mental Disorders Collaborators. Global, regional, and national burden of 12 mental disorders in 204 countries and territories, 1990–2019: A systematic analysis for the Global Burden of Disease Study 2019. (2022). *The Lancet Psychiatry*, *9*(2), 137–150.

Generaal, E., Timmermans, E. J., Dekkers, J. E. C., Smit, J. H., & Penninx, B. W. J. H. (2019). Not urbanization level but socioeconomic, physical and social neighbourhood characteristics are associated with presence and severity of depressive and anxiety disorders. *Psychological Medicine*, *49*(1), 149–161.

Ghafghazi, G., & Hatzopoulou, M. (2014). Simulating the environmental effects of isolated and area-wide traffic calming schemes using traffic simulation and microscopic emission modeling. *Transportation*, *41*(3), 633–649. https://doi.org/10.1007/s11116-014-9513-x

Giles-Corti, B., Vernez-Moudon, A., Reis, R., Turrell, G., Dannenberg, A. L., Badland, H., Foster, S., Lowe, M., Sallis, J. F., Stevenson, M., & Owen, N. (2016). City planning and population health: A global challenge. *The Lancet*. https://doi.org/10.1016/S0140-6736(16)30066-6

Glass, R. (1964). Aspects of change. *The Gentrification Debates: A Reader*, 19–30.

DRAFT

Global Advocacy for Physical Activity (GAPA) the Advocacy Council of the International Society for Physical Activity and Health (ISPAH). (2011). *NCD Prevention: Investments that Work for Physical Activity*. https://doi.org/10.1093/bmb/ldq037

Gold, J., Mendelsohn, M., & Mowat Centre for Policy Innovation. (2014). *Better Outcomes for Public Services: Achieving Social Impact Through Outcomes-Based Funding*. Mowat Center. http://www.deslibris.ca/ID/243716

Google. (2022). *Google Search*. https://www.google.com/

GPRBA. (2021). *Results-Based Financing | The Global Partnership for Results-Based Approaches*. https://www.gprba.org/results-based-financing

Grant, M., Bird, C., & Marno, P. (2012). Health inequalities and determinants in the physical urban environment: Evidence briefing. *WHO Collaborating Centre for Healthy Urban Environments: Bristol, UK*.

Grasser, G., Van Dyck, D., Titze, S., & Stronegger, W. (2012). Objectively measured walkability and active transport and weight-related outcomes in adults: A systematic review. *International Journal of Public Health*, *58*, 615–625.

Grasser, G., Van Dyck, D., Titze, S., & Stronegger, W. (2013). Objectively measured walkability and active transport and weight-related outcomes in adults: A systematic review. *Int J Public Health*, *58*(4), 615–625. https://doi.org/10.1007/s00038-012-0435-0

Grigsby, W. (1986). *The Dynamics of Neighborhood Change and Decline.*

Grittner, A. M. (2013). *Results-based financing: Evidence from performance-based financing in the health sector*. Dt. Inst. für Entwicklungspolitik.

Groenewegen, P. P., Van den Berg, A. E., De Vries, S., & Verheij, R. A. (2006). Vitamin G: effects of green space on health, well-being, and social safety. *BMC Public Health*, *6*(1), 1–9.

Gulcimen, S., Aydogan, E. K., & Uzal, N. (2021). Life cycle sustainability assessment of a light rail transit system: Integration of environmental, economic, and social impacts. *Integrated Environmental Assessment and Management*, *17*(5), 1070–1082. https://doi.org/10.1002/ieam.4428

Hackworth, J., & Smith, N. (2001). The changing state of gentrification. *Tijdschrift Voor Economische En Sociale Geografie*, *92*(4), 464–477.

Hammel, D. J., & Wyly, E. K. (1996). A MODEL FOR IDENTIFYING GENTRIFIED AREAS WITH CENSUS DATA. *Urban Geography*, *17*(3), 248–268. https://doi.org/10.2747/0272-3638.17.3.248

Hamnett, C. (1994). Social polarisation in global cities: Theory and evidence. *Urban Studies*, *31*(3), 401–424.

DRAFT

Harnisch, T. L. (2011). *Performance-based Funding: A Re-Emerging Strategy in Public Higher Education Financing*. 12.

Hartig, T. (2008). Green space, psychological restoration, and health inequality. *The Lancet*, *372*(9650), 1614–1615.

Hartig, T., Mitchell, R., De Vries, S., & Frumkin, H. (2014). Nature and health. *Annual Review of Public Health*, *35*, 207–228.

Harvard Kennedy School Government Performance Lab. (2017). *Social Impact Bonds 101*. https://govlab.hks.harvard.edu/files/govlabs/files/sibs_101_gpl_2017.pdf

Hassanpour, A., & Bigazzi, A. (2023). What is on the Bicycle Paths? A Detailed Vehicle Taxonomy with Mode Share Data for Off-Street Paths in Metropolitan Vancouver, Canada. *Transportation Research Record*, *2677*(11), 258–271. https://doi.org/10.1177/03611981231165017

Hawkins, R., Bieretz, B., & Brown, M. (2019, June 24). *Incentivizing Results: Contracting for Outcomes in Social Service Delivery*. Urban Institute. https://www.urban.org/research/publication/incentivizing-results-contracting-outcomes-social-service-delivery

Hedman, L. (2011). *Residential mobility and neighbourhood effects: A holistic approach*. Acta Universitatis Upsaliensis.

Helbich, M., Poppe, R., Oberski, D., van Emmichoven, M. Z., & Schram, R. (2021). Can't see the wood for the trees? An assessment of street view-and satellite-derived greenness measures in relation to mental health. *Landscape and Urban Planning*, *214*, 104181.

Hirsch, J. A., Roux, A. V. D., Moore, K. A., Evenson, K. R., & Rodriguez, D. A. (2014). Change in walking and body mass index following residential relocation: The multi-ethnic study of atherosclerosis. *American Journal of Public Health*, *104*(3), 49–56. https://doi.org/10.2105/AJPH.2013.301773

Hirschfeld, R. M. A., & Weissman, M. M. (2002). Risk factors for major depression and bipolar disorder. *Neuropsychopharmacology: The Fifth Generation of Progress*, 1017–1025.

Hochstenbach, C., & van Gent, W. P. (2015). An anatomy of gentrification processes: Variegating causes of neighbourhood change. *Environment and Planning A: Economy and Space*, *47*(7), 1480–1501. https://doi.org/10.1177/0308518X15595771

Hystad, P., Payette, Y., Noisel, N., & Boileau, C. (2019). Green space associations with mental health and cognitive function: Results from the Quebec CARTaGENE cohort. *Environmental Epidemiology*, *3*(1).

DRAFT

Insurance Corporation of British Columbia (ICBC). (2020). *British Columbia Vehicle Population Data* [dataset]. https://public.tableau.com/views/VehiclePopulationIntroPage/VehiclePopulationData?%3Adisplay_static_image=y&%3AbootstrapWhenNotified=true&%3Aembed=true&%3Alanguage=en-US&:embed=y&:showVizHome=n&:apiID=host0#navType=0&navSrc=Parse

Ipsos. (2018). *2017 Regional Trip Diary Technical Report*. TransLink.

Istrate, I., Iribarren, D., Dufour, J., Ortiz Cebolla, R., Arrigoni, A., Moretto, P., & Dolci, F. (2022). *Quantifying Emissions in the European Maritime Sector: A Review on Life Cycle Assessments of Maritime Systems Combined With an Analysis of the THETIS-MRV Portal* (JRC128870). https://trid.trb.org/view/1948241

Jacobs, P., Dewa, C. S., Lesage, A., Vasiliadis, H.-M., Escober, C., Mulvale, G., & Yim, R. (2010). *The cost of mental health and substance abuse services in Canada: A report to the Mental Health Commission of Canada*. Institute of Health Economics.

Janus, H., Klingebiel, S., & Paulo, S. (2015). Beyond Aid: A Conceptual Perspective on the Transformation of Development Cooperation. *Journal of International Development*, *27*(2), 155–169.

Johnson, D., & Zajonc, T. (2006). *Can Foreign Aid Create an Incentive for Good Governance? Evidence from the Millennium Challenge Corporation* [SSRN Scholarly Paper]. Social Science Research Network. https://doi.org/10.2139/ssrn.896293

Jones, A. C., Chaudhary, N. S., Patki, A., Howard, V. J., Howard, G., Colabianchi, N., Judd, S. E., & Irvin, M. R. (2021). Neighborhood Walkability as a Predictor of Incident Hypertension in a National Cohort Study. *Frontiers in Public Health*, *9*(February), 1–7. https://doi.org/10.3389/fpubh.2021.611895

Jongbloed, B., & De Boer, H. (2020). *Performance Agreements in Denmark, Ontario and the Netherlands*. University of Twente. https://doi.org/10.1787/735e1f44-en

Julien, D., Richard, L., Gauvin, L., & Kestens, Y. (2012). Neighborhood characteristics and depressive mood among older adults: An integrative review. *International Psychogeriatrics*, *24*(8), 1207–1225.

Kahn, M. E. (1998). A household level environmental Kuznets curve. *Economics Letters*, *59*(2), 269–273. https://doi.org/10.1016/S0165-1765(98)00035-4

Kannangara, M., Bensebaa, F., & Vasudev, M. (2021). An adaptable life cycle greenhouse gas emissions assessment framework for electric, hybrid, fuel cell and conventional vehicles: Effect of electricity mix, mileage, battery capacity and

DRAFT

battery chemistry in the context of Canada. *Journal of Cleaner Production*, *317*, 128394. https://doi.org/10.1016/j.jclepro.2021.128394

Kaplan, R., & Kaplan, S. (1989). *The experience of nature: A psychological perspective*. Cambridge university press.

Keats, M. R., Cui, Y., DeClercq, V., Grandy, S. A., Sweeney, E., & Dummer, T. J. B. (2020). Associations between neighborhood walkability, physical activity, and chronic disease in Nova Scotian adults: An Atlantic PATH cohort study. *International Journal of Environmental Research and Public Health*, *17*(22), 8643.

Kessler, R. C., Aguilar-Gaxiola, S., Alonso, J., Chatterji, S., Lee, S., Ormel, J., Üstün, T. B., & Wang, P. S. (2009). The global burden of mental disorders: An update from the WHO World Mental Health (WMH) surveys. *Epidemiology and Psychiatric Sciences*, *18*(1), 23–33.

Khan, S., Pinault, L., Tjepkema, M., & Wilkins, R. (2018). Positional accuracy of geocoding from residential postal codes versus full street addresses. *Health Reports*, *29*(2), 3–9.

Kim, E. J., Kim, J., & Kim, H. (2020). Does Environmental Walkability Matter? The Role of Walkable Environment in Active Commuting. *International Journal of Environmental Research and Public Health*, *17*(4), 1261. https://doi.org/10.3390/ijerph17041261

Kim, T. J., & Von Dem Knesebeck, O. (2018). Income and obesity: What is the direction of the relationship? A systematic review and meta-analysis. *BMJ Open*, *8*(1). https://doi.org/10.1136/bmjopen-2017-019862

King, A. C., Sallis, J. F., Frank, L. D., Saelens, B. E., Cain, K., Conway, T. L., Chapman, J. E., Ahn, D. K., & Kerr, J. (2011a). Aging in neighborhoods differing in walkability and income: Associations with physical activity and obesity in older adults. *Social Science & Medicine (1982)*, *73*(10), 1525–1533. https://doi.org/10.1016/j.socscimed.2011.08.032

King, A. C., Sallis, J. F., Frank, L. D., Saelens, B. E., Cain, K., Conway, T. L., Chapman, J. E., Ahn, D. K., & Kerr, J. (2011b). Aging in neighborhoods differing in walkability and income: Associations with physical activity and obesity in older adults. *Social Science & Medicine*, *73*(10), 1525–1533. https://doi.org/10.1016/J.SOCSCIMED.2011.08.032

Klompmaker, J. O., Hoek, G., Bloemsma, L. D., Wijga, A. H., van den Brink, C., Brunekreef, B., Lebret, E., Gehring, U., & Janssen, N. A. H. (2019). Associations of combined exposures to surrounding green, air pollution and traffic noise on mental health. *Environment International*, *129*, 525–537.

DRAFT

Ko, J., Park, D., Lim, H., & Hwang, I. C. (2011). Who produces the most CO2 emissions for trips in the Seoul metropolis area? *Transportation Research Part D: Transport and Environment*, *16*(5), 358–364. https://doi.org/10.1016/j.trd.2011.02.001

Koohsari, M. J., McCormack, G. R., Nakaya, T., Shibata, A., Ishii, K., Yasunaga, A., Hanibuchi, T., & Oka, K. (2019). Urban design and Japanese older adults' depressive symptoms. *Cities*, *87*, 166–173.

Koohsari, M. J., Owen, N., Cole, R., Mavoa, S., Oka, K., Hanibuchi, T., & Sugiyama, T. (2017). Built environmental factors and adults' travel behaviors: Role of street layout and local destinations. *Preventive Medicine*, *96*, 124–128. https://doi.org/10.1016/j.ypmed.2016.12.021

Koohsari, M. J., Yasunaga, A., McCormack, G. R., Shibata, A., Ishii, K., Nakaya, T., Hanibuchi, T., Nagai, Y., & Oka, K. (2023). Depression among middle-aged adults in Japan: The role of the built environment design. *Landscape and Urban Planning*, *231*, 104651.

Koren, H. S., & Butler, C. D. (2006). The interconnection between the built environment ecology and health. *Environmental Security and Environmental Management: The Role of Risk Assessment*, 111–125.

Kotval-K, Z., & Vojnovic, I. (2015). The socio-economics of travel behavior and environmental burdens: A Detroit, Michigan regional context. *Transportation Research Part D: Transport and Environment*, *41*, 477–491. https://doi.org/10.1016/j.trd.2015.10.017

Krols, J., Aerts, R., Vanlessen, N., Dewaelheyns, V., Dujardin, S., & Somers, B. (2022). Residential green space, gardening, and subjective well-being: A cross-sectional study of garden owners in northern Belgium. *Landscape and Urban Planning*, *223*, 104414.

Lai, K. Y., Webster, C., Gallacher, J. E., & Sarkar, C. (2023). Associations of Urban Built Environment with Cardiovascular Risks and Mortality: A Systematic Review. In *Journal of Urban Health* (Vol. 100, Issue 4). Springer US. https://doi.org/10.1007/s11524-023-00764-5

Lajunen, A., & Lipman, T. (2016). Lifecycle cost assessment and carbon dioxide emissions of diesel, natural gas, hybrid electric, fuel cell hybrid and electric transit buses. *Energy*, *106*, 329–342. https://doi.org/10.1016/j.energy.2016.03.075

Lang, D. W. (2016). *Incentive Funding Meets Incentive-Based Budgeting: Can They Coexist? 46*(4), 22.

Lang, I. M., Antonakos, C. L., Judd, S. E., & Colabianchi, N. (2022). A longitudinal examination of objective neighborhood walkability, body mass index, and waist

DRAFT

circumference: The REasons for Geographic And Racial Differences in Stroke study. *International Journal of Behavioral Nutrition and Physical Activity*, *19*(1), 1–15. https://doi.org/10.1186/s12966-022-01247-7

Le Hong, Z., & Zimmerman, N. (2021). Air quality and greenhouse gas implications of autonomous vehicles in Vancouver, Canada. *Transportation Research Part D: Transport and Environment*, *90*, 102676. https://doi.org/10.1016/j.trd.2020.102676

Lederer, J., Ott, C., Brunner, P. H., & Ossberger, M. (2016). The life cycle energy demand and greenhouse gas emissions of high-capacity urban transport systems: A case study from Vienna's subway line U2. *International Journal of Sustainable Transportation*, *10*(2), 120–130. https://doi.org/10.1080/15568318.2013.869704

Lee, S., & Lee, B. (2020). Comparing the impacts of local land use and urban spatial structure on household VMT and GHG emissions. *Journal of Transport Geography*, *84*, 102694. https://doi.org/10.1016/j.jtrangeo.2020.102694

Lees, L. (2000). A reappraisal of gentrification: Towards a 'geography of gentrification.' *Progress in Human Geography*, *24*(3), 389–408.

Leon, B. M., & Maddox, T. M. (2015). Diabetes and cardiovascular disease: Epidemiology , biological mechanisms , treatment recommendations and future research. *World Journal of Diabetes*, *6*(13), 1246–1258. https://doi.org/10.4239/wjd.v6.i13.1246

Lesage, A., Vasiliadis, H. M., Gagné, M. A., Dudgeon, S., Kasman, N., & Hay, C. (2012). *Prevalence of mental illnesses and related service utilization in Canada: An analysis of the Canadian Community Health Survey. Mississauga, ON: Canadian Collaborative Mental Health Initiative; 2006*.

Levelton Engineering Ltd. (2002). *Marine Vessel Air Emissions in B.C. and Washington State outside the GVRD and FVRD for the Year 2000*. Greater Vancouver Regional District. https://georgiastrait.org/wp-content/uploads/2015/03/MarineVesselEmission2000Outside.pdf

Ley, D. (1986). Alternative Explanations for Inner-City Gentrification: A Canadian Assessment. *Annals of the Association of American Geographers*, *76*(4), 521–535. https://doi.org/10.1111/j.1467-8306.1986.tb00134.x

Ley, D. (2003). Artists, Aestheticisation and the Field of Gentrification. *Urban Studies*, *40*(12), 2527–2544. https://doi.org/10.1080/0042098032000136192

Ley, D., & Dobson, C. (2008). Are There Limits to Gentrification? The Contexts of Impeded Gentrification in Vancouver. *Urban Studies*, *45*(12), 2471–2498. https://doi.org/10.1177/0042098008097103

DRAFT

Li, T., Qi, G.-J., & Stern, R. (2022). Taxi Utilization Rate Maximization by Dynamic Demand Prediction: A Case Study in the City of Chicago. *Transportation Research Record*, *2676*(4), 367–379. https://doi.org/10.1177/03611981211059769

Li, T., Wu, X., Ban, X., & Wang, Y. (2020, August). *"Centralized" Taxi Services in Big Metropolitan Areas: Evidenced by Chicago Data*. International Conference on Transportation and Development 2020American Society of Civil Engineers. https://trid.trb.org/view/1735651

Liao, B., E. W. Van Den Berg, P., Van Wesemael, P. J. V., & A. Arentze, T. (2020). How Does Walkability Change Behavior? A Comparison between Different Age Groups in the Netherlands. *International Journal of Environmental Research and Public Health*, *17*(2), 540. https://doi.org/10.3390/ijerph17020540

Lim, G. Y., Tam, W. W., Lu, Y., Ho, C. S., Zhang, M. W., & Ho, R. C. (2018). Prevalence of depression in the community from 30 countries between 1994 and 2014. *Scientific Reports*, *8*(1), 2861.

Liu, Y., Wang, R., Xiao, Y., Huang, B., Chen, H., & Li, Z. (2019). Exploring the linkage between greenness exposure and depression among Chinese people: Mediating roles of physical activity, stress and social cohesion and moderating role of urbanicity. *Health & Place*, *58*, 102168.

Logtenberg, R., Pawley, J., & Saxifrage, B. (2018). *Comparing Fuel and Maintenance Costs of Electric and Gas Powered Vehicles in Canada*. 2 Degrees Institute.

Ma, J., Heppenstall, A., Harland, K., & Mitchell, G. (2014). Synthesising carbon emission for mega-cities: A static spatial microsimulation of transport CO2 from urban travel in Beijing. *Computers, Environment and Urban Systems*, *45*, 78–88. https://doi.org/10.1016/j.compenvurbsys.2014.02.006

Maas, J., Verheij, R. A., de Vries, S., Spreeuwenberg, P., Schellevis, F. G., & Groenewegen, P. P. (2009). Morbidity is related to a green living environment. *Journal of Epidemiology & Community Health*, *63*(12), 967–973.

Maas, J., Verheij, R. A., Spreeuwenberg, P., & Groenewegen, P. P. (2008). Physical activity as a possible mechanism behind the relationship between green space and health: A multilevel analysis. *BMC Public Health*, *8*, 1–13.

Mackenbach, J. D., Rutter, H., Compernolle, S., Glonti, K., Oppert, J. M., Charreire, H., De Bourdeaudhuij, I., Brug, J., Nijpels, G., & Lakerveld, J. (2014). Obesogenic environments: A systematic review of the association between the physical environment and adult weight status, the SPOTLIGHT project. *BMC Public Health*, *14*(1). https://doi.org/10.1186/1471-2458-14-233

DRAFT

Mahmud, M. A. P., Huda, N., Farjana, S. H., & Lang, C. (2019). Comparative Life Cycle Environmental Impact Analysis of Lithium-Ion (LiIo) and Nickel-Metal Hydride (NiMH) Batteries. *Batteries*, *5*(1), Article 1. https://doi.org/10.3390/batteries5010022

Mair, C., Roux, A. V. D., & Galea, S. (2008). Are neighbourhood characteristics associated with depressive symptoms? A review of evidence. *Journal of Epidemiology & Community Health*, *62*(11), 940–946.

Majeau-Bettez, G., Hawkins, T. R., & Strømman, A. H. (2011). Life Cycle Environmental Assessment of Lithium-Ion and Nickel Metal Hydride Batteries for Plug-In Hybrid and Battery Electric Vehicles. *Environmental Science & Technology*, *45*(10), 4548–4554. https://doi.org/10.1021/es103607c

Marcuse, P. (1985). Gentrification, abandonment, and displacement: Connections, causes, and policy responses in New York City. *Wash. UJ Urb. & Contemp. L.*, *28*, 195.

Martin, E., & Shaheen, S. (2016). *Impacts of car2go on Vehicle Ownership, Modal Shift, Vehicle Miles Traveled, and Greenhouse Gas Emissions: An Analysis of Five North American Cities*. Transportation Sustainability Research Center. https://tsrc.berkeley.edu/publications/impacts-car2go-vehicle-ownership-modal-shift-vehicle-miles-traveled-and-greenhouse-gas

Martínez, J., Pearson, M., & Sørensen, B. H. (2012). *Evaluation of the Health Results Innovation Trust Fund*. Norad Evaluation Department.

McCormack, G. R., & Shiell, A. (2011). In search of causality: A systematic review of the relationship between the built environment and physical activity among adults. *International Journal of Behavioral Nutrition and Physical Activity*, *8*, 1–11.

McElhanney. (2018). *2017 Vancouver Panel Survey*. City of Vancouver. https://vancouver.ca/files/cov/2017-transportation-panel-survey-final-draft-20180516.pdf

McKinnish, T., Walsh, R., & White, T. K. (2010). Who Gentrifies Low-Income Neighborhoods? *Journal of Urban Economics*, *67*(2), 180–193. https://doi.org/10.1016/j.jue.2009.08.003

Meegan, R., & Mitchell, A. (2001). "It's not community round here, it's neighbourhood": Neighbourhood change and cohesion in urban regeneration policies. *Urban Studies*, *38*(12), 2167–2194.

Mehta, U., Wilt, G. E., Okereke, O. I., Coull, B., James, P., Laden, F., Iyer, H. S., Deville, N. V, & Hart, J. E. (2022). Interactions between multiple environmental factors and

DRAFT

associations with generalized anxiety disorder in Nurses' Health Study II. *ISEE Conference Abstracts*, *2022*(1).

Metro Vancouver. (2014). *The Metro Vancouver Car Share Study: Technical Report*. https://learn.sharedusemobilitycenter.org/overview/the-metro-vancouver-car-share-study-technical-report-british-columbia-canada-2014/

Metro Vancouver. (2018). *2015 Lower Fraser Valley Air Emissions Inventory and Forecast* [Final Report]. https://metrovancouver.org/services/air-quality-climate-change/Documents/lower-fraser-valley-air-emissions-inventory-forecast-2015.pdf#search=2015%20emission%20inventory

Metro Vancouver. (2020). *Regional Land Use Designation*. http://www.metrovancouver.org:80/metro2040/land-use-designation/Pages/default.aspx

Miao, K. (2012). *Performance-Based Funding of Higher Education* (p. 12). Center for American Progress.

Michael, Y., Gold, R., Perrin, N., & Hillier, T. (2013). Built environment and change in body mass index in older women. *Health Place.*, *22*(July), 7–10. https://doi.org/10.1016/j.healthplace.2013.02.001

Mills, K. T., Stefanescu, A., & He, J. (2020). The global epidemiology of hypertension. *Nature Reviews Nephrology*, *16*(April). https://doi.org/10.1038/s41581-019-0244-2

Mio, A., Fermeglia, M., & Favi, C. (2022). A critical review and normalization of the life cycle assessment outcomes in the naval sector. Articles description. *Journal of Cleaner Production*, *370*, 133476. https://doi.org/10.1016/j.jclepro.2022.133476

Mitchell, R. J., Richardson, E. A., Shortt, N. K., & Pearce, J. R. (2015). Neighborhood environments and socioeconomic inequalities in mental well-being. *American Journal of Preventive Medicine*, *49*(1), 80–84.

Mitchell, R., & Popham, F. (2007). Greenspace, urbanity and health: Relationships in England. *Journal of Epidemiology & Community Health*, *61*(8), 681–683.

Mitchell, R., & Popham, F. (2008). Effect of exposure to natural environment on health inequalities: An observational population study. *The Lancet*, *372*(9650), 1655–1660.

Moreira, T. C. L., Polize, J. L., Brito, M., da Silva Filho, D. F., Chiavegato Filho, A. D. P., Viana, M. C., Andrade, L. H., & Mauad, T. (2022). Assessing the impact of urban environment and green infrastructure on mental health: Results from the São Paulo Megacity Mental Health Survey. *Journal of Exposure Science & Environmental Epidemiology*, *32*(2), 205–212.

DRAFT

Musgrove, P. (2011). *Financial and Other Rewards for Good Performance or Results: A Guided Tour of Concepts and Terms and a Short Glossary* (p. 12). World Bank.

Mytton, O. T., Townsend, N., Rutter, H., & Foster, C. (2012). Green space and physical activity: An observational study using Health Survey for England data. *Health & Place*, *18*(5), 1034–1041.

Natural Resources Canada. (2010). *Canadian Vehicle Survey 2008 Update Report*. Governement of Canada. https://oee.nrcan.gc.ca/publications/statistics/cvs08/summary.cfm?attr=0

Natural Resources Canada. (2022). *Fuel consumption ratings*. https://open.canada.ca/data/en/dataset/98f1a129-f628-4ce4-b24d-6f16bf24dd64

Newman, K., & Wyly, E. K. (2006). The Right to Stay Put, Revisited: Gentrification and Resistance to Displacement in New York City. *Urban Studies*, *43*(1), 23–57. https://doi.org/10.1080/00420980500388710

Ng, E., Vanderloo, S. E., Geiss, L., & Johnson, J. A. (2013). Concordance between self-report and a survey-based algorithm for classification of type 1 and type 2 diabetes using the 2011 population-based survey on living with chronic diseases in canada (slcdc)-diabetes component. *Canadian Journal of Diabetes*, *37*(4), 249–253. https://doi.org/10.1016/j.jcjd.2013.05.007

Nordelöf, A., Romare, M., & Tivander, J. (2019). Life cycle assessment of city buses powered by electricity, hydrogenated vegetable oil or diesel. *Transportation Research Part D: Transport and Environment*, *75*, 211–222. https://doi.org/10.1016/j.trd.2019.08.019

Núñez-González, S., Delgado-Ron, J. A., Gault, C., Lara-Vinueza, A., Calle-Celi, D., Porreca, R., & Simancas-Racines, D. (2020). Overview of “systematic reviews” of the built environment’s effects on mental health. *Journal of Environmental and Public Health*, *2020*.

OECD. (2020). *Resourcing Higher Education: Challenges, Choices and Consequences*. OECD. https://doi.org/10.1787/735e1f44-en

Ontario. (2018, May 9). *College and university Strategic Mandate Agreements*. Ontario.Ca. https://www.ontario.ca/page/all-college-and-university-strategic-mandate-agreements

Ortuzar, J., & Willumsen, L. (2011). *Modelling Transport* (4th ed.). Wiley.

Oxman, A. D., Lewin, S., Lavis, J. N., & Fretheim, A. (2009). Support Tools for Evidence-Informed Health Policymaking (stp) 15: Engaging the Public in Evidence-Informed Policymaking. *Health Research Policy and Systems*, *7*(1), 1–9.

DRAFT

Pacific Climate Impacts Consortium. (2020). *BC Station Data Portal*. https://pacificclimate.org/data/bc-station-data-portal-notice

Pardy, A. (2018). *Densification of Vancouver's neighbourhoods: Energy use, emissions, and affordability* [Simon Fraser University]. https://summit.sfu.ca/item/18772

Pearson, C., Janz, T., & Ali, J. (2013a). *Mental and substance use disorders in Canada*. Statistics Canada Ottawa, ON.

Pearson, C., Janz, T., & Ali, J. (2013b). *Mental and substance use disorders in Canada*. Statistics Canada Ottawa, ON.

Pearson, M., Johnson, M., & Ellison, R. (2010). *Review of major Results Based Aid (RBA) and Results Based Financing (RBF) schemes* (p. 98). DFID Human Development Resource Centre.

Perakis, R., & Savedoff, W. (2015). Does results-based aid change anything? Pecuniary interests, attention, accountability and discretion in four case studies. *CGD Policy Paper*, *52*.

Perakis, R., & Savedoff, W. D. (2014). An Introduction to Cash on Delivery Aid for Funders. *Note. Washington, DC: CGD*.

Pereira, R. H. M., Saraiva, M., Herszenhut, D., Braga, C. K. V., & Conway, M. W. (2021). r5r: Rapid Realistic Routing on Multimodal Transport Networks with R^5 in R. *Findings*. https://doi.org/10.32866/001c.21262

Perrino, T., Lombard, J., Rundek, T., Wang, K., Dong, C., Gutierrez, C. M., Toro, M., Byrne, M. M., Nardi, M. I., Kardys, J., Szapocznik, J., & Brown, S. C. (2019). Neighbourhood greenness and depression among older adults. *Br J Psychiatry*, *215*(2), 476–480. https://doi.org/10.1192/bjp.2019.129

Pinault, L., Khan, S., & Tjepkema, M. (2020). Accuracy of matching residential postal codes to census geography. *Health Reports*, *31*(3), 3–13. https://doi.org/10.25318/82-003-x202000300001-eng

Poister, T. H., Aristigueta, M. P., & Hall, J. L. (2014). *Managing and Measuring Performance in Public and Nonprofit Organizations: An Integrated Approach*. John Wiley & Sons, Incorporated. http://ebookcentral.proquest.com/lib/utoronto/detail.action?docID=1776337

Pommier, R., Grimaud, G., Prinçaud, M., Perry, N., & Sonnemann, G. (2016). Comparative environmental life cycle assessment of materials in wooden boat ecodesign. *International Journal of Life Cycle Assessment*, *21*(2), 265–275. https://doi.org/10.1007/s11367-015-1009-1

Pourahmadiyan, A., Ahmadi, P., & Kjeang, E. (2021). Dynamic simulation and life cycle greenhouse gas impact assessment of CNG, LNG, and diesel-powered transit

DRAFT

buses in British Columbia, Canada. *Transportation Research Part D: Transport and Environment*, *92*, 102724. https://doi.org/10.1016/j.trd.2021.102724

Pun, V. C., Manjourides, J., & Suh, H. H. (2018). Association of neighborhood greenness with self-perceived stress, depression and anxiety symptoms in older US adults. *Environmental Health*, *17*, 1–11.

R Core Team. (2019). *R: A language and environment for statistical computing* (3.3.0) [Computer software]. R Foundation for Statistical Computing. http://www.R-project.org/

Ramos, H., Kaida, L., Singh, D., Pritchard, P., & Wijesingha, R. (2021). The power of a simple index of neighbourhood change: Challenging the perception that there is no such thing as simplicity in creating indexes. *The Canadian Geographer / Le Géographe Canadien*, *n/a*(n/a). https://doi.org/10.1111/cag.12711

RAND. (2016). *Evaluating the World's First Social Impact Bond*. https://www.rand.org/randeurope/research/projects/social-impact-bonds.html

Reichert, A., Holz-Rau, C., & Scheiner, J. (2016). GHG emissions in daily travel and long-distance travel in Germany – Social and spatial correlates. *Transportation Research Part D: Transport and Environment*, *49*, 25–43. https://doi.org/10.1016/j.trd.2016.08.029

Renalds, A., Smith, T. H., & Hale, P. J. (2010). A systematic review of built environment and health. *Family and Community Health*, 68–78.

Requia, W. J., Higgins, C. D., Adams, M. D., Mohamed, M., & Koutrakis, P. (2018). The health impacts of weekday traffic: A health risk assessment of PM2.5 emissions during congested periods. *Environment International*, *111*, 164–176. https://doi.org/10.1016/j.envint.2017.11.025

Rickwood, P., Glazebrook, G., & Searle, G. (2008). Urban Structure and Energy—A Review. *Urban Policy and Research*, *26*(1), 57–81. https://doi.org/10.1080/08111140701629886

Rodriguez, D., Suardi, Mario, Ham, Marcel, Mimmi, Luisa, & Goksu, Amanda. (2014). *Applying Results-Based Financing in Water Investments*. The Global Partnership on Output-Based Aid. https://openknowledge.worldbank.org/handle/10986/16997

Roe, J. J., Thompson, C. W., Aspinall, P. A., Brewer, M. J., Duff, E. I., Miller, D., Mitchell, R., & Clow, A. (2013). Green space and stress: Evidence from cortisol measures in deprived urban communities. *International Journal of Environmental Research and Public Health*, *10*(9), 4086–4103.

DRAFT

Rose, D. (1984). Rethinking Gentrification: Beyond the Uneven Development of Marxist Urban Theory. *Environment and Planning D: Society and Space*, *2*(1), 47–74. https://doi.org/10.1068/d020047

Rothschild, S. (2019). *An Exploratory Statistical Analysis of Gentrification and Neighborhood Change in Seattle*. 42.

Saarloos, D., Alfonso, H., Giles-Corti, B., Middleton, N., & Almeida, O. P. (2011). The built environment and depression in later life: The health in men study. *The American Journal of Geriatric Psychiatry*, *19*(5), 461–470.

Saelens, B. E., & Handy, S. L. (2008). Built environment correlates of walking: A review. *Medicine and Science in Sports and Exercise*, *40*(7 Suppl), S550-66. https://doi.org/10.1249/MSS.0b013e31817c67a4

Saleh, M., & Hatzopoulou, M. (2020). Greenhouse gas emissions attributed to empty kilometers in automated vehicles. *Transportation Research Part D: Transport and Environment*, *88*, 102567. https://doi.org/10.1016/j.trd.2020.102567

Sallis, J., Cerin, E., Conway, T., Adams, M., Frank, L., Pratt, M., Salvo, D., Schipperijn, J., Smith, G., Cain, K., Davey, R., Kerr, J., Lai, P., Mitas, J., Reis, R., Sarmiento, O., Schofield, G., Troelsen, J., Van Dyck, D., … Owen, N. (2016). Physical activity in relation to urban environments in 14 cities worldwide: A cross-sectional study. *The Lancet*, *387*(10034), 2207–2217. https://doi.org/10.1016/S0140-6736(15)01284-2

Sallis, J. F., Floyd, M. F., Rodríguez, D. A., & Saelens, B. E. (2012). Role of built environments in physical activity, obesity, and cardiovascular disease. *Circulation*, *125*(5), 729–737.

Sallis, J. F., Saelens, B. E., Frank, L. D., Conway, T. L., Slymen, D. J., Cain, K. L., Chapman, J. E., & Kerr, J. (2009). Neighborhood built environment and income: Examining multiple health outcomes. *Social Science and Medicine*, *68*(7), 1285–1293. https://doi.org/10.1016/j.socscimed.2009.01.017

Salmi, J., & Hauptman, A. M. (2006). *Innovations in Tertiary Education Financing:* (p. 98).

San Francisco County Transportation Authority. (2017). *TNCs Today: A Profile of San Francisco Transportation Network Company Activity* [Final Report]. https://www.sfcta.org/sites/default/files/2019-02/TNCs_Today_112917_0.pdf

Sayers, J. (2001). The world health report 2001—Mental health: New understanding, new hope. *Bulletin of the World Health Organization*, *79*(11), 1085.

Schmidt, J. H., & Watson, J. (2014). *Eco Island Ferry: Comparative LCA of island ferry with carbon fibre composite based and steel based structures*. 2.-0 LCA consultants.

DRAFT

Scottish Funding Council. (2020). *Outcome Agreements*. http://www.sfc.ac.uk/funding/outcome-agreements/outcome-agreements.aspx
Shekar, M., & Popkin, B. M. (2020). *Obesity Health and Economic Consequences of an Impending Global Challenge*.
Shekarrizfard, M., Minet, L., Miller, E., Yusuf, B., Weichenthal, S., & Hatzopoulou, M. (2020). Influence of travel behaviour and daily mobility on exposure to traffic-related air pollution. *Environmental Research*, *184*, 109326. https://doi.org/10.1016/j.envres.2020.109326
Shen, Y. (2014). Community building and mental health in mid-life and older life: Evidence from China. *Social Science & Medicine*, *107*, 209–216.
Sider, T., Alam, A., Zukari, M., Dugum, H., Goldstein, N., Eluru, N., & Hatzopoulou, M. (2013). Land-use and socio-economics as determinants of traffic emissions and individual exposure to air pollution. *Journal of Transport Geography*, *33*, 230–239. https://doi.org/10.1016/j.jtrangeo.2013.08.006
Siqueira Junior, J. de A., Lopes, A. A. dos S., Godtsfriedt, C. E. S., Justina, M. D. Della, Paiva, K. M. de, d'Orsi, E., & Rech, C. R. (2022). Neighbourhood walkability and mental health in older adults: A cross-sectional analysis from EpiFloripa Aging Study. *Frontiers in Aging*, *3*, 915292.
Slater, T. (2011). Gentrification of the city. *The New Blackwell Companion to the City*, *1*.
Smetanin, P., Stiff, D., Briante, C., Adair, C. E., Ahmad, S., & Khan, M. (2011). *The life and economic impact of major mental illnesses in Canada: 2011 to 2014. Toronto, ON: RiskAnalytica on behalf of Mental Health Commission of Canada*.
Social Finance. (2016). Connecticut Family Stability. *Social Finance*. https://socialfinance.org/project/connecticut-family-stability/
Spreafico, C., & Russo, D. (2020). Exploiting the Scientific Literature for Performing Life Cycle Assessment about Transportation. *Sustainability*, *12*(18), Article 18. https://doi.org/10.3390/su12187548
(S&T) Squared Consultants Inc. (2022). *GHGenius*. https://www.ghgenius.ca/index.php
Statistics Canada. (n.d.). https://www150.statcan.gc.ca/n1/en/catalogue/92-166-X
Statistics Canada. (2010). *Canadian Vehicle Survey* (Catalogue no. 53-223-X). http://www.statcan.gc.ca/pub/53-223-x/2009000/userinfo-usagerinfo-eng.htm
Statistics Canada. Canadian Community Health Survey, 2019: Mental HealthStatistics. Canada Catalogue no. 11–001-X. (2020). In *The Daily*.
StatsCan. (n.d.). *Canada's national statistical agency—Statistics Canada*. https://www.statcan.gc.ca/eng/start

DRAFT

Steemers, K. (2003). Energy and the city: Density, buildings and transport. *Energy and Buildings*.

Sugiyama, T., Leslie, E., Giles-Corti, B., & Owen, N. (2008). Associations of neighbourhood greenness with physical and mental health: Do walking, social coherence and local social interaction explain the relationships? *Journal of Epidemiology & Community Health*, *62*(5), e9–e9.

Sun, S., & Ertz, M. (2021). Environmental impact of mutualized mobility: Evidence from a life cycle perspective. *The Science of the Total Environment*, *772*, 145014. https://doi.org/10.1016/j.scitotenv.2021.145014

Sundquist, K., Eriksson, U., Mezuk, B., & Ohlsson, H. (2015). Neighborhood walkability, deprivation and incidence of type 2 diabetes: A population-based study on 512,061 Swedish adults. *Health Place*, *0*, 24–30. https://doi.org/10.1016/j.healthplace.2014.10.011

Tarlov, E., Silva, A., Wing, C., Slater, S., Matthews, S. A., Jones, K. K., & Zenk, S. N. (2020a). Neighborhood Walkability and BMI Change: A National Study of Veterans in Large Urban Areas. *Obesity*, *28*(1), 46–54. https://doi.org/10.1002/oby.22611

Tarlov, E., Silva, A., Wing, C., Slater, S., Matthews, S. A., Jones, K. K., & Zenk, S. N. (2020b). Neighborhood Walkability and Body Mass Index Change: A National Study of Veterans in Large Urban Areas. *Obesity (Silver Spring, Md.)*, *28*(1), 46. https://doi.org/10.1002/OBY.22611

Temkin, K., & Rohe, W. (1996). Neighborhood Change and Urban Policy. *Journal of Planning Education and Research*, *15*(3), 159–170. https://doi.org/10.1177/0739456X9601500301

Thielman, J., Rosella, L., Copes, R., Lebenbaum, M., & Manson, H. (2015). Neighborhood walkability: Differential associations with self-reported transport walking and leisure-time physical activity in Canadian towns and cities of all sizes. *Preventive Medicine*, *77*, 174–180. https://doi.org/10.1016/j.ypmed.2015.05.011

Thomassen, M. A., Dalgaard, R., Heijungs, R., & de Boer, I. (2008). Attributional and consequential LCA of milk production. *The International Journal of Life Cycle Assessment*, *13*(4), 339–349. https://doi.org/10.1007/s11367-008-0007-y

Timmermans, E. J., Visser, M., Wagtendonk, A. J., Noordzij, J. M., & Lakerveld, J. (2021). Associations of changes in neighbourhood walkability with changes in walking activity in older adults: A fixed effects analysis. *BMC Public Health*, *21*(1), 1323. https://doi.org/10.1186/s12889-021-11368-6

Toftager, M., Ekholm, O., Schipperijn, J., Stigsdotter, U., Bentsen, P., Grønbæk, M., Randrup, T. B., & Kamper-Jørgensen, F. (2011). Distance to green space and

DRAFT

physical activity: A Danish national representative survey. *Journal of Physical Activity and Health*, *8*(6), 741–749.
TransLink. (2013a). *2011 Metro Vancouver Regional Screenline Survey* (p. 64) [Final Report]. TransLink. https://www.translink.ca/-/media/translink/documents/about-translink/customer-service/trip-diary/2011-screenline-survey-report.pdf
TransLink. (2013b). *2011 Metro Vancouver Regional Trip Diary—Analysis Report*. http://www.translink.ca/-/media/Documents/customer_info/translink_listens/customer_surveys/trip_diaries/2011%20Metro%20Vancouver%20Regional%20Trip%20Diary%20%20Analysis%20Report.pdf
TransLink. (2018). *Greater Vancouver Regional Travel Model Phase 3* [Development and Validation Report].
TransLink. (2019). *Transit Service Performance Review* [Final Report]. https://www.translink.ca/plans-and-projects/strategies-plans-and-guidelines/managing-the-transit-network#transit-network-review
TransLink. (2020a). *2021 Business Plan Operating and Capital Budget Summary*. https://www.translink.ca/resources/translink/about%20translink/corporate%20reports/business_plan/2021%20business%20plan%20operating%20and%20capital%20budget%20summary
TransLink. (2020b). *Low Carbon Fleet Transition Plan* [Final Report]. https://www.translink.ca/-/media/translink/documents/about-translink/policies/translink_low_carbon_fleet_transition_plan_2020_02_24.pdf
TransLink. (2022a). *TransLink GTFS - Open Mobility Data* [dataset]. https://transitfeeds.com/p/translink-vancouver/29?p=29
TransLink. (2022b). *Transport 2050* [Regional Transportation Strategy].
Transport Canada. (2020). *Transportation in Canada 2020*. https://tc.canada.ca/sites/default/files/2021-07/transportation_canada_2020_overview_report.pdf
Transport Canada. (2021). *Canadian Vehicle Specifications (CVS)*. https://open.canada.ca/data/en/dataset/913f8940-036a-45f2-a5f2-19bde76c1252
Twardzik, E., Judd, S., Bennett, A., Hooker, S., Howard, V., Hutto, B., Clarke, P., & Colabianchi, N. (2019). Walk Score and objectively measured physical activity within a national cohort. *J Epidemiol Community Health*, *73*(6), 549–556.
United Nations (UN). World Urbanization Prospects 2018. (2018). United Nations. https://www.un.org/development/desa/pd/news/world-urbanization-prospects-2018

DRAFT

U.S. Department of Energy & U.S. Environmental Protection Agency. (2022). *FuelEconomy.Gov*. https://www.fueleconomy.gov/feg/download.shtml

U.S. Environmental Protection Agency. (2016). *MOVES: MOtor Vehicle Emission Simulator* (Version MOVES2014) [Computer software]. https://www.epa.gov/moves/moves-onroad-technical-reports#moves2014

U.S. Environmental Protection Agency. (2019, February 22). *Can I model emissions from Electric, Fuel-Cell, and Hybrid Vehicles and Equipment in MOVES?* [Overviews and Factsheets]. https://www.epa.gov/moves/can-i-model-emissions-electric-fuel-cell-and-hybrid-vehicles-and-equipment-moves

U.S. Environmental Protection Agency. (2022a). *2022 EPA Automotive Trends Report* [Data and Tools]. www.epa.gov/automotive-trends/explore-automotive-trends-data

U.S. Environmental Protection Agency. (2022b). *MOVES Onroad Technical Reports* [Reports and Assessments]. https://www.epa.gov/moves/moves-onroad-technical-reports

Van den Berg, A. E., Maas, J., Verheij, R. A., & Groenewegen, P. P. (2010). Green space as a buffer between stressful life events and health. *Social Science & Medicine*, *70*(8), 1203–1210.

Vancouver Bus Charters. (2021). *Vancouver Bus Charters*. https://vancouverbuscharters.com/#

Vancouver School Bus Charters Inc. (2022). *Vancouver School Bus Charters—Fleet*. https://www.vancouverschoolbus.com/fleet/

Venigalla, M., Dixit, S., & Pulugurtha, S. (2018). A methodology to derive land use specific auto-trip emission footprints from household travel survey data. *Urban, Planning and Transport Research*, *6*(1), 111–128. https://doi.org/10.1080/21650020.2018.1555055

Vivid Economics. (2013). *Results-Based Financing in the Energy Sector: An Analytical Guide* [Text/HTML]. World Bank. https://documents.worldbank.org/en/publication/documents-reports/documentdetail/847181468344642825/Results-based-financing-in-the-energy-sector-an-analytical-guide

Walks, R. A., & Maaranen, R. (2008). Gentrification, Social Mix, and Social Polarization: Testing the Linkages in Large Canadian Cities. *Urban Geography*, *29*(4), 293–326. https://doi.org/10.2747/0272-3638.29.4.293

Wang, A., Stogios, C., Gai, Y., Vaughan, J., Ozonder, G., Lee, S., Posen, I. D., Miller, E. J., & Hatzopoulou, M. (2018). Automated, electric, or both? Investigating the

DRAFT

effects of transportation and technology scenarios on metropolitan greenhouse gas emissions. *Sustainable Cities and Society*, *40*, 524–533. https://doi.org/10.1016/j.scs.2018.05.004

Wang, A., Weichenthal, S., Lloyd, M., Hong, K., Saxe, S., & Hatzopoulou, M. (2023). Personal Mobility Choices and Disparities in Carbon Emissions. *Environmental Science & Technology*, *57*(23), 8548–8558. https://doi.org/10.1021/acs.est.2c06993

Wang, R., Liu, Y., Xue, D., & Helbich, M. (2019). Depressive symptoms among Chinese residents: How are the natural, built, and social environments correlated? *BMC Public Health*, *19*(1), 1–8.

Wang, S., Yu, J., & Okubo, K. (2021). Life cycle assessment on the reuse and recycling of the nickel-metal hydride battery: Fleet-based study on hybrid vehicle batteries from Japan. *Journal of Industrial Ecology*, *25*(5), 1236–1249. https://doi.org/10.1111/jiec.13126

Warnecke, C., Röser, F., Hänsel, G., & Höhne, N. (2015). *Connecting the dots: Results-based financing in climate policy*. New Climate Institute.

Weather Underground. (2022). *Vancouver, Canada Weather Conditions*. https://www.wunderground.com/weather/ca/vancouver

Weier, J., & Herring, D. (n.d.). *Measuring vegetation (NDVI & EVI)[Internet]. 2000 [cited 2013 Dec 30]*.

Where Matters: Health & Economic Benefits Study. (n.d.).

(WHO), W. H. O. (2022). *Mental health*. https://www.who.int/news-room/fact-sheets/detail/mental-health-strengthening-our-response

WHO (World Health Organization). (2017). Other common mental disorders: Global health estimates. *Geneva: World Health Organization*, *24*.

WHO (World Health Organization). (2018). *mhGAP operations manual- Mental Health Gap Action Programme*.

Wilson, J., Spinney, J., Millward, H., Scott, D., Hayden, A., & Tyedmers, P. (2013). Blame the exurbs, not the suburbs: Exploring the distribution of greenhouse gas emissions within a city region. *Energy Policy*, *62*, 1329–1335. https://doi.org/10.1016/j.enpol.2013.07.012

World Health Organization (WHO). (n.d.). *Obesity*.

World Health Organization (WHO). (2016). *GLOBAL REPORT ON DIABETES*.

World Health Organization (WHO). (2018). *Global Action Plan on Physical Activity 2018-2030*.

World Health Organization (WHO). (2022). *Global status report on physical activity 2022*.

DRAFT

World Health Organization (WHO). Mental health action plan 2013–2020. (2013).
World Resources Institute (WRI). (2014). *Policy and Action Standard | Greenhouse Gas Protocol*. https://ghgprotocol.org/policy-and-action-standard
World Resources Institute (WRI). (2015). *Scope 2 Guidance | Greenhouse Gas Protocol*. https://ghgprotocol.org/scope_2_guidance
Wu, X., Tao, T., Cao, J., Fan, Y., & Ramaswami, A. (2019). Examining threshold effects of built environment elements on travel-related carbon-dioxide emissions. *Transportation Research Part D: Transport and Environment*, *75*, 1–12. https://doi.org/10.1016/j.trd.2019.08.018
Wyly, E. K., & Hammel, D. J. (1998). Modeling the Context and Contingency of Gentrification. *Journal of Urban Affairs*, *20*(3), 303–326. https://doi.org/10.1111/j.1467-9906.1998.tb00424.x
Xiao, Z., Lenzer Jr., J. H., & Chai, Y. (2017). Examining the Uneven Distribution of Household Travel Carbon Emissions Within and Across Neighborhoods: The Case of Beijing. *Journal of Regional Science*, *57*(3), 487–506. https://doi.org/10.1111/jors.12278
Xu, J., Saleh, M., Wang, A., Tu, R., & Hatzopoulou, M. (2019). Embedding local driving behaviour in regional emission models to increase the robustness of on-road emission inventories. *Transportation Research Part D: Transport and Environment*, *73*, 1–14. https://doi.org/10.1016/j.trd.2019.05.011
Xu, L., Cui, S., Tang, J., Yan, X., Huang, W., & Lv, H. (2018). Investigating the comparative roles of multi-source factors influencing urban residents' transportation greenhouse gas emissions. *Science of The Total Environment*, *644*, 1336–1345. https://doi.org/10.1016/j.scitotenv.2018.07.072
Yang, L., Wang, Y., Han, S., & Liu, Y. (2019). Urban transport carbon dioxide (CO2) emissions by commuters in rapidly developing Cities: The comparative study of Beijing and Xi'an in China. *Transportation Research Part D: Transport and Environment*, *68*, 65–83. https://doi.org/10.1016/j.trd.2017.04.026
Zeileis, A., & Hothorn, T. (2002). Diagnostic Checking in Regression Relationships (lmtest). *R News*, *3*(2), 7–10.
Zhang, Y., Liu, N., Li, Y., Long, Y., Baumgartner, J., Adamkiewicz, G., Bhalla, K., Rodriguez, J., & Gemmell, E. (2023). Neighborhood infrastructure-related risk factors and non-communicable diseases: A systematic meta-review. *Environmental Health: A Global Access Science Source*, *22*(1), 1–15. https://doi.org/10.1186/s12940-022-00955-8

DRAFT

Zhao, E., Walker, P. D., & Surawski, N. C. (2022). Emissions life cycle assessment of diesel, hybrid and electric buses. *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, *236*(6). https://trid.trb.org/view/1937361

Zlatinov, A., & Gillette, R. (2018). *Implementation of California's AB1837 Pay for Success Initiative and Opportunities for Expanded Impact* (p. 4). Harvard Kennedy School.

Zwiers, M., Kleinhans, R., & Van Ham, M. (2017). The Path-Dependency of Low-Income Neighbourhood Trajectories: An Approach for Analysing Neighbourhood Change. *Applied Spatial Analysis and Policy*, *10*(3), 363–380. https://doi.org/10.1007/s12061-016-9189-z

DRAFT

16. Appendix F: Health Impacts - Full Article - The Effect of Residential Greenness and Walkability on Cancer Risk in the Greater Vancouver Region

16.1. Background

Cancer is the leading cause of death in Canada with lung, breast, colorectal, and prostate cancer accounting for approximately half of the cancer cases diagnosed[1,2]. Two out of five Canadians are expected to receive a diagnosis of cancer in their lifetime resulting in one in four cancer related deaths after diagnosis. Furthermore, due to aging population demographics, Canada is expected to face an increased burden of cancer[1]. Despite advances in detection and treatment, lung cancer is the leading cause of death in Canada with a 5-year survival of 19%[1]. While estimated mortality rates for breast cancer declined by 49% from 1986 to 2020[2], improvements are mainly limited to women with early-stage cancers[3,4]. The incidence of colorectal cancers is lowest among persons under 50 years but is increasing in younger age groups[1,5,6]. Similarly, the incidence of prostate cancer has been decreasing since 2007, yet it is the most commonly diagnosed cancer in men accounting for 20% of new cases in 2021[1,3]. Cancer morbidity and mortality can be mitigated by interventions reducing exposure to risk factors. Smoking, alcohol consumption, physical activity, and diet have been shown to affect cancer risk15, but interventions to influence these factors are focused on individual-level behavior change which can be ineffective if they fail to account for multi-faceted socio-cultural barriers to change[7,8]. The built environment, which influences behaviors, can be altered to reduce cancer incidence[7].

The built environment is the infrastructure and its layout made by humans[9] including, but not limited to, urban green spaces, road and pedestrian networks, and residential and commercial establishments. Environmental models consider the built environment as a factor affecting health status moderated through factors such as dietary choices, physical activity, obesity, social engagement, greenness, hormonal changes, air pollution, and ambient exposures[10-12]. Walkable city designs with access to transit, healthy food environments, and amenities like parks can lead to increased physical activity and promote healthier diets[9-11], which are associated with reduced risks of lung, breast, prostate, and colorectal cancers[13-18]. Walkability indices are a measure of characteristics like sidewalk completeness, and residential and commercial densities, and are correlated with physical activity[19,20]. However, studies investigating associations of walkability

DRAFT

with cancer risk are few, have produced mixed findings, and have mostly focused on all-cancer risk[21-23]. A higher measure of greenness or normalized difference vegetation index (NDVI), which is rarer in urban environments, has been associated with decreased risk of breast[24,25], prostate[26,27], and lung cancers[28,29], but a recent meta-analysis reported no association with these cancers[30]. There is growing evidence of the association between morbidity and the built environment in recent times, but the majority of research has focused on the association with mortality, acute outcomes, or post-treatment rehabilitation.

With studies mainly focusing on the built environment and mortality rates, the mixed associations reported for NDVI, and the lack of research for walkability with cancer risk, it is essential to further investigate the causal associations using longitudinal study designs. Through this study, we examined the effect of residential greenspace and walkability on the risk of lung, colorectal, breast, and prostate cancers. We hypothesize that after accounting for socio-demographic and other individual factors the built environment with infrastructure promoting healthier lifestyles such as increased physical activity, or access to urban green space would lead to a lower risk of cancer outcomes compared to areas with poorly built infrastructures. However, the decreased risk could potentially be offset by collinear factors such as increased air, noise, and light pollution.

16.2. Methods

Data Sources: We conducted a longitudinal analysis using secondary data merged from multiple sources.

i) The British Columbia Generations Project is a longitudinal cohort established in October 2009 and designed to follow participants for 50 years. A total of 29,500 participants were recruited from 2009-2016 using volunteer sampling methods, and follow-up data were collected between 2016-2019. Participants were 35 years or above at recruitment and residents of British Columbia. Information about socio-demographic characteristics, health, diet, and other lifestyle factors such as physical activity, smoking habits, alcohol intake, and medical and family history was collected through questionnaires. A subset of participants also provided physical measurements which were either self-reported or measured at assessment centers. The environmental exposures were linked to participants based on self-reported residential postal codes and income tax records over time.

DRAFT

ii) The Where Matters project developed an annual walkability index for the Greater Vancouver region in the province of British Columbia, Canada from 2000-2016. The index was developed at the postal code level using four components, *viz.* residential density, intersection density, commercial floor density, and land use mix. We averaged the measurements from 2000-2006 to create the components for the 2006 index. Similarly, measurements from 2007-2011 and 2012-2016 were averaged for the 2011 and 2016 indices respectively. We calculated z-scores for each component standardized to the mean and standard deviation of the 2006 measurements. The z-scores were summed to compute a composite walk score for each time point.

iii) The Canadian Urban Environmental and Health Research Consortium (CANUE) provided data on the 2006 Canadian Active Living Environment (Can-ALE) walkability index and the Normalized Difference Vegetation Index (NDVI). The Can-ALE index was developed for dissemination areas and was computed using z-scores for individual components of intersection and residential densities. The NDVI is the measured vegetation in an area derived from satellite (LANDSAT 5 and 8) readings. Annual measurements are available from enrolment to 2016 and were calculated as the ratio of the difference between and the sum of the red and near infrared band values: (NIR – R)/(NIR + R), ranging from -1 to 1. The NDVI measurements were considered only from cloud free annual composites and after the masking of water features. Annual nitrogen dioxide (NO_2) and fine particulate matter ($PM_{2.5}$) concentrations were available as air pollution metrics.

iv) Based on passive annual follow-up, the British Columbia Cancer Registry provided information on mortality and cancer diagnoses which were categorized according to the International Classification of Diseases for Oncology, third edition (ICD-O-3) site codes. Only primary cancer diagnoses for each cancer type were considered for their individual analysis.

Analytical Sample and Variables: A total of 10,929 BCGP participants were included in the study sample (Figure 16-1). To be eligible, participants had to be residing in the Greater Vancouver

DRAFT

region. Participants who developed cancer prior to enrolment, and with missing information about the year of enrolment were excluded from the analysis.

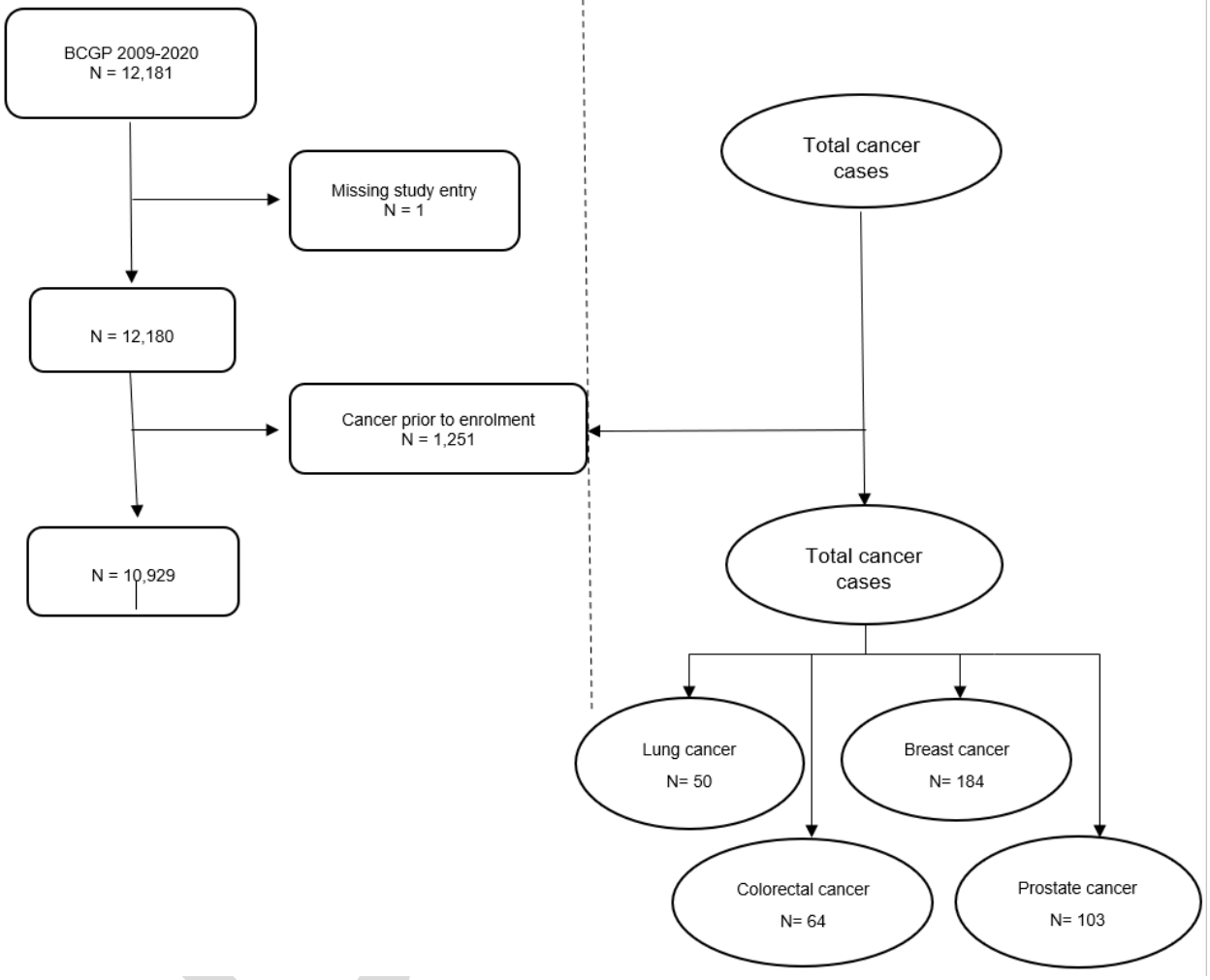


Figure 16-1: BCGP Sample and Cancer Case Distribution

The Where Matters walkability scores were lagged by using the 2006 walkability index for the years 2006-2010, the 2011 index for the years 2011-2015, and the 2016 index for 2016 and onwards. The final z-scores were standardized using the mean and standard deviation of the 2006 measurements of the sample to facilitate the assessment of longitudinal changes. Since CanALE was measured only in 2006, the same index was attributed to the entire length of follow-up. Due to the limited number of incident cancer cases the environmental exposures were classified into three equal groups of low, medium, and high exposure based on the sample size. We calculated a rolling average of NDVI values (1983-2015) and the distribution at the time of enrolment was utilized to determine the cut points of the three groups. We considered responses such as "Don't know" or "Refused" as missing data. Family history denoted the occurrence of the primary cancer in biological parents or siblings. Similar to NDVI, rolling averages were calculated for $PM_{2.5}$, and NO_2, which were simultaneously used to impute missing values. Other variables were imputed using the last observed value over the follow-up period. Categorizations of the covariates considered for the model are provided in Table 1.

Statistical Analysis: We conducted separate time-varying Cox proportional hazards models to assess the hazard ratio for the primary diagnosis of each cancer type based on the annual environmental exposures. Participants were censored at the year of cancer diagnosis, death, or end of follow-up. The analyses for lung and colorectal cancers were conducted in the entire sample, while the analyses for breast and prostate cancers were restricted to females and males respectively. Age, sex, race, marital status, education level, and income were considered as socio-economic and demographic factors, while alcohol intake, smoking habits, hormonal replacement therapy (HRT), contraceptive use, family history of the primary cancer diagnosis, and air pollution factors ($PM_{2.5}$ and NO_2) were considered as risk factors. Variables were selected for each cancer type based on established risk factors, researcher assumptions, and change in effect estimates. due to the limited number of incident cases the number of variables in the models estimating the hazard ratio for lung and colorectal cancers were limited to a maximum of 7 and 9 respectively. Greenness was adjusted in all models while assessing walkability to account for any confounding effect. After variable selection, a second model was created which included NO_2 to adjust for the effects of air pollution. The assumption of proportional hazards was verified by using Schoenfeld residuals. In case of deviations from the proportional hazards assumption, we introduced interaction terms with time for continuous variables and stratified by categorical variables.

DRAFT

16.3. Results

Baseline characteristics of BCGP participants are provided in Table 1. The eligible study sample consisted of 10,298 participants. The average age of the participants was 55 years and were mostly female (70%). The majority of the participants (83%) had a level of education greater than high school. Approximately 83% of the population was Caucasian and 61% had moderate to high total family income of ≥$75,000. Only 5% of the participants were current smokers while 90% were current drinkers. The average length of follow-up was 5.5 years with participants accounting for a total of 59,935.60 person-years. A total of 50 lung cancer, 64 colorectal cancer, 184 breast cancer, and 103 prostate cancer cases were eligible over follow-up. The results from the Cox analyses studying the association between the primary environmental exposures and individual cancer risks are presented in Tables 2-5.

Table 1. Baseline characteristics of eligible British Columbia Generations Project participants stratified by sex

Characteristics		Sex	
	Overall N = 10,929	Females N = 7,611	Males N = 3,318
Normalized Difference Vegetation Index	0.33 (0.12)	0.34 (0.12)	0.33 (0.12)
Canadian Active Living Environment, z-score	1.19(2.21)	1.14 (2.16)	1.30 (2.30)
Walk Index- WM Mean(SD), z-score	-0.22 (3.10)	-0.26 (3.06)	-0.13 (3.18)
Nitrogen Dioxide, Mean(SD), µg/m^3	13.20	13.11 (4.56)	13.43 (4.66)
Fine Particulate Matter, Mean(SD), µg/m^3	5.38 (0.91)	5.38 (0.91)	5.38 (0.90)
Age Mean(SD), years	54.56 (8.96)	61.48 (6.78)	55.69 (8.91)
Race n(%)			
Caucasian	8,667 (82.50)	6,061 (82.90)	2,606 (81.40)
Others	1,844 (17.50)	1,247 (17.10)	597 (18.60)
Education n(%)			
≤ High School	1,824 (16.80)	1,348 (17.80)	476 (14.40)
> High School & ≤ Bachelor's Degree	6,889 (63.30)	4,858 (64.10)	2,031 (61.50)
≥ Graduate Degree	2,162 (19.90)	1,368 (18.10)	794 (24.10)
Income n(%)			
<$55,000	2,090 (20.50)	1,549 (22.00)	541 (17.20)
$55,000-$74,999	1,926 (18.90)	1,366 (19.40)	560 (17.80)
$75,000-$99,999	1,764 (17.30)	1,239 (17.60)	525 (16.70)
≥$100,000	4,406 (43.30)	2,884 (41.00)	1,522 (48.30)
Marital Status n(%)			
Not Married	2,939 (27.00)	2,327 (30.70)	612 (18.50)
Married/Live-in Relationship	7,944 (73.00)	5,255(69.30)	2,689 (81.50)

DRAFT

Family History of Cancer n(%)			
No	4,033 (38.10)	2,739 (37.10)	1,294 (40.40)
Yes	6,546 (61.90)	5,255 (62.90)	1,910 (59.60)
Smoking History n(%)			
Never Smoker	6,141 (57.00)	4,318 (57.60)	1,823 (55.60)
Former Smoker	4,058 (37.60)	2,789 (37.20)	1,269 (38.70)
Current Smoker	580 (5.40)	395 (5.30)	185 (5.60)
Alcohol n(%)			
Never Drinker	452 (4.20)	342 (4.50)	110 (3.30)
Former Drinker	647 (6.00)	441 (5.80)	206 (6.20)
Current Drinker	9,740 (89.90)	6,759 (89.60)	2,981 (90.40)

Associations with lung cancer risk

There was no significant association between NDVI and lung cancer risk in the primary model (Table 2). Similarly, the CanALE walkability index showed no significant associations while comparing the lung cancer risk in moderate (HR = 0.95, 95% CI = 0.47 - 1.93) and high (HR = 0.48, 95% CI = 0.22 - 1.06) walkability regions to low walkability regions. Results for the Where Matters walkability index were very similar to those of the CanALE estimates in magnitude and trend. Although the findings were not statistically significant, an increase in both CANUE and Where Matters walkability metrics showed noticeable decreasing trends for lung cancer hazards. The Cox proportional hazards analysis for NDVI from Model 2, which was additionally adjusted for rolling averages of NO_2, elicited a reversal in the direction of effect for lung cancer risk while comparing the high NDVI group to the low NDVI group (HR = 0.96, 95% CI = 0.46 - 1.99). While assessing the walkability indices, model 2 estimates showed similar estimates and trends to those from Model 1.

DRAFT

Table 2. Results for lung cancer: Hazard ratio using Cox proportional models

N = 10,929	Lung Cancer (N= 50)		
Environmental Exposures	**Model 1**	**Model 2[c]**	**Cases (N)**
Normalized Difference Vegetation Index[a]			46 (10,274)
Medium	0.71 (0.33, 1.50)	0.63 (0.29, 1.37)	
High	1.14 (0.58, 2.23)	0.96 (0.46, 1.99)	
Canadian Active Living Environment[b]			45 (10,137)
Medium	0.95 (0.47, 1.93)	0.99 (0.48, 2.03)	
High	0.48 (0.22, 1.06)	0.53 (0.23, 1.23)	
Where Matters Walkability Index[b]			44 (10,028)
Medium	0.86 (0.39, 1.85)	0.89 (0.41, 1.96)	
High	0.54 (0.24, 1.23)	0.60 (0.26, 1.40)	

a: adjusted for age, race, family history of lung cancer, and smoking history

b: adjusted for tertiles of NDVI, age, race, family history of lung cancer, and smoking history

c: adjusted for tertiles of NDVI, age, race, family history of lung cancer, smoking history, and rolling average of nitrogen dioxide concentrations

Associations with colorectal cancer risk

Colorectal cancer risk was not significantly associated with NDVI, the CanALE walkability index, and the Where Matters walkability index in the primary model. However, there was a decreasing trend in the estimates with increasing NDVI exposure when compared to low NDVI exposure (HR = 0.96, 95% CI =0.53, 1.77 vs. HR = 0.75, 95% CI =0.40, 1.42). Adjusting for rolling averages of NO_2 in Model 2 did not result in changes in estimates or trends.

DRAFT

Table 3. Results for colorectal cancer: Hazard ratio using Cox proportional models

N = 10,929	Colorectal Cancer (N= 64)		
Environmental Exposure	**Model 1**	**Model 2[c]**	**Cases (N)**
Normalized Difference Vegetation Index[a]			61 (10,431)
Medium	0.96 (0.53, 1.77)	0.99 (0.54, 1.84)	
High	0.75 (0.40, 1.42)	0.79 (0.40, 1.56)	
Canadian Active Living Environment[b]			59 (9,912)
Medium	1.00 (0.53, 1.91)	0.98 (0.51, 1.87)	
High	0.88 (0.44, 1.74)	0.82 (0.40, 1.69)	
Where Matters Walkability Index[b]			56 (9,824)
Medium	0.88 (0.43, 1.83)	0.90 (0.43, 1.87)	
High	1.11 (0.54, 2.25)	1.15 (0.55, 2.40)	

a: adjusted for age, marital status, race, alcohol intake, and smoking history

b: adjusted for tertiles of NDVI, age, marital status, income, alcohol intake, and smoking history

c: adjusted for tertiles of NDVI, age, race, family history of colorectal cancer, smoking history, and rolling average of nitrogen dioxide concentrations

Associations with breast cancer risk

There was no association between NDVI and breast cancer risk in both models analyzed (Table 4). While analyzing breast cancer risk with the CanALE walkability index, we found a decreased risk of breast cancer nearing statistical significance when comparing the highest walkable areas to the lowest walkable area (HR = 0.65, 95% CI = 0.42-1.00). Similar point estimates and trends were obtained from model 2, although with wider confidence intervals (HR = 0.68 95% CI =0.43, 1.08). We found no significant association while analyzing the association of breast cancer risk with the Where Matters walkability index. However, a reducing trend in breast cancer risk approaching statistical significance was observed (medium vs. low walkability: HR = 0.83, 95% CI =0.56, 1.24, high vs. low walkability: HR = 0.70 95% CI =0.46, 1.07).

DRAFT

Table 4. Results for breast cancer: Hazard ratio using Cox proportional models

N = 7,611	Breast Cancer (N= 184)		
Environmental Exposure	**Model 1**	**Model 2[c]**	**Cases (N)**
Normalized Difference Vegetation Index[a]			162 (6,822)
Medium	0.95 (0.65, 1.40)	0.91 (0.62, 1.34)	
High	0.91 (0.62, 1.34)	0.84 (0.56, 1.27)	
Canadian Active Living Environment[b]			161 (6,736)
Medium	1.24 (0.85, 1.82)	1.27 (0.86, 1.87)	
High	0.65 (0.42, 1.00)	0.68 (0.43, 1.08)	
Where Matters Walkability Index[b]			157 (6,655)
Medium	0.83 (0.56, 1.24)	0.86 (0.57, 1.29)	
High	0.70 (0.46, 1.07)	0.73 (0.47, 1.14)	

a: adjusted for age, marital status, income, education status, race, family history of breast cancer, alcohol intake, smoking history, history of oophorectomy/hysterectomy, history of hormone replacement therapy, and interaction term of age with time

b: adjusted for tertiles of NDVI, age, marital status, income, education status, race, family history of breast cancer, alcohol intake, smoking history, history of oophorectomy/hysterectomy, history of hormone replacement therapy, and interaction term of age with time

c: adjusted for age, marital status, income, education status, race, family history of breast cancer, alcohol intake, smoking history, history of oophorectomy/hysterectomy, history of hormone replacement therapy, interaction term of age with time, and rolling average of nitrogen dioxide concentrations

Associations with prostate cancer risk

There was no significant association between NDVI and prostate cancer risk in the results from Model 1 (medium vs. low NDVI: HR = 0.92, 95% CI =0.52, 1.63, high vs. low NDVI: HR = 1.48 95% CI =0.88, 2.47). Similarly, while analyzing the CanALE (medium vs. low walkability: HR = 1.18, 95% CI =0.70, 2.00, high vs. low walkability: HR = 0.97 95% CI =0.53, 1.77) and Where Matters (medium vs. low walkability: HR = 0.92, 95% CI =0.54, 1.57, high vs. low walkability: HR = 0.87 95% CI =0.50, 1.54) walkability indices, there were no significant associations or noticeable trends in prostate cancer risk. Identical results were observed in Model 2 after adjusting for NO_2 concentrations for all three exposures.

DRAFT

Table 5. Results for prostate cancer: Hazard ratio using Cox proportional models

N = 3,318	Prostate Cancer (N= 103)		
Environmental Exposure	**Model 1**	**Model 2[c]**	**Cases (N)**
Normalized Difference Vegetation Index[a]			91 (3,016)
Medium	0.92 (0.52, 1.63)	0.91 (0.51, 1.62)	
High	1.48 (0.88, 2.47)	1.43 (0.83, 2.45)	
Canadian Active Living Environment[b]			89 (2,971)
Medium	1.18 (0.70, 2.00)	1.23 (0.72, 2.12)	
High	0.97 (0.53, 1.77)	1.04 (0.55, 1.97)	
Where Matters Walkability Index[b]			88 (2,955)
Medium	0.92 (0.54, 1.57)	0.98 (0.57, 1.67)	
High	0.87 (0.50, 1.54)	0.99 (0.56, 1.79)	

a: adjusted for age, marital status, income, education status, race, family history of prostate cancer, alcohol intake, and smoking history

b: adjusted for tertiles of NDVI, age, marital status, income, education status, race, family history of prostate cancer, alcohol intake, and smoking history

c: adjusted for tertiles of NDVI, age, race, family history of prostate cancer, smoking history, and rolling average of nitrogen dioxide concentrations

16.4. Discussion

Our study investigates the association between residential environmental exposures of greenness (NDVI) and walkability with cancer risk using a longitudinal cohort design. Although none of the effects were statistically significant, we observed potentially important trends through our analyses.

Greenness and cancer risk

We did not find statistically significant associations between NDVI exposure levels and lung and colorectal cancer risk in our analysis. However, on adjusting for air pollution factors we found a change in the direction of association from harmful to protective for lung cancer risk while comparing the highest NDVI exposures to the lowest (Table 2), highlighting the importance of accounting for the confounding effect of multiple collinear environmental exposures. Our analyses for lung and colorectal cancers were hampered by the low number of eligible incident cases, 50 and 64 respectively. However, previous research has shown a protective trend with lung cancer and no association with colorectal cancers[24,30,31]. A study by Huang et al. (2022) found a 5%

DRAFT

decrease in lung cancer risk using a Cox proportional hazards model with baseline covariates and lung cancer (HR: 0.95, 95% CI: 0.91–0.99)[28] while Kayyal-Tarabeia et al. (2022) found a 25% reduction in risk with a unit IQR increase in NDVI (HR = 0.75, 95% CI: 0.66–0.85)[29]. A third study by Sakhvidi et al. (2021) found no association between NDVI at a 100 m buffer and lung cancer risk (HR = 0.870, 95% CI= 0.691 - 1.095) but still exhibited a decreasing trend with increasing NDVI[32]. Both Huang et al. (2022) and Kayyal-Tarabeia et al. (2022) had a considerably larger number of cases and longer follow-up periods. Consequently, we believe the finding of no associations from the primary analysis could be a chance finding or an attribute of the limited number of cases developed in the cohort due to the short follow-up time. The proportional hazards Cox model performs better with more events and longer follow-up which helps in informed censoring.

While assessing breast cancer risk with measures of greenness findings have been mixed. Sakhvidi et al. (2021) and Kayyal-Tarabeia et al. (2022) found a decreased risk of breast cancer incidence[29,32]. However, similar to our findings Huang et al. (2022) found no association with NDVI[28]. We also found no association between NDVI and incidence of prostate cancer. While using low NDVI as the reference group, high NDVI exposure had higher point estimates of prostate cancer compared to medium NDVI exposure (medium vs. low NDVI: HR = 0.92, 95% CI =0.52, 1.63, high vs. low NDVI: HR = 1.48 95% CI =0.88, 2.47), but the estimates are likely the attribute of the wider confidence intervals, due to limited male sample size living in areas with the highest NDVI exposure, and not an actual increase in cancer risk.

From our findings and previous research, we surmise that exposure to increased green space can potentially decrease the risk of lung and breast cancer. While we could account for NO_2 as an air pollution factor, there could be other significant collinear exposures such as ambient night at light and noise pollution we have not considered in our analysis. Although NDVI is a popular method for measuring surrounding greenness[33], several other vegetation indices are available[34] in addition to discrete measures such as park count, and the choice of metric can affect research findings. Although dependent on the type of greenness (urban greenspace amenities vs. dense vegetation), increased exposure could also promote health by means of increased physical activity, and other physiological and psychological impacts[35].

Walkability and cancer risk

To our knowledge, there are no longitudinal studies investigating the direct effect of residential walkability on individual cancers making our study the first of its kind. A study by Keats et al. (2020) based on the Atlantic PATH cohort found no association between quintiles of the CanALE

DRAFT

index and all-cancer risk[21]. Given that different cancer types have different etiologies, it is important to conduct epidemiologic studies for each cancer type. Although statistically non-significant, we found a decrease in lung cancer risk estimates with increased walkability while analyzing the 2006 CanALE index. Similar trends and estimates were obtained from the Where Matters (WM) walkability index. We did not find any significant associations or remarkable trends while examining the effect of walkability on colorectal and prostate cancer risk. However, all hazard ratio estimates for breast cancer risk, with the exception of the medium walkability exposure while assessing the CanALE index, were below the null effect of 1. This potentially signals a protective effect with longer follow-up durations as the cancer diagnoses in the initial follow-up could likely belong to susceptible individuals.

The difference in estimates from the two walkability indices could be the result of multiple factors. One is the difference in geographical units utilized to estimate the exposure. The Where Matters walkability was created at the residential postal code level while the CanALE index was created by using dissemination areas (DA) as the smallest unit. Dissemination areas are larger geographical units comprising of multiple postal codes. Secondly, the WM index also considers commercial floor area and land use mix to measure walkability, in addition to the residential and intersection density assessed by CanALE. As a result, we believe the WM index captures greater variability in the exposure, which also led to larger confidence intervals in the estimates. Moreover, the WM index is longitudinal in nature and able to account for changes in the participant's exposure over time.

Strengths and Limitations

The study has multiple strengths due to the longitudinal design, especially the ability to investigate temporal associations. Based on residential postal codes linked by self-report and tax records our analysis incorporates changes in residential exposures for greenness and the Where Matters walkability index and is not restricted to baseline estimates. With respect to cancer risk, the longitudinal design of the study enables us to evaluate causal relationships using highly quantitative spatially resolved exposure data.

The recruitment process for BCGP was based on non-probability sampling leading to non-representative samples for the province. The study population could differ in characteristics such as health-seeking behaviors from the general population, with differences potentially extending into the unobserved characteristics of individuals residing in well-developed areas with better infrastructure compared to those in lesser developed areas. Although we could account for behavioral risk factors like smoking and alcohol intake, observational studies always suffer from

DRAFT

residual and/or unmeasured confounding. Self-reported data such as alcohol consumption, smoking habits, diet, and physical activity may suffer from social desirability bias. These factors might affect external validity to a certain extent; however, we expect strong internal validity due to the in-depth questionnaires curated to assess cancer risk and confounders. The sample sizes and cancer cases were limited to support detailed analyses of clinically relevant cancer subgroups. Nevertheless, the study sample, consisting of approximately 11,000 individuals, allowed us to study a range of environmental exposures over the Greater Vancouver Region increasing the variability in exposures.

16.5. Conclusion

Through our study, we were able to identify potential protective trends for greenness and walkability on certain cancer types. Individual-level behaviour interventions can influence public health considerably. As an example, due to effective public health campaigns about the ill effects of smoking, we have seen decreasing trends in tobacco-use and lung cancer incidence. However, lung cancer is still the leading cause of cancer death in Canada and other avenues, such as modifying the built environment, must be explored to reduce its burden on a wide-reaching scale. Given the complex nature of the built environment and the potential for interaction between multiple environmental factors, further research is required to confirm our findings.

16.6. References

1. CCS. Canadian Cancer Statistics 2021. 2021; https://cdn.cancer.ca/-/media/files/research/cancer-statistics/2021-statistics/2021-pdf-en-final.pdf. Accessed March, 2022.
2. Brenner DR, Weir HK, Demers AA, et al. Projected estimates of cancer in Canada in 2020. *CMAJ : Canadian Medical Association journal = journal de l'Association medicale canadienne.* 2020;192(9):E199-e205.
3. CCS. Canadian Cancer Statistics 2019. 2019; https://cdn.cancer.ca/-/media/files/research/cancer-statistics/2020-statistics/canadian-cancer-statistics/res-cancerstatistics-canadiancancerstatistics-2019-en.pdf?rev=82dc3652fe3648988b9174ad4b397a24&hash=6D3186DF3AC76787C58EE95D1712033C.
4. CCS. Survival statistics for breast cancer. *Breast Cancer* https://www.cancer.ca/en/cancer-information/cancer-type/breast/prognosis-and-survival/survival-statistics/?region=on. Accessed 17/8, 2021.

5. Brenner DR, Heer E, Sutherland RL, et al. National Trends in Colorectal Cancer Incidence Among Older and Younger Adults in Canada. *JAMA network open.* 2019;2(7):e198090-e198090.
6. Brenner DR, Ruan Y, Shaw E, De P, Heitman SJ, Hilsden RJ. Increasing colorectal cancer incidence trends among younger adults in Canada. *Preventive medicine.* 2017;105:345-349.
7. Klein WMP, Bloch M, Hesse BW, et al. Behavioral Research in Cancer Prevention and Control: A Look to the Future. *American journal of preventive medicine.* 2014;46(3):303-311.
8. Klein WMP, O'Connell ME, Bloch MH, et al. Behavioral Research in Cancer Prevention and Control: Emerging Challenges and Opportunities. *JNCI: Journal of the National Cancer Institute.* 2021;114(2):179-186.
9. Sallis JF, Floyd MF, Rodríguez DA, Saelens BE. Role of built environments in physical activity, obesity, and cardiovascular disease. *Circulation.* 2012;125(5):729-737.
10. Bird EL, Ige JO, Pilkington P, Pinto A, Petrokofsky C, Burgess-Allen J. Built and natural environment planning principles for promoting health: an umbrella review. *BMC Public Health.* 2018;18(1):930.
11. Koren HS, Butler CD. The Interconnection between the Built Environment Ecology and Health. Paper presented at: Environmental Security and Environmental Management: The Role of Risk Assessment; 2006//, 2006; Dordrecht.
12. Frank LD, Iroz-Elardo N, MacLeod KE, Hong A. Pathways from built environment to health: A conceptual framework linking behavior and exposure-based impacts. *Journal of Transport & Health.* 2019;12:319-335.
13. Moazzen S, van der Sloot KWJ, Bock GHd, Alizadeh BZ. Systematic review and meta-analysis of diet quality and colorectal cancer risk: is the evidence of sufficient quality to develop recommendations? *Critical Reviews in Food Science and Nutrition.* 2021;61(16):2773-2782.
14. Brown JC, Winters-Stone K, Lee A, Schmitz KH. Cancer, physical activity, and exercise. *Compr Physiol.* 2012;2(4):2775-2809.
15. NCI. Physical Activity and Cancer. https://www.cancer.gov/about-cancer/causes-prevention/risk/obesity/physical-activity-fact-sheet. Accessed 2/2, 2021.
16. Fakhri G, Al Assaad M, Tfayli A. Association of various dietary habits and risk of lung cancer: an updated comprehensive literature review. *Tumori Journal.* 2020;106(6):445-456.
17. Laudisio D, Barrea L, Muscogiuri G, Annunziata G, Colao A, Savastano S. Breast cancer prevention in premenopausal women: role of the Mediterranean diet and its components. *Nutrition Research Reviews.* 2019;33(1):19-32.
18. Wilson KM, Mucci LA. Diet and Lifestyle in Prostate Cancer. In: Dehm SM, Tindall DJ, eds. *Prostate Cancer: Cellular and Genetic Mechanisms of Disease Development and Progression*. Cham: Springer International Publishing; 2019:1-27.
19. Twardzik E, Judd S, Bennett A, et al. Walk Score and objectively measured physical activity within a national cohort. *Journal of Epidemiology and Community Health.* 2019;73(6):549-556.

DRAFT

20. Camhi SM, Troped PJ, Garvey M, et al. Associations between Walk Score and objective measures of physical activity in urban overweight and obese women. *PloS one.* 2019;14(3):e0214092.
21. Keats MR, Cui Y, DeClercq V, Grandy SA, Sweeney E, Dummer TJB. Associations between Neighborhood Walkability, Physical Activity, and Chronic Disease in Nova Scotian Adults: An Atlantic PATH Cohort Study. *International journal of environmental research and public health.* 2020;17(22):8643.
22. Celis-Morales CA, Lyall DM, Welsh P, et al. Association between active commuting and incident cardiovascular disease, cancer, and mortality: prospective cohort study. *BMJ.* 2017;357:j1456.
23. Harrigan SP. *Built environment and post-menopausal breast cancer risk : analysis of a linked British Columbian cohort* [Text]2021.
24. Datzmann T, Markevych I, Trautmann F, Heinrich J, Schmitt J, Tesch F. Outdoor air pollution, green space, and cancer incidence in Saxony: a semi-individual cohort study. *BMC Public Health.* 2018;18(1):715.
25. O'Callaghan-Gordo C, Kogevinas M, Cirach M, et al. Residential proximity to green spaces and breast cancer risk: The multicase-control study in Spain (MCC-Spain). *International journal of hygiene and environmental health.* 2018;221(8):1097-1106.
26. Iyer HS, James P, Valeri L, et al. The association between neighborhood greenness and incidence of lethal prostate cancer: A prospective cohort study. *Environmental epidemiology (Philadelphia, Pa).* 2020;4(2):e091.
27. Demoury C, Thierry B, Richard H, Sigler B, Kestens Y, Parent ME. Residential greenness and risk of prostate cancer: A case-control study in Montreal, Canada. *Environ Int.* 2017;98:129-136.
28. Huang Y-J, Lee P-H, Chen L-C, Lin B-C, Lin C, Chan T-C. Relationships among green space, ambient fine particulate matter, and cancer incidence in Taiwan: A 16-year retrospective cohort study. *Environmental research.* 2022;212:113416.
29. Kayyal-Tarabeia I, Michael Y, Lensky IM, Blank M, Agay-Shay K. "Residential greenness and site-specific cancer: A registry based cohort of 144,427 participants with a 21-years of follow-up, Tel-Aviv district, Israel". *Environmental research.* 2022;212:113460.
30. Zare Sakhvidi MJ, Yang J, Mehrparvar AH, et al. Exposure to greenspace and cancer incidence, prevalence, and mortality: A systematic review and meta-analyses. *Science of The Total Environment.* 2022;838:156180.
31. Masdor NA, Abu Bakar MF, Hod R, Mohammed Nawi A. Green space exposure and colorectal cancer: A systematic review. *Heliyon.* 2023;9(5).
32. Zare Sakhvidi MJ, Yang J, Siemiatycki J, et al. Greenspace exposure and cancer incidence: A 27-year follow-up of the French GAZEL cohort. *The Science of the total environment.* 2021;787:147553.
33. Huang S, Tang L, Hupy JP, Wang Y, Shao G. A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing. *Journal of Forestry Research.* 2021;32(1):1-6.

DRAFT

34. Xue J, Su B. Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications. *Journal of Sensors.* 2017;2017:1353691.
35. Bertram C, Rehdanz K. The role of urban green space for human well-being. *Ecological Economics.* 2015;120:139-152.
36. Hasselback P, Taylor E. Air Quality Health Index Variation across British Columbia (September 2010), B.C. Ministry of Environment, B.C. Interior Health Authority. Last Accesssed: February 10, 2024. Available at: https://www2.gov.bc.ca/assets/gov/environment/air-land-water/air/reports-pub/aqhi-variation-bc.pdf
37. India-Aldana s, Rundle AG, Quinn JW, Clendenen TV, Afanasyeva Y, Koenig KL, Liu M, Neckerman KM, Thorpe LE, Zeleniuch-Jacquotte A, and Chen Y. Long-Term Exposure to Walkable Residential Neighborhoods and Risk of Obesity-Related Cancer in the New York University Women's Health Study (NYUWHS) Environmental Health Perspectives 131:10 CID: 107001 https://doi.org/10.1289/EHP11538

DRAFT

17. Appendix G: Travel & Climate Impacts - Full Article - The Association of Built Environment Factors on Active and Sedentary Travel Behaviour: A Cross-Sectional Travel Diary Study

17.1. Background

In North American we are currently facing both an epidemic of sedentary behaviour as well as a need to reduce greenhouse gas (GHG) emissions to mitigate further climate change. Initiatives to reduce the reliance on private vehicle travel, and instead promote the use of active travel modes (walking and cycling) and public transportation, may serve as a strategy to promote public health, and mitigate GHG emissions. Previous work has found a number of built environment factors to be associated with the amount of active travel (E. J. Kim et al., 2020; Koohsari et al., 2017; Liao et al., 2020; Thielman et al., 2015). This current study builds upon these previous works by utilizing detailed trips diary data from a regionally representative sample of households as well as more robustly attributing neighbourhood walkability through the use of the previous described walkability index.

The aim of this study is to examine the association between neighbourhood walkability and travel behaviour across mode (walking, biking, transit, and vehicle). We hypothesize that living in a more walkable neighbourhood would be associated with more trips made by an active mode (walking, biking, and/or transit) whereas living in a less walkable neighbourhood would be associated with more trips made by a sedentary mode (vehicle).

17.2. Methods

17.2.1. Data source, survey design, and ethics

This cross-sectional analysis utilized regionally representative data collected through TransLink's 2017 Trip Diary Data (TDD)[33]. Households through the Metro Vancouver

[33] https://public.tableau.com/app/profile/translink/viz/Trip_Diary_2017/TripDiary2017

DRAFT

Regional District (MVRD) and Fraser Valley Regional District (FVRD) were recruited through a stratified random sample with approximately 2.5% of households in the region completing the survey (83% via web survey and 17% using smartphone app). The TDD collected data on weekday travel patterns for all individuals living in the recruited households between September 15 and December 12, 2017. In addition to information about the origins and destination, travel mode, and trip purposes, household and individual demographic data was collected.

Neighbourhood walkability was calculated using a composite *Walkability Index* comprised of four component measures (net residential density, commercial floor area, intersection density, and land use mix). This study was reviewed and approved by the University of British Columbia's Research Ethics board (#H20-03032).

17.2.2. Study sample and study variables

The Walkability Index is a composite measure of neighbourhood walkability, comprised of 4 component variables (net residential density, commercial floor area, intersection density, and land use mix). Within this current analysis, the walkability value for each household was defined as the composite index value within a 1-kilometre network buffer, which follow a walkable road network, surrounding the location of the home (as defined by home 6-digit postal code). The values for each component measure were calculated beginning at the home postal code location and were then converted to z-scores to calculate the overall walkability index. The 1-km network buffer size was selected to represent the distance individuals could reasonably travel in a 10–15-minute walking trip and has been previous used to define the home "neighbourhood" area. (Colabianchi et al., 2007).

Individual and household demographic data were obtained from the TDD. For this current analysis the following variables were utilized and categorized as follows: gender (dichotomized as female or male), age (categorized as child/youth [age 5-18], adult [age 19-64], and older adult [65+]), driver's license status (dichotomous yes/no), car share status (continuous 0-4, the number of car share membership participants reporting having), employment status (categorized as 'full time employed', 'full time student', 'part

DRAFT

time worker or student, or self-employed' or 'non-worker/non-student'), household income (categorized as <$50,000, $50,000-100,000, and >$100,000), household size (continuous 1-10), number of household bicycles (continuous 0-10), number of vehicles per adult in the home (dichotomized as less vehicles than adults [vehicles < adults] and 1 or more vehicle per adult in the home [vehicles > = adults]).

In addition to neighbourhood walkability, regional accessibility and sidewalk connectivity were calculated at the 6-digit postal code level and linked to the residential location. Regional accessibility was calculated by the mean number of minutes to travel to regional growth centers from the home location in morning peak traffic. These values were calculated for both vehicle travel, which provides an estimation of peak travel time from the home location if traveling by vehicle, as well as for transit travel, which conversely provides as estimation of peak travel time from the home if traveling by transit. Additionally, sidewalk connectivity, a measure of the completely of the pedestrian infrastructure, was calculated using methods similar to the walkability index in the 1-km network buffer surrounding the home.

17.2.3. Statistical analysis

We calculated descriptive statistics to characterize the study sample stratified by neighhourhood walkability. All analyses were completed in R version 3.6.1; we used the glmer function within the 'lme4' package to run generalized linear mixed-effect models.

Adjusted odds ratios (OR) and 95% confidence intervals (CI) were calculated using logistic regression and three iterations of adjustment variables. Three adjustment models were developed based on existing literature and conceptual understanding of individual and environmental factors associated with travel behaviour. Multi-level (or mixed effects) models were developed to account for the hierarchical nature of the TDD (e.g., multiple participants living in the same household). A two-level model was used to account for clustering of participants within households. Additionally, survey weights obtained from the TDD were utilized in these analyses.

DRAFT

17.3. Results

Walking

Certain individual and household characteristics increased the odds of reporting walking trips (

DRAFT

Table 17-1). Numerous individual variables were significantly associated across each iteration of these analyses including gender, age, employment status, car share status, and driver's licence status. Female participants had 1.22 times the odds of males to make a walking trip in the minimally adjusted model, when accounting for additional variables these results were attenuated, but remained statistically significant. Younger participants reported the most walking trips, with a 15% increase in odds of walking compared to adults (in the fully adjusted model). Participants who reported non-worker/non-student status reported the most walking trips, with 11% increase in odds of walking compared to full time workers. Conversely, participants who reported having a driver's licence had 14% reduced odds of reporting a walking trip compared to those without a driver's licences.

Regional accessibility did not have a significant effect on walking trips, however increased sidewalk connectivity did have a small but significant association with walk trips. There was a graded relationship between walkability and walking, for each increase in walkability there was a corresponding increase in walking trips, with this association being significant across each level of walkability. Participants in the most walkable neighbourhoods reported 13% increased odds in making a walk trip compared to those living in the least walkable neighbourhoods.

DRAFT

Table 17-1: Odds of walking trips across walkability quintiles

	Mod 1		Mod 2		Mod 3	
	OR	95% CI	OR	95% CI	OR	95% CI
Gender						
Male	REF		REF		REF	
Female	**1.22**	**1.15, 1.30**	**1.02**	**1.01, 1.03**	**1.03**	**1.02, 1.03**
Age						
5-18	**2.32**	**1.98, 2.72**	**1.14**	**1.12, 1.17**	**1.15**	**1.12, 1.18**
19-64	REF		REF		REF	
65+	**0.54**	**0.48, 0.62**	**0.97**	**0.95, 0.98**	**0.97**	**0.95, 0.98**
Drivers License						
No	REF		REF		REF	
Yes	**0.30**	**0.27, 0.33**	**0.85**	**0.84, 0.87**	**0.86**	**0.84, 0.87**
Car share						
+1	**2.73**	**2.55, 2.94**	**1.10**	**1.08, 1.12**	**1.09**	**1.08, 1.11**
Status						
Full time employed	REF		REF		REF	
Full time student	**1.23**	**1.07, 1.41**	**1.03**	**1.01, 1.05**	**1.03**	**1.01, 1.05**
Part time employed/student or self-employed	**1.43**	**1.29, 1.58**	**1.05**	**1.03, 1.06**	**1.05**	**1.03, 1.06**
Non-worker/non-student	**2.09**	**1.87, 2.35**	**1.11**	**1.09, 1.12**	**1.11**	**1.09, 1.11**
Household income						
< $50,000	REF		REF		REF	
$50,000 - $100,000	**0.78**	**0.70, 0.87**	**0.98**	**0.97, 0.99**	0.98	0.97, 1.00
>$100,000	**0.89**	**0.80, 0.99**	**0.98**	**0.96, 0.99**	0.98	0.99, 1.00
Household size						
+1	**0.75**	**0.73, 0.77**	**0.99**	**0.98, 0.99**	0.99	0.99, 1.00
Household vehicles						
Vehicles < Adults	-		REF		REF	
Vehicles > = Adults	-		0.95	0.90, 1.00	0.96	0.91, 1.01
Bicycles						
+1	-		**1.02**	**1.01, 1.04**	**1.03**	**1.01, 1.04**
Regional Accessibility						
Vehicle	-		1.00	1.00, 1.00	1.00	1.00, 1.00
Transit	-		0.99	0.99, 0.99	0.99	0.99, 0.99
Sidewalk connectivity					**1.05**	**1.01, 1.09**
Walkability						
1	-		-		REF	

DRAFT

	2	-		-	**1.04**	**1.01, 1.06**
	3	-		-	**1.07**	**1.04, 1.10**
	4	-		-	**1.11**	**1.08, 1.14**
	5	-		-	**1.13**	**1.08, 1.19**

Notes: bolded results indicate statistical significance at p<0.05
Model 1 adjusted for gender, age, having a driver's licence, car share membership, employment status, household income, and household size. Model 2 adjusted for Model 1 variables, plus ratio of household vehicles to number of adults in household, number of household bicycles, and vehicle and transit regional accessibility. Model 3 adjusted for Model 2 variables, plus, sidewalk connectivity and 1km-network based walkability surrounding residential location.
Vehicle regional accessibility = AM vehicle trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations; Transit regional accessibility = AM transit trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations

Cycling

The patterns for cycling trips differed considerable compared to the trends for walking trips (Table 17-2). Females had 58% decreased odds of making a bike trip, and full-time students reported lower odds of cycling trips (81% decrease in odds) compared to full time workers. Participants in households with more bicycles reported increased odds in making a cycling trip. There was no significant association between neighbourhood walkability and odds of participants making a cycling trip.

Table 17-2: Odds of cycling trips across walkability quintiles

		Mod 1		Mod 2		Mod 3	
		OR	95% CI	OR	95% CI	OR	95% CI
Gender							
	Male	REF		REF		REF	
	Female	**0.37**	**0.31, 0.45**	**0.41**	**0.41, 0.42**	**0.42**	**0.30, 0.58**
Age							
	5-18	**1.46**	**0.88, 2.43**	**4.86**	**4.85, 4.86**	**4.72**	**1.83, 12.2**
	19-64	REF		REF		REF	
	65+	**0.38**	**0.24, 0.59**	**0.73**	**0.73, 0.73**	0.68	0.32, 1.42
Drivers License							
	No	REF		REF		REF	
	Yes	**0.67**	**0.47, 0.95**	**0.56**	**0.56, 0.56**	**0.55**	**0.30, 0.99**
Car share							
	+1	**3.29**	**2.86, 3.80**	**2.74**	**2.74, 2.74**	**2.71**	**1.94, 3.77**
Status							

DRAFT

Full time employed	REF		REF		REF	
Full time student	**0.42**	**0.28, 0.67**	**0.18**	**0.18, 0.18**	**0.19**	**0.07, 0.48**
Part time employed/student or self-employed	0.79	0.58, 1.05	**0.69**	**0.68, 0.69**	0.68	0.39, 1.19
Non-worker/non-student	0.98	0.67, 1.41	**1.37**	**1.37, 1.37**	1.40	0.73, 2.67
Household income						
< $50,000	REF		REF		REF	
$50,000 - $100,000	0.84	0.59, 1.20	**1.39**	**1.39, 1.39**	1.39	0.68, 2.85
>$100,000	1.15	0.82, 1.63	**1.34**	**1.34, 1.34**	1.31	0.64, 2.68
Household size						
+1	0.81	**0.73, 0.88**	**0.97**	**0.96, 0.97**	0.95	0.81, 1.11
Household vehicles						
Vehicles < Adults	-		REF		REF	
Vehicles > = Adults	-		0.47	0.09, 2.31	0.52	0.08, 3.47
Bicycles						
+1	-		**4.75**	**4.75, 4.76**	**4.75**	**3.56, 6.34**
Regional Accessibility						
Vehicle	-		**1.04**	**1.04, 1.04**	1.02	0.95, 1.01
Transit	-		**0.97**	**0.97, 0.97**	0.98	0.95, 1.01
Sidewalk connectivity	-		-		2.66	0.73, 9.68
Walkability						
1	-		-		REF	
2	-		-		0.83	0.39, 1.73
3	-		-		0.84	0.36, 1.98
4	-		-		0.42	0.12, 1.42
5	-		-		1.76	0.53, 5.85

Notes: bolded results indicate statistical significance at p<0.05

Model 1 adjusted for gender, age, having a driver's licence, car share membership, employment status, household income, and household size. Model 2 adjusted for Model 1 variables, plus ratio of household vehicles to number of adults in household, number of household bicycles, and vehicle and transit regional accessibility. Model 3 adjusted for Model 2 variables, plus, sidewalk connectivity and 1km-network based walkability surrounding residential location.

Vehicle regional accessibility = AM vehicle trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations

Transit regional accessibility = AM transit trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations

DRAFT

Transit

Female participants reported increased odds (17%) of making a transit trip compared to male participants (

DRAFT

Table 17-3). Both child/youth respondents and older adult participants had lower odds of transit trips compared to adult participants. Similar to the effects for both walking and cycling travel mode, participants with a driver's license has lower odds of transit trips (89%), whereas participants with car share memberships were more likely to make a transit trip (119%). There was a large effect for employment status, with full-time student participants reporting 12.8 times (95% CI 10.6, 15.4) the odds of making a transit trip compared to participants who were employed full time. Unlike walking and cycling, income was associated with odds of participants reporting a transit trip, with higher income associated with lower odds of transit trips (45% decrease in the middle-income category, and 37% decrease in the higher income category compared to the lower income category), with these results remaining significant in the fully adjusted model. Increased neighbourhood walkability was also associated with greater odds of transit use, however, these results were less consistent across the levels of walkability when compared to the trends for walking trips. Participants with neighbourhood walkability in the 4th and 5th levels (e.g., the most walkability and second most walkable), reported greater odds of making a transit trip when compared to participants living in the least walkable neighbourhoods. However, these results do not follow the same graded response as for walking trips.

DRAFT

Table 17-3: Odds of transit trips across walkability quintiles

	Mod 1		Mod 2		Mod 3	
	OR	95% CI	OR	95% CI	OR	95% CI
Gender						
Male	REF		REF		REF	
Female	**1.18**	**1.11, 1.26**	**1.15**	**1.05, 1.26**	**1.17**	**1.07, 1.28**
Age						
5-18	**0.01**	**0.01, 0.02**	**0.01**	**0.01, 0.02**	**0.02**	**0.01, 0.02**
19-64	REF		REF		REF	REF
65+	**0.73**	**0.64, 0.83**	**0.82**	**0.68, 0.99**	**0.81**	**0.67, 0.98**
Drivers License						
No	REF		REF		REF	
Yes	**0.09**	**0.08, 0.11**	**0.10**	**0.09, 0.12**	**0.11**	**0.10, 0.13**
Car share						
+1	**2.15**	**2.00, 2.30**	**2.30**	**1.98, 2.67**	**2.19**	**1.88, 2.55**
Status						
Full time employed	REF		REF		REF	
Full time student	**12.0**	**10.5, 13.7**	**13.8**	**11.4, 16.6**	**12.8**	**10.6, 15.4**
Part time employed/student or self-employed	0.93	0.84, 1.03	1.07	0.93, 1.25	1.08	0.93, 1.25
Non-worker/non-student	**0.60**	**0.53, 0.68**	**0.52**	**0.44, 0.63**	**0.53**	**0.44, 0.63**
Household income						
< $50,000	REF		REF		REF	
$50,000 - $100,000	**0.51**	**0.46, 0.57**	**0.56**	**0.47, 0.66**	**0.57**	**0.48, 0.67**
>$100,000	**0.54**	**0.48, 0.60**	**0.61**	**0.51, 0.73**	**0.63**	**0.53, 0.75**
Household size						
+1	**0.89**	**0.86, 0.92**	**0.93**	**0.89, 0.98**	**0.95**	**0.91, 0.99**
Household vehicles						
Vehicles < Adults	-		REF		REF	
Vehicles > = Adults	-		**0.18**	**0.08, 0.41**	**0.28**	**0.13, 0.60**
Bicycles						
+1	-		**0.75**	**0.66, 0.85**	**0.74**	**0.65, 0.84**
Regional Accessibility						
Vehicle	-		**1.08**	**1.06, 1.10**	**1.07**	**1.05, 1.09**
Transit	-		**0.94**	**0.93, 0.95**	**0.94**	**0.94, 0.95**
Sidewalk connectivity			-		**2.13**	**1.44, 3.16**
Walkability						
1	-		-		REF	

DRAFT

	2	-	-	1.10	0.88, 1.38
	3	-	-	1.22	0.95, 1.58
	4	-	-	**1.78**	**1.32, 2.42**
	5	-	-	**1.58**	**1.02, 2.44**

Notes: bolded results indicate statistical significance at p<0.05
Model 1 adjusted for gender, age, having a driver's licence, car share membership, employment status, household income, and household size. Model 2 adjusted for Model 1 variables, plus ratio of household vehicles to number of adults in household, number of household bicycles, and vehicle and transit regional accessibility. Model 3 adjusted for Model 2 variables, plus, sidewalk connectivity and 1km-network based walkability surrounding residential location.
Vehicle regional accessibility = AM vehicle trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations; Transit regional accessibility = AM transit trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations

Vehicle

Individual and household characteristics that were associated with participants reporting a vehicle trip (either as the driver or passenger) differed considerable from the other modes of travel (

DRAFT

Table 17-4). Both child/youth participants and older adult participants reported significantly increased odds of making a vehicle trip compared to participants aged 19-64 years, with children/youth reporting the greatest odds of making a vehicle trip. Reporting being full time employed was associated with the greatest odds of vehicle travel, with full time students (86% reduced), part time employed/student or self-employed (33% reduced), and non-worker/non-student (51% reduced) categories reporting reduced odds of any vehicle trip. Unlike the other modes of travel, higher income was associated with greater odds of making a vehicle trip (this is opposite to transit travel, whereas there was no significant association for income and either walking or cycling trips). Additionally, participants with a driver's license had over 15 times the odds of taking a vehicle trip (either as the driver or passenger), compared to participants without a driver's licence. In the fully adjusted model, the ratio of household vehicles to adults in the home was not significantly associated with vehicle trips. Participants in the least walkable neighbourhoods reported the greatest odds of vehicle travel, however, only 4th walkability bin was associated with a significant decreased in odds of vehicle travel.

DRAFT

Table 17-4: Odds of vehicle trips across walkability quintiles

	Mod 1		Mod 2		Mod 3	
	OR	95% CI	OR	95% CI	OR	95% CI
Gender						
Male	REF		REF		REF	
Female	**1.10**	**1.03, 1.18**	1.08	0.98, 1.18	1.07	0.97, 1.17
Age						
5-18	**9.06**	**7.69, 10.7**	**8.37**	**6.68, 10.5**	**7.72**	**6.16, 9.66**
19-64	REF		REF		REF	
65+	**1.34**	**1.17, 1.53**	**1.29**	**1.06, 1.57**	**1.29**	**1.06, 1.58**
Drivers License						
No	REF		REF		REF	
Yes	**14.5**	**13.0, 16.3**	**16.5**	**14.0, 19.4**	**15.7**	**13.3, 18.4**
Car share						
+1	**0.46**	**0.43, 0.50**	**0.60**	**0.51, 0.71**	**0.63**	**0.53, 0.74**
Status						
Full time employed	REF		REF		REF	
Full time student	**0.18**	**0.16, 0.20**	**0.13**	**0.11, 0.16**	**0.14**	**0.11, 0.17**
Part time employed/student or self-employed	**0.91**	**0.82, 1.01**	**0.67**	**0.57, 0.79**	**0.67**	**0.57, 0.79**
Non-worker/non-student	**0.71**	**0.62, 0.79**	**0.49**	**0.41, 0.58**	**0.49**	**0.41, 0.59**
Household income						
< $50,000	REF		REF		REF	
$50,000 - $100,000	**2.10**	**1.87, 2.35**	**1.85**	**1.55, 2.21**	**1.82**	**1.52, 2.18**
>$100,000	**2.31**	**2.06, 2.60**	**2.31**	**1.91, 2.80**	**2.24**	**1.85, 2.72**
Household size						
+1	**1.14**	**1.10, 1.17**	0.96	0.91, 1.01	**0.95**	**0.90, 0.99**
Household vehicles						
Vehicles < Adults	-		REF		REF	
Vehicles > = Adults	-		**2.23**	**1.08, 4.62**	1.93	0.93, 3.98
Bicycles						
+1	-		**1.31**	**1.14, 1.51**	**1.33**	**1.16, 1.53**
Regional Accessibility						
Vehicle	-		**0.93**	**0.91, 0.95**	**0.93**	**0.91, 0.95**
Transit	-		**1.07**	**1.06, 1.08**	**1.06**	**1.05, 1.07**

DRAFT

Sidewalk connectivity			-	**0.41**	**0.26, 0.63**
Walkability					
	1	-	-	REF	
	2	-	-	0.91	0.71, 1.17
	3	-	-	0.76	0.57, 1.02
	4	-	-	**0.59**	**0.42, 0.82**
	5	-	-	0.69	0.42, 1.14

Notes: bolded results indicate statistical significance at p<0.05
Model 1 adjusted for gender, age, having a driver's licence, car share membership, employment status, household income, and household size. Model 2 adjusted for Model 1 variables, plus ratio of household vehicles to number of adults in household, number of household bicycles, and vehicle and transit regional accessibility. Model 3 adjusted for Model 2 variables, plus, sidewalk connectivity and 1km-network based walkability surrounding residential location.
Vehicle regional accessibility = AM vehicle trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations
Transit regional accessibility = AM transit trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations

17.4. Discussion

This chapter describes the relationship between individual, household, and neighbourhood factors and trip mode reported in TransLink's 2017 Trip Diary Data. Overall, these analyses found an increase in active travel mode trips completed (in particular walking trips) and a reduction in sedentary modes (vehicle trips) as neighrbouhood walkability increased, when adjusting for other individual, households, and neighbourhood factors. This effect was most apparent for walking trips, with each increase in niehgbourhood walkability associated with a further significant increase in walking trips. These results are consistent with previous work which found an increase in walking trips completed in more walkable neighbourhoods (Kim et al., 2020), additionally, similar individual and household characteristics were found, with women, younger age, and lower household incomes associated with completing more walking trips. This same pattern was also seen when examining utilitarian walking trips across urban areas in Canada, with increased walking trips reported in more walkable neighbourhoods (Wasfi et al., 2016). Additionally, previous work which looked at

DRAFT

components of walkability, found that residential density and land use mixed were also independently associated with increased transportation walking (Eriksson et al., 2012).

Similar to previous work (Riggs & Sethi, 2020), there were increased odds of transit trips in more walkable neighbourhoods, however, this effect was only significant and in the two most walkable quintiles. Previous work also tended to find more biking trips complete in more walkable areas, however this was only seen in the most walkable quintile in this current analysis.

There are a number of strengths of this current work, including the generalizability to the population of the MVRD. However, the cross-sectional nature of these data limit the ability to determine cause and effect, and therefore these results represent correlations rather than causal relationships.

17.5. Conclusions

Analysis results showed that individual, household, and neighbourhood characteristics are all associated with trip mode. When controlling for other factors, living in more walkable areas was associated most strongly with reporting walking trips.

DRAFT

17.6. References

Eriksson, U., Arvidsson, D., Gebel, K., Ohlsson, H., & Sundquist, K. (2012). Walkability parameters, active transportation and objective physical activity: Moderating and mediating effects of motor vehicle ownership in a cross-sectional study. *International Journal of Behavioral Nutrition and Physical Activity*, *9*(1), 123. https://doi.org/10.1186/1479-5868-9-123

Kim, E. J., Kim, J., & Kim, H. (2020). Does Environmental Walkability Matter? The Role of Walkable Environment in Active Commuting. *International Journal of Environmental Research and Public Health*, *17*(4), 1261. https://doi.org/10.3390/ijerph17041261

Koohsari, M. J., Owen, N., Cole, R., Mavoa, S., Oka, K., Hanibuchi, T., & Sugiyama, T. (2017). Built environmental factors and adults' travel behaviors: Role of street layout and local destinations. *Preventive Medicine*, *96*, 124–128. https://doi.org/10.1016/j.ypmed.2016.12.021

Liao, Y., Lin, C.-Y., Lai, T.-F., Chen, Y.-J., Kim, B., & Park, J.-H. (2019). Walk Score® and Its Associations with Older Adults' Health Behaviors and Outcomes. *International Journal of Environmental Research and Public Health*, *16*(4), 622. https://doi.org/10.3390/ijerph16040622

Riggs, W., & Sethi, S. A. (2020). Multimodal travel behaviour, walkability indices, and social mobility: How neighbourhood walkability, income and household characteristics guide walking, biking & transit decisions. *Local Environment*, *25*(1), 57–68. https://doi.org/10.1080/13549839.2019.1698529

Thielman, J., Rosella, L., Copes, R., Lebenbaum, M., & Manson, H. (2015). Neighborhood walkability: Differential associations with self-reported transport walking and leisure-time physical activity in Canadian towns and cities of all sizes. *Preventive Medicine*, *77*, 174–180. https://doi.org/10.1016/j.ypmed.2015.05.011

Wasfi, R. A., Dasgupta, K., Eluru, N., & Ross, N. A. (2016). Exposure to walkable neighbourhoods in urban areas increases utilitarian walking: Longitudinal study of Canadians. *Journal of Transport & Health*, *3*(4), 440–447. https://doi.org/10.1016/j.jth.2015.08.001

DRAFT

18. Appendix H: Travel & Climate Impacts - Full Report - Transportation Emissions Estimates for Integrated Environment-Health Modelling

18.1. Methods for emission estimates

18.1.1. Data sources

Trip Diary Data

The main source of travel information is TransLink's 2017 Trip Diary Data (TDD) (Ipsos, 2018). Sample households for the TDD were recruited from Grater Vancouver Regional District and Fraser Valley Regional District[34] by a pre-notification letter and followed up by telephone recruitment. Participants completed the survey primarily online and some opted to use a smartphone app. A travel diary instrument was used to record all travel by members of the sampled households over 1 day (or 3 days if they used the smartphone app) between September 15 and December 12, 2017. Person and household sampling weights[35] are included in the TDD to account for representation differences between the sample and the regional population (as indicated by census data). This study was reviewed and approved by the University of British Columbia's Research Ethics board (#H20-03032).

The TDD were initially processed and cleaned by data verifications (e.g., verifying trip mode based on trip characteristics) and logic checks (e.g., changing underage drivers to passengers) as part of the data collection process before we gained access to the data. For our analysis, two additional data processing steps were undertaken.

1. We executed automated and manual corrections of the text string descriptions of vehicles to enable matching to external vehicle datasets, as described below. For example, "F150" was replaced by "F-150".
2. We filtered to remove trips with at least one trip-end (origin or destination) outside the geographic scope of our analysis: metropolitan Vancouver (which is provided

[34] Illustrated in https://public.tableau.com/app/profile/translink/viz/Trip_Diary_2017/TripDiary2017

[35] The TDD provides expansion weights (sometimes referred to as expansion factors), which we normalize to sampling weights by dividing by the mean expansion weight (to avoid inflating standard errors in subsequent weighted regression analysis).

DRAFT

as a variable in the TDD). This eliminated 1,333 trips (0.59% of the TDD), primarily auto driver (65%) or auto passenger (26%) trips.

In total, the TDD consist of 224,525 trips by 57,431 persons in 27,980 households, who collectively own 37,148 motor vehicles and 35,146 bicycles. Based on the geographic study scope (see above), 1333 trips (0.59%) were excluded, leaving 223,192 trips for analysis. The primary mode shares for the analyzed trips were auto driver (55%), auto passenger (14%), walk (15%), transit (13%), and bicycle (2%) – see Table 18-1.

The key information extracted from the TDD for emissions estimates included:

1. Trip-end locations (origin and destination)
2. Departure time
3. Travel modes
4. Vehicle
5. Vehicle occupancy

Table 18-1. Modal distribution of trips in the TDD

Primary mode	Single mode	Multi-mode	Total	
Auto Driver	122,880	142	123,022	55.1%
Auto Passenger	31,336	68	31,404	14.1%
Taxi	518	3	521	0.2%
Transit Bus	11,867	819	12,686	5.7%
Sky Train	6,919	9,061	15,980	7.2%
Westcoast Express	69	161	230	0.1%
Handy Dart	150	3	153	0.1%
Sea Bus	97	90	187	0.1%
Walk	33,516	0	33,516	15.0%
Bike	4,266	5	4,271	1.9%
School bus	609	21	630	0.3%
Other mode	591	1	592	0.3%
Total	212,818	10,374	223,192	100.0%

DRAFT

Some trips reported in the TDD involved the use of multiple modes of travel. The TDD defines the "primary" mode as the mode that was most likely used for the largest proportion of the trip, with a hierarchy of rail transit, bus transit, then automobile and other modes for multi-modal trips (TransLink, 2013b). For emissions estimation, we disaggregate multi-modal trips into modal "segments", as described below (after the description of methods for uni-modal trips).

Regional travel model data

TransLink's regional travel model (RTM) provided essential additional information to enhance the precision of the emissions estimates. TransLink's RTM is a four-step, trip-based travel model, implemented in EMME software (TransLink, 2018). The current version of the RTM was estimated using data from TransLink's 2011 trip diary data (the predecessor to the TDD) (TransLink, 2013b).

The main use for the RTM data was for link-level information on peak and off-peak period network congestion levels. Roadway congestion is an important factor in motor vehicle emission rates, and integration of travel demand and emissions models has been a key environmental analysis tool for decades. In fact, application to travel demand model outputs was a key use case in MOVES model development (U.S. Environmental Protection Agency, 2022b). Mesoscopic emissions models like MOVES enable modellers to account for the emissions impacts of typical microscopic (second-by-second) traffic dynamics in an aggregate analysis through the use of archetypal facility-specific driving patterns (or "drive cycles"), applied at each network link traversed in a trip.

For this application of the RTM, transportation network data were used in the form of shapefiles identifying the locations and attributes of network links. Separate road and transit networks were provided. The RTM road network consists of 20,043 links with an average length of 61.5 m. The road network is a simplification typically used in travel demand models, representing only the facilities used to travel between Transportation Analysis Zones (TAZ), which are themselves aggregations of travel-generating geographic areas (Ortuzar & Willumsen, 2011). The road network data include almost all the primary and secondary roadways, but not most local streets (i.e., most arterials, some collectors, and few local streets). As only inter-zonal (between-TAZ) trips are modelled on the network, "centroid connectors" (synthetic links) are designed and added to the network to represent the intra-zonal portions of inter-zonal trips (i.e., the portion which typically occurs on collector and local streets).

DRAFT

Link attributes in the roadway network include: 1) road type: 19 classes describing modal access (autos, high-occupant vehicles, buses, bicycles, pedestrians, etc.), and 2) mean travel time at 3 modelled time periods: Morning peak (6 to 10 hr), Afternoon peak (15 to 18 hr), and Off peak (all other hours). The transit network includes all of the regularly serviced transit lines in the region, including bus, Sky Train, Sea Bus, and West Coast Express services (i.e., road, rail, and marine transit).

The RTM network data were further processed for application with the TDD and MOVES to emissions estimation. Firstly, to meet the formatting requirements of the routing software used (see below), two-way roads (represented as paired 1-way links in the RTM) were converted into a single 2-way link. Secondly, centroid connectors were manually corrected for 5 TAZ. Thirdly, in accordance with MOVES guidance, link attributes were added to align with the MOVES "Road Type" designation, which is the four combinations of setting (Urban or Rural) and access (Restricted or Unrestricted) (U.S. Environmental Protection Agency, 2016). The setting attribute (Urban/Rural) was based on Metro Vancouver's land use designations (Metro Vancouver, 2020) for the majority of the link length, illustrated in Table 18-2. The access attribute (Restricted/Unrestricted) was based on the RTM link types, using the mapping shown in Figure 18-1.

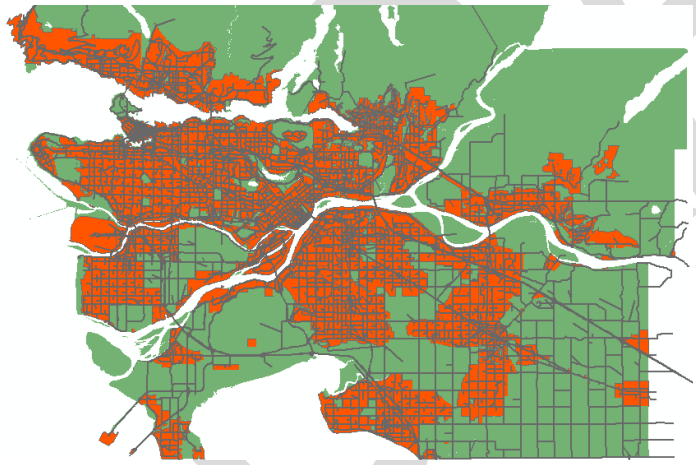


Figure 18-1. Urban (orange) and rural (green) link settings, based on Metro land use designations

DRAFT

Table 18-2. Mapping of RTM to MOVES road types for the network data

RTM network link type	MOVES Road Type
Highway	Restricted
Highway directional ramp	Restricted
Highway loop ramp	Restricted
Freeway	Restricted
Ramp	Restricted
HOV lane	Restricted
Centroid connector	Unrestricted
Arterial	Unrestricted
Collector	Unrestricted
Local	Unrestricted
Commercial vehicle access only	Unrestricted
Other roads	Unrestricted

Transit system operations data

TransLink transit system operation data were used to generate regional, fleet-specific vehicle emission factors and vehicle occupancy (i.e., passenger loads) for metro Vancouver. These data were taken from the 2019 Transit Service Performance Review (TransLink, 2019). Data processing for emissions estimates is described below.

The RTM transit network consists of 16,214 links with an average length of 390 m. These transit network data were enhanced with TransLink's General Transit Feed Specification (GTFS) data for the period September to December 2017, including transit line attributes (TransLink, 2022a).

18.2. Automobile trips

This section describes the estimation of emissions associated with uni-modal trips in automobiles, which includes private automobiles (cars, passenger trucks, vans, sport utility vehicles, etc.) and shared automobiles (both car-share and taxi/ride-hail). Similar methods are also applied to the estimation for Automobile segments of multi-modal trips.

Emissions for automobile trips are calculated as the summation of four components: operating (start and running) and non-operating (fuel and vehicle lifecycles). Non-operating emissions are attributed to vehicle-trips based on the amount of fuel and

DRAFT

proportion of vehicle-life consumed by the trip. Vehicle-trip emissions are then attributed to person-trips based on vehicle occupancy (excluding working drivers for ride-hail services). All four automobile emission components are vehicle-dependent, and the operating emissions also vary with facility type, congestion level, and temperature.

Vehicle information

Automobile emissions vary greatly across vehicle types. In the TDD, auto driver and passenger trips were self-reported as made by: 1) a household vehicle, 2) another household's vehicle, 3) a car-share vehicle, or 4) in a taxi/ride-hail vehicle. The vehicle information reported in the TDD for each of these trip types is summarized in Table 18-3, and described next.

Table 18-3. Passenger vehicle information reported in the TDD and assumptions used in analysis

Type of vehicle	Number (share) of automobile trips	TDD vehicle information	Assumptions
Private, traveler's household	148,412 (96%)	Make, model, year, fuel	Imputations for missing data
Private, another household	5,127 (3.3%)	None	Most common registered vehicle in Metro Vancouver in 2017 (2015 Toyota Corolla)
Car-share	677 (0.4%)	None	Representative vehicles based on car-share membership
Taxi	518 (0.3%)	None	2017 Toyota Prius HEV

18.2.1.1. Household private vehicles

For trips made using a private vehicle from the traveler's household, the TDD included self-reported information on the vehicle's make, model, model-year, and fuel type. The entire TDD dataset included trips made by 8,086 unique combinations of vehicle make-model-year. However, vehicle information was missing or incomplete for many trips. Table 18-4 summarizes the extent of missing/incomplete data and the imputation of missing vehicle attributes. Individual missing attributes were assumed as the mode (i.e., most frequent observation) for vehicles with similar non-missing attributes in the 2017 Metro Vancouver automobile fleet (excluding coach and other heavy-duty vehicles), as reported by the Insurance Corporation of British Columbia (ICBC) (2020). The ICBC dataset includes all registered passenger vehicles in British Columbia, filtered to only

DRAFT

vehicles registered to households in Metro Vancouver. The ICBC dataset does not include joint distributions of model and year, so the make/model frequency distribution is year-invariant.

Table 18-4. Summary of missing vehicle information for trips by household vehicles

Missing field(s)	Trips as driver of household vehicle	Trips as passenger in household vehicle	Imputation assumptions
None	108,196 (92%)	2 (0%)	Not applicable
Only make	914 (1%)	0 (0%)	Inferred from model
Only year	2004 (2%)	0 (0%)	Most common model-year (2015)
Make and model	112 (0%)	0 (0%)	Most common make/model (Toyota Corolla)
Make and year	551 (0%)	0 (0%)	Most common model-year; make inferred from model
All three (make, model, year)	5,300 (5%)	31,333 (100%)	Concurrent household trip, most-used household vehicle, or random vehicle from Metro Vancouver fleet
Total	117,077 (100%)	31,335 (100%)	Not applicable

If no vehicle information was available for the reported trip (i.e., all three attributes were missing), the following imputation process was used.

1) Look for concurrent (time and location) auto trips within the same household, and use the vehicle information reported for those trips; this was particularly effective for auto passenger trips, for which a concurrent auto driver trip in the same household yielded vehicle information for 14,155 trips (45% of the missing values).
2) For the remaining trips made by household vehicles, the trip was assumed to be made by the most-used vehicle in the traveller's household.
3) For the 883 households with no reported vehicle information but trips reported as having been made by household vehicles, household vehicle information (model-year and then make/model) was drawn from the 2017 Metro Vancouver fleet distribution (ICBC data). Because ICBC provides marginal (not joint) distributions, an existence criterion was imposed (i.e., available models were restricted by the model-year of manufacture).

DRAFT

To obtain additional vehicle attributes, each vehicle make-model-year was matched to US/Canada vehicle fleet datasets from Natural Resources Canada (NRCAN) (Natural Resources Canada, 2022), Canadian Vehicle Specifications (CVS) (Transport Canada, 2021) and the US Department of Energy and Environmental Protection Agency (EPA) (U.S. Department of Energy & U.S. Environmental Protection Agency, 2022), using string matching in R with manual corrections for automated match failures. Missing or erroneous fuel/powertrain types were imputed from the matched vehicle fleet datasets. Fuel type was unknown for only 12 unique make/model/year combinations in the dataset, and powertrain type was unknown for 3. We assumed these vehicles were gasoline ICE, based on the majority of the non-missing vehicle fleet attributes. The final processed fuel/powertrain types for vehicles in the TDD were 92.7% gasoline ICE, 4.6% diesel ICE, 1.9% gasoline-electric hybrid (HEV), 0.3% plug-in gasoline-electric hybrid (PHEV), and 0.5% battery-electric vehicles (BEV).

Vehicle models were not differentiated by engine size or transmission type, consistent with both the emissions model and travel survey scopes. The NRCAN data can contain multiple entries for varying transmission type, engine size, or number of cylinders within a given make, model, and year. Table 18-5 gives the number of unique household vehicles (out of 8086) with multiple matches in the NRCAN data (60% overall) and the number for which the NRCAN data vary by each vehicle attribute (some vary across multiple attributes). The BEV with multiple matches varies by range. The range of NRCAN reported fuel economy within a given make, model, and year averaged 1.2 L per 100 km, or 10% of the mean fuel economy. For these vehicles, we use the average NRCAN fuel economy within the make, model, and year.

DRAFT

Table 18-5. Number of unique household vehicles (out of 8086) matching multiple entries in the NRCAN fuel economy dataset for a given make, model, and year

Powertrain type	Number of matches in NRCAN data[1]			Varying attributes across matches		
	1	2	3+	Transmission type	Engine size	Number of cylinders
ICE	3031	3272	1555	4032	2135	1315
HEV	158	2	0	1	0	0
PHEV	23	0	0	0	0	0
BEV	44	1	0	0	0	0
All	3256	3275	1555	4033	2135	1315

[1] (Natural Resources Canada, 2022)

18.2.1.2. Non-household private vehicles

No vehicle information was recorded for trips made using a private vehicle from another household (#2 above). For these trips, we assigned the most common vehicle registered in Metro Vancouver in the ICBC 2017 fleet data: a 2015 Toyota Corolla (gasoline).

18.2.1.3. Car-share vehicles

For car-share trips (#3 above), the TDD does not include vehicle nor car-share service information. However, the TDD does include person-level car-share memberships for ZipCar, Modo, Car2Go, and Evo (the four major car-share services operating in Metro Vancouver in 2017). We identified a representative vehicle for each car-share service based on their respective fleets (Martin & Shaheen, 2016; Metro Vancouver, 2014) – see Table 18-6.

Table 18-6. Car-share services and vehicles

Service	Service type	Representative vehicle
Evo	A-to-B (1-way)	2017 Toyota Prius
Car2Go	A-to-B (1-way)	2015 Smart for two
Modo	A-to-A (2-way)	2015 Toyota Corolla
ZipCar	A-to-A (2-way)	2015 Toyota Corolla

DRAFT

We then assigned a vehicle to the trip based on the traveller's memberships (for driving trips) or the household's memberships (for passenger trips). Most people (91.6%) in the TDD were not car-share members, while 5.2% had 1 membership, 2.7% had 2 memberships, and 0.6% had 3 or 4 memberships. If multiple memberships were available, we used the following heuristic:

1) The representative vehicle for both 2-way services are the same, so no differentiation is needed.
2) If both 1-way services were available, we assign Evo based on higher overall usage.
3) If both 1-way and 2-way services were available (rare), we assumed a 2-way service was used for complete car-share tours (i.e., no other modes used), and a 1-way service was used otherwise.

18.2.1.4. Taxi vehicles

For taxi or ride-hail trips (#4 above), the specific service was not reported. At the time of the survey, no major ride-hail companies (such as Uber or Lyft) were operating in Metro Vancouver. Hence, it is assumed that the vast majority of the reported trips were by traditional taxi service, which in Metro Vancouver is mostly gasoline-electric hybrid vehicles[36]. We assume all taxi trips are made by 2017 Toyota Prius HEV, based on the most common HEV vehicle in the ICBC 2017 fleet data described above; this make and model is consistent with our observations of the regional taxi fleet.

Occupancy

Vehicle occupancy is a key factor for attributing vehicle emissions passenger-trips. Vehicle occupancy (excluding the driver for taxi/ride-hail trips) was reported for automobile trips in the TDD. If occupancy was missing, occupancy was assumed to be 1.24 for taxi trips (TransLink, 2013a), and 1.60 for all other automobile trips (the average occupancy in the TDD) .

[36] The largest two operators are Yellow Cab: https://www.yellowcabonline.com/about/about-the-team/ and Black Top & Checker Cabs: https://btccabs.ca/about-us/

DRAFT

Operating emissions

Operating emissions are calculated using the variables shown in Table 18-7. The total person-trip emissions are calculated by summing the start and running vehicle emissions (by link l), adjusted for deadheading, and then dividing by vehicle occupancy:

$$E_o = \frac{e_s + \frac{\sum_l L}{1 - D_r} e_r MF}{\theta}$$

Because MOVES emission rates are uniform within Source Type categories (for a given Model Year and Fuel Type), we apply a make/model-specific adjustment factor (MF) to the MOVES rates (separately for each Road Type), based on model-specific fuel economy test data. This approach enables us to leverage both the link-level congestion-sensitive emission rates from the MOVES model (by Source Type, Fuel Type, Model Year, and Road Type), and the detailed vehicle information (make/model/year) in the TDD to account for efficiency differences by make/model within a given vehicle class. The following sub-sections describe these analysis steps in detail.

Table 18-7. Variables used to calculate automobile operating emissions

Variable	Description	Units	Parameters[1]	Source
θ	Occupancy	People per vehicle (PKT per VKT)	None	TDD
MF	Model factor, to adjust MOVES rates by source type	None	MM, MY, RT	Fleet datasets
L	Link length	km	None	Network and route
D_r	Deadheading rate	Proportion	None	Literature
e_r	Running emission rate	g per km	MY, ST, FT, RT, SP	MOVES modelling
e_s	Start emission rate	g per start	MY, ST, FT, HR	MOVES modelling

[1] Conditioning factors for the variable: FT (fuel type), HR (hour of day), MM (make/model), MY (model year), RT (road type), SP (average speed), ST (source type)

18.2.1.5. MOVES emission rate modelling

Emission rates were estimated in MOVES2014, the latest version of the MOVES (MOtor Vehicle Emissions Simulator) model at the time of analysis (EPA has since released a new version: "MOVES3"). Detailed information about MOVES can be found in EPA

DRAFT

reports on its development over several decades (U.S. Environmental Protection Agency, 2022b). Briefly, MOVES is a modal model, which estimates second-by-second emissions for archetypal drive cycles (1-sec speed profiles). The emission rates are conditioned on vehicle fleet parameters such as Source Type (passenger car, passenger truck, motorcycle, transit bus, etc.), Fuel Type (gasoline, diesel, ethanol, compressed natural gas (CNG), electricity, etc.), and Model Year. The drive cycles are conditioned on the Source Type and contextual parameters such as Road Type (combinations of urban/rural and restricted/unrestricted, as well as off-network) and Average Speed Bin (representing link congestion levels, specific to each Road Type). In addition to running exhaust, MOVES includes modules to estimate emissions from vehicle starts, refuelling, evaporation, brake/tire wear, and other processes.

The MOVES model was used to create emission rate lookup tables for application to the TDD, which is one of the recommended modes of operation. For this application, the MOVES Run Specification was set to generate Emissions Rates for a Custom Domain in October 2017 (the time of the TDD). MOVES requires an extensive input database, but not all tables are required for disaggregate emission rates (rather than an emissions inventory). Some MOVES input information was provided by Metro Vancouver's Air Quality and Climate Change team (Metro), which conducts regional air quality modelling and analysis for the Vancouver region. Metro provided the MOVES input files they used to model 2015 regional motor vehicle emissions for air quality analysis (Metro Vancouver, 2018). Metro prepared these input files using local information on the vehicle fleet composition, fuels, vehicle activity distributions across hours, road types, speed bins, weather, inspection/maintenance programs, etc. The values in the provided files were checked by comparison to alternate data sources on the vehicle fleets (Insurance Corporation of British Columbia (ICBC), 2020; Natural Resources Canada, 2022; Statistics Canada, 2010; Transport Canada, 2021), vehicle activity (TransLink, 2013a, 2013b, 2018), and archived weather station data for meteorology (Environment and Climate Change Canada, 2020; Pacific Climate Impacts Consortium, 2020; Weather Underground, 2022). One adjustment was necessary for application to the TDD: MOVES default fuel formulation was used for the E85 ethanol fuel type, which was reported in the TDD (for just 6 automobile trips by one vehicle) but excluded from the Metro modelling.

MOVES execution provided emission rates for GHG (CO2e) and CAC (VOC, CO, NOx, PM2.5, PM10), as well as fuel consumption rates. *Running* emission rates (per VKT) were generated for each unique combination of: Source Type, Fuel Type, Model Year, Road

DRAFT

Type, and Average Speed Bin. Running emissions included the emission processes: running exhaust, brakewear and tirewear, running evaporative emissions, crankcase running exhaust, and refueling losses. *Start* emission rates (per start) were generated for each unique combination of: Source Type, Fuel Type, Model Year, and Hour (to account for varying ambient and engine temperatures).

18.2.1.6. Assigning vehicles to MOVES categories

A mapping is required to apply the MOVES rates to the TDD automobile trip data. The NRCAN (Natural Resources Canada, 2022) and EPA (U.S. Department of Energy & U.S. Environmental Protection Agency, 2022) fuel economy data were used to determine the Source Type for each unique vehicle (make-model-year) in the TDD, based on MOVES guidance (U.S. Environmental Protection Agency, 2022b). MOVES Passenger cars (Source Type 21) includes sedans, compacts, station wagons, and two-seaters; MOVES Passenger trucks (Source Type 31) includes vans, minivans, pickup trucks, and SUV. The size distribution of vehicles in the TDD is illustrated in Figure 18-2.

DRAFT

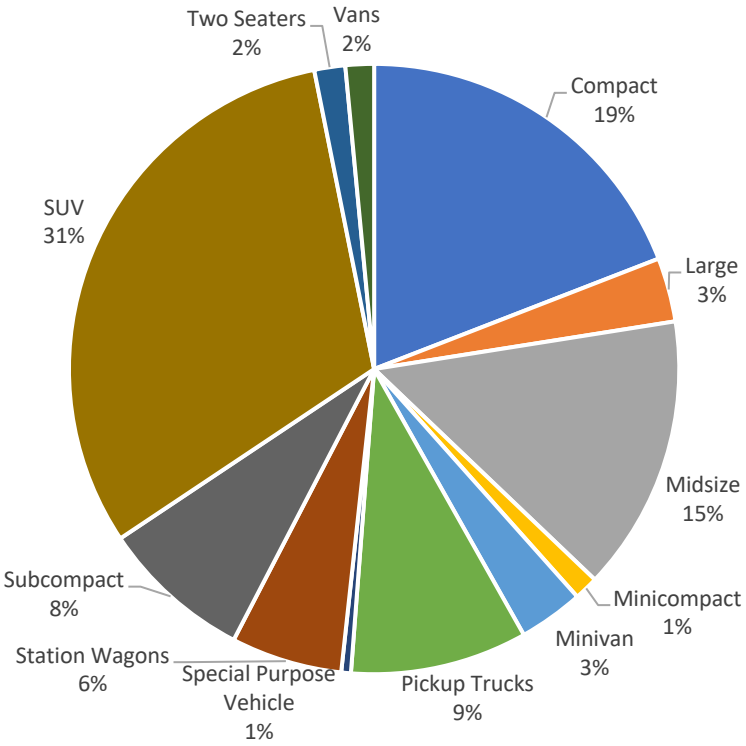


Figure 18-2. Vehicle sizes in the TDD

MOVES does not differentiate powertrains within Fuel Type categories, hence the gasoline Fuel Type includes ICEV, HEV, and PHEV (U.S. Environmental Protection Agency, 2019). This limitation is accounted for with our model-specific MF adjustment. For PHEV, which includes both gasoline and electricity fuel types, we assume a weighted combination of 52.5% gasoline and 47.5% electricity energy sources, based on literature (Kannangara et al. 2021 and Dunn et al., 2015).

18.2.1.7. Model-specific efficiency adjustment

To account for emission rate variation of specific vehicle models within Source Type categories, we develop and apply a Model Factor (MF), calculated as:

$$MF = \frac{FE_{MM,MY,RT}}{FE_{ST,MY,RT}}$$

were $FE_{MM,MY,RT}$ is the fuel economy for the trip-vehicle's specific make/model/year, and $FE_{ST,MY,RT}$ is the fleet-average fuel economy for the relevant MOVES Source Type and Model Year. Fuel economy for the trip's vehicle (in L/100km) is taken from NRCAN data (Natural Resources Canada, 2022), averaged across variations in engine size or transmission type within a given make/model/year as described above. Fleet-average fuel economy for the MOVES Source Type and Model Year (in miles/gallon) is taken from EPA data (U.S. Environmental Protection Agency, 2022a), and then converted into L/100km. For ICE vehicles, fuel economy and MF are separately calculated for "city" and "highway" driving/rates – which are then applied separately to the MOVES unrestricted and restricted link Road Types, respectively.

Figure 18-3 shows the distribution of MF values for the TDD automobile trips. The mean trip-averaged MF was 0.93, indicating that the Metro Vancouver automobile fleet is more fuel-efficient (lower-emitting) than the U.S. average. The mean trip fraction on city (vs. highway) links was 88%, reflecting the urban context and relatively low share of limited-access highways/freeways in the Vancouver region.

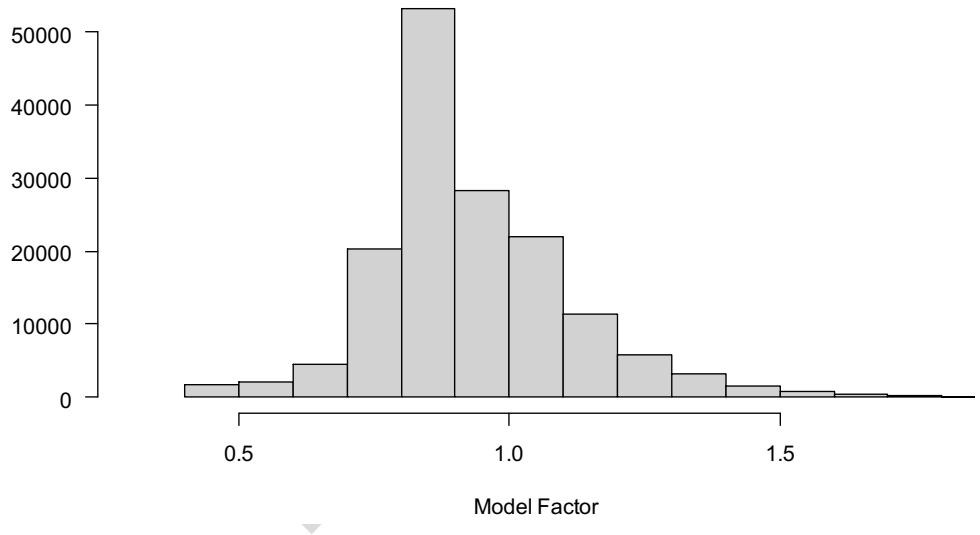


Figure 18-3. Distribution of Model Factor (MF) values

18.2.1.8. Vehicle routing

Automobile trips were routed from origin to destination on the road network data as represented in the RTM. The following RTM network adjustments were made for automobile routing:

1. Remove non-roadway links (pedestrian, water, rail, gondola),
2. Remove non-automobile links (bus only, commercial vehicle access only),
3. Select link travel times based on the start time of the trip (to account for typical congestion level), and
4. Conditionally assign HOV links a travel time of 10,000 minutes if automobile occupancy was 1 (so that they are not used by SOV).

Precise locations (latitude – longitude) for origins and destinations were "snapped" (orthogonal projection) to the nearest centroid connector within their respective TAZ. The network shortest (time) path sequences of links were determined using R software (R Core Team, 2019) with the package igraph (Csárdi et al., 2023). Ties for shortest time routes were broken by similarity to the self-reported distance (km) in the TDD.

The estimated travel times for the routed trips averaged 13.9 min (standard deviation of 12.9), whereas the travel times reported in the TDD averaged 17.1 min (standard deviation of 14.6). The linear correlation between the two travel time estimates was 0.91 ($p<0.01$). Travel times reported in the TDD were estimated using the Google Maps API. This tool was not used for the emissions analysis because it generates route rather than link information, in addition to TDD privacy restrictions.

18.2.1.9. Vehicle starts

Each automobile trip was assumed to generate a single start event. The relevant per-start emission rate from MOVES was determined by the vehicle (Source Type, Model Year, Fuel Type) and the hour of the day that the trip began. No model-specific adjustment was made due to a lack of model-specific start emissions data. The hour parameter serves to account for the effects of varying ambient and engine temperatures on start emissions. We attempted to track vehicle activity through the TDD to calculate soak time (i.e., elapsed time since the last engine-off event) for each vehicle start, but the results were too uncertain. So instead, the hour parameter accounts for the typical distribution of soak times for vehicle starts within given hour of the day.

DRAFT

Non-operating (upstream & downstream) emissions

The non-operating emissions accounted in this analysis include those attributable to 1) upstream activities for fuel provision (i.e., "well-to-tank" emissions), and 2) upstream (production), downstream (disposal/scrappage), and non-operating in-use (maintenance) phases of the vehicle lifecycle. The fuel and vehicle cycle calculations are described in the next two sub-sections.

18.2.1.10. Fuel cycle

Upstream fuel emissions are calculated as proportionate to the amount of fuel consumption (in litres for petrol fuels and kWh for electricity), which assumes that the trip-level fuel consumption is negligibly small with respect to the total vehicle fuel demand (i.e., these specific trips have no direct impact on decisions in the fuel sector). Fixed upstream or "well-to-tank" (WTT) emission rates (in kg CO_2e per unit fuel type) are applied to the operating fuel consumption.

For petrol fuels (gasoline, ethanol, and diesel), WTT emission rates are taken from GHGenius[37] ((S&T) Squared Consultants Inc., 2022), which is supported by Natural Resources Canada and approved for regulatory use in B.C. (B.C. Ministry of Energy, Mines and Petroleum Resources, 2017). GHGenius provides geography-specific lifecycle emissions data for the Canadian context, and is widely used in practice. WTT emission rates are extracted for BC in 2017. The shares of feedstock used in fuel production (fossil versus biomass) are set consistently with the MOVES fuel formulation data provided by Metro Vancouver: fossil feedstocks of 94% for gasoline, 100% for diesel, and 26% for ethanol (and the rest assumed biomass). The resulting WTT emission intensities (in kg CO_2e per L) are 0.8297 for gasoline, 0.8365 for ethanol, and 0.9128 for diesel.

The WTT emission rate for operating electricity (used by PHEV and BEV) is assumed to be 0.0317 kg CO_2e per kWh, based on the GHG intensity of electricity consumed from BC's electricity grid in 2017 as reported by the BC government (B.C. Ministry of Environment and Climate Change Strategy, 2022). Note that this is the GHG intensity of electricity consumption in BC, some of which is produced outside of the province. The GHG intensity of BC's electricity production is substantially lower, for example 0.01067 kg CO_2e per kWh

[37] https://www.ghgenius.ca/

DRAFT

for BC Hydro production (BC Ministry of Environment and Climate Change Strategy, 2022), but inappropriate for calculation of consumption-side intensity.

18.2.1.11. Vehicle cycle

Non-operating emissions attributable to the vehicle cycle are calculated using the emission estimation framework applied in Kannangara et al. (2021), which is consistent with wide practice. The framework in Kannangara et al. is highly parameterized, enabling adaptability, while parameter values are also provided specifically for the BC context. Total vehicle production and end-of-life emissions are summed and then distributed evenly over the lifetime of the vehicle (in km) to generate a per-VKT emission intensity, to which a fixed per-VKT maintenance emission intensity is added.

From Kannangara et al. (2021) – excluding operating phase – total vehicle production and end-of-life emissions (E_V) are parameterized on vehicle (m_V) and battery (m_B) mass, separately for materials, electricity, and end-of-life, and calculated as:

$$E_V = m_V(C_V + C_{El-V} \times EI_E + eol_V) + m_B(C_B + C_{El-B} \times EI_E + eol_B)$$

Lifetime vehicle maintenance emissions are also parameterized on vehicle mass, at a constant rate over the lifetime of the vehicle (Lt): $E_M = Lt \cdot m_V \cdot C_M$. Combining these and dividing by the vehicle lifetime in km, the non-operating vehicle cycle GHG emission intensity (in kg CO_2e per km) is

$$e_{VC} = \frac{E_V + E_M}{Lt} = \frac{m_V}{Lt}(C_V + C_{El-V}EI_E + eol_V) + \frac{m_B}{Lt}(C_B + C_{El-B}EI_E + eol_B) + m_V C_M$$

All parameter definitions and values are given in Table 18-8. The per-km GHG intensity $\left(\frac{E_V+E_M}{L}\right)$ is multiplied by the trip length in km to obtain the upstream emissions attributable to a specific trip.

As shown in Table 18-8, several of the parameter values from Kannangara et al. (2021) (which only included best-selling mid-size gasoline cars in Canada) were modified for better applicability and utilization of the TDD (which included a full spectrum of the vehicle fleet). Firstly, vehicle curb weights by make, model, and year for each vehicle in the TDD were extracted from the comprehensive Canadian Vehicle Specifications (CVS) (Transport Canada, 2021). As with other vehicle datasets, string matching was used for most

DRAFT

of the TDD, with manual entry for 248 vehicles that failed matching, using information from a general internet search with the Google search engine (Google, 2022). The CVS curb weight includes traction batteries (for HEV, PHEV, and BEV), and so the traction battery weight (see below) was subtracted to determine m_V.

Only 226 unique vehicles in the TDD (3%) had a traction battery (HEV, PHEV, or BEV), consisting of 93 unique make/model over varying model years. A general internet search with the Google search engine (Google, 2022) was used to determine the traction battery weight and cathode chemistry for each from publicly available information, which were assumed to be constant over model years. Traction battery weight could not be determined for 12 vehicles, for which average battery weights by powertrain and battery type were assumed based on the non-missing data. Battery chemistry could not be determined for 6 vehicles, for which the mode (most common) battery chemistry by powertrain type was assumed based on the non-missing data (nickel-metal hydride (NiMH) for HEV and lithium-ion (Li-ion) for PHEV and BEV).

DRAFT

Table 18-8. Upstream & downstream emissions parameters[1]

Parameter	Units	Description	Value
m_V	kg	Vehicle weight without traction battery	**Vehicle-specific (make, model, year), see below for sources**
m_B	kg	Traction battery weight (=0 for ICE)	**Vehicle-specific (make, model, year), see below for sources**
C_V	kg CO_2e per kg m_V	Emission intensity of vehicle materials and processing for production (without traction battery)	ICEV: 5.294 BEV: 7.813 HEV/PHEV: 5.212+2.602*H
C_B	kg CO_2e per kg m_B	Emission intensity of traction battery materials and processing for production **(added NiMH batteries)**	Li-ion, nickel cobalt aluminum: 11.7 Li-ion, nickel manganese cobalt: 10.9 Li-ion, iron phosphate: 9.49 NiMH: 19.65 **(from Mahmud, 2019)**
C_{El-V}	kWh per kg m_V	Electricity intensity of vehicle production	ICEV/HEV/PHEV: 1.127 BEV: 0.897
C_{El-B}	kWh per kg m_B	Electricity intensity of battery production	16.8
EI_E	kg CO_2e per kWh	Emission intensity of production-phase electricity	0.70
C_M	kg CO_2e/VKT per kg m_V	Emission intensity of vehicle service and maintenance	ICEV, HEV, PHEV: 0.000010 BEV: 0.000008
H	%	Hybridization factor for hybrid vehicles	HEV: 30% PHEV: 60%
Lt	km	Lifetime vehicle kilometres travelled	150,000
eol_V	kg CO_2e per kg m_V	Emissions during end-of-life treatment of vehicle	ICEV: 0.300 HEV: 0.402 PHEV: 0.401 BEV: 0.542
eol_B	kg CO_2e per kg m_B	Emissions during end-of-life treatment of battery	0.5

[1] From Kannangara et al. (2021), unless otherwise indicated **in bold text**

DRAFT

Some TDD vehicles had NiMH traction batteries, which were missing from the Kannangara et al. values/analysis. A value for the GHG intensity of NiMH traction battery material and production (per kg) was taken from Mahmud et al. (2019), supported by earlier findings from Majeau-Bettez et al. (2011). The Kannangara et al. value for battery end-of-life emissions is applied to NiMH as well, based on support from Wang et al. (2021).

Because vehicle lifetime is a critical parameter in the calculations, we undertook additional analysis for the most representative value. A summary of relevant literature values for vehicle lifetimes is given in Table 18-9. Based on this evidence, we decided to apply the value of 150,000 km suggested in Kannangara et al., which was near the center of the distribution reported by a range of sources. A main shortcoming of this assumption, as with previous estimates of vehicle lifecycle emissions, is that the lifetime is not vehicle type or powertrain specific.

DRAFT

Table 18-9. Reference values for vehicle lifetime in vehicle-kilometres travelled (VKT)

Source	Annual VKT	Lifetime VKT	Scope
McElhanney (2018)	9,450	94,500*	Vancouver, 2017
Pardy (2018)	12,000	120,000*	Vancouver, 2025
B.C. Ministry of Environment and Climate Change Strategy (2017)	12,367	123,670*	Vancouver, 2012
Natural Resources Canada (2010)	13,100	131,000*	BC, 2008
Azarafshar and Vermeulen (2020)	13,700	137,000	Canada, 2016 (Ford BEV)
Transport Canada (2020)	14,310	143,100	BC, 2020
Kannangara et al. (2021)	15,000*	150,000	Canada
Sun and Ertz (2021)	14,520	159,720	Canada
Transport Canada (2020)	17,000	170,000	Canada, 2020
Azarafshar and Vermeulen (2020)	17,300	173,000	Canada, 2016 (Ford PHEV)
Statistics Canada (2010)	22,173	221,730*	BC, 2009
Antweiler and Gulati (2015)	12,100	237,160	BC, 2008-2010
Logtenberg et al. (2018)	25,000	250,000	Canada

* Assumes 10 year lifetime, based on other sources

Deadheading

For taxi/ride-hail trips, a deadheading adjustment is applied to each reported trip to account for the induced VKT without the traveller present in the vehicle. The deadheading rate, D_r, is the percent of operating VKT for taxis and ridehail vehicles without a passenger present. Relevant literature reports D_r values of 41% to 61% (Cramer & Krueger, 2016; Li et al., 2020, 2022; San Francisco County Transportation Authority, 2017; Sun & Ertz, 2021). The mean across these studies is $D_r = 55\%$, which we apply to all taxi/ridehail trips in the TRR. The deadheading rate for non-taxi trips is set at $D_r = 0$. The deadheading adjustment of $\left(\frac{1}{1-D_r}\right)$ is only applied to running and upstream (not start) emissions.

Combining the phases

Combining the operating and non-operating phases, per-trip GHG emissions (in kg CO_2e per person-trip) are calculated as:

DRAFT

$$E = \frac{e_s + \frac{\sum_l L}{1 - D_r} e_r MF + e_{FC}\left(f_s + \frac{\sum_l L}{1 - D_r} f_r MF\right) + \frac{\sum_l L}{1 - D_r} e_{VC}}{\theta}$$

where e_{FC} is the upstream (WTT) fuel cycle emissions (in kg CO_2e per unit fuel), f_s and f_r are the start and running fuel consumption rates (derived from MOVES in the same way as e_s and e_r, respectively), and all other variables are as defined above. This equation includes the operating emissions E_o and the non-operating emissions

$$E_{no} = \frac{e_{FC}\left(f_s + \frac{\sum_l L}{1 - D_r} f_r MF\right) + \frac{\sum_l L}{1 - D_r} e_{VC}}{\theta}$$

which combine the fuel and vehicle cycle emission components.

18.3. Public transit trips

This section describes the estimation of emissions associated with uni-modal trips on the main TransLink public transit system, which includes city buses, commuter and rapid rail (Sky Train, West Coast Express), transit ferry (Sea Bus), and paratransit (Handy Dart). Similar methods are also applied to the estimation for public transit segments of multi-modal trips. The 29,236 reported transit trips in the TDD (65% uni-modal) were 55% by Sky Train, 43% by transit bus, and the other 2% divided among West Coast Express, Sea Bus, and Handy Dart.

Emissions for transit trips are calculated as the summation of operating and non-operating (fuel and vehicle lifecycle) components. Operating and non-operating emissions are attributed to transit vehicle operation (per VKT) based on emission and fuel consumption rates and vehicle lifecycle, and then attributed to person-trips by transit based on the transit vehicle passenger occupancy (excluding working drivers).

Operating emissions

18.3.1.1. MOVES emission rate modelling

Per-VKT emission rates for CAC from buses are estimated using MOVES, with the same general model setup and input datasets as described above for automobiles. One additional input required for transit bus emissions estimates was to use the MOVES

DRAFT

default fuel formulation for compressed natural gas (CNG), which fueled some of the transit bus fleet but was excluded from the Metro modelling. Fuel type (diesel, gasoline, or CNG) is based on the predominant bus type per line in the TSPR data. Average line speed was taken from the TSPR data as well. Age distributions for buses were based on local MOVES input data from Metro.

18.3.1.2. GHG estimates from transit operator data

Fuel consumption and GHG emissions for transit vehicles are based on TransLink reporting of measured transit fleet fuel consumption data for the year 2019, rather than relying on MOVES estimates. Annual fleet fuel consumption and GHG emissions are attributed equally to annual service km (by mode) using TransLink reported annual operations data (TransLink, 2019, 2020a). The service km exclude deadheading, and so this approach incorporates deadheading emissions into the operations-phase emissions rates.

Table 18-10. Fuel consumption rates by transit service

Transit fleet component	Fuel type	Fuel units	Fuel consumption	Service km	Fuel rate per VKT
Coast Mountain Bus Company	Diesel	litres	31,465,643	49,057,261	0.6414
Coast Mountain Bus Company	CNG	kg	8,469,201	15,939,292	0.5314
Coast Mountain Bus Company	Electricity	kw-hr	32,076,466	23,339,515	1.3744
Community shuttle	Gasoline	litres	3,244,650	13,567,537	0.2391
West Vancouver Transit (bus)	Diesel	litres	1,312,093	2,322,393	0.5650
Sea Bus (transit ferry)	Marine diesel	litres	1,320,272	172,369	7.6596
Handy Dart (paratransit)	Diesel	litres	570,324	2,530,437	0.2256
Handy Dart (paratransit)	Gasoline	litres	1,983,059	7,714,246	0.2570
West Coast Express (commuter rail)*	Diesel	litres	1,328,321	1,377,260	0.9645
SkyTrain, Expo/Millenium lines (rapid rail) *	Electricity	kw-hr	141,620,704	53,274,170	2.6583
Canada Line (rapid rail) *	Electricity	kw-hr	22,859,701	6,531,343	3.5000

* Rail service km are reported in car-km, with typically 2-8 cars per train

DRAFT

Several assumptions were required to match the service km to the fuel consumption, due to aggregation of some fuel types by service. A single aggregate annual service km was given for the three types of fuel used by Coast Mountain Bus Company (CMBC) buses. We disaggregate by assuming relative fuel consumption rates per VKT of 0.8284 and 2.1427 for CNG (in kg CNG per VKT) and electric (in kw-hr per VKT) buses, respectively, relative to litre of diesel per VKT for diesel buses, based on (Pourahmadiyan et al., 2021; TransLink, 2020b). Applying these relative rates to the annual fuel consumption data, we can solve for a VKT distribution of the CMBC fleet of 56% diesel, 18% CNG, and 26% electric. Note that this excludes renewable natural gas buses, which were added to the fleet in 2019 and so do not apply to the 2017 TDD. CNG conversions assume 1 kg CNG is equivalent to 0.0538 GJ CNG.

Similarly, for Handy Dart, the aggregate annual service km were disaggregated by assuming relative fuel consumption rates per VKT of 1.1390 for gasoline buses (in litres per VKT), relative to litre of diesel per VKT for diesel buses, based on (B.C. Ministry of Environment and Climate Change Strategy, 2019). This led to a VKT distribution of 25% diesel and 75% gasoline for Handy Dart service km.

Reported fuel consumption is converted into GHG emissions using the TransLink operations data and BC guidance on fuel emissions intensity (B.C. Ministry of Energy, Mines and Petroleum Resources, 2017; BC Ministry of Environment and Climate Change Strategy, 2022, 2022; (S&T) Squared Consultants Inc., 2022; TransLink, 2020b). CNG feedstock is assumed to be 100% fossil in GHGenius. The GHG intensity of fuels is given in Table 18-11 and the resulting GHG intensity of transit operations are given in Table 18-12.

Table 18-11. GHG intensity of transit fuels

Fuel	Units	Operating (tank-to-wheels) kg CO2e per unit fuel	Upstream (well-to-tank) kg CO2e per unit fuel
Gasoline	litres	2.261	0.8297
Diesel	litres	2.630	0.9128
Marine diesel	litres	2.914	0.9128
Compressed natural gas	kg	3.089	0.5635
Electricity	kw-hr	0	0.0317

DRAFT

Table 18-12. Transit operating GHG emissions rates

Transit fleet component	Fuel type	kg CO_2e per VKT
Coast Mountain Bus Company	Diesel	1.6867
Coast Mountain Bus Company	CNG	1.6415
Coast Mountain Bus Company	Electricity	0.0436
Community shuttle	Gasoline	0.5756
West Vancouver Transit (bus)	Diesel	1.4855
Sea Bus (transit ferry)	Marine diesel	22.3184
Handy Dart (paratransit)	Diesel	0.5928
Handy Dart (paratransit)	Gasoline	0.5813
West Coast Express (commuter rail)*	Diesel	2.5362
SkyTrain, Expo/Millenium lines (rapid rail) *	Electricity	0.0843
Canada Line (rapid rail) *	Electricity	0.1110

* Rail VKT is in car-km, with typically 2-8 cars per train

Fuel type for CMBC buses was determined based on vehicle type by line from the 2019 TSPR data (TransLink, 2019), manually corrected to address line changes (discontinued, renumbered, or introduced) between 2017 and 2019 or missing data in the TSPR before adding the information to the GTFS routing network (described below). Because the TSPR does not distinguish diesel and CNG CMBC buses by line, fuel type proportions were assumed to be equal to annual VKT for each fuel type, and a weighted average GHG emission rate was applied to non-electric CMBC services (1.6751 kg CO_2e per VKT). Similarly, Handy Dart does not distinguish between gasoline and diesel vehicles, and so a weighted average (by annual service VKT) as applied of 0.5841 kg CO_2e per VKT.

18.3.1.3. Transit routing

Transit trip routing was undertaken using the r5r package in R (Pereira et al., 2021) for all modes except Handy Dart trips (the on-demand paratransit service), which were routed using the same procedure as automobile trips. The r5r package executes a least-cost routing algorithm between two points (from an origin to a destination) on a network with

DRAFT

link costs conditional on travel mode and departure time. For a detailed description of the r5r algorithm, see (Conway & Stewart, 2019). The transit network is a combination of General Transit Feed Specification (GTFS) links for transit segments (for September 13 through December 13, 2017, corresponding to the TDD dates) and Open Street Maps (OSM) links for access and egress. For routing, the maximum number of transfers was set at 3 (consistent with the TDD), and the default access/egress mode (not recorded in the survey) was set to walk. The link cost function used trip purpose-specific walking, transfer, and waiting time penalties from the Regional Travel Model (RTM) (TransLink, 2018). If trip purpose was missing, the weighted average of non-missing trips was used (2.0, 10.4, and 2.5 times the in-vehicle time for walking, transfer, and waiting time penalties, respectively). Note that we do not know if the traveller took the least-cost path for the reported trip, but we expect relatively small deviations from the least-cost path, resulting in similar in-vehicle and access/egress distances for the trip.

The routing algorithm failed to generate a uni-modal transit route for 442 of the 19,102 uni-modal transit trips. Re-categorizing these as multi-modal transit trips (i.e., allowing a bus segment in a rail trip) produced routes for 206 of the trips, and another 10 were routed with manual mode corrections based on visual inspection. Still no route was found for 179 reported uni-modal transit but trips. For these, we use the TDD reported trip length, and assume walk access and egress comprising a total of 17% of the trip distance, based on the non-missing transit bus routes. Bus emissions for the remaining portion of these trips are assumed to be from CMBC transit buses on urban unrestricted facilities (MOVES Road Type 5), with average speed and occupancy for those vehicles on non-missing routes. For the 47 remaining uni-modal transit rail trips with no route found, we assume a rail line/service based on closest stations to the origin and/or destination. Similar to bus trips, we assume walk access and egress comprising a total of 15% of the trip distance, based on the non-missing transit rail routes. Occupancy for the remaining rail portion of these trips is based on average occupancy by line for non-missing routes with similar segment distance.

Non-operating (upstream & downstream) emissions

Upstream fuel cycle emissions rates are given. For the vehicle cycle, we include the same three elements as for automobiles (manufacture, maintenance, and end-of-life), attributing lifecycle emissions equally across a vehicle's operating life VKT. Figure 18-4 shows the range and mean values in the literature for transit bus vehicle cycle emissions (Chan et al., 2013; M. V. Chester, 2008; Condon & Dow, 2011; Cooney et al., 2013; Lajunen &

DRAFT

Lipman, 2016; Nordelöf et al., 2019; Pourahmadiyan et al., 2021; Spreafico & Russo, 2020; Zhao et al., 2022). Based on this, we assume 116, 27, and 24 g CO2e per VKT for manufacture, maintenance, and end-of-life vehicle cycle emissions, respectively. This approach fails to account for vehicle cycle emission differences by powertrain/fuel type, body type/articulation, and other factors, for which the literature provides insufficient evident to discriminate. The lifetime VKT in the literature ranged from 650,000 to 1,270,000 km.

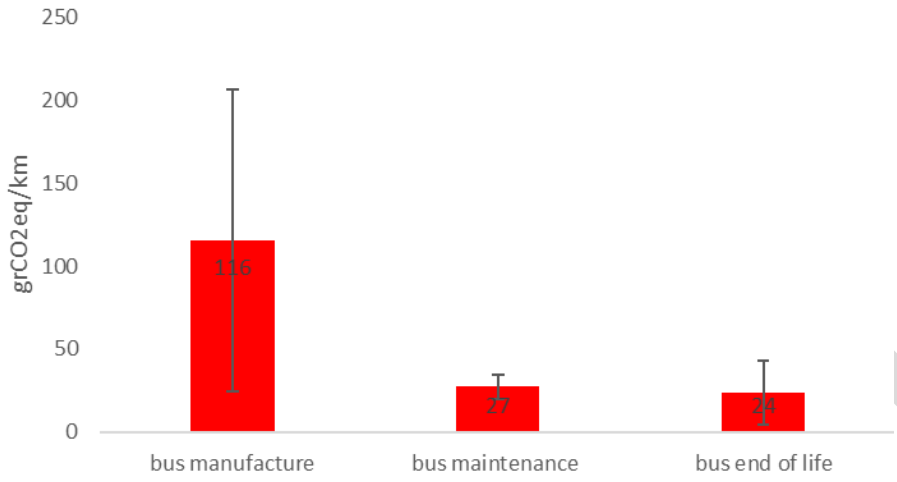


Figure 18-4. Literature values for bus vehicle cycle emissions

Table 18-13 shows the assumed vehicle cycle emissions for rail transit per car-km, based on the limited existing literature reporting applicable values from North America or Europe (M. V. Chester, 2008; Del Pero et al., 2015; Gulcimen et al., 2021; Lederer et al., 2016). No end-of-life information were available for commuter rail, so the light/rapid rail value was applied. Extraction of per-car-km rates for these studies required assumptions about the number of cars per train from transit system information (typically 2-6 cars/train).

Table 18-13. Rail vehicle cycle emissions in g CO2e per car-km

Vehicle cycle phase	Light/rapid rail (Sky Train)	Commuter rail (West Coast Express)
Manufacture	63	186
Maintenance	15	121
End-of-life	139	111

Transit ferry (Sea Bus) vehicle cycle emissions are also extracted from the literature, although few life-cycle studies have addressed passenger ships (Istrate et al., 2022). Based one particularly relevant study with ferries similar to the Sea Bus, we assume 1405, 301, and -376 g CO2e per VKT for ferry vehicle cycle emissions (Schmidt & Watson, 2014).

Occupancy

Transit vehicle occupancy is a key factor in the per-PKT emissions intensity of passenger travel. For transit bus and Sea Bus, average peak loads by line-direction are taken from the 2019 TSPR (TransLink, 2019), with missing values imputed from non-missing values for the line. This measure gives the average of the highest number of people on each bus trip, aggregated by line, direction, season, day, and hour. This peak measure can overestimate average loads, but provides a spatial and temporal resolution over these 5 dimensions that is superior to a simple system-average occupancy. The temporal effect of this aggregation is likely small because the measure is hour-specific, and only misses the within-hour variation by line-direction. The larger aggregation effect is with respect to spatial variability along the line (e.g., over-representing occupancy for distal parts of a radial transit line). We note that the proper attribution of line emissions to different segments of that line is arguable, with potential equity impacts of assigning higher emissions to people who must travel farther due to reach the urban core. Also, an occupancy-inflating effect from using this measure would be compensated by the use of average (versus marginal) accounting methods which tend to overestimate the per-passenger emissions impact of transit travel (A. Bigazzi, 2019, 2020). Ultimately, we decided the analytical benefits of using temporally resolved occupancy data outweighed the risks.

DRAFT

Also, this measure would not distort Sea Bus occupancy because it operates between a single station pair.

Rail occupancy was extracted from station boarding and alighting data in the TSPR with a higher spatial resolution of station-by-station rather than line-average (still by line, direction, day, and hour). Because the rail occupancy is by train, train lengths are needed to computer car occupancy for emissions attribution. The Canada and Millennium lines operate 2-car trains, whereas the Expo line runs 4 to 6 cars in each train and West Coast Express runs 3 to 10 bi-level cars per train. Moreover, Millennium and Expo line data are combined in some reference sources because they share stations/track. Lacking dynamic train length data for the Expo line and West Coast Express, we examined the operations data and explored several possible assumptions for train length. Ultimately, we decided to assume a fixed number of cars per train, which implied that car occupancy is proportional to train occupancy. We expect this measure to be more dynamic than real occupancy, because operators would likely provide longer trains for higher-occupancy trips. Average train lengths were inferred from annual service car-km and train frequency data: 4.29 cars/train for Expo and Millennium Lines and 4.56 cars/train for West Coast Express.

18.4. Other modes

Walking, wheelchair, and cycling

Walking trips (33,516) and trips by wheelchair (41) were assumed to have zero GHG impact.

Lifecycle (all upstream) GHG emissions for the 4,266 bicycle trips were calculated from the trip distance using a factor of 10.5 g CO_2e per km, based on (Sun & Ertz, 2021). There was no way to distinguish electric bicycle trips from non-motorized cycles, but they were probably a small portion (<5%) of the reported trips (Hassanpour & Bigazzi, 2023). Bicycle trips were routed on the OSM network using the r5r package in R (Pereira et al., 2021), similar to transit trips, which returned a trip length and duration (using the default 12 km/hr network speed). Cyclist type was set to allow the most permissive use of the network (i.e., tolerant of Level of Traffic Stress 4: Strong and Fearless). For 19 of the 4,266 reported bicycle trips, no route could be found on the OSM network, and so the TDD distance data were used. Figure 18-5 compares the trip duration distributions between the TDD and the routed bicycle trips, showing good agreement.

DRAFT

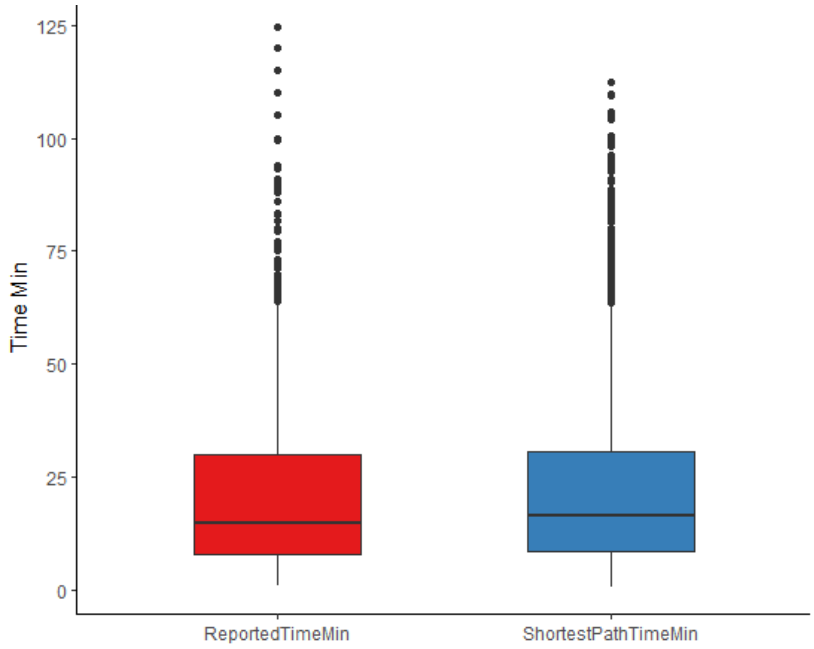


Figure 18-5. Comparison of TDD and routed estimates of trip duration

School bus (609 trips)

School bus emissions rates were generated by MOVES modelling, as described above for automobiles. Routing was based on the automobile network, as well, with access to HOV lanes. However, auto network speeds were found to be substantially higher than those observed for school bus trips reported in the TDD, presumably primarily due to additional stops. Based on the mean travel time ratio, we apply a scaling factor of 0.44 to network link speeds to better represent school bus operating speeds. Lacking local or trip-specific data, school bus occupancy was assumed to be 56 (M. V. Chester, 2008; Vancouver School Bus Charters Inc, 2022). All school bus fuel is assumed to be diesel, although an unknown portion operate on other fuels. Upstream fuel cycle emission rate is the same as for automobile diesel (0.9128 kg CO2e per L). Upstream vehicle cycle emissions are taken as 0.2525 kg CO2e per VKT based on the little available literature (M. V. Chester, 2008; Nordelöf et al., 2019; Zhao et al., 2022).

DRAFT

Motorcycle, moped, and scooter (236 trips)

Motorcycle emissions rates were generated from MOVES using the same general modelling approach described above for automobile trips. Motorcycle, moped, and scooter trips are grouped together in the TDD. Based on 2017 ICBC motor vehicle population data (Insurance Corporation of British Columbia (ICBC), 2020), full-speed motorcycles comprise 92% of the registered motorcycle fleet, with most of the rest limited-speed motorcycles (registered mopeds and scooters). In 2017, we expect a very small portion of reported motorcycle trips were made with other types of scooters or micromobility devices (A. Y. Bigazzi & Hassanpour, 2022; Hassanpour & Bigazzi, 2023). Limited-speed motorcycles in BC have a maximum speed of 70 km/hr; the MOVES motorcycle category includes vehicles capable of travelling at least 25 mi/hr (40 km/hr). Therefore, we are confident modelling reported motorcycle trips reported in the TDD using MOVES emissions rates.

The 236 motorcycle trips were routed on the automobile network, including HOV lanes, which they are allowed to use. Operating emissions were calculated from MOVES using the same method as for automobile trips described above. Occupancy not reported in the TDD was assumed to be 1.15, based on an aggregation of the literature in this area, which ranged from 1 to 1.3 (Bureau of Transportation Statistics, U.S. Department of Transportation, n.d.; M. Chester & Horvath, 2009; de Bortoli, 2021). All motorcycles are assumed to use gasoline fuel, with an upstream fuel cycle emissions intensity of 0.8297 kg CO_2e per litre ((S&T) Squared Consultants Inc., 2022). Based on the literature, the upstream vehicle cycle emissions were set at 0.06403 kg CO_2e per VKT (0.05155 for manufacture + 0.01198 for maintenance + 0.00050 for disposal) (Carranza et al., 2022; M. Chester & Horvath, 2009; Cox & Mutel, 2018; de Bortoli, 2021).

Shuttle and charter bus (105 trips)

Shuttle and charter bus trips are grouped together in the TDD. The local vehicles used as shuttle/charter buses resemble community shuttle buses, with passenger capacity ranging from 11 to 36 persons (Ace Charters Vancouver, 2023; Vancouver Bus Charters, 2021). Operating emission rates are based on MOVES modeling, as described above for automobiles and transit buses. Shuttle/charter vehicles resemble the transit bus fleet, but operate with fewer stops on a non-fixed route with higher average speeds. Therefore, we route on the automobile network, including HOV lanes (only 18 of the routed trips include

DRAFT

HOV lanes), and use auto network speeds (rather than transit bus speeds). Lacking trip-specific occupancy data, we assumed an occupancy of 21 persons, which is the mean occupancy of community shuttle buses (averaging 10 persons) and non-articulated standard transit buses (averaging 32 persons). We also assume an even proportion of VKT by gasoline and diesel buses (i.e., averaging the two emission rates). No deadheading adjustment is made, due to a lack of data. Upstream fuel cycle emissions are consistent with the other modes, with gasoline and diesel upstream rates of 0.8297 and 0.9128 kg CO2e per L, respectively. Upstream vehicle cycle emissions are set equal to transit buses (0.1665 kg CO2e per VKT).

Aqua bus, boat, and tram (47 trips)

Trips by Aqua bus, boat, and tram were reported together in the TDD. The Aqua bus is fixed-route small-vessel ferry service operating in False Creek in Vancouver, running marine diesel on a return route of 6 km at 15 min headways, with 5 daily trips from their 13-vessel fleet over a 15 hr window (Aquabus, 2022). There was no tram or streetcar operating in Metro Vancouver in 2017, so we assume all these trips are in fact by aqua bus or other boat (private or water taxi). With no explicit marine network (other than for Aqua bus), we use trip distance reported in the TDD.

Operating fuel consumption is derived from a 2002 report on BC marine vessel emissions (Levelton Engineering Ltd., 2002). For small vessels "(patrol, rescue, work boats, water taxis, etc.)" they report average power of 300 hp and power load of 30%, which consumes 13.98 kg (16.21 L) of marine diesel per hour. Assuming an average speed of 19.8 km/hr (10.7 knots) from the TDD data, this temporal fuel consumption rate translates to 0.706 kg (0.819 L) of marine diesel per VKT. Using GHG emissions rates from the same report of 3.671 kg CO2e per kg fuel (3.164 kg CO2e per L fuel) yields 2.591 kg CO2e per VKT by Aqua bus or boat. The same report provides CAC emission rates of 7.4, 60.6, 2.4, and 1.2 g per kg fuel for CO, NOx, VOC, and PM respectively.

Upstream fuel cycle emissions are based on a marine diesel rate of 0.9128 kg CO2e per L (B.C. Ministry of Energy, Mines and Petroleum Resources, 2017). Upstream vehicle cycle emissions are based on an aggregation of past studies reporting average annualized marine vessel lifecycle emissions (manufacture, maintenance, and disposal) of 159 kg CO2e (Mio et al., 2022; Pommier et al., 2016). We attribute this to annual VKT for Aqua bus vessels of 10,920 km, based on 30 km per vessel per day over 364 days (Aquabus, 2022),

DRAFT

yielding 0.01456 kg CO2e per VKT. Note that these upstream emission rates are comparable to the Sea Bus emissions, scaled down for weight.

The Aqua bus vessels have a passenger capacity of 12. We assume an average passenger load of 30% (4 passengers), which is the average occupancy of Sea Bus (29%) and (land) taxis (31%). Not all the trips in this category in the TDD were made on Aqua bus, but considering the small number of trips, and lacking further information about these trips, we apply the same small vessel emission rates for all 47 trips in this category.

Bowen Island ferry (18 trips)

BC Ferries operates a longer-distance ferry (besides Sea Bus) within metropolitan Vancouver between Horseshoe Bay and Bowen Island (Snug Cove). Travel distance between the ferry terminals was taken from the RTM network, and average ferry occupancy of 80% was assumed, based on (B.C. Ministry of Environment and Climate Change Strategy, 2019). The Queen of Capilano ship that runs this route has an occupancy of 457 (BC Ferries, 2022), and so we assume a passenger load of 366.

Operating emissions are assumed to be 69.936 kg CO2e per VKT, based on a fuel consumption rate of 24 L per VKT (B.C. Ministry of Environment and Climate Change Strategy, 2019). That fuel consumption rate is also used to compute upstream fuel cycle emissions using a rate of 0.9128 kg CO2e per L for marine diesel (B.C. Ministry of Energy, Mines and Petroleum Resources, 2017), yielding 21.907 kg CO2e per VKT.

Upstream vehicle cycle emission factors are based on a study that provides estimates for roll-on/roll-off steel-hull passenger ships (Blanco-Davis et al., 2014). We scale their 25-year lifetime emissions based on displacement weight (down from 20,250 t to 2,500 t) and then attribute to annual VKT of 62,339.2 (assuming 5,566 annual return trips of 11.2 km each, based on BC Ferries operations data). This yields upstream vehicle cycle emissions of 2.673 kg CO2e per VKT (2.301, 0.369, and 0.004 kg CO2e per VKT from manufacture, maintenance, and end-of-life, respectively).

Other/unclassified modes (143 trips)

The primary mode was designated as “Other/unclassified” for 143 uni-modal trips. To infer a mode for these trips, we applied a Support Vector Machine (SVM) classification algorithm with the svm function in R (from the package ‘e1071’), using the parameters 0.1

for gamma, 10 for cost, and a radian kernel based on our previous analysis which required inference of active transport modes (Berjisian & Bigazzi, 2022). The SVM was trained on the following input data:

1. Modal frequency of other uni-modal trips by that person,
2. Automobile availability,
3. Trip distance (km),
4. Mean trip speed (km/hr), and
5. Trip purpose.

The trained SVM successfully predicted 92% of modes for 212,675 single trips in the travel diary. The results of the application of the SVM to the 143 missing-mode trips are shown in Figure 18-6. While these modes might be inaccurate, they are our best estimate of the trip's modal characteristics, preferable to omitting the trips (which would bias the emissions results low). Because they are based on trip attributes (distance, speed, etc.), erroneous labels from the SVM are likely similar to the actual travel modes within the broad categories of automobile, transit, and active transportation (walking, cycling). For example, if the actual travel mode were e-scooter, it would likely be labelled as bicycle by the SVM (which would have similar emissions characteristics).

DRAFT

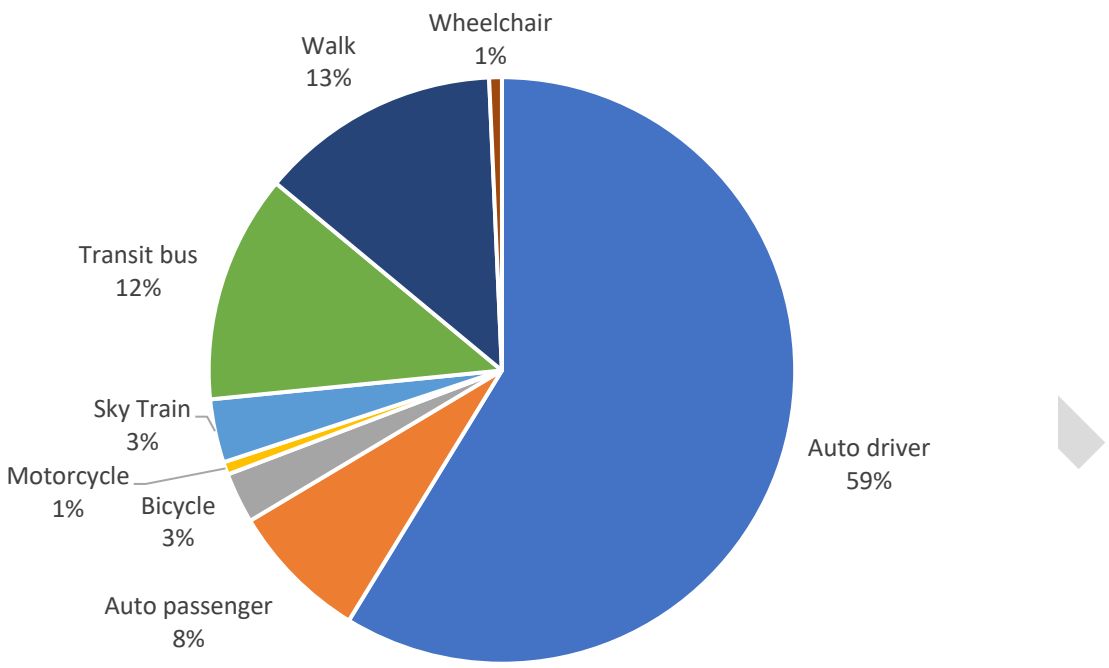


Figure 18-6. SVM-inferred modes for 143 uni-modal trips with mode designated as "Other/unclassified"

18.5. Multimodal trips

The TDD include 10,374 trips (4.6%) reported as multi-modal, but without specific mode-change locations or sub-division of trip attributes such as distance or duration by mode. The designated primary mode for these trips is based on a hierarchy of rail transit, bus transit, then auto modes. We use one of two approaches to disaggregate these trips into uni-modal segments for emissions estimation. For trips including fixed-route services (e.g., rail transit, Sea Bus), we use the r5r routing function in R described above for transit routes, input with the reported mode sequence for the trip. Emissions are then estimated for each of the modal segments comprising the returned route as if the segment were a uni-modal trip, using the methods described above. No valid route was found for 3,197 trips using the reported mode sequence; emissions for these trips were estimated using the method described next for non-fixed-route services.

For trips without fixed-route services, we have no way to confidently infer the modal transitions. For these trips, our approach is to assume that trip segment distances for each mode in a multi-modal trip are proportional to their respective typical trip distances for uni-modal trips, and so aggregate multi-modal trip emissions as a weighted average of each constituent mode. To do this, we first estimate emissions for each trip as if it were a uni-modal trip made by each of the trip's constituent modes $m \in M$, using the methods described above. We then take a weighted average of those emissions, with weights based on the median trip distance for uni-modal trips by each mode, D_m, as $\frac{D_m}{\sum_{m \in M} D_m}$. The median uni-modal trip distances are given in Table 18-14.

Table 18-14. Median trip lengths for uni-modal trips used in weighting for multi-modal trips

Mode	Median uni-modal trip distance (km)
Auto driver	5.88
Auto passenger	4.96
Taxi [1]	4.41
Transit bus	3.52
Sky Train	6.73
West Coast Express	25.21
Sea Bus	3.17
Handy Dart	7.41
Walk (access/egress) [2]	0.32
Wheelchair	0.70
Bicycle	3.18
School bus	6.34
Motorcycle, moped, scooter	4.94
Shuttle/charter bus	9.29
Aqua bus, boat, tram	3.68
Bowen Island Ferry	7.47

[1] Not adjusted for deadheading

[2] Only access/egress for transit trips included here, not exclusive walk trips (which had a median length of 0.76 km)

The TDD includes 9,222 multi-modal trips with the primary mode as transit rail (Sky Train, West Coast Express). The most common other modes in these trips were transit bus

DRAFT

(8,293), auto driver (1,059), and auto passenger (998). The TDD includes 819 multi-modal trips with the primary mode as transit bus. The most common other modes in these trips were auto driver (238), auto passenger (251), and Sea Bus (164).

The TDD includes 213 multi-modal trips with the primary mode as auto driver (142), auto passenger (68), or taxi (3). The most common other modes in these trips were auto driver (68), auto passenger (26), bicycle (43), ferry (30), and other (24). Only a single (highest) occupancy is recorded in the TDD for multi-modal auto trips, which was applied to all auto segments. All other emission estimation processes are as described above for uni-modal auto trips.

For 86 segments of multi-modal trips designated as “Other/unclassified” mode, we use the same SVM algorithm to infer a mode as for uni-modal “Other/unclassified” trips, to avoid introducing negative emissions bias. The results are shown in Figure 18-7.

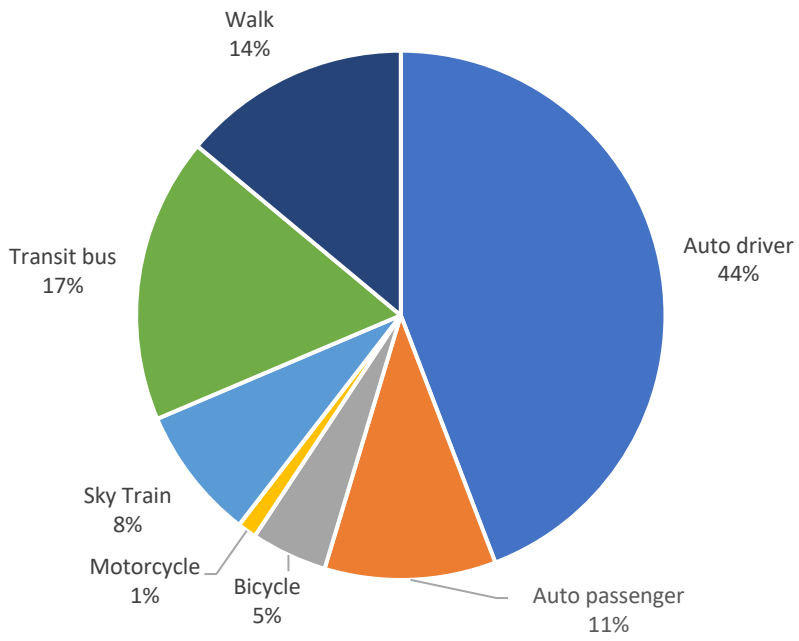


Figure 18-7. SVM-inferred modes for 86 legs of multi-modal trips with mode designated as "Other/unclassified"

18.6. Marginal emissions adjustments

Calculation of marginal adjustment factors

The methods up to this point have used an attributional accounting framework, apportioning vehicle emissions equally across vehicle occupants. To our knowledge, consequential emissions accounting has never been applied to household travel data. We build on previous work that developed a framework for estimating marginal emissions rates for passenger travel (consequential accounting) from average emissions rates (attributional accounting) (A. Bigazzi, 2019). That framework was further developed and applied to city-scale transit systems in Bigazzi (2020), demonstrating the substantial difference (bias) between the apparent climate impacts of travel by each framework.

The estimated emissions attributed to the traveller for each reported person-trip (or person-trip segment) in the TDD using the average-rate (attributional) approach above is:

$$E_P = \frac{E_V}{\theta}$$

where E_V is the trip's total vehicle emissions and θ is the vehicle occupancy in persons. Based on the past work cited above (A. Bigazzi, 2019), the marginal emissions can be calculated:

$$E'_P = \frac{E_V}{\theta}\left(\varepsilon_v^p + \varepsilon_e^\theta - \varepsilon_e^\theta \varepsilon_v^p\right) = E_P\left(\varepsilon_v^p + \varepsilon_e^\theta - \varepsilon_e^\theta \varepsilon_v^p\right)$$

where ε_v^p is the elasticity of VKT to PKT, and ε_e^θ is the elasticity of vehicle fuel or emission rates (per VKT) to vehicle occupancy. We call $\left(\varepsilon_v^p + \varepsilon_e^\theta - \varepsilon_e^\theta \varepsilon_v^p\right)$ the marginal/average emissions ratio, $MAER$.

The MAER was developed based on operating and fuel-cycle emissions. The MAER can also apply to vehicle-cycle emissions that are calculated on a per-VKT basis, because ε_v^p accounts for the marginal change in VKT with PKT. One further assumption is that the sensitivity of operating emissions intensity to passenger loads, represented by ε_e^θ, also applies to vehicle-cycle emissions due to increased wear-and-tear with higher passenger loads. In other words, ε_e^θ is assumed to represent higher per-VKT vehicle-cycle emissions caused by shorter vehicle lifespan in VKT and higher maintenance needs. The

DRAFT

relationships between vehicle occupancy and vehicle-cycle emissions needs to be examined in future research; meanwhile, we apply ε_e^θ as the best available estimate.

Local values for ε_v^p can be estimated where dynamic vehicle occupancy data are available. The TDD reports occupancy for automobile trips, and passenger load data are reported for bus and rail services in TransLink's operating (TSPR) data, so we estimate Vancouver-specific values of ε_v^p for automobile, bus, and rail transit trips (as described in the next sub-sections). For other modes and for ε_e^θ, we rely on the U.S.-average values reported in Bigazzi (2019, 2020), as given in Table 18-15.

Table 18-15. Elasticities for calculation of MAER

Mode	ε_e^θ	ε_v^p
Auto driver or passenger	0.040	Calculated from local data
Motorcycle or taxi	0.040	Calculated from local data[1]
Transit bus	0.160	Calculated from local data
SkyTrain	0.050	Calculated from local data
Westcoast Express	0.050	Calculated from local data
School bus	0.160	Calculated from local data[2]
Shuttle	0.100	0.858
SeaBus, Aqua Bus, ferry	0.050	0.431
HandyDart	0.100	0.763
Bicycle, walk, wheelchair	0.000	1.000

[1] Assumed equal to automobile, because motorcycle and taxi trip occupancy not reported in the TDD
[2] Assumed equal to transit bus

Elasticity of vehicle to passenger travel in Vancouver

As shown in Bigazzi (2019, 2020), ε_v^p can be estimated for any system with dynamic vehicle occupancy data using a regression model specified as:

$$\ln(VKT) = \alpha_0 + \alpha_1 \ln(PKT) + \beta_j X_j + \gamma_j \ln(PKT)\, X_j$$

DRAFT

where X_j are covariates over which we may want to allow the elasticity to vary (such as service type, time period, or household attributes). From the estimated parameters, elasticity is calculated as

$$\varepsilon_v^p = \alpha_1 + \gamma_j X_j$$

Longitudinal data can be used to measure long-term elasticity of vehicle to passenger travel, including major service changes such as the introduction of new transit services or routes. Cross-sectional data can be used as well, but may not capture dimensions of transport system dynamics that change over a long time scale.

For automobile trips, we apply the model at the household level, which is typically considered the main decision-making unit for private vehicle travel (Ortuzar and Willumsen, 2011). Trip segments with a mode of Auto driver or Auto passenger are aggregated up to the household for daily PKT by summing segment length for reported person-trips, and for daily VKT by summing person-trip segment lengths divided by segment vehicle occupancy. This approach attributes VKT equally across vehicle occupants, due to a lack of more specific information about agency in trip generation. Summary data for the 21,430 households with automobile travel are reported in Table 18-16. The model is estimated using household weights from the TDD.

Table 18-16. Summary of data used to estimate vehicle to passenger travel elasticity

Travel variable	Minimum	First quartile	Median	Mean	Third quartile	Maximum
Auto PKT per day	0.1	21.4	46.8	71.4	93.7	1459.6
Auto VKT per day	0.0	17.0	36.8	55.7	73.1	1019.7
Bus passengers per hour	0.1	20.5	71.0	192.4	205.4	5587.7
Bus vehicles per hour	0.5	1.3	2.0	2.5	3.0	19.7
Rail passengers per hour	4	400	800	1221	1700	14900
Rail vehicles per hour	1.0	9.0	10.0	13.1	18.0	31.0

The automobile elasticity model reveals whether households with higher automobile PKT produce proportionally higher automobile VKT $\left(\varepsilon_v^p = 1\right)$, or whether increasing PKT is

DRAFT

partially accommodated by increased ride sharing (higher occupancy), leading to $\varepsilon_v^p < 1$ and $MAER < 1$. To understand the elasticity patterns, we test household characteristics as moderating variables (X_j), including household size and composition, vehicle availability, housing type and tenure, and household income. We also examine separate elasticities for Auto driver and Auto passenger modes. Note that the model could not be applied to motorcycle or taxi trips because trip-level occupancy data for these modes were not reported in the TDD.

For bus transit trips, we estimate the model using cross-sectional data from the 2019 TSPR of bus trips and boardings per hour, which are reported by line, direction, day type (workday or weekend/holiday), season (fall or summer), time period (0-4 hr, 4-6 hr, 6-9 hr, 9-15 hr, 15-18 hr, 18-21 hr, and 21-24 hr). A multi-level (mixed effects) model is estimated with random effects by line for 216 unique lines, with a total of 12,315 complete observations. Because the TSPR reports trips, not kilometres travelled, this model neglects possible systematic changes in trip lengths with passenger volumes. Tested moderating variables include day type, season, and time period.

For rail transit trips, we estimate the model using cross-sectional data from the 2019 TSPR of train passenger volumes per hour, which are reported by service (Millennium/Expo lines, Canada line, West Coast Express), station, direction, day type (workday or weekend/holiday), and hour of the day (over 21 service hours). The TSPR data are augmented with average train (vehicle) trips per hour over the same segmenting variables, derived from the GTFS data for September through December 2019. A multi-level (mixed effects) model is estimated with random effects by station for 55 unique stations, with a total of 6,268 complete observations. Tested moderating variables include day type and service.

All elasticity models are estimated using the plm package in R (Croissant & Millo, 2008), with heteroscedasticity-consistent standard errors estimated using the lmtest package (Zeileis & Hothorn, 2002).

Application to TDD emissions estimates

After estimating modal elasticities of vehicle to passenger travel from local data, modal MAER are calculated as $\left(\varepsilon_v^p + \varepsilon_e^\theta - \varepsilon_e^\theta \varepsilon_v^p\right)$. These MAER are applied to the segment-level total lifecycle CO_2e emissions estimates based on segment mode by multiplication. The

DRAFT

segment-level marginal lifecycle CO_2e emission estimates are then summed to the trip, person, and household levels.

18.7. Results of emissions estimates

This section summarizes the emission estimation results for the observed trips in the TDD. Unless stated otherwise, this section reports estimation results with unweighted summary values (i.e., without applying sampling or expansion weights), and so are not representative of regional emissions.

18.7.1. Segment emissions

Table 18-17 gives the cumulative estimated GHG emissions by segment mode, disaggregated by emissions component (operating, non-operating). The vast majority of the travel in the TDD is by auto drivers or passengers, and those two modes comprise the bulk of the estimated emissions. Most emissions are generated directly from vehicle operations (running), followed by non-operating fuel and vehicle cycle emissions. Figure 18-8 shows these results visually, with emissions normalized to PKT for each segment mode to represent GHG intensity.

DRAFT

Table 18-17. Cumulative GHG emissions by segment mode (kg CO_2e)

Segment mode	Segment length (km)	Operating (running)	Operating (start)	Non-operating (fuel)	Non-operating (vehicle)	Total
Aqua Bus	318	18	0	12	1	31
Auto Driver	1,250,340	257,796	13,617	98,817	88,547	458,777
Auto Passenger	279,765	25,734	1,746	9,974	9,402	46,856
Bicycle	20,370	0	0	0	214	214
Ferry	762	146	0	46	6	197
Handy Dart	1,266	565	15	204	160	944
Motorcycle	2,409	488	25	188	134	834
School bus	6,567	108	2	37	30	176
Sea Bus	2,020	375	0	117	22	514
Shuttle	2,738	108	2	38	21	169
Sky Train	160,499	0	0	676	1,696	2,372
Taxi	4,274	457	28	143	824	1,451
Transit bus	127,377	5,455	92	1,709	708	7,964
Walk	57,201	0	0	0	0	0
West Coast Express	11,999	340	0	119	58	517
Wheelchair	104	0	0	0	0	0
Total	1,928,010	291,589	15,525	112,079	101,824	521,017

DRAFT

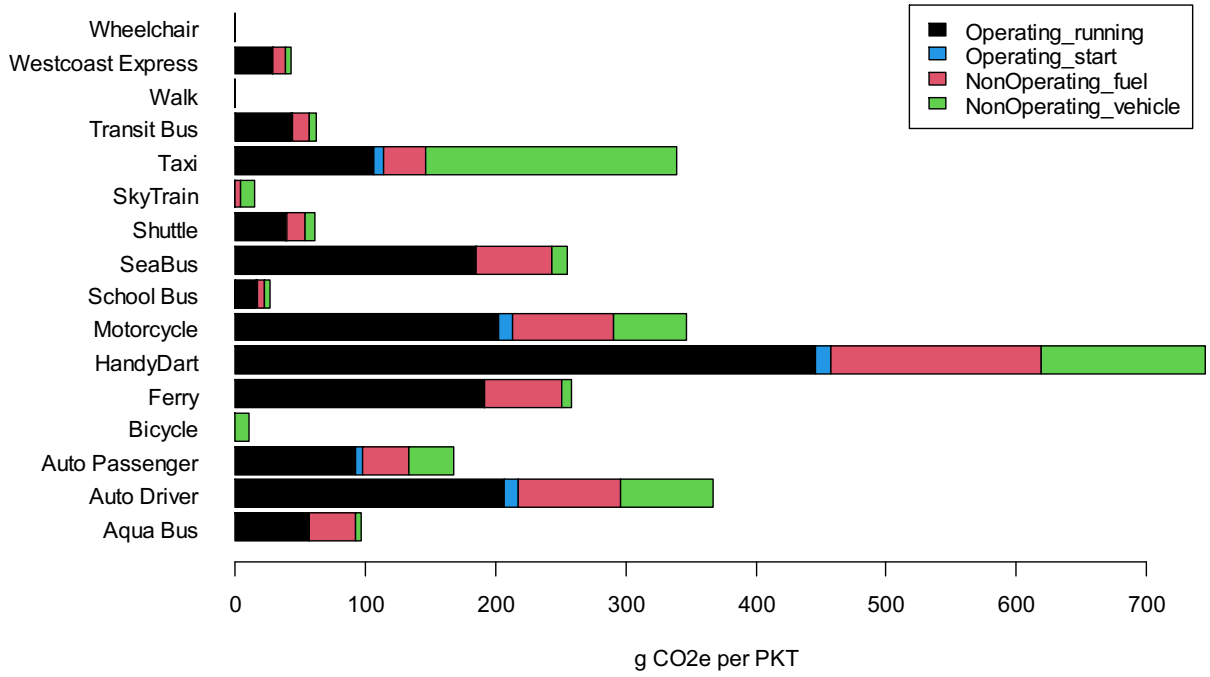


Figure 18-8. Mean emissions intensity per PKT by segment mode

Table 18-18 summarizes the segment-level occupancy, PKT, and emissions intensity by segment mode. The values are aggregated across segments (not weighted by distance). Start and running emissions are combined to give per-PKT operating emissions. The table shows that emissions intensity varies widely across trips, especially for the automobile and main transit modes (bus and rail), for which dynamic occupancy values were used. Occupancy is a key determinant of per-PKT emissions intensity. Per-VKT emission rates vary as well, depending on vehicle type, fuel, congestion level, and other factors (varying across modes). The varying emissions intensities within modes is a strength of this analysis, which produced emissions estimates more sensitive to trip attributes than the more common approach of applying fixed per-PKT emissions rates by mode.

Table 18-18. Occupancy, PKT, and GHG intensity by segment mode

Segment mode	Occupancy (persons/vehicle)		PKT		Operating (g CO2e/PKT)		Non-operating fuel (g CO2e/PKT)		Non-operating vehicle (g CO2e/PKT)	
	mean	s.d.[1]	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
Auto driver	1.38	0.68	10.04	11.52	257.53	216.11	91.83	71.46	69.28	26.09
Auto passenger	2.45	0.85	8.60	10.93	121.97	141.48	43.15	44.07	33.03	10.38
Taxi	1.24	0.00	7.28	8.91	130.03	24.36	37.37	5.70	192.73	0.00
Motorcycle	1.15	0.00	9.81	13.53	243.60	74.84	88.39	25.65	55.68	0.00
Transit bus	35.26	16.29	4.67	5.07	42.38	43.76	13.05	12.27	6.13	5.32
School bus	56.00	0.00	10.37	12.53	18.97	11.28	6.36	3.68	4.52	0.00
Shuttle	21.37	0.00	13.49	22.76	38.80	4.15	13.63	1.45	7.77	0.00
SkyTrain	40.19	31.89	8.54	6.79	0.00	0.00	3.90	4.03	9.70	10.02
Westcoast Express	120.47	71.70	19.95	14.92	19.70	18.34	8.28	6.38	6.96	10.84
SeaBus	124.82	23.39	2.78	1.10	185.46	36.81	58.10	11.53	11.05	2.19
Aqua Bus	4.00	0.00	5.87	7.15	56.34	0.00	36.51	0.00	3.64	0.00
Ferry	366.00	0.00	11.12	8.56	191.08	0.00	59.86	0.00	7.30	0.00
HandyDart	1.31	0.00	7.96	5.60	467.97	60.00	161.40	0.00	126.72	0.00

[1] standard deviation

18.8. Trip emissions

Table 18-19 gives GHG emissions estimates per trip by primary mode. Figure 18-9 illustrates these values normalized by PKT to illustrate GHG intensity by primary mode. Note that the trip-aggregated values include emissions from other modal segments in the trips. For example, the Sky Train generates no operating emissions, but Sky Train trips that are accessed by automobile or transit bus include those operating emissions.

DRAFT

Table 18-19. Mean GHG emissions per trip by primary mode (g CO2e)

Primary mode	Number of trips	PKT	Operating (running)	Operating (start)	Non-operating (fuel)	Non-operating (vehicle)	Total
Auto Driver	123021	10.1	2079	109	797	714	3699
Auto Passenger	31404	8.6	785	52	304	287	1428
Taxi	521	7.3	790	47	247	1408	2491
Transit bus	12686	7.8	310	7	101	52	471
Sky Train	15980	15.1	300	15	145	176	635
West Coast Express	230	36.1	1668	77	605	456	2806
Sea Bus	187	8.6	996	30	338	197	1560
Handy Dart	153	8.1	3579	95	1296	1019	5988
School bus	630	10.6	206	5	70	54	335
Bike	4271	4.5	1	0	0	48	49
Walk	33516	1.0	0	0	0	0	0
Other mode	591	11.0	1379	54	526	366	2325
Total	223190	8.6	1306	70	502	456	2334

DRAFT

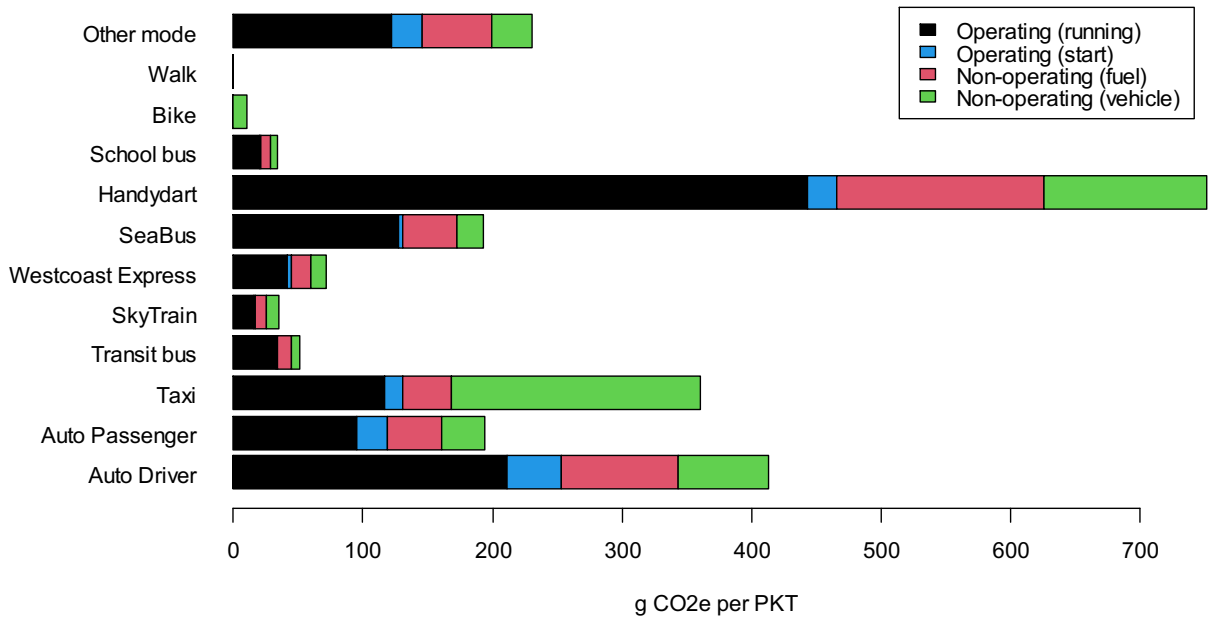


Figure 18-9. Average emissions intensity per PKT by primary mode

Table 18-20 gives average CAC emissions per trip by the same set of primary modes – again aggregating emissions from all trip segments.

DRAFT

Table 18-20. Average trip CAC emissions (g) by primary mode

Primary mode	CO	NOx	VOC	$PM_{2.5}$
Auto Driver	21.905	2.011	1.311	0.097
Auto Passenger	6.220	0.469	0.362	0.034
Taxi	2.987	0.165	0.204	0.073
Transit bus	1.825	0.786	0.125	0.027
Sky Train	2.195	0.572	0.145	0.022
West Coast Express	8.344	0.638	0.493	0.037
Sea Bus	4.541	0.419	0.288	0.022
Handy Dart	107.546	14.212	6.391	0.437
School bus	0.850	1.011	0.223	0.097
Bike	0.007	0.000	0.000	0.000
Walk	0.000	0.000	0.000	0.000
Other mode	41.020	2.402	4.649	0.090
Total	13.414	1.280	0.809	0.063

18.9. Person and Household emissions

Table 18-21 reports summary statistics for further aggregated emissions up to the person and household levels, as both total daily GHG and GHG intensity per PKT. Emissions rates across the TDD sample vary widely, with interquartile ranges larger than the mean values. The 75th percentile persons and households are generating 8 to 10 times the daily emissions of the 25th percentile persons and households. Some of this is due to higher PKT, but emissions intensity (g CO2e per PKT) also varies by a factor of 3 to 5.

DRAFT

Table 18-21. Person- and household-level aggregate GHG measures

Measure	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
Person-level total PKT	0.10	11.47	26.01	40.02	51.92	672.33
Household-level total PKT	0.16	21.59	47.95	73.10	96.60	1,463.80
Person-level total daily GHG (g CO2e)	0	1,347	5,483	10,814	14,158	396,433
Household-level total daily GHG (g CO2e)	0	3,502	11,964	19,753	26,562	589,654
Person-level GHG intensity (g CO2e per PKT)	0	82	232	251	385	2,700
Household-level GHG intensity (g CO2e per PKT)	0	122	269	265	388	2,406

Applying the TDD person and household sampling weights, the weighted mean daily PKT is 36.91 per person and 91.39 per household, generating weighted mean emissions of 10.18 kg CO_2e per person and 25.21 kg CO_2e per household. Weighted mean GHG intensity of travel is 251.6 or 276.6 g CO_2e per PKT, averaged at the person or household levels, respectively. The weighted median daily PKT is 21.22 per person and 61.80 per household, generating weighted median emissions of 3.90 kg CO_2e per person and 16.12 kg CO_2e per household. Weighted median GHG intensity of travel is 234.2 or 283.3 g CO_2e per PKT, averaged at the person or household levels, respectively. The household weighting has a greater impact than person weighting, due to a stronger relationship between weights and emissions at the household level. Household and person weights both range from 0.169 to 808.696, with median values of 26.087 and 24.453 and mean values of 47.736 and 39.569 for person and household weights, respectively. Person weights have a correlation of 0.052 with person-level GHG, whereas household weights have a correlation of 0.202 with household-level GHG. In other words, the sampled households are expected to generate less travel-related GHG than the region overall.

18.10. External comparisons

As an external validation, in Figure 18-10 we compare our running emissions estimates to the emission rates from BC's Provincial emission factors by vehicle type and fuel type, which applied in 2017 (BC Ministry of Environment and Climate Change Strategy, 2022). Upstream fuel cycle emissions are included for battery electric and hybrid vehicles only,

DRAFT

for comparability to the reference BC data. The central values are similar, but with greater variation in our estimates due to the inclusion of additional influencing factors (vehicle make, speed, road type, etc.).

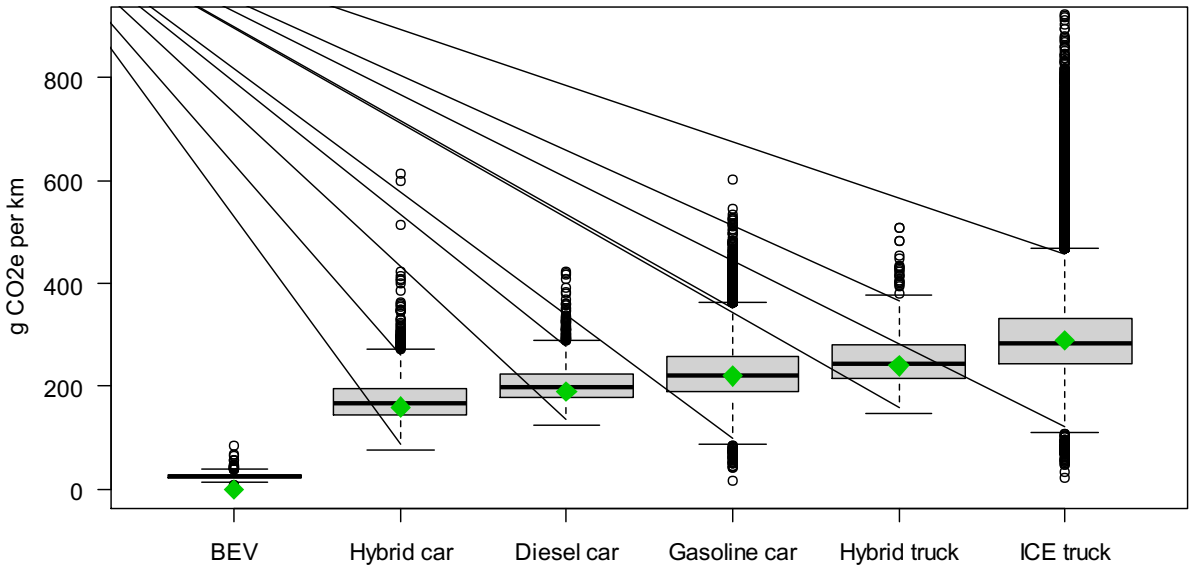


Figure 18-10. Comparison of our emission estimates for automobile trips (boxplots) to rates in BC Provincial guidance (green diamonds); including upstream fuel cycle emissions for BEV and hybrid powertrains for comparability

As another external validation, Wang et al. (2023) computed daily GHG emissions for the sample of trips in Toronto's 2016 household travel survey data. They report median personal daily GHG emissions from travel of 6.5 kg CO2e, and median GHG intensity of travel of 210 g CO2e per PKT. In comparison, we calculate median values of 5.5 kg CO2e/person/day and 232 g CO2e per PKT for the TDD. These values are similar, providing a good external validation on the estimates, despite different regions of analysis (Toronto is a larger but less dense region). In addition, there were several important differences in the estimation methods, including:

1. We include vehicle cycle emissions while they do not,
2. We include vehicle make/model adjustments to MOVES-modeled fuel efficiency by vehicle class/fuel, which they do not,

3. We use vehicle-specific fuel and powertrain types (gasoline, diesel, HEV, PHEV, and BEV) rather than assuming all passenger vehicles are gasoline-fuelled and all buses are diesel-fuelled,
4. We include dynamic passenger occupancy for automobile (from the TDD) and the primary transit modes (from operational data) rather than fixed occupancy by mode and time period (extracted from a travel demand model),
5. Our transit emission factors (per VKT) are based on measured fuel consumption data, rather than MOVES estimates (petrol buses) or manufacturer information (electric buses and trains),
6. We use a fixed GHG intensity for Provincial electricity *consumption*, rather than a dynamic GHG intensity for Provincial electricity *production*,
7. We attribute automobile emissions equally to all vehicle occupants, rather than only to the driver, and
8. We estimate emissions from all reported trips (with necessary assumptions) rather than excluding "other" modes.

Note also that due to skewed distributions and varying trip lengths and household sizes, these aggregate measures vary greatly if using mean versus median values, or aggregating by trip, person, or household. For further comparisons, mean daily GHG emissions per person from travel has been reported as 6.8 kg CO2e in Quebec City in the early 2000's (Barla et al., 2011a), and just 0.6 kg CO2e in Xiamen City, China in 2015 (L. Xu et al., 2018).

18.11. Marginal emissions

Regression model estimates are given in

DRAFT

Table 18-22 for all three modes. Adjusted R-squared values for the models were 0.931 for automobile, 0.717 for bus transit, and 0.364 for rail transit. The individual (versus idiosyncratic) error component was 58% and 38% of the total error for bus transit and rail transit, respectively, in the random effects models.

DRAFT

Table 18-22. Elasticity regression model results

Model	Parameter[1]	Estimate	Standard error[2]
Automobile	Intercept	-0.152	0.0125
Automobile	Passenger travel	0.977	0.0032
Bus transit	Intercept	-0.799	0.0423
Bus transit	Passenger travel	0.365	0.0090
Rail transit	Intercept	0.300	0.1043
Rail transit	Passenger travel	0.323	0.0152

[1] Dependent variables were vehicle travel; dependent and independent variables were log-transformed

[2] All significantly different from both 0 and 1 at $p<0.05$

The parameters of interest in are the estimates for Passenger travel, which indicate the elasticity of vehicle to passenger travel, ε_v^p. As explained in the literature, ε_v^p is expected to be between 0 and 1 (A. Bigazzi, 2019). A ε_v^p of 0 indicates that the quantity of vehicle travel is independent of the quantity of passenger travel, and increasing passenger trips are accomplished through higher vehicle occupancy (and vice versa). A ε_v^p of 1 indicates that the quantity of vehicle travel increases proportionately with the quantity of passenger travel, resulting in (or a consequence of) a fixed vehicle occupancy. The elasticity of vehicle to passenger travel for automobile trips in

DRAFT

Table 18-22 is 0.977, indicating that 98% of the variation PKT by household is matched with variation in household VKT (the rest is accommodated by varying occupancy). The elasticity of vehicle to passenger travel for bus and rail transit in

DRAFT

Table 18-22 is 0.365 and 0.323, respectively, indicating that variation in transit vehicle trips is about 1/3rd the magnitude of variation in transit passenger trips (higher for bus than rail). Hence, VKT is much less sensitive to variation in passenger PKT for transit than automobile trips – consistent with past analysis of data from the USA (A. Bigazzi, 2019).

We explored a range of household and transit system co-variates to understand the moderators of vehicle to travel elasticity, ε_v^p. Higher elasticity indicates that the quantity of vehicle travel is more sensitive to passenger demand, and that vehicle occupancy is less sensitive. For automobile trips, elasticity increases (significantly at $p<0.05$) for households with fewer people, no family members co-habituating, less vehicle availability, higher income, and for renters (vs. owners). Although statistically significant, the magnitude of these moderating effects is small, changing elasticity by <0.07. These results indicate that vehicle occupancy is more dynamic (i.e., lower ε_v^p) in households with more potential for coordination of automobile trips among household members. Elasticity was not sensitive ($p>0.05$) to housing type (single detached or not).

For transit trips, elasticity increases for weekday (vs. weekend) and for daytime (vs. 21 hr to 4 hr) services. The magnitudes of these differences are around 0.03. Rail transit elasticity is also substantially higher for SkyTrain (0.332) than West Coast Express (0.135) services. Given these differences, we apply separate elasticities to SkyTrain and West Coast Express trips in the analysis below. These results are consistent with expectations, with peak-period and higher-ridership services being more demand-sensitive and so having higher elasticity (A. Bigazzi, 2020).

As a comparison, past analysis applying similar modelling methods to national-level household travel survey data from the USA reported lower vehicle to passenger elasticity for automobile trips of 0.90 (versus 0.98 here) (A. Bigazzi, 2019). A key conceptual and methodological difference between the studies is the aggregation of VKT to households; the USA analysis assigned VKT based on the household of the vehicle driver, whereas we assign VKT proportionately to all vehicle occupants. We believe our method is a better approximation of the unknown distribution of agency for trip production among vehicle occupants. Note that if the vehicle occupants are from the same household, the results are equivalent. Re-estimating our elasticity model with all VKT assigned to the vehicle driver's household results in an elasticity of 0.914, which is closer to the results of the USA analysis. We believe this approach gives passengers in another household's

DRAFT

automobile an emissions “free ride”, and underestimates the sensitivity of VKT to PKT. In addition to this methodological difference, the difference in elasticities is likely also due to the data scope, with the USA national data including more households in low-density suburban and rural contexts, which would correspond with factors that were shown above to decrease elasticity (larger, family households with more vehicles in owned housing).

Past analysis applying similar modelling methods to national-level transit system data from the USA reported similar vehicle to passenger elasticity for bus transit of 0.38 (versus 0.37 here), but much higher elasticity for rail transit of 0.83 (versus 0.32 here) (A. Bigazzi, 2020). In addition to the different national context, a major difference between these models is the scale, with the local model representing changes in VKT with ridership for the TransLink system within a given year, and the USA model representing changes at the metropolitan scale over time. Hence, the previous analysis would represent long-term elasticity, include changes such as new rail lines, whereas the local analysis would represent short-term elasticity within a relatively fixed system extent. Given the very low GHG emissions rate for SkyTrain segments (on par with bicycles), the selection of an elasticity value to calculate MAER for SkyTrain ultimately have little impacts on the results. Still, the contextual factors influencing vehicle to passenger travel elasticity for rail transit require further investigation with a composite set of transit data from diverse cities.

Applying the estimated local elasticities with the previous assumptions in Table 18-23. MAER applied to the TDD emissions estimates we generate the MAER (marginal to average emissions ratios). The MAER scaling factors are applied to trip segments by mode (multiplying by the previously-calculated attributional g CO_2e), and then summed to trip total consequential (marginal) emissions estimates in g CO_2e.

DRAFT

Table 18-23. MAER applied to the TDD emissions estimates

Mode	ε_e^θ	ε_v^p	MAER
Auto driver or passenger	0.040	0.977[1]	0.978
Motorcycle or taxi	0.040	0.977[1]	0.978
Transit bus	0.160	0.365[1]	0.467
SkyTrain	0.050	0.332[1]	0.365
Westcoast Express	0.050	0.135[1]	0.178
School bus	0.160	0.365[1]	0.467
Shuttle	0.100	0.858	0.872
SeaBus, Aqua Bus, ferry	0.050	0.431	0.459
HandyDart	0.100	0.763	0.787
Bicycle, walk, wheelchair	0.000	1.000	1.000

[1] From local data; others from Bigazzi (2019, 2020)

Figure 18-11 and Figure 18-12 illustrate the consequential versus attributional (i.e., marginal versus average rate) emissions estimates by segment and trip, respectively. Since the MAER are applied by segment mode, segments by each mode form a line at a slope corresponding to the MAER. The trip-level comparison aggregates the segment-level differences of multi-modal trips. This aggregation is particularly relevant for transit trips with substantial (high-emitting) access and egress segments.

DRAFT

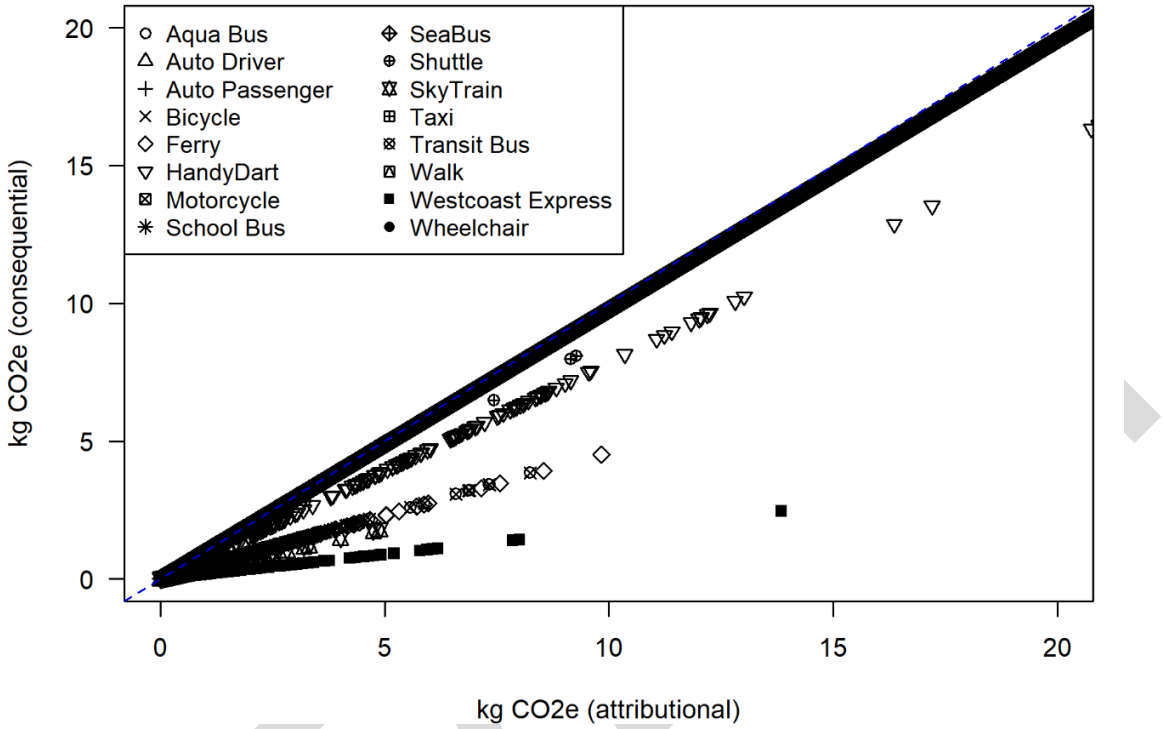


Figure 18-11. Segment-level attributional (average-rate) versus consequential (marginal-rate) emissions by segment mode; bounds truncated for legibility; blue dashed line denotes equivalent values

DRAFT

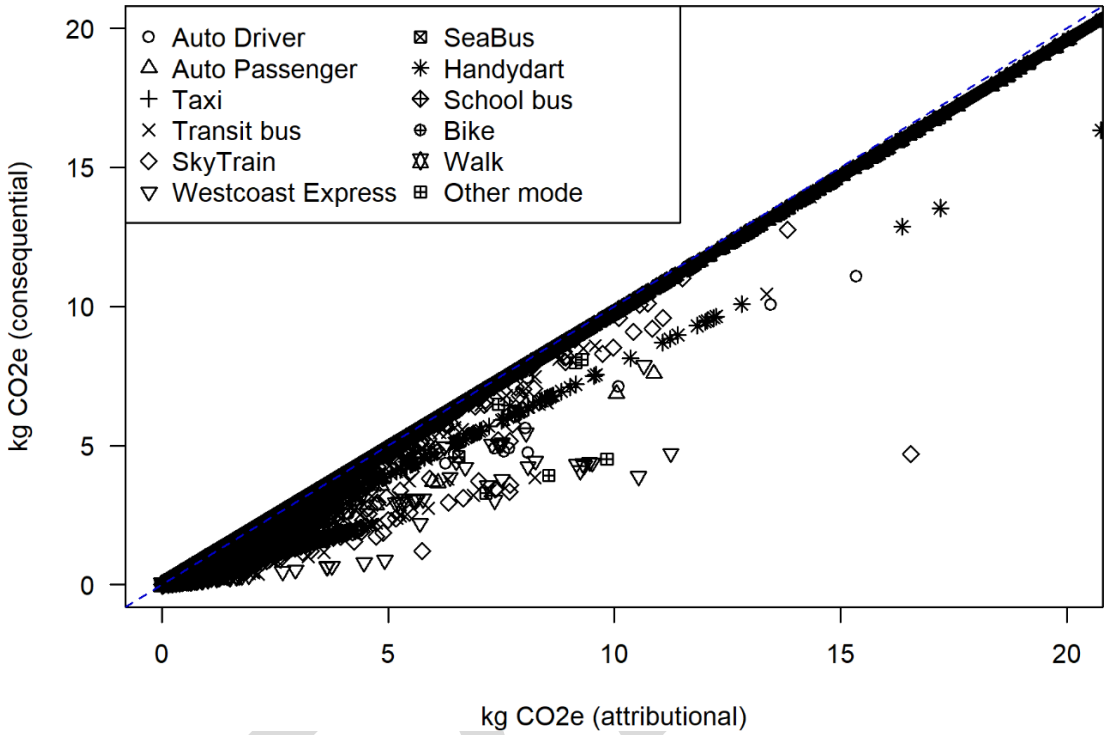


Figure 18-12. Trip-level attributional (average-rate) versus consequential (marginal-rate) emissions by primary trip mode; bounds truncated for legibility; blue dashed line denotes equivalent values

Figure 18-12 shows that the consequential and attributional accounting frameworks generate substantially different emissions estimates for some but not all trips. The ratio of consequential to attributional emissions estimates by trip averages 0.91 (0.97 if emissions-weighted) and ranges from 0.18 to 1.00, with 25th, 50th, and 75th percentile values of 0.98 (due to the preponderance of automobile trips).

Given the variability in the effect of accounting framework on trip-level emissions, we estimate a regression model to examine the relationships between person and household-level factors and the difference between the two types of emissions estimates. The model is specified with person and household variables as independent variables and estimated using person and household weights from the TDD. Two different dependent variables are investigated: 1) the difference in emissions (in g CO2e) estimated by a consequential versus an attributional framework (i.e., $E'_P - E_P$), and 2) the

percent difference in emissions estimated by a consequential versus an attributional framework (i.e., $\frac{2(E_P' - E_P)}{E_P' + E_P} * 100\%$).

Model estimation results are given in Table 18-24. The results show that applying a consequential versus an attributional framework disproportionately impacts the apparent climate impacts of travel systematically with person and household attributes including age, gender, income, and vehicle ownership. The differences are larger for people and households who use more low-MAER modes (particularly transit). A consequential framework disproportionately decreases the estimated climate impacts of travel for non-senior adult travellers (19-64 y), renters, larger households, and households with lower vehicle ownership or detached housing. The model results are inconsistent for some factors because the magnitudes of the two measures of difference depend on the total amount of VKT and the proportion by transit. For example, higher income households have significantly more transit VKT but even more automobile VKT. More transit travel produces a negative effect of income on total consequential GHG, but a smaller proportion of household VKT from transit produces a positive effect of income on the percent difference between the two GHG measures. This contrast is illustrated in Figure 18-13, which shows the mean consequential and attributional daily household GHG by income tier. Higher income households have a larger absolute differential between their consequential and attributional GHG estimates, but that difference is smaller on a percentage basis.

Table 18-24. Model of personal factors influencing difference between consequential and attributional emissions estimates

Variable	Difference model[1]	Percent difference model[2]
Intercept	-413.35*	-37.52*
Age <19 yr	315.21*	22.16*
Age 65+ yr	179.69*	2.08*
Male	-59.06*	0.08
Licensed driver	-8.92	22.78*
Carshare member	23.17*	-4.52*

[1] Dependent variable: difference between consequential and attributional estimates (g CO_2e)
[2] Dependent variable: percent difference between consequential and attributional estimates (%)
* $p < 0.05$

DRAFT

Table 18-25. Model of household factors influencing difference between consequential and attributional emissions estimates

Variable	Difference model[1]	Percent difference model[2]
Intercept	-178.97*	-5.85*
Persons of age 5+ (up to 6)	-202.27*	-0.29*
Vehicles ≥ adults	-28.94	2.70*
Detached housing	-92.95*	0.18
Renting housing	-12.67	-0.91*
Income middle ($50k-$100k)	-100.85*	0.53*
Income high (>$100k)	-243.77*	0.59*
Cohabitating with 1+ family member	-3.62	0.94*

[1] Dependent variable: difference between consequential and attributional estimates (g CO_2e)
[2] Dependent variable: percent difference between consequential and attributional estimates (%)
* $p < 0.05$

DRAFT

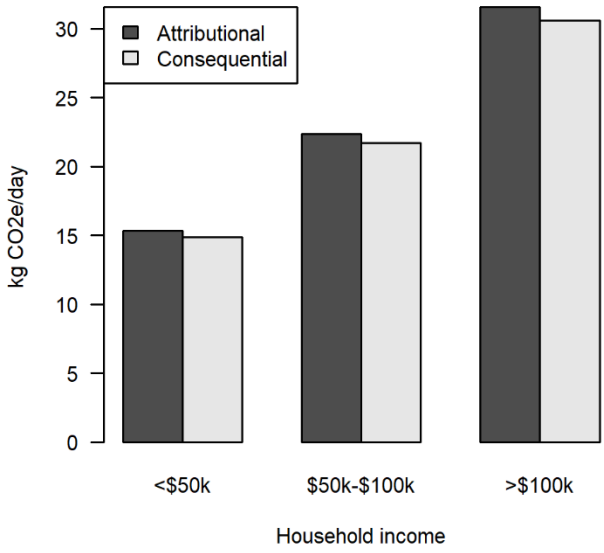


Figure 18-13. Mean consequential and attributional daily household GHG by income tier

18.12. Analysis of statistical relationship between emissions and walkability

Study sample and study variables

The Walkability Index is a composite measure of neighbourhood walkability, comprised of four component variables (net residential density, commercial floor area, intersection density, and land use mix). Within this current analysis, the walkability value for each household was defined as the composite index value within a 1-kilometre network buffer, which follow a walkable road network, surrounding the location of the home (as defined by home 6-digit postal code). The values for each component measure were calculated beginning at the home postal code location and were then converted to z-scores to calculate the overall walkability index. The 1-km network buffer size was selected to represent the distance individuals could reasonably travel in a 10–15-minute walking trip and has been previous used to define the home "neighbourhood" area. (Colabianchi et al., 2007).

DRAFT

In addition to neighbourhood walkability, regional accessibility and sidewalk connectivity were calculated at the 6-digit postal code level and linked to the residential location. These values were calculated for both vehicle travel, which provides an estimation of peak travel time from the home location if traveling by vehicle, as well as for transit travel, which conversely provides as estimation of peak travel time from the home if traveling by transit. Additionally, sidewalk connectivity, a measure of the completely of the pedestrian infrastructure, was calculated using methods similar to the walkability index in the 1-km network buffer surrounding the home.

Individual and household demographic data were obtained from the TDD. For this current analysis the following variables were utilized and categorized as follows: gender (dichotomized as female or male), age (categorized as child/youth [age 5-18], adult [age 19-64], and older adult [65+]), driver's license status (dichotomous yes/no), car share status (continuous 0-4, the number of car share membership participants reporting having), employment status (categorized as 'full time employed', 'full time student', 'part time worker or student, or self-employed' or 'non-worker/non-student'), household income (categorized as <$50,000, $50,000-100,000, and >$100,000), household size (continuous 1-10), number of household bicycles (continuous 0-10), number of vehicles per adult in the home (dichotomized as less vehicles than adults [vehicles < adults] and 1 or more vehicle per adult in the home [vehicles > = adults]).

Statistical analysis

Adjusted associations and 95% confidence intervals (CI) were calculated using linear regression and three iterations of adjustment variables. Three adjustment models were developed based on existing literature and conceptual understanding of individual and environmental factors associated with travel behaviour. Multi-level (mixed effects) models were developed to account for the hierarchical nature of the TDD (e.g., multiple participants living in the same household). A two-level model was used to account for clustering of participants within households. Additionally, survey weights obtained from the TDD were utilized in these analyses.

Table 18-26 through Table 18-30 show the association between individual, household, and built environment factors and individual emissions (CO_2, CO, NOX, $PM_{2.5}$, VOC) across trips reported in the TDD. Across each emission analyzed, a trend emerged of reduced emissions associated with living in more walkable areas. Walkability results are presented as change in travel related emissions generated compared to the reference

DRAFT

least walkable areas. A graded relationship (dose-response) was shown across walkability bins for CO_2 emissions – with each increase in walkability associated with further reductions in CO_2 emissions, all of which were statistically significant. The results for consequential and attributional CO_2 emissions are similar, with a slightly stronger relationship between walkability and CO2 emissions when using the consequential estimates. For $PM_{2.5}$ and NOX, more walkable (e.g., all walkability bins compared to the reference "least walkable" level) neighbourhoods were associated with statistically significant reduction in emissions. However, although CO emissions were reduced across all walkability bins compared to the reference level, this reduction in CO emissions were no longer significant in the most walkable bin. A similar pattern was shown for VOC emissions, where more walkable areas were associated with lower emissions, however these results did not remain statistically significant at the two most walkable bins.

Across all models and emissions, reporting female gender (compared to male) was associated with lower emissions, as was being in the youngest age group (5-18). Having a driver's licence, and higher ratio of vehicles to adults living in the home was associated with significantly higher emissions estimates across all models. Higher household income tended to be associated with higher emissions, however these results were not consistently significant. Additionally, being a full-time student, or a non-worker/non-student was associated with significantly lower emissions across all models compared to full-time workers.

These results are consistent with previous findings in other locations which tended to find both individual and neighbourhood factors were associated with the individual emissions generated for daily travel purpose. Previous work across multiple locations have found that individuals and households living in more walkable neighbourhoods tended to generate lower travel related emissions, which may be attributed to the features of these neighbourhoods promoting the use of active travel modes, as opposed to private vehicles, being used to make daily trips (Darwish et al., 2023; L. D. Frank, Jr, et al., 2000, p. 200; Rickwood et al., 2008; Steemers, 2003). Additionally, these current results found similar patterns in individual characteristics which tended to be associated with emissions generates, including that higher income households tend to produce higher travel based emissions, which has previously been attributed to these households making more driving trips and owning more household vehicles (Barla et al., 2011b; Brand & Preston, 2010; Kahn, 1998; Ko et al., 2011; Sider et al., 2013).

DRAFT

In conclusion, both individual and neighbourhood characteristics were associated with travel related emissions estimates. When controlling for other individual, household, and neighourhood factors, living in more walkable areas was associated with generating lower travel related emissions.

DRAFT

Table 18-26. Estimated model of individual daily g CO_2e emissions (attributional) from travel

Variable	Model 1	95% CI	Model 2	95% CI	Model 3	95% CI
Gender (reference: male)						
Female	**-4511.80**	**-4796, -4228**	**-4490.43**	**-4774, -4207**	**-4500.78**	**-4785, -4217**
Age (reference: 19-64)						
5-18	**-2904.20**	**-3683, -2126**	**-3112.33**	**-3890, -2334**	**-3214.63**	**-3992, -2437**
65+	-245.73	-904, 413	-463.88	-1122, 195	-537.02	-1195, 121
Driver's License						
Yes	**12294.72**	**11741, 12848**	**12037.38**	**11484, 12591**	**11892.29**	**11339, 12446**
Car share						
+1	**-652.38**	**-1267, -38**	-461.19	-1074, 152	-223.51	-837, 390
Status (reference: full-time employed)						
Full time student	**-5460.86**	**-6109, -4813**	**-5555.48**	**-6203, -4908**	**-5607.68**	**-6254, -4961**
Part time or self-employed	**-2680.23**	**-3182, -2179**	**-2864.64**	**-3366, -2363**	**-2946.09**	**-3447, -2445**
Non-worker/non-student	**-11006.51**	**-11562, -10451**	**-11196.14**	**-11752, -10641**	**-11322.57**	**-11878, -10767**
Household income						
$50,000 - $100,000	**1685.85**	**855, 2517**	**1249.66**	**421, 2078**	**1044.57**	**218, 1871**
>$100,000	**3336.48**	**2435, 4238**	**2389.88**	**1476, 3304**	**2021.93**	**1110, 2934**
Household size						
+1	**-563.56**	**-825, -303**	**-506.82**	**-820, -301**	**-686.09**	**-947, -425**
Household vehicles						
Vehicles > = Adults	-		**3438.15**	**1006, 5870**	**3054.38**	**630, 5479**
Bicycles						
+1	-		**1024.67**	**450, 1599**	**862.31**	**2886, 1436**
Regional Accessibility						
Vehicle	-		32.47	-40, 105	**73.85**	**0, 147**
Transit	-		**102.96**	**78, 127**	**58.53**	**32, 85**
Sidewalk connectivity					-1113.23	-2912, 685
Walkability (reference level 1)						
2	-		-		**-1656.90**	**-2677, -637**
3	-		-		**-3167.94**	**-4357, -1979**
4	-		-		**-4393.76**	**-5868, -2919**
5	-		-		**-4561.15**	**-6710, -2413**
Greenness (reference level 1)						
2	-		-		**1331.10**	**246, 2416**
3	-		-		**1236.04**	**284, 2188**
4	-		-		**2679.11**	**1588, 3771**
5	-		-		**3356.95**	**2376, 4338**

Notes: bolded results indicate statistical significance at p<0.05

Vehicle regional accessibility = AM vehicle trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations; Transit regional accessibility = AM transit trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations

Table 18-27. Estimated model of individual daily g CO emissions from travel

DRAFT

Variable	Model 1	95% CI	Model 2	95% CI	Model 3	95% CI
Gender (reference: male)						
Female	**-19.83**	**-21.73, -17.94**	**-19.66**	**-21.55, -17.77**	**-19.68**	**-21.57, -17.79**
Age (reference: 19-64)						
5-18	**-18.29**	**-23.48, -13.10**	**-19.46**	**-24.65, -14.27**	**-19.80**	**-24.99. -14.61**
65+	-1.76	-6.19, 2.67	-2.65	-7.08, 1.79	-2.91	-7.35, 1.52
Driver's License						
Yes	**58.02**	**54.32, 61.73**	**56.68**	**52.97, 60.38**	**56.16**	**52.45, 59.86**
Car share						
+1	**-7.86**	**-12.00, -3.73**	**-6.90**	**-11.03, -2.76**	**-6.03**	**-10.17, -1.89**
Status (reference: full-time employed)						
Full time student	**-24.88**	**-29.20, -20.56**	**-25.38**	**-29.70, -21.06**	**-25.59**	**-29.91, -21.27**
Part time or self-employed	0.67	-2.69, 4.02	-0.36	-3.71, 3.00	-0.66	-4.01, 2.69
Non-worker/non-student	**-41.78**	**-45.50, -38.06**	**-42.84**	**-46.56, -39.11**	**-43.33**	**-47.06, -39.61**
Household income						
$50,000 - $100,000	**8.00**	**2.24, 13.77**	5.14	-0.62, 10.90	4.30	-1.46, 10.07
>$100,000	**7.67**	**1.39, 13.95**	1.45	-4.94, 7.83	-0.13	-6.52, 6.25
Household size						
+1	**-3.39**	**-5.22, -1.56**	**-3.12**	**-4.94, -1.29**	**-3.60**	**-5.44, -1.76**
Household vehicles						
Vehicles > = Adults	-		**38.76**	**21.86, 55.66**	**37.20**	**20.31, 54.08**
Bicycles						
+1	-		**8.20**	**4.20, 12.20**	**7.34**	**3.34, 11.34**
Regional Accessibility						
Vehicle	-		0.25	-0.25, 0.75	0.44	-0.06, 0.95
Transit	-		**0.51**	**0.34, 0.68**	**0.31**	**0.13, 0.49**
Sidewalk connectivity			-		-4.19	-16.64, 8.27
Walkability (reference level 1)						
2	-		-		**-9.57**	**-16.68, -2.45**
3	-		-		**-19.32**	**-16.68, -2.45**
4	-		-		**-17.47**	**-27.75, -7.18**
5	-		-		-12.71	-27.67, 2.24
Greenness (reference level 1)						
2	-		-		0.21	-7.30, 7.72
3	-		-		-0.14	-6.74, 6.45
4	-		-		**8.63**	**1.07, 16.18**
5	-		-		**11.07**	**4.27, 17.87**

Notes: bolded results indicate statistical significance at p<0.05

Vehicle regional accessibility = AM vehicle trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations; Transit regional accessibility = AM transit trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations

DRAFT

Table 18-28. Estimated model of individual daily g NO_x emissions from travel

Variable	Model 1	95% CI	Model 2	95% CI	Model 3	95% CI
Gender (reference: male)						
Female	**-3.01**	**-3.30, -2.72**	**-2.99**	**-3.28, -2.70**	**-2.99**	**-3.28, -2.69**
Age (reference: 19-64)						
5-18	**-4.08**	**-4.88, -3.29**	**-4.25**	**-5.04, -3.45**	**-4.29**	**-5.09, -3.49**
65+	-0.32	-1.00, 0.35	-0.46	-1.13, 0.22	-0.48	-1.16, 0.19
Driver's License						
Yes	**4.11**	**3.55, 4.68**	**3.92**	**3.35, 4.49**	**3.86**	**3.29, 4.43**
Car share						
+1	**-1.48**	**-2.11, -0.85**	**-1.33**	**-1.95, -0.70**	**-1.21**	**-1.84, -0.58**
Status (reference: full-time employed)						
Full time student	**-0.10**	**-0.76, 0.57**	**-0.17**	**-0.83, 0.50**	**-0.19**	**-0.85, 0.47**
Part time or self-employed	**0.33**	**-0.18, 0.85**	**0.19**	**-0.32, 0.70**	**0.15**	**-0.36, 0.66**
Non-worker/non-student	**-3.24**	**-3.81, -2.68**	**-3.39**	**-3.96, -2.82**	**-3.45**	**-4.02, -2.88**
Household income						
$50,000 - $100,000	**0.65**	**-0.19, 1.50**	**0.29**	**-0.56, 1.14**	**0.19**	**-0.66, 1.04**
>$100,000	**0.37**	**-0.55, 1.29**	**-0.40**	**-1.33, 0.53**	**-0.58**	**-1.51, 0.36**
Household size						
+1	**-0.42**	**-0.69, -0.16**	**-0.39**	**-0.65, -0.12**	**-0.41**	**-0.68, -0.15**
Household vehicles						
Vehicles > = Adults	-		**5.58**	**3.09, 8.07**	**5.33**	**2.85, 7.82**
Bicycles						
+1	-		**0.79**	**0.21, 1.38**	**0.67**	**0.08, 1.26**
Regional Accessibility						
Vehicle	-		-0.03	-0.11, 0.04	**0.00**	**-0.07, 0.08**
Transit	-		**0.09**	**0.06, 0.11**	**0.06**	**0.03, 0.08**
Sidewalk connectivity			-		-2.33	-4.07, -0.39
Walkability						
2	-		-		**-1.68**	**-2.73, -0.64**
3	-		-		**-2.14**	**-3.36, -0.92**
4	-		-		**-2.01**	**-3.52, -0.50**
5	-		-		**-1.13**	**-3.33, -1.08**
Greenness						
2	-		-		-0.25	-1.36, 0.85
3	-		-		0.10	-0.88, 1.07
4	-		-		1.10	-0.11, 2.13
5	-		-		1.40	0.40, 2.41

Notes: bolded results indicate statistical significance at p<0.05

Vehicle regional accessibility = AM vehicle trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations; Transit regional accessibility = AM transit trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations

DRAFT

Table 18-29. Estimated model of individual daily g $PM_{2.5}$ emissions from travel

Variable	Model 1	95% CI	Model 2	95% CI	Model 3	95% CI
Gender (reference: male)						
Female	**-0.12**	**-0.13, -0.11**	**-0.12**	**-0.13,-0.11**	**-0.12**	**-0.13, -0.11**
Age (reference: 19-64)						
5-18	**-0.14**	**-0.17, -0.12**	**-0.15**	**-0.18, -0.12**	**-0.15**	**-0.18, -0.13**
65+	-0.02	-0.05, -0.00	**-0.03**	**-0.06, -0.01**	**-0.03**	**-0.06, -0.01**
Driver's License						
Yes	**0.26**	**0.24, 0.28**	**0.25**	**0.23, 0.28**	**0.25**	**0.23, 0.27**
Car share						
+1	**-0.03**	**-0.05, -0.01**	-0.02	-0.05, -0.00	-0.02	-0.04, 0.01
Status (reference: full-time employed)						
Full time student	**-0.09**	**-0.12, -0.07**	**-0.10**	**-0.12, -0.07**	**-0.10**	**-0.12, -0.07**
Part time or self-employed	**-0.07**	**-0.09, -0.05**	**-0.08**	**-0.10, -0.06**	**-0.08**	**-0.10, -0.06**
Non-worker/non-student	**-0.24**	**-0.26, -0.22**	**-0.25**	**-0.27, -0.23**	**-0.25**	**-0.27, -0.23**
Household income						
$50,000 - $100,000	**0.04**	**0.01, 0.07**	0.03	-0.00, 0.06	0.02	-0.00, 0.05
>$100,000	**0.08**	**0.05, 0.11**	**0.05**	**0.02, 0.08**	**0.04**	**0.01, 0.07**
Household size						
+1	**-0.02**	**-0.03, -0.01**	**-0.02**	**-0.03, -0.01**	**-0.02**	**-0.03, -0.01**
Household vehicles						
Vehicles > = Adults	-		**0.12**	**0.03, 0.20**	**0.11**	**0.02, 0.19**
Bicycles						
+1	-		**0.03**	**0.01, 0.05**	**0.03**	**0.01, 0.05**
Regional Accessibility						
Vehicle	-		0.00	-0.00, 0.00	0.00	-0.00, 0.01
Transit	-		0.00	0.00, 0.00	0.00	0.00, 0.00
Sidewalk connectivity					-0.07	-0.14, -0.01
Walkability (reference level 1)						
2	-		-		**-0.07**	**-0.10, -0.03**
3	-		-		**-0.09**	**-0.13, -0.05**
4	-		-		**-0.11**	**-0.16, -0.05**
5	-		-		**-0.10**	**-0.17, -0.02**
Greenness (reference level 1)						
2	-		-		0.02	-0.02, 0.06
3	-		-		0.02	-0.02, 0.05
4	-		-		**0.06**	**0.02, 0.10**
5	-		-		**0.08**	**0.05, 0.12**

Notes: bolded results indicate statistical significance at p<0.05

Vehicle regional accessibility = AM vehicle trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations; Transit regional accessibility = AM transit trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations

DRAFT

Table 18-30. Estimated model of individual daily g VOC emissions from travel

Variable	Model 1	95% CI	Model 2	95% CI	Model 3	95% CI
Gender (reference: male)						
Female	**-1.33**	**-1.49, -1.16**	**-1.31**	**-1.48, -1.15**	**-1.31**	**-1.48, -1.15**
Age (reference: 19-64)						
5-18	**-1.17**	**-1.62, -0.73**	**-1.25**	**-1.69, -0.80**	**-1.27**	**-1.71, -0.82**
65+	0.24	-0.14, 0.62	0.18	-0.20, 0.56	0.17	-0.21, 0.55
Driver's License						
Yes	**2.97**	**2.65, 3.29**	**2.88**	**2.57, 3.20**	**2.86**	**2.54, 3.18**
Car share						
+1	**-0.75**	**-1.10, -0.39**	**-0.68**	**-1.04, -0.33**	**-0.64**	**-1.00, -0.29**
Status (reference: full-time employed)						
Full time student	**-1.07**	**-1.44, -0.70**	**-1.10**	**-1.47, -0.73**	**-1.11**	**-1.48, -0.74**
Part time or self-employed	**0.31**	**0.02, 0.59**	0.24	-0.05, 0.53	0.23	-0.06, 0.51
Non-worker/non-student	**-2.06**	**-2.38, -1.74**	**-2.13**	**-2.45, -1.81**	**-2.15**	**-2.47, -1.83**
Household income						
$50,000 - $100,000	0.35	-0.15, 0.84	0.16	-0.33, 0.66	0.13	-0.37, 0.62
>$100,000	0.04	-0.50, 0.58	-0.36	-0.90, 0.19	-0.43	-0.98, 0.12
Household size						
+1	**-0.22**	**-0.37, -0.06**	**-0.19**	**-0.35, -0.04**	**-0.21**	**-0.36, -0.05**
Household vehicles						
Vehicles > = Adults	-		**3.02**	**1.57, 4.47**	**2.93**	**1.48, 4.38**
Bicycles						
+1	-		**0.51**	**0.16, 0.85**	**0.46**	**0.11, 0.80**
Regional Accessibility						
Vehicle	-		0.02	-0.02, 0.06	0.03	-0.01, 0.08
Transit	-		0.03	0.02, 0.04	0.02	0.00, 0.03
Sidewalk connectivity			-		-0.62	-1.69, 0.45
Walkability (reference level 1)						
2	-		-		**-0.67**	**-1.29, -0.06**
3	-		-		**-1.01**	**-1.72, -0.30**
4	-		-		-0.79	-1.67, 0.09
5	-		-		-0.09	-1.37, 1.19
Greenness (reference level 1)						
2	-		-		-0.09	-0.73, 0.56
3	-		-		-0.19	-0.75, 0.38
4	-		-		0.25	-0.40, 0.90
5	-		-		0.55	-0.03, 1.13

Notes: bolded results indicate statistical significance at p<0.05

Vehicle regional accessibility = AM vehicle trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations; Transit regional accessibility = AM transit trip weighted mean minutes to Metro Vancouver and Fraser Valley destinations

DRAFT

18.13. References

(2023), R. C. T. (2019). R: A language and environment for statistical computing. *R Foundation for Statistical Computing, Vienna, Austria*.

Ace Charters Vancouver. (2023). *Vancouver Shuttle & Charter Service*. Ace Charters Vancouver. https://www.acechartersvancouver.com/

Agbai, C. O. (2021). Shifting neighborhoods, shifting health: A longitudinal analysis of gentrification and health in Los Angeles County. *Social Science Research*, *100*, 102603. https://doi.org/10.1016/j.ssresearch.2021.102603

Allen, J., & Taylor, Z. (2018). A new tool for neighbourhood change research: The Canadian Longitudinal Census Tract Database, 1971-2016: Canadian Longitudinal Tract Database. *The Canadian Geographer / Le Géographe Canadien*, *62*(4), 575–588. https://doi.org/10.1111/cag.12467

Al-Rijleh, M.-K., Alam, A., Foti, R., Gurian, P. L., Spatari, S., & Hatzopoulou, M. (2018). Strategies to achieve deep reductions in metropolitan transportation GHG emissions: The case of Philadelphia. *Transportation Planning and Technology*, *41*(8), 797–815. https://doi.org/10.1080/03081060.2018.1526879

Alshehri, Y. M. (2016). Performance-Based Funding: History, Origins, Outcomes, and Obstacles. *Journal of Higher Education Theory & Practice*, *16*(4).

Antweiler, W., & Gulati, S. (2015). Scrapping for clean air: Emissions savings from the BC SCRAP-IT program. *Journal of Environmental Economics and Management*, *71*, 198–214. https://doi.org/10.1016/j.jeem.2015.03.002

Aquabus. (2022). *Aquabus Granville Island False Creek Ferry*. Aquabus. https://theaquabus.com/

Astell-Burt, T., Navakatikyan, M., Eckermann, S., Hackett, M., & Feng, X. (2022). Is urban green space associated with lower mental healthcare expenditure? *Social Science & Medicine*, *292*, 114503.

Atkinson, R., Wulff, M. G., & Australian Housing and Urban Research Institute. (2009). *Gentrification and displacement: A review of approaches and findings in the literature*. The Institute.

Australia Department of Education. (2020). *Mission based Compacts* [Text]. Department of Education, Skills and Employment; scheme=AGLSTERMS.AglsAgent; corporateName=Department of Education, Skills and Employment; address=50 Marcus Clarke St, Canberra City, ACT 2601; contact=+61 1300 566 046. https://www.dese.gov.au/higher-education-funding/mission-based-compacts

DRAFT

Azarafshar, R., & Vermeulen, W. N. (2020). Electric vehicle incentive policies in Canadian provinces. *Energy Economics*, *91*, 104902. https://doi.org/10.1016/j.eneco.2020.104902

Bailey, N., van Gent, W. P. C., & Musterd, S. (2017). Remaking Urban Segregation: Processes of Income Sorting and Neighbourhood Change. *Population, Space and Place*, *23*(3), e2013. https://doi.org/10.1002/psp.2013

Baker, D. C., Sipe, N. G., & Gleeson, B. J. (2006). Performance-Based Planning: Perspectives from the United States, Australia, and New Zealand. *Journal of Planning Education and Research*, *25*(4), 396–409. https://doi.org/10.1177/0739456X05283450

Barbosa, J. P. D. A. S., Guerra, P. H., Santos, C. de O., Nunes, A. P. de O. B., Turrell, G., & Florindo, A. A. (2019). Walkability, overweight, and obesity in adults: A systematic review of observational studies. *International Journal of Environmental Research and Public Health*, *16*(17). https://doi.org/10.3390/ijerph16173135

Barbosa, S., Guerra, P. H., Santos, C. D. O., Paula, A., Barbosa, D. O., & Turrell, G. (2019). Walkability , Overweight , and Obesity in Adults: A Systematic Review of Observational Studies. *International Journal of Environmental Research and Public Health*, *16*(3135).

Barker, D., Cassidy, J., & Chen, W. (2018). *Paying for Results: Reforming How the Public Sector Funds Social Services*. Bank of America. https://investinresults.org/chapter/paying-results.html

Barla, P., Miranda-Moreno, L. F., & Lee-Gosselin, M. (2011a). Urban travel CO2 emissions and land use: A case study for Quebec City. *Transportation Research Part D: Transport and Environment*, *16*(6), 423–428. https://doi.org/10.1016/j.trd.2011.03.005

Barla, P., Miranda-Moreno, L. F., & Lee-Gosselin, M. (2011b). Urban travel CO2 emissions and land use: A case study for Quebec City. *Transportation Research Part D: Transport and Environment*, *16*(6), 423–428. https://doi.org/10.1016/j.trd.2011.03.005

Barton, M. (2016). An exploration of the importance of the strategy used to identify gentrification. *Urban Studies*, *53*(1), 92–111. https://doi.org/10.1177/0042098014561723

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, *67*(1). https://doi.org/10.18637/jss.v067.i01

BC Ferries. (2022). *Our Fleet*. https://www.bcferries.com/on-the-ferry/our-fleet

DRAFT

B.C. Ministry of Energy, Mines and Petroleum Resources. (2017). *Using GHGenius in B.C.* (Renewable and Low Carbon Fuel Requirements Regulation Information Bulletin RLCF-010). https://www2.gov.bc.ca/assets/gov/farming-natural-resources-and-industry/electricity-alternative-energy/transportation/renewable-low-carbon-fuels/rlcf010_-_using_ghgenius_for_bc.pdf

B.C. Ministry of Environment and Climate Change Strategy. (2017). *Community energy and emissions inventory (CEEI)*. Province of British Columbia. https://www2.gov.bc.ca/gov/content/environment/climate-change/data/ceei

B.C. Ministry of Environment and Climate Change Strategy. (2019). *B.C. Methodological Guidance for Quantifying Greenhouse Gas Emissions*. https://www2.gov.bc.ca/assets/gov/environment/climate-change/cng/methodology/2018-pso-methodology.pdf

B.C. Ministry of Environment and Climate Change Strategy. (2021). *CleanBC Roadmap to 2030*.

BC Ministry of Environment and Climate Change Strategy. (2022). *B.C. Best Practices Methodology for Quantifying Greenhouse Gas Emissions*.

B.C. Ministry of Environment and Climate Change Strategy. (2022). *Electricity emission intensity factors for grid-connected entities—Province of British Columbia*. Province of British Columbia. https://www2.gov.bc.ca/gov/content/environment/climate-change/industry/reporting/quantify/electricity

BCGP. (2019). *Across Generations: BC Generations Project Newsletter, Winter 2019/20*.

Bel, G., & Rosell, J. (2017). The impact of socioeconomic characteristics on CO2 emissions associated with urban mobility: Inequality across individuals. *Energy Economics*, *64*, 251–261. https://doi.org/10.1016/j.eneco.2017.04.002

Berjisian, E., & Bigazzi, A. (2022). Evaluation of methods to distinguish trips from activities in walking and cycling GPS data. *Transportation Research Part C: Emerging Technologies*, *137*, 103588. https://doi.org/10.1016/j.trc.2022.103588

Beyer, K. M. M., Kaltenbach, A., Szabo, A., Bogar, S., Nieto, F. J., & Malecki, K. M. (2014). Exposure to neighborhood green space and mental health: Evidence from the survey of the health of Wisconsin. *International Journal of Environmental Research and Public Health*, *11*(3), 3453–3472.

Bigazzi, A. (2019). Comparison of marginal and average emission factors for passenger transportation modes. *Applied Energy*, *242*, 1460–1466. https://doi.org/10.1016/j.apenergy.2019.03.172

DRAFT

Bigazzi, A. (2020). Marginal emission factors for public transit: Effects of urban scale and density. *Transportation Research Part D: Transport and Environment*, *88*, 102585. https://doi.org/10.1016/j.trd.2020.102585

Bigazzi, A. Y., & Hassanpour, A. (2022). *Human-electric hybrid vehicles: Implications of new non-auto mobility options for street design and policy in the Vancouver region* (p. 105) [Final Report]. Prepared for TransLink. https://reactlab.civil.ubc.ca/human-electric-hybrid-vehicles/

Bird, E. L., Ige, J. O., Pilkington, P., Pinto, A., Petrokofsky, C., & Burgess-Allen, J. (2018). Built and natural environment planning principles for promoting health: An umbrella review. *BMC Public Health*, *18*(1), 1–13.

Blanco-Davis, E., Castillo, F. del, & Zhou, P. (2014). Fouling release coating application as an environmentally efficient retrofit: A case study of a ferry-type ship. *The International Journal of Life Cycle Assessment*, *19*(10), Article 10. https://doi.org/10.1007/s11367-014-0780-8

Bleyen, P., Klimovský, D., Bouckaert, G., & Reichard, C. (2017). Linking budgeting to results? Evidence about performance budgets in European municipalities based on a comparative analytical model. *Public Management Review*, *19*(7), 932–953. https://doi.org/10.1080/14719037.2016.1243837

Bloom, D. E., Cafiero, E., Jané-Llopis, E., Abrahams-Gessel, S., Bloom, L. R., Fathima, S., Feigl, A. B., Gaziano, T., Hamandi, A., & Mowafi, M. (2012). *The global economic burden of noncommunicable diseases*. Program on the Global Demography of Aging.

Brand, C., & Preston, J. M. (2010). '60-20 emission'—The unequal distribution of greenhouse gas emissions from personal, non-business travel in the UK. *Transport Policy*, *17*(1), 9–19. https://doi.org/10.1016/j.tranpol.2009.09.001

Brander, M., & Ascui, F. (2015). The Attributional-Consequential Distinction and Its Applicability to Corporate Carbon Accounting. In S. Schaltegger, D. Zvezdov, I. Alvarez Etxeberria, M. Csutora, & E. Günther (Eds.), *Corporate Carbon and Climate Accounting* (pp. 99–120). Springer International Publishing. https://doi.org/10.1007/978-3-319-27718-9_5

Brander, M., Gillenwater, M., & Ascui, F. (2018). Creative accounting: A critical perspective on the market-based method for reporting purchased electricity (scope 2) emissions. *Energy Policy*, *112*, 29–33. https://doi.org/10.1016/j.enpol.2017.09.051

DRAFT

Bratman, G. N., Hamilton, J. P., Hahn, K. S., Daily, G. C., & Gross, J. J. (2015). Nature experience reduces rumination and subgenual prefrontal cortex activation. *Proceedings of the National Academy of Sciences*, *112*(28), 8567–8572.

Braun, L., Rodriguez, D., Song, Y., Meyer, K., Lewis, C., Reis, J., & Gordon-Larsen, P. (2016). Changes in walking, body mass index, and cardiometabolic risk factors following residential relocation: Longitudinal results from the CARDIA study. *J Transp Health.*, *3*(4), 426–439. https://doi.org/10.1016/j.jth.2016.08.006

Brown, M., Eldridge, M., & Bieretz, B. (2019). *Performance-Based Strategies: Defining Terms and Comparing Common Strategies* (p. 5). Urban Institute.

Brown, N. M. (2019). *Millennium Challenge Corporation: Overview and Issues* (p. 36). Congressional Research Service.

Bureau of Transportation Statistics, U.S. Department of Transportation. (n.d.). *National Transportation Statistics*. Retrieved December 20, 2017, from http://www.bts.gov/publications/national_transportation_statistics/

Burvill, A. J., Murray, K., Knuiman, M. W., & Hung, J. (2022). Comparing self-reported and measured hypertension and hypercholesterolaemia at standard and more stringent diagnostic thresholds: The cross-sectional 2010–2015 Busselton Healthy Ageing study. *Clinical Hypertension*, *28*(1), 1–10. https://doi.org/10.1186/s40885-022-00199-1

Buzar, S., Ogden, P., Hall, R., Haase, A., Kabisch, S., & Steinfiihrer, A. (2007). Splintering Urban Populations: Emergent Landscapes of Reurbanisation in Four European Cities. *Urban Studies*, *44*(4), 651–677. https://doi.org/10.1080/00420980601185544

Camhi, S. M., Troped, P. J., Garvey, M., Hayman, L. L., Must, A., Lichtenstein, A. H., & Crouter, S. E. (2019). Associations between Walk Score and objective measures of physical activity in urban overweight and obese women. *PLoS One*, *14*(3), e0214092.

CANUE. (n.d.). *The Canadian Urban Environmental Health Research Consortium: Understanding urban living and human health*.

Carlson, J. A., Saelens, B. E., Kerr, J., Schipperijn, J., Conway, T. L., Frank, L. D., Chapman, J. E., Glanz, K., Cain, K. L., & Sallis, J. F. (2017). Association between neighborhood walkability and GPSmeasured walking, bicycling and vehicle time in adolescents. *Health & Place*, *32*, 1–7. https://doi.org/10.1016/j.healthplace.2014.12.008.Association

Carranza, G., Do Nascimiento, M., Fanals, J., Febrer, J., & Valderrama, C. (2022). Life cycle assessment and economic analysis of the electric motorcycle in the city of

DRAFT

Barcelona and the impact on air pollution. *Science of The Total Environment*, *821*, 153419. https://doi.org/10.1016/j.scitotenv.2022.153419

Cerin, E., Nathan, A., Van Cauwenberg, J., Barnett, D. W., & Barnett, A. (2017). The neighbourhood physical environment and active travel in older adults: A systematic review and meta-analysis on behalf of the Council on Environment and Physical Activity (CEPA) – Older Adults working group. *International Journal of Behavioral Nutrition and Physical Activity*, *14*(15). https://doi.org/10.1186/s12966-017-0471-5

Cerqueira, E. D. V., Motte-Baumvol, B., Chevallier, L. B., & Bonin, O. (2020). Does working from home reduce CO2 emissions? An analysis of travel patterns as dictated by workplaces. *Transportation Research Part D: Transport and Environment*, *83*, 102338. https://doi.org/10.1016/j.trd.2020.102338

Chan, S., Miranda-Moreno, L., Alam, A., & Hatzopoulou, M. (2013). Assessing the impact of bus technology on greenhouse gas emissions along a major corridor: A lifecycle analysis. *World Transit Research*. https://www.worldtransitresearch.info/research/4746

Chandrabose, M., Cerin, E., Mavoa, S., Dunstan, D., Carver, A., Turrell, G., Owen, N., Giles-Corti, B., & Sugiyama, T. (2019). Neighborhood walkability and 12-year changes in cardio-metabolic risk: The mediating role of physical activity. *The International Journal of Behavioral Nutrition and Physical Activity*, *16*(1), 86. https://doi.org/10.1186/s12966-019-0849-7

Chandrabose, M., Rachele, J. N., Gunn, L., Kavanagh, A., Owen, N., Turrell, G., Giles-Corti, B., & Sugiyama, T. (2019a). Built environment and cardio-metabolic health: Systematic review and meta-analysis of longitudinal studies. *Obesity Reviews*, *20*(1), 41–54. https://doi.org/10.1111/obr.12759

Chandrabose, M., Rachele, J. N., Gunn, L., Kavanagh, A., Owen, N., Turrell, G., Giles-Corti, B., & Sugiyama, T. (2019b). Built environment and cardio-metabolic health: Systematic review and meta-analysis of longitudinal studies. *Obesity Reviews*, *20*(1), 41–54. https://doi.org/10.1111/obr.12759

Chester, M., & Horvath, A. (2009). *Life-cycle Energy and Emissions Inventories for Motorcycles, Diesel Automobiles, School Buses, Electric Buses, Chicago Rail, and New York City Rail*. https://escholarship.org/uc/item/6z37f2jr

Chester, M. V. (2008). *Life-cycle Environmental Inventory of Passenger Transportation in the United States*. https://escholarship.org/uc/item/7n29n303

Choi, K., & Zhang, M. (2017). The net effects of the built environment on household vehicle emissions: A case study of Austin, TX. *Transportation Research Part D:*

DRAFT

Transport and Environment, *50*, 254–268. https://doi.org/10.1016/j.trd.2016.10.036

Clark, C., Menifield, C. E., & Stewart, L. M. (2018). Policy Diffusion and Performance-based Budgeting. *International Journal of Public Administration*, *41*(7), 528–534. https://doi.org/10.1080/01900692.2016.1278384

Condon, P. M., & Dow, K. (2011). *Transportation for Sustainable Communities: A cost and impact comparison between alternative transportation modes*.

Conway, M. W., & Stewart, A. F. (2019). Getting Charlie off the MTA: A multiobjective optimization method to account for cost constraints in public transit accessibility metrics. *International Journal of Geographical Information Science*, *33*(9), 1759–1787. https://doi.org/10.1080/13658816.2019.1605075

Cooney, G., Hawkins, T. R., & Marriott, J. (2013). Life Cycle Assessment of Diesel and Electric Public Transportation Buses. *Journal of Industrial Ecology*, *17*(5), 689–699. https://doi.org/10.1111/jiec.12024

Corradi, O., McCormick, G., Richardson, H., & Hinkle, T. (2021). *A vision for how ambitious organizations can accurately measure electricity emissions to take genuine action*. Tomorrow and Watt Time. https://www.watttime.org/app/uploads/2021/08/GHG-Frameworks-WhitePaper-Tomorrow-WattTime-202108.pdf

Cottagiri, S. A., Villeneuve, P. J., Raina, P., Griffith, L. E., Rainham, D., Dales, R., Peters, C. E., Ross, N. A., & Crouse, D. L. (2022). Increased urban greenness associated with improved mental health among middle-aged and older adults of the Canadian Longitudinal Study on Aging (CLSA). *Environmental Research*, *206*, 112587.

Cox, B. L., & Mutel, C. L. (2018). The environmental and cost performance of current and future motorcycles. *Applied Energy*, *212*, 1013–1024. https://doi.org/10.1016/j.apenergy.2017.12.100

Cramer, J., & Krueger, A. B. (2016). Disruptive Change in the Taxi Business: The Case of Uber. *American Economic Review*, *106*(5), 177–182. https://doi.org/10.1257/aer.p20161002

Croissant, Y., & Millo, G. (2008). Panel Data Econometrics in R: The plm Package. *Journal of Statistical Software*, *27*. https://doi.org/10.18637/jss.v027.i02

Csárdi, G., Nepusz, T., Müller, K., Horvát, S., Traag, V., Zanini, F., & Noom, D. (2023). *igraph for R: R interface of the igraph library for graph theory and network analysis* [Computer software]. Zenodo. https://doi.org/10.5281/zenodo.8046777

Darwish, A. M., Zagow, M., & Elkafoury, A. (2023). Impact of land use, travel behavior, and socio-economic characteristics on carbon emissions in cool-climate cities,

DRAFT

USA. *Environmental Science and Pollution Research*, *30*(39), 91108–91124. https://doi.org/10.1007/s11356-023-28487-9

DC Water. (2016). *DC Water, Goldman Sachs and Calvert Foundation pioneer environmental impact bond; | DCWater.com*. https://www.dcwater.com/whats-going-on/news/dc-water-goldman-sachs-and-calvert-foundation-pioneer-environmental-impact-bond

De Boer, H., Jongbloed, B., Benneworth, P., Cremonini, L., Kolster, R., Kottmann, A., Lemmens-Krug, K., & Vossensteyn, H. (2015). Performance-based funding and performance agreements in fourteen higher education systems. *Center for Higher Education Policy Studies*.

de Bortoli, A. (2021). Environmental performance of shared micromobility and personal alternatives using integrated modal LCA. *Transportation Research Part D: Transport and Environment*, *93*, 102743. https://doi.org/10.1016/j.trd.2021.102743

Del Pero, F., Delogu, M., Pierini, M., & Bonaffini, D. (2015). Life Cycle Assessment of a heavy metro train. *Journal of Cleaner Production*, *87*, 787–799. https://doi.org/10.1016/j.jclepro.2014.10.023

DenBraver, N. R., Lakerveld, J., Rutters, F., Schoonmade, L. J., Brug, J., & Beulens, J. W. J. (2018). Built environmental characteristics and diabetes: A systematic review and meta-analysis. *BMC Medicine*, *16*(1). https://doi.org/10.1186/s12916-017-0997-z

Dendup, T., Feng, X., Clingan, S., & Astell-Burt, T. (2018). Environmental risk factors for developing type 2 diabetes mellitus: A systematic review. *International Journal of Environmental Research and Public Health*, *15*(1). https://doi.org/10.3390/ijerph15010078

Des Rosiers, F., Thériault, M., Biba, G., & Vandersmissen, M.-H. (2017). Greenhouse gas emissions and urban form: Linking households' socio-economic status with housing and transportation choices. *Environment and Planning B: Urban Analytics and City Science*, *44*(5), 964–985. https://doi.org/10.1177/0265813516656862

Dey, S., Caulfield, B., & Ghosh, B. (2019). Modelling uncertainty of vehicular emissions inventory: A case study of Ireland. *Journal of Cleaner Production*, *213*, 1115–1126. https://doi.org/10.1016/j.jclepro.2018.12.125

Dhalla, A., McDonald, T. E., Gallagher, R. P., Spinelli, J. J., Brooks-Wilson, A. R., Lee, T. K., Lai, C., Borugian, M. J., Woods, R. R., Le, N. D., & Dummer, T. J. B. (2019). Cohort profile: The British Columbia Generations Project (BCGP). *International Journal of Epidemiology*, *48*(2), 377–378k. https://doi.org/10.1093/ije/dyy160

DRAFT

DMTISpatial. CanMap® GIS Data for GIS Mapping Software—DMTI Spatial. (n.d.). https://www.dmtispatial.com/canmap/

Environment and Climate Change Canada. (2020). *Historical Data—Climate*. https://climate.weather.gc.ca/historical_data/search_historic_data_e.html

Environment and Climate Change Canada. (2021). *Greenhouse gas sources and sinks in Canada*. Government of Canada. https://www.canada.ca/en/environment-climate-change/services/climate-change/greenhouse-gas-emissions/inventory.html

Environment and Climate Change Canada. (2022). *Canada's air pollutant emissions inventory report 2022*. https://publications.gc.ca/site/eng/9.869731/publication.html

Facts about Physical Activity| CDC. (n.d.). Retrieved April 8, 2017, from https://www.cdc.gov/physicalactivity/data/facts.htm

Fan, V. Y., Duran, D., Silverman, R., & Glassman, A. (2013). Performance-based financing at the Global Fund to Fight AIDS, Tuberculosis and Malaria: An analysis of grant ratings and funding, 2003–12. *The Lancet Global Health*, *1*(3), e161–e168.

Fan, Y., Das, K. V, & Chen, Q. (2011). Neighborhood green, social support, physical activity, and stress: Assessing the cumulative impact. *Health & Place*, *17*(6), 1202–1211.

Fazeli Dehkordi, Z. S., Khatami, S. M., & Ranjbar, E. (2022). The Associations Between Urban Form and Major Non-communicable Diseases: A Systematic Review. *Journal of Urban Health*, *99*(5), 941–958. https://doi.org/10.1007/s11524-022-00652-4

Fong, K. C., Hart, J. E., & James, P. (2018). A review of epidemiologic studies on greenness and health: Updated literature through 2017. *Current Environmental Health Reports*, *5*, 77–87.

Frank, L. D., Adhikari, B., White, K. R., Dummer, T., Sandhu, J., Demlow, E., Hu, Y., Hong, A., & Van den Bosch, M. (2022). Chronic disease and where you live: Built and natural environment relationships with physical activity, obesity, and diabetes. *Environment International*, *158*, 106959. https://doi.org/10.1016/J.ENVINT.2021.106959

Frank, L. D., Iroz-Elardo, N., MacLeod, K. E., & Hong, A. (2019). Pathways from built environment to health: A conceptual framework linking behavior and exposure-based impacts. *Journal of Transport & Health*, *12*, 319–335.

Frank, L. D., Jr, B. S., & Bachman, W. (2000). *Linking land use with household vehicle emissions in the central puget sound: Methodological framework and ®ndings*.

DRAFT

Frank, L. D., Saelens, B. E., Powell, K. E., & Chapman, J. E. (2007). Stepping towards causation: Do built environments or neighborhood and travel preferences explain physical activity, driving, and obesity? *Social Science and Medicine*, *65*(9), 1898–1914. https://doi.org/10.1016/j.socscimed.2007.05.053

Frank, L. D., Sallis, J. F., Saelens, B. E., Leary, L., Cain, K., Conway, T. L., & Hess, P. M. (2010a). The development of a walkability index: Application to the Neighborhood Quality of Life Study. *British Journal of Sports Medicine*, *44*(13), 924–933. https://doi.org/10.1136/bjsm.2009.058701

Frank, L. D., Sallis, J. F., Saelens, B. E., Leary, L., Cain, K., Conway, T. L., & Hess, P. M. (2010b). The development of a walkability index: Application to the Neighborhood Quality of Life Study. *British Journal of Sports Medicine*, *44*(13), 924–933. https://doi.org/10.1136/bjsm.2009.058701

Frank, L. D., Schmid, T. L., Sallis, J. F., Chapman, J., & Saelens, B. E. (2005). Linking objectively measured physical activity with objectively measured urban form: Findings from SMARTRAQ. *American Journal of Preventive Medicine*, *28*(2), 117–125. https://doi.org/10.1016/J.AMEPRE.2004.11.001

Frank, L. D., Stone, B., & Bachman, W. (2000). Linking land use with household vehicle emissions in the central puget sound: Methodological framework and findings. *Transportation Research Part D: Transport and Environment*, *5*(3), 173–196. https://doi.org/10.1016/S1361-9209(99)00032-2

Frank, L., Giles-Corti, B., & Ewing, R. (2016). *The influence of the built environment on transport and health*. https://doi.org/10.1016/j.jth.2016.11.004

Freeman, L. (2005). Displacement or Succession?: Residential Mobility in Gentrifying Neighborhoods. *Urban Affairs Review*, *40*(4), 463–491. https://doi.org/10.1177/1078087404273341

Freeman, L., & Braconi, F. (2004). Gentrification and Displacement New York City in the 1990s. *Journal of the American Planning Association*, *70*(1), 39–52. https://doi.org/10.1080/01944360408976337

Frey, H. C. (2007). *Quantification of Uncertainty in Emission Factors and Inventories*. Environmental Protection Agency,; Google Scholar.

Gabrio, A., Plumpton, C., Banerjee, S., & Leurent, B. (2022). Linear mixed models to handle missing at random data in trial-based economic evaluations. *Health Economics (United Kingdom)*, *31*(6), 1276–1287. https://doi.org/10.1002/hec.4510

Gariepy, G., Blair, A., Kestens, Y., & Schmitz, N. (2014). Neighbourhood characteristics and 10-year risk of depression in Canadian adults with and without a chronic illness. *Health & Place*, *30*, 279–286.

DRAFT

GBD Mental Disorders Collaborators. Global, regional, and national burden of 12 mental disorders in 204 countries and territories, 1990–2019: A systematic analysis for the Global Burden of Disease Study 2019. (2022). *The Lancet Psychiatry*, *9*(2), 137–150.

Generaal, E., Timmermans, E. J., Dekkers, J. E. C., Smit, J. H., & Penninx, B. W. J. H. (2019). Not urbanization level but socioeconomic, physical and social neighbourhood characteristics are associated with presence and severity of depressive and anxiety disorders. *Psychological Medicine*, *49*(1), 149–161.

Ghafghazi, G., & Hatzopoulou, M. (2014). Simulating the environmental effects of isolated and area-wide traffic calming schemes using traffic simulation and microscopic emission modeling. *Transportation*, *41*(3), 633–649. https://doi.org/10.1007/s11116-014-9513-x

Giles-Corti, B., Vernez-Moudon, A., Reis, R., Turrell, G., Dannenberg, A. L., Badland, H., Foster, S., Lowe, M., Sallis, J. F., Stevenson, M., & Owen, N. (2016). City planning and population health: A global challenge. *The Lancet*. https://doi.org/10.1016/S0140-6736(16)30066-6

Glass, R. (1964). Aspects of change. *The Gentrification Debates: A Reader*, 19–30.

Global Advocacy for Physical Activity (GAPA) the Advocacy Council of the International Society for Physical Activity and Health (ISPAH). (2011). *NCD Prevention: Investments that Work for Physical Activity*. https://doi.org/10.1093/bmb/ldq037

Gold, J., Mendelsohn, M., & Mowat Centre for Policy Innovation. (2014). *Better Outcomes for Public Services: Achieving Social Impact Through Outcomes-Based Funding*. Mowat Center. http://www.deslibris.ca/ID/243716

Google. (2022). *Google Search*. https://www.google.com/

GPRBA. (2021). *Results-Based Financing | The Global Partnership for Results-Based Approaches*. https://www.gprba.org/results-based-financing

Grant, M., Bird, C., & Marno, P. (2012). Health inequalities and determinants in the physical urban environment: Evidence briefing. *WHO Collaborating Centre for Healthy Urban Environments: Bristol, UK*.

Grasser, G., Van Dyck, D., Titze, S., & Stronegger, W. (2012). Objectively measured walkability and active transport and weight-related outcomes in adults: A systematic review. *International Journal of Public Health*, *58*, 615–625.

Grasser, G., Van Dyck, D., Titze, S., & Stronegger, W. (2013). Objectively measured walkability and active transport and weight-related outcomes in adults: A systematic review. *Int J Public Health*, *58*(4), 615–625. https://doi.org/10.1007/s00038-012-0435-0

DRAFT

Grigsby, W. (1986). *The Dynamics of Neighborhood Change and Decline.*
Grittner, A. M. (2013). *Results-based financing: Evidence from performance-based financing in the health sector*. Dt. Inst. für Entwicklungspolitik.
Groenewegen, P. P., Van den Berg, A. E., De Vries, S., & Verheij, R. A. (2006). Vitamin G: effects of green space on health, well-being, and social safety. *BMC Public Health*, *6*(1), 1–9.
Gulcimen, S., Aydogan, E. K., & Uzal, N. (2021). Life cycle sustainability assessment of a light rail transit system: Integration of environmental, economic, and social impacts. *Integrated Environmental Assessment and Management*, *17*(5), 1070–1082. https://doi.org/10.1002/ieam.4428
Hackworth, J., & Smith, N. (2001). The changing state of gentrification. *Tijdschrift Voor Economische En Sociale Geografie*, *92*(4), 464–477.
Hammel, D. J., & Wyly, E. K. (1996). A MODEL FOR IDENTIFYING GENTRIFIED AREAS WITH CENSUS DATA. *Urban Geography*, *17*(3), 248–268. https://doi.org/10.2747/0272-3638.17.3.248
Hamnett, C. (1994). Social polarisation in global cities: Theory and evidence. *Urban Studies*, *31*(3), 401–424.
Harnisch, T. L. (2011). *Performance-based Funding: A Re-Emerging Strategy in Public Higher Education Financing*. 12.
Hartig, T. (2008). Green space, psychological restoration, and health inequality. *The Lancet*, *372*(9650), 1614–1615.
Hartig, T., Mitchell, R., De Vries, S., & Frumkin, H. (2014). Nature and health. *Annual Review of Public Health*, *35*, 207–228.
Harvard Kennedy School Government Performance Lab. (2017). *Social Impact Bonds 101*. https://govlab.hks.harvard.edu/files/govlabs/files/sibs_101_gpl_2017.pdf
Hassanpour, A., & Bigazzi, A. (2023). What is on the Bicycle Paths? A Detailed Vehicle Taxonomy with Mode Share Data for Off-Street Paths in Metropolitan Vancouver, Canada. *Transportation Research Record*, *2677*(11), 258–271. https://doi.org/10.1177/03611981231165017
Hawkins, R., Bieretz, B., & Brown, M. (2019, June 24). *Incentivizing Results: Contracting for Outcomes in Social Service Delivery*. Urban Institute. https://www.urban.org/research/publication/incentivizing-results-contracting-outcomes-social-service-delivery
Hedman, L. (2011). *Residential mobility and neighbourhood effects: A holistic approach*. Acta Universitatis Upsaliensis.

DRAFT

Helbich, M., Poppe, R., Oberski, D., van Emmichoven, M. Z., & Schram, R. (2021). Can't see the wood for the trees? An assessment of street view-and satellite-derived greenness measures in relation to mental health. *Landscape and Urban Planning*, *214*, 104181.

Hirsch, J. A., Roux, A. V. D., Moore, K. A., Evenson, K. R., & Rodriguez, D. A. (2014). Change in walking and body mass index following residential relocation: The multi-ethnic study of atherosclerosis. *American Journal of Public Health*, *104*(3), 49–56. https://doi.org/10.2105/AJPH.2013.301773

Hirschfeld, R. M. A., & Weissman, M. M. (2002). Risk factors for major depression and bipolar disorder. *Neuropsychopharmacology: The Fifth Generation of Progress*, 1017–1025.

Hochstenbach, C., & van Gent, W. P. (2015). An anatomy of gentrification processes: Variegating causes of neighbourhood change. *Environment and Planning A: Economy and Space*, *47*(7), 1480–1501. https://doi.org/10.1177/0308518X15595771

Hystad, P., Payette, Y., Noisel, N., & Boileau, C. (2019). Green space associations with mental health and cognitive function: Results from the Quebec CARTaGENE cohort. *Environmental Epidemiology*, *3*(1).

Insurance Corporation of British Columbia (ICBC). (2020). *British Columbia Vehicle Population Data* [dataset]. https://public.tableau.com/views/VehiclePopulationIntroPage/VehiclePopulationData?%3Adisplay_static_image=y&%3AbootstrapWhenNotified=true&%3Aembed=true&%3Alanguage=en-US&:embed=y&:showVizHome=n&:apiID=host0#navType=0&navSrc=Parse

Ipsos. (2018). *2017 Regional Trip Diary Technical Report*. TransLink.

Istrate, I., Iribarren, D., Dufour, J., Ortiz Cebolla, R., Arrigoni, A., Moretto, P., & Dolci, F. (2022). *Quantifying Emissions in the European Maritime Sector: A Review on Life Cycle Assessments of Maritime Systems Combined With an Analysis of the THETIS-MRV Portal* (JRC128870). https://trid.trb.org/view/1948241

Jacobs, P., Dewa, C. S., Lesage, A., Vasiliadis, H.-M., Escober, C., Mulvale, G., & Yim, R. (2010). *The cost of mental health and substance abuse services in Canada: A report to the Mental Health Commission of Canada*. Institute of Health Economics.

Janus, H., Klingebiel, S., & Paulo, S. (2015). Beyond Aid: A Conceptual Perspective on the Transformation of Development Cooperation. *Journal of International Development*, *27*(2), 155–169.

DRAFT

Johnson, D., & Zajonc, T. (2006). *Can Foreign Aid Create an Incentive for Good Governance? Evidence from the Millennium Challenge Corporation* [SSRN Scholarly Paper]. Social Science Research Network. https://doi.org/10.2139/ssrn.896293

Jones, A. C., Chaudhary, N. S., Patki, A., Howard, V. J., Howard, G., Colabianchi, N., Judd, S. E., & Irvin, M. R. (2021). Neighborhood Walkability as a Predictor of Incident Hypertension in a National Cohort Study. *Frontiers in Public Health*, *9*(February), 1–7. https://doi.org/10.3389/fpubh.2021.611895

Jongbloed, B., & De Boer, H. (2020). *Performance Agreements in Denmark, Ontario and the Netherlands*. University of Twente. https://doi.org/10.1787/735e1f44-en

Julien, D., Richard, L., Gauvin, L., & Kestens, Y. (2012). Neighborhood characteristics and depressive mood among older adults: An integrative review. *International Psychogeriatrics*, *24*(8), 1207–1225.

Kahn, M. E. (1998). A household level environmental Kuznets curve. *Economics Letters*, *59*(2), 269–273. https://doi.org/10.1016/S0165-1765(98)00035-4

Kannangara, M., Bensebaa, F., & Vasudev, M. (2021). An adaptable life cycle greenhouse gas emissions assessment framework for electric, hybrid, fuel cell and conventional vehicles: Effect of electricity mix, mileage, battery capacity and battery chemistry in the context of Canada. *Journal of Cleaner Production*, *317*, 128394. https://doi.org/10.1016/j.jclepro.2021.128394

Kaplan, R., & Kaplan, S. (1989). *The experience of nature: A psychological perspective*. Cambridge university press.

Keats, M. R., Cui, Y., DeClercq, V., Grandy, S. A., Sweeney, E., & Dummer, T. J. B. (2020). Associations between neighborhood walkability, physical activity, and chronic disease in Nova Scotian adults: An Atlantic PATH cohort study. *International Journal of Environmental Research and Public Health*, *17*(22), 8643.

Kessler, R. C., Aguilar-Gaxiola, S., Alonso, J., Chatterji, S., Lee, S., Ormel, J., Üstün, T. B., & Wang, P. S. (2009). The global burden of mental disorders: An update from the WHO World Mental Health (WMH) surveys. *Epidemiology and Psychiatric Sciences*, *18*(1), 23–33.

Khan, S., Pinault, L., Tjepkema, M., & Wilkins, R. (2018). Positional accuracy of geocoding from residential postal codes versus full street addresses. *Health Reports*, *29*(2), 3–9.

Kim, E. J., Kim, J., & Kim, H. (2020). Does Environmental Walkability Matter? The Role of Walkable Environment in Active Commuting. *International Journal of*

DRAFT

Environmental Research and Public Health, *17*(4), 1261. https://doi.org/10.3390/ijerph17041261

Kim, T. J., & Von Dem Knesebeck, O. (2018). Income and obesity: What is the direction of the relationship? A systematic review and meta-analysis. *BMJ Open*, *8*(1). https://doi.org/10.1136/bmjopen-2017-019862

King, A. C., Sallis, J. F., Frank, L. D., Saelens, B. E., Cain, K., Conway, T. L., Chapman, J. E., Ahn, D. K., & Kerr, J. (2011a). Aging in neighborhoods differing in walkability and income: Associations with physical activity and obesity in older adults. *Social Science & Medicine (1982)*, *73*(10), 1525–1533. https://doi.org/10.1016/j.socscimed.2011.08.032

King, A. C., Sallis, J. F., Frank, L. D., Saelens, B. E., Cain, K., Conway, T. L., Chapman, J. E., Ahn, D. K., & Kerr, J. (2011b). Aging in neighborhoods differing in walkability and income: Associations with physical activity and obesity in older adults. *Social Science & Medicine*, *73*(10), 1525–1533. https://doi.org/10.1016/J.SOCSCIMED.2011.08.032

Klompmaker, J. O., Hoek, G., Bloemsma, L. D., Wijga, A. H., van den Brink, C., Brunekreef, B., Lebret, E., Gehring, U., & Janssen, N. A. H. (2019). Associations of combined exposures to surrounding green, air pollution and traffic noise on mental health. *Environment International*, *129*, 525–537.

Ko, J., Park, D., Lim, H., & Hwang, I. C. (2011). Who produces the most CO2 emissions for trips in the Seoul metropolis area? *Transportation Research Part D: Transport and Environment*, *16*(5), 358–364. https://doi.org/10.1016/j.trd.2011.02.001

Koohsari, M. J., McCormack, G. R., Nakaya, T., Shibata, A., Ishii, K., Yasunaga, A., Hanibuchi, T., & Oka, K. (2019). Urban design and Japanese older adults' depressive symptoms. *Cities*, *87*, 166–173.

Koohsari, M. J., Owen, N., Cole, R., Mavoa, S., Oka, K., Hanibuchi, T., & Sugiyama, T. (2017). Built environmental factors and adults' travel behaviors: Role of street layout and local destinations. *Preventive Medicine*, *96*, 124–128. https://doi.org/10.1016/j.ypmed.2016.12.021

Koohsari, M. J., Yasunaga, A., McCormack, G. R., Shibata, A., Ishii, K., Nakaya, T., Hanibuchi, T., Nagai, Y., & Oka, K. (2023). Depression among middle-aged adults in Japan: The role of the built environment design. *Landscape and Urban Planning*, *231*, 104651.

Koren, H. S., & Butler, C. D. (2006). The interconnection between the built environment ecology and health. *Environmental Security and Environmental Management: The Role of Risk Assessment*, 111–125.

DRAFT

Kotval-K, Z., & Vojnovic, I. (2015). The socio-economics of travel behavior and environmental burdens: A Detroit, Michigan regional context. *Transportation Research Part D: Transport and Environment*, *41*, 477–491. https://doi.org/10.1016/j.trd.2015.10.017

Krols, J., Aerts, R., Vanlessen, N., Dewaelheyns, V., Dujardin, S., & Somers, B. (2022). Residential green space, gardening, and subjective well-being: A cross-sectional study of garden owners in northern Belgium. *Landscape and Urban Planning*, *223*, 104414.

Lai, K. Y., Webster, C., Gallacher, J. E., & Sarkar, C. (2023). Associations of Urban Built Environment with Cardiovascular Risks and Mortality: A Systematic Review. In *Journal of Urban Health* (Vol. 100, Issue 4). Springer US. https://doi.org/10.1007/s11524-023-00764-5

Lajunen, A., & Lipman, T. (2016). Lifecycle cost assessment and carbon dioxide emissions of diesel, natural gas, hybrid electric, fuel cell hybrid and electric transit buses. *Energy*, *106*, 329–342. https://doi.org/10.1016/j.energy.2016.03.075

Lang, D. W. (2016). *Incentive Funding Meets Incentive-Based Budgeting: Can They Coexist? 46*(4), 22.

Lang, I. M., Antonakos, C. L., Judd, S. E., & Colabianchi, N. (2022). A longitudinal examination of objective neighborhood walkability, body mass index, and waist circumference: The REasons for Geographic And Racial Differences in Stroke study. *International Journal of Behavioral Nutrition and Physical Activity*, *19*(1), 1–15. https://doi.org/10.1186/s12966-022-01247-7

Le Hong, Z., & Zimmerman, N. (2021). Air quality and greenhouse gas implications of autonomous vehicles in Vancouver, Canada. *Transportation Research Part D: Transport and Environment*, *90*, 102676. https://doi.org/10.1016/j.trd.2020.102676

Lederer, J., Ott, C., Brunner, P. H., & Ossberger, M. (2016). The life cycle energy demand and greenhouse gas emissions of high-capacity urban transport systems: A case study from Vienna's subway line U2. *International Journal of Sustainable Transportation*, *10*(2), 120–130. https://doi.org/10.1080/15568318.2013.869704

Lee, S., & Lee, B. (2020). Comparing the impacts of local land use and urban spatial structure on household VMT and GHG emissions. *Journal of Transport Geography*, *84*, 102694. https://doi.org/10.1016/j.jtrangeo.2020.102694

Lees, L. (2000). A reappraisal of gentrification: Towards a 'geography of gentrification.' *Progress in Human Geography*, *24*(3), 389–408.

DRAFT

Leon, B. M., & Maddox, T. M. (2015). Diabetes and cardiovascular disease: Epidemiology , biological mechanisms , treatment recommendations and future research. *World Journal of Diabetes*, *6*(13), 1246–1258. https://doi.org/10.4239/wjd.v6.i13.1246

Lesage, A., Vasiliadis, H. M., Gagné, M. A., Dudgeon, S., Kasman, N., & Hay, C. (2012). *Prevalence of mental illnesses and related service utilization in Canada: An analysis of the Canadian Community Health Survey. Mississauga, ON: Canadian Collaborative Mental Health Initiative; 2006*.

Levelton Engineering Ltd. (2002). *Marine Vessel Air Emissions in B.C. and Washington State outside the GVRD and FVRD for the Year 2000*. Greater Vancouver Regional District. https://georgiastrait.org/wp-content/uploads/2015/03/MarineVesselEmission2000Outside.pdf

Ley, D. (1986). Alternative Explanations for Inner-City Gentrification: A Canadian Assessment. *Annals of the Association of American Geographers*, *76*(4), 521–535. https://doi.org/10.1111/j.1467-8306.1986.tb00134.x

Ley, D. (2003). Artists, Aestheticisation and the Field of Gentrification. *Urban Studies*, *40*(12), 2527–2544. https://doi.org/10.1080/0042098032000136192

Ley, D., & Dobson, C. (2008). Are There Limits to Gentrification? The Contexts of Impeded Gentrification in Vancouver. *Urban Studies*, *45*(12), 2471–2498. https://doi.org/10.1177/0042098008097103

Li, T., Qi, G.-J., & Stern, R. (2022). Taxi Utilization Rate Maximization by Dynamic Demand Prediction: A Case Study in the City of Chicago. *Transportation Research Record*, *2676*(4), 367–379. https://doi.org/10.1177/03611981211059769

Li, T., Wu, X., Ban, X., & Wang, Y. (2020, August). *"Centralized" Taxi Services in Big Metropolitan Areas: Evidenced by Chicago Data*. International Conference on Transportation and Development 2020American Society of Civil Engineers. https://trid.trb.org/view/1735651

Liao, B., E. W. Van Den Berg, P., Van Wesemael, P. J. V., & A. Arentze, T. (2020). How Does Walkability Change Behavior? A Comparison between Different Age Groups in the Netherlands. *International Journal of Environmental Research and Public Health*, *17*(2), 540. https://doi.org/10.3390/ijerph17020540

Lim, G. Y., Tam, W. W., Lu, Y., Ho, C. S., Zhang, M. W., & Ho, R. C. (2018). Prevalence of depression in the community from 30 countries between 1994 and 2014. *Scientific Reports*, *8*(1), 2861.

Liu, Y., Wang, R., Xiao, Y., Huang, B., Chen, H., & Li, Z. (2019). Exploring the linkage between greenness exposure and depression among Chinese people: Mediating

DRAFT

roles of physical activity, stress and social cohesion and moderating role of urbanicity. *Health & Place*, *58*, 102168.
Logtenberg, R., Pawley, J., & Saxifrage, B. (2018). *Comparing Fuel and Maintenance Costs of Electric and Gas Powered Vehicles in Canada*. 2 Degrees Institute.
Ma, J., Heppenstall, A., Harland, K., & Mitchell, G. (2014). Synthesising carbon emission for mega-cities: A static spatial microsimulation of transport CO2 from urban travel in Beijing. *Computers, Environment and Urban Systems*, *45*, 78–88. https://doi.org/10.1016/j.compenvurbsys.2014.02.006
Maas, J., Verheij, R. A., de Vries, S., Spreeuwenberg, P., Schellevis, F. G., & Groenewegen, P. P. (2009). Morbidity is related to a green living environment. *Journal of Epidemiology & Community Health*, *63*(12), 967–973.
Maas, J., Verheij, R. A., Spreeuwenberg, P., & Groenewegen, P. P. (2008). Physical activity as a possible mechanism behind the relationship between green space and health: A multilevel analysis. *BMC Public Health*, *8*, 1–13.
Mackenbach, J. D., Rutter, H., Compernolle, S., Glonti, K., Oppert, J. M., Charreire, H., De Bourdeaudhuij, I., Brug, J., Nijpels, G., & Lakerveld, J. (2014). Obesogenic environments: A systematic review of the association between the physical environment and adult weight status, the SPOTLIGHT project. *BMC Public Health*, *14*(1). https://doi.org/10.1186/1471-2458-14-233
Mahmud, M. A. P., Huda, N., Farjana, S. H., & Lang, C. (2019). Comparative Life Cycle Environmental Impact Analysis of Lithium-Ion (LiIo) and Nickel-Metal Hydride (NiMH) Batteries. *Batteries*, *5*(1), Article 1. https://doi.org/10.3390/batteries5010022
Mair, C., Roux, A. V. D., & Galea, S. (2008). Are neighbourhood characteristics associated with depressive symptoms? A review of evidence. *Journal of Epidemiology & Community Health*, *62*(11), 940–946.
Majeau-Bettez, G., Hawkins, T. R., & Strømman, A. H. (2011). Life Cycle Environmental Assessment of Lithium-Ion and Nickel Metal Hydride Batteries for Plug-In Hybrid and Battery Electric Vehicles. *Environmental Science & Technology*, *45*(10), 4548–4554. https://doi.org/10.1021/es103607c
Marcuse, P. (1985). Gentrification, abandonment, and displacement: Connections, causes, and policy responses in New York City. *Wash. UJ Urb. & Contemp. L.*, *28*, 195.
Martin, E., & Shaheen, S. (2016). *Impacts of car2go on Vehicle Ownership, Modal Shift, Vehicle Miles Traveled, and Greenhouse Gas Emissions: An Analysis of Five North American Cities*. Transportation Sustainability Research Center.

DRAFT

https://tsrc.berkeley.edu/publications/impacts-car2go-vehicle-ownership-modal-shift-vehicle-miles-traveled-and-greenhouse-gas
Martínez, J., Pearson, M., & Sørensen, B. H. (2012). *Evaluation of the Health Results Innovation Trust Fund*. Norad Evaluation Department.
McCormack, G. R., & Shiell, A. (2011). In search of causality: A systematic review of the relationship between the built environment and physical activity among adults. *International Journal of Behavioral Nutrition and Physical Activity*, *8*, 1–11.
McElhanney. (2018). *2017 Vancouver Panel Survey*. City of Vancouver. https://vancouver.ca/files/cov/2017-transportation-panel-survey-final-draft-20180516.pdf
McKinnish, T., Walsh, R., & White, T. K. (2010). Who Gentrifies Low-Income Neighborhoods? *Journal of Urban Economics*, *67*(2), 180–193. https://doi.org/10.1016/j.jue.2009.08.003
Meegan, R., & Mitchell, A. (2001). "It's not community round here, it's neighbourhood": Neighbourhood change and cohesion in urban regeneration policies. *Urban Studies*, *38*(12), 2167–2194.
Mehta, U., Wilt, G. E., Okereke, O. I., Coull, B., James, P., Laden, F., Iyer, H. S., Deville, N. V, & Hart, J. E. (2022). Interactions between multiple environmental factors and associations with generalized anxiety disorder in Nurses' Health Study II. *ISEE Conference Abstracts*, *2022*(1).
Metro Vancouver. (2014). *The Metro Vancouver Car Share Study: Technical Report*. https://learn.sharedusemobilitycenter.org/overview/the-metro-vancouver-car-share-study-technical-report-british-columbia-canada-2014/
Metro Vancouver. (2018). *2015 Lower Fraser Valley Air Emissions Inventory and Forecast* [Final Report]. https://metrovancouver.org/services/air-quality-climate-change/Documents/lower-fraser-valley-air-emissions-inventory-forecast-2015.pdf#search=2015%20emission%20inventory
Metro Vancouver. (2020). *Regional Land Use Designation*. http://www.metrovancouver.org:80/metro2040/land-use-designation/Pages/default.aspx
Miao, K. (2012). *Performance-Based Funding of Higher Education* (p. 12). Center for American Progress.
Michael, Y., Gold, R., Perrin, N., & Hillier, T. (2013). Built environment and change in body mass index in older women. *Health Place.*, *22*(July), 7–10. https://doi.org/10.1016/j.healthplace.2013.02.001

DRAFT

Mills, K. T., Stefanescu, A., & He, J. (2020). The global epidemiology of hypertension. *Nature Reviews Nephrology*, *16*(April). https://doi.org/10.1038/s41581-019-0244-2

Mio, A., Fermeglia, M., & Favi, C. (2022). A critical review and normalization of the life cycle assessment outcomes in the naval sector. Articles description. *Journal of Cleaner Production*, *370*, 133476. https://doi.org/10.1016/j.jclepro.2022.133476

Mitchell, R. J., Richardson, E. A., Shortt, N. K., & Pearce, J. R. (2015). Neighborhood environments and socioeconomic inequalities in mental well-being. *American Journal of Preventive Medicine*, *49*(1), 80–84.

Mitchell, R., & Popham, F. (2007). Greenspace, urbanity and health: Relationships in England. *Journal of Epidemiology & Community Health*, *61*(8), 681–683.

Mitchell, R., & Popham, F. (2008). Effect of exposure to natural environment on health inequalities: An observational population study. *The Lancet*, *372*(9650), 1655–1660.

Moreira, T. C. L., Polize, J. L., Brito, M., da Silva Filho, D. F., Chiavegato Filho, A. D. P., Viana, M. C., Andrade, L. H., & Mauad, T. (2022). Assessing the impact of urban environment and green infrastructure on mental health: Results from the São Paulo Megacity Mental Health Survey. *Journal of Exposure Science & Environmental Epidemiology*, *32*(2), 205–212.

Musgrove, P. (2011). *Financial and Other Rewards for Good Performance or Results: A Guided Tour of Concepts and Terms and a Short Glossary* (p. 12). World Bank.

Mytton, O. T., Townsend, N., Rutter, H., & Foster, C. (2012). Green space and physical activity: An observational study using Health Survey for England data. *Health & Place*, *18*(5), 1034–1041.

Natural Resources Canada. (2010). *Canadian Vehicle Survey 2008 Update Report*. Governement of Canada. https://oee.nrcan.gc.ca/publications/statistics/cvs08/summary.cfm?attr=0

Natural Resources Canada. (2022). *Fuel consumption ratings*. https://open.canada.ca/data/en/dataset/98f1a129-f628-4ce4-b24d-6f16bf24dd64

Newman, K., & Wyly, E. K. (2006). The Right to Stay Put, Revisited: Gentrification and Resistance to Displacement in New York City. *Urban Studies*, *43*(1), 23–57. https://doi.org/10.1080/00420980500388710

Ng, E., Vanderloo, S. E., Geiss, L., & Johnson, J. A. (2013). Concordance between self-report and a survey-based algorithm for classification of type 1 and type 2 diabetes using the 2011 population-based survey on living with chronic diseases in canada

DRAFT

(slcdc)-diabetes component. *Canadian Journal of Diabetes*, *37*(4), 249–253. https://doi.org/10.1016/j.jcjd.2013.05.007
Nordelöf, A., Romare, M., & Tivander, J. (2019). Life cycle assessment of city buses powered by electricity, hydrogenated vegetable oil or diesel. *Transportation Research Part D: Transport and Environment*, *75*, 211–222. https://doi.org/10.1016/j.trd.2019.08.019
Núñez-González, S., Delgado-Ron, J. A., Gault, C., Lara-Vinueza, A., Calle-Celi, D., Porreca, R., & Simancas-Racines, D. (2020). Overview of "systematic reviews" of the built environment's effects on mental health. *Journal of Environmental and Public Health*, *2020*.
OECD. (2020). *Resourcing Higher Education: Challenges, Choices and Consequences*. OECD. https://doi.org/10.1787/735e1f44-en
Ontario. (2018, May 9). *College and university Strategic Mandate Agreements*. Ontario.Ca. https://www.ontario.ca/page/all-college-and-university-strategic-mandate-agreements
Ortuzar, J., & Willumsen, L. (2011). *Modelling Transport* (4th ed.). Wiley.
Oxman, A. D., Lewin, S., Lavis, J. N., & Fretheim, A. (2009). Support Tools for Evidence-Informed Health Policymaking (stp) 15: Engaging the Public in Evidence-Informed Policymaking. *Health Research Policy and Systems*, *7*(1), 1–9.
Pacific Climate Impacts Consortium. (2020). *BC Station Data Portal*. https://pacificclimate.org/data/bc-station-data-portal-notice
Pardy, A. (2018). *Densification of Vancouver's neighbourhoods: Energy use, emissions, and affordability* [Simon Fraser University]. https://summit.sfu.ca/item/18772
Pearson, C., Janz, T., & Ali, J. (2013a). *Mental and substance use disorders in Canada*. Statistics Canada Ottawa, ON.
Pearson, C., Janz, T., & Ali, J. (2013b). *Mental and substance use disorders in Canada*. Statistics Canada Ottawa, ON.
Pearson, M., Johnson, M., & Ellison, R. (2010). *Review of major Results Based Aid (RBA) and Results Based Financing (RBF) schemes* (p. 98). DFID Human Development Resource Centre.
Perakis, R., & Savedoff, W. (2015). Does results-based aid change anything? Pecuniary interests, attention, accountability and discretion in four case studies. *CGD Policy Paper*, *52*.
Perakis, R., & Savedoff, W. D. (2014). An Introduction to Cash on Delivery Aid for Funders. *Note. Washington, DC: CGD*.

DRAFT

Pereira, R. H. M., Saraiva, M., Herszenhut, D., Braga, C. K. V., & Conway, M. W. (2021). r5r: Rapid Realistic Routing on Multimodal Transport Networks with R^5 in R. *Findings*. https://doi.org/10.32866/001c.21262

Perrino, T., Lombard, J., Rundek, T., Wang, K., Dong, C., Gutierrez, C. M., Toro, M., Byrne, M. M., Nardi, M. I., Kardys, J., Szapocznik, J., & Brown, S. C. (2019). Neighbourhood greenness and depression among older adults. *Br J Psychiatry*, *215*(2), 476–480. https://doi.org/10.1192/bjp.2019.129

Pinault, L., Khan, S., & Tjepkema, M. (2020). Accuracy of matching residential postal codes to census geography. *Health Reports*, *31*(3), 3–13. https://doi.org/10.25318/82-003-x202000300001-eng

Poister, T. H., Aristigueta, M. P., & Hall, J. L. (2014). *Managing and Measuring Performance in Public and Nonprofit Organizations: An Integrated Approach*. John Wiley & Sons, Incorporated. http://ebookcentral.proquest.com/lib/utoronto/detail.action?docID=1776337

Pommier, R., Grimaud, G., Prinçaud, M., Perry, N., & Sonnemann, G. (2016). Comparative environmental life cycle assessment of materials in wooden boat ecodesign. *International Journal of Life Cycle Assessment*, *21*(2), 265–275. https://doi.org/10.1007/s11367-015-1009-1

Pourahmadiyan, A., Ahmadi, P., & Kjeang, E. (2021). Dynamic simulation and life cycle greenhouse gas impact assessment of CNG, LNG, and diesel-powered transit buses in British Columbia, Canada. *Transportation Research Part D: Transport and Environment*, *92*, 102724. https://doi.org/10.1016/j.trd.2021.102724

Pun, V. C., Manjourides, J., & Suh, H. H. (2018). Association of neighborhood greenness with self-perceived stress, depression and anxiety symptoms in older US adults. *Environmental Health*, *17*, 1–11.

R Core Team. (2019). *R: A language and environment for statistical computing* (3.3.0) [Computer software]. R Foundation for Statistical Computing. http://www.R-project.org/

Ramos, H., Kaida, L., Singh, D., Pritchard, P., & Wijesingha, R. (2021). The power of a simple index of neighbourhood change: Challenging the perception that there is no such thing as simplicity in creating indexes. *The Canadian Geographer / Le Géographe Canadien*, *n/a*(n/a). https://doi.org/10.1111/cag.12711

RAND. (2016). *Evaluating the World's First Social Impact Bond*. https://www.rand.org/randeurope/research/projects/social-impact-bonds.html

Reichert, A., Holz-Rau, C., & Scheiner, J. (2016). GHG emissions in daily travel and long-distance travel in Germany – Social and spatial correlates. *Transportation*

DRAFT

Research Part D: Transport and Environment, *49*, 25–43. https://doi.org/10.1016/j.trd.2016.08.029

Renalds, A., Smith, T. H., & Hale, P. J. (2010). A systematic review of built environment and health. *Family and Community Health*, 68–78.

Requia, W. J., Higgins, C. D., Adams, M. D., Mohamed, M., & Koutrakis, P. (2018). The health impacts of weekday traffic: A health risk assessment of PM2.5 emissions during congested periods. *Environment International*, *111*, 164–176. https://doi.org/10.1016/j.envint.2017.11.025

Rickwood, P., Glazebrook, G., & Searle, G. (2008). Urban Structure and Energy—A Review. *Urban Policy and Research*, *26*(1), 57–81. https://doi.org/10.1080/08111140701629886

Rodriguez, D., Suardi, Mario, Ham, Marcel, Mimmi, Luisa, & Goksu, Amanda. (2014). *Applying Results-Based Financing in Water Investments*. The Global Partnership on Output-Based Aid. https://openknowledge.worldbank.org/handle/10986/16997

Roe, J. J., Thompson, C. W., Aspinall, P. A., Brewer, M. J., Duff, E. I., Miller, D., Mitchell, R., & Clow, A. (2013). Green space and stress: Evidence from cortisol measures in deprived urban communities. *International Journal of Environmental Research and Public Health*, *10*(9), 4086–4103.

Rose, D. (1984). Rethinking Gentrification: Beyond the Uneven Development of Marxist Urban Theory. *Environment and Planning D: Society and Space*, *2*(1), 47–74. https://doi.org/10.1068/d020047

Rothschild, S. (2019). *An Exploratory Statistical Analysis of Gentrification and Neighborhood Change in Seattle*. 42.

Saarloos, D., Alfonso, H., Giles-Corti, B., Middleton, N., & Almeida, O. P. (2011). The built environment and depression in later life: The health in men study. *The American Journal of Geriatric Psychiatry*, *19*(5), 461–470.

Saelens, B. E., & Handy, S. L. (2008). Built environment correlates of walking: A review. *Medicine and Science in Sports and Exercise*, *40*(7 Suppl), S550-66. https://doi.org/10.1249/MSS.0b013e31817c67a4

Saleh, M., & Hatzopoulou, M. (2020). Greenhouse gas emissions attributed to empty kilometers in automated vehicles. *Transportation Research Part D: Transport and Environment*, *88*, 102567. https://doi.org/10.1016/j.trd.2020.102567

Sallis, J., Cerin, E., Conway, T., Adams, M., Frank, L., Pratt, M., Salvo, D., Schipperijn, J., Smith, G., Cain, K., Davey, R., Kerr, J., Lai, P., Mitas, J., Reis, R., Sarmiento, O., Schofield, G., Troelsen, J., Van Dyck, D., … Owen, N. (2016). Physical activity in relation to urban environments in 14 cities worldwide: A cross-sectional study.

DRAFT

The Lancet, *387*(10034), 2207–2217. https://doi.org/10.1016/S0140-6736(15)01284-2

Sallis, J. F., Floyd, M. F., Rodríguez, D. A., & Saelens, B. E. (2012). Role of built environments in physical activity, obesity, and cardiovascular disease. *Circulation*, *125*(5), 729–737.

Sallis, J. F., Saelens, B. E., Frank, L. D., Conway, T. L., Slymen, D. J., Cain, K. L., Chapman, J. E., & Kerr, J. (2009). Neighborhood built environment and income: Examining multiple health outcomes. *Social Science and Medicine*, *68*(7), 1285–1293. https://doi.org/10.1016/j.socscimed.2009.01.017

Salmi, J., & Hauptman, A. M. (2006). *Innovations in Tertiary Education Financing:* (p. 98).

San Francisco County Transportation Authority. (2017). *TNCs Today: A Profile of San Francisco Transportation Network Company Activity* [Final Report]. https://www.sfcta.org/sites/default/files/2019-02/TNCs_Today_112917_0.pdf

Sayers, J. (2001). The world health report 2001—Mental health: New understanding, new hope. *Bulletin of the World Health Organization*, *79*(11), 1085.

Schmidt, J. H., & Watson, J. (2014). *Eco Island Ferry: Comparative LCA of island ferry with carbon fibre composite based and steel based structures*. 2.-0 LCA consultants.

Scottish Funding Council. (2020). *Outcome Agreements*. http://www.sfc.ac.uk/funding/outcome-agreements/outcome-agreements.aspx

Shekar, M., & Popkin, B. M. (2020). *Obesity Health and Economic Consequences of an Impending Global Challenge*.

Shekarrizfard, M., Minet, L., Miller, E., Yusuf, B., Weichenthal, S., & Hatzopoulou, M. (2020). Influence of travel behaviour and daily mobility on exposure to traffic-related air pollution. *Environmental Research*, *184*, 109326. https://doi.org/10.1016/j.envres.2020.109326

Shen, Y. (2014). Community building and mental health in mid-life and older life: Evidence from China. *Social Science & Medicine*, *107*, 209–216.

Sider, T., Alam, A., Zukari, M., Dugum, H., Goldstein, N., Eluru, N., & Hatzopoulou, M. (2013). Land-use and socio-economics as determinants of traffic emissions and individual exposure to air pollution. *Journal of Transport Geography*, *33*, 230–239. https://doi.org/10.1016/j.jtrangeo.2013.08.006

Siqueira Junior, J. de A., Lopes, A. A. dos S., Godtsfriedt, C. E. S., Justina, M. D. Della, Paiva, K. M. de, d'Orsi, E., & Rech, C. R. (2022). Neighbourhood walkability and mental health in older adults: A cross-sectional analysis from EpiFloripa Aging Study. *Frontiers in Aging*, *3*, 915292.

DRAFT

Slater, T. (2011). Gentrification of the city. *The New Blackwell Companion to the City*, *1*.
Smetanin, P., Stiff, D., Briante, C., Adair, C. E., Ahmad, S., & Khan, M. (2011). *The life and economic impact of major mental illnesses in Canada: 2011 to 2014. Toronto, ON: RiskAnalytica on behalf of Mental Health Commission of Canada*.
Social Finance. (2016). Connecticut Family Stability. *Social Finance*. https://socialfinance.org/project/connecticut-family-stability/
Spreafico, C., & Russo, D. (2020). Exploiting the Scientific Literature for Performing Life Cycle Assessment about Transportation. *Sustainability*, *12*(18), Article 18. https://doi.org/10.3390/su12187548
(S&T) Squared Consultants Inc. (2022). *GHGenius*. https://www.ghgenius.ca/index.php
Statistics Canada. (n.d.). https://www150.statcan.gc.ca/n1/en/catalogue/92-166-X
Statistics Canada. (2010). *Canadian Vehicle Survey* (Catalogue no. 53-223-X). http://www.statcan.gc.ca/pub/53-223-x/2009000/userinfo-usagerinfo-eng.htm
Statistics Canada. Canadian Community Health Survey, 2019: Mental HealthStatistics. Canada Catalogue no. 11–001-X. (2020). In *The Daily*.
StatsCan. (n.d.). *Canada's national statistical agency—Statistics Canada*. https://www.statcan.gc.ca/eng/start
Steemers, K. (2003). Energy and the city: Density, buildings and transport. *Energy and Buildings*.
Sugiyama, T., Leslie, E., Giles-Corti, B., & Owen, N. (2008). Associations of neighbourhood greenness with physical and mental health: Do walking, social coherence and local social interaction explain the relationships? *Journal of Epidemiology & Community Health*, *62*(5), e9–e9.
Sun, S., & Ertz, M. (2021). Environmental impact of mutualized mobility: Evidence from a life cycle perspective. *The Science of the Total Environment*, *772*, 145014. https://doi.org/10.1016/j.scitotenv.2021.145014
Sundquist, K., Eriksson, U., Mezuk, B., & Ohlsson, H. (2015). Neighborhood walkability, deprivation and incidence of type 2 diabetes: A population-based study on 512,061 Swedish adults. *Health Place*, *0*, 24–30. https://doi.org/10.1016/j.healthplace.2014.10.011
Tarlov, E., Silva, A., Wing, C., Slater, S., Matthews, S. A., Jones, K. K., & Zenk, S. N. (2020a). Neighborhood Walkability and BMI Change: A National Study of Veterans in Large Urban Areas. *Obesity*, *28*(1), 46–54. https://doi.org/10.1002/oby.22611
Tarlov, E., Silva, A., Wing, C., Slater, S., Matthews, S. A., Jones, K. K., & Zenk, S. N. (2020b). Neighborhood Walkability and Body Mass Index Change: A National

DRAFT

Study of Veterans in Large Urban Areas. *Obesity (Silver Spring, Md.)*, *28*(1), 46. https://doi.org/10.1002/OBY.22611

Temkin, K., & Rohe, W. (1996). Neighborhood Change and Urban Policy. *Journal of Planning Education and Research*, *15*(3), 159–170. https://doi.org/10.1177/0739456X9601500301

Thielman, J., Rosella, L., Copes, R., Lebenbaum, M., & Manson, H. (2015). Neighborhood walkability: Differential associations with self-reported transport walking and leisure-time physical activity in Canadian towns and cities of all sizes. *Preventive Medicine*, *77*, 174–180. https://doi.org/10.1016/j.ypmed.2015.05.011

Thomassen, M. A., Dalgaard, R., Heijungs, R., & de Boer, I. (2008). Attributional and consequential LCA of milk production. *The International Journal of Life Cycle Assessment*, *13*(4), 339–349. https://doi.org/10.1007/s11367-008-0007-y

Timmermans, E. J., Visser, M., Wagtendonk, A. J., Noordzij, J. M., & Lakerveld, J. (2021). Associations of changes in neighbourhood walkability with changes in walking activity in older adults: A fixed effects analysis. *BMC Public Health*, *21*(1), 1323. https://doi.org/10.1186/s12889-021-11368-6

Toftager, M., Ekholm, O., Schipperijn, J., Stigsdotter, U., Bentsen, P., Grønbæk, M., Randrup, T. B., & Kamper-Jørgensen, F. (2011). Distance to green space and physical activity: A Danish national representative survey. *Journal of Physical Activity and Health*, *8*(6), 741–749.

TransLink. (2013a). *2011 Metro Vancouver Regional Screenline Survey* (p. 64) [Final Report]. TransLink. https://www.translink.ca/-/media/translink/documents/about-translink/customer-service/trip-diary/2011-screenline-survey-report.pdf

TransLink. (2013b). *2011 Metro Vancouver Regional Trip Diary—Analysis Report*. http://www.translink.ca/-/media/Documents/customer_info/translink_listens/customer_surveys/trip_diaries/2011%20Metro%20Vancouver%20Regional%20Trip%20Diary%20%20Analysis%20Report.pdf

TransLink. (2018). *Greater Vancouver Regional Travel Model Phase 3* [Development and Validation Report].

TransLink. (2019). *Transit Service Performance Review* [Final Report]. https://www.translink.ca/plans-and-projects/strategies-plans-and-guidelines/managing-the-transit-network#transit-network-review

TransLink. (2020a). *2021 Business Plan Operating and Capital Budget Summary*. https://www.translink.ca/resources/translink/about%20translink/corporate%20rep

DRAFT

orts/business_plan/2021%20business%20plan%20operating%20and%20capital%20budget%20summary
TransLink. (2020b). *Low Carbon Fleet Transition Plan* [Final Report]. https://www.translink.ca/-/media/translink/documents/about-translink/policies/translink_low_carbon_fleet_transition_plan_2020_02_24.pdf
TransLink. (2022a). *TransLink GTFS - Open Mobility Data* [dataset]. https://transitfeeds.com/p/translink-vancouver/29?p=29
TransLink. (2022b). *Transport 2050* [Regional Transportation Strategy].
Transport Canada. (2020). *Transportation in Canada 2020*. https://tc.canada.ca/sites/default/files/2021-07/transportation_canada_2020_overview_report.pdf
Transport Canada. (2021). *Canadian Vehicle Specifications (CVS)*. https://open.canada.ca/data/en/dataset/913f8940-036a-45f2-a5f2-19bde76c1252
Twardzik, E., Judd, S., Bennett, A., Hooker, S., Howard, V., Hutto, B., Clarke, P., & Colabianchi, N. (2019). Walk Score and objectively measured physical activity within a national cohort. *J Epidemiol Community Health*, *73*(6), 549–556.
United Nations (UN). World Urbanization Prospects 2018. (2018). United Nations. https://www.un.org/development/desa/pd/news/world-urbanization-prospects-2018
U.S. Department of Energy & U.S. Environmental Protection Agency. (2022). *FuelEconomy.Gov*. https://www.fueleconomy.gov/feg/download.shtml
U.S. Environmental Protection Agency. (2016). *MOVES: MOtor Vehicle Emission Simulator* (Version MOVES2014) [Computer software]. https://www.epa.gov/moves/moves-onroad-technical-reports#moves2014
U.S. Environmental Protection Agency. (2019, February 22). *Can I model emissions from Electric, Fuel-Cell, and Hybrid Vehicles and Equipment in MOVES?* [Overviews and Factsheets]. https://www.epa.gov/moves/can-i-model-emissions-electric-fuel-cell-and-hybrid-vehicles-and-equipment-moves
U.S. Environmental Protection Agency. (2022a). *2022 EPA Automotive Trends Report* [Data and Tools]. www.epa.gov/automotive-trends/explore-automotive-trends-data
U.S. Environmental Protection Agency. (2022b). *MOVES Onroad Technical Reports* [Reports and Assessments]. https://www.epa.gov/moves/moves-onroad-technical-reports

DRAFT

Van den Berg, A. E., Maas, J., Verheij, R. A., & Groenewegen, P. P. (2010). Green space as a buffer between stressful life events and health. *Social Science & Medicine*, *70*(8), 1203–1210.

Vancouver Bus Charters. (2021). *Vancouver Bus Charters*. https://vancouverbuscharters.com/#

Vancouver School Bus Charters Inc. (2022). *Vancouver School Bus Charters—Fleet*. https://www.vancouverschoolbus.com/fleet/

Venigalla, M., Dixit, S., & Pulugurtha, S. (2018). A methodology to derive land use specific auto-trip emission footprints from household travel survey data. *Urban, Planning and Transport Research*, *6*(1), 111–128. https://doi.org/10.1080/21650020.2018.1555055

Vivid Economics. (2013). *Results-Based Financing in the Energy Sector: An Analytical Guide* [Text/HTML]. World Bank. https://documents.worldbank.org/en/publication/documents-reports/documentdetail/847181468344642825/Results-based-financing-in-the-energy-sector-an-analytical-guide

Walks, R. A., & Maaranen, R. (2008). Gentrification, Social Mix, and Social Polarization: Testing the Linkages in Large Canadian Cities. *Urban Geography*, *29*(4), 293–326. https://doi.org/10.2747/0272-3638.29.4.293

Wang, A., Stogios, C., Gai, Y., Vaughan, J., Ozonder, G., Lee, S., Posen, I. D., Miller, E. J., & Hatzopoulou, M. (2018). Automated, electric, or both? Investigating the effects of transportation and technology scenarios on metropolitan greenhouse gas emissions. *Sustainable Cities and Society*, *40*, 524–533. https://doi.org/10.1016/j.scs.2018.05.004

Wang, A., Weichenthal, S., Lloyd, M., Hong, K., Saxe, S., & Hatzopoulou, M. (2023). Personal Mobility Choices and Disparities in Carbon Emissions. *Environmental Science & Technology*, *57*(23), 8548–8558. https://doi.org/10.1021/acs.est.2c06993

Wang, R., Liu, Y., Xue, D., & Helbich, M. (2019). Depressive symptoms among Chinese residents: How are the natural, built, and social environments correlated? *BMC Public Health*, *19*(1), 1–8.

Wang, S., Yu, J., & Okubo, K. (2021). Life cycle assessment on the reuse and recycling of the nickel-metal hydride battery: Fleet-based study on hybrid vehicle batteries from Japan. *Journal of Industrial Ecology*, *25*(5), 1236–1249. https://doi.org/10.1111/jiec.13126

DRAFT

Warnecke, C., Röser, F., Hänsel, G., & Höhne, N. (2015). *Connecting the dots: Results-based financing in climate policy*. New Climate Institute.
Weather Underground. (2022). *Vancouver, Canada Weather Conditions*. https://www.wunderground.com/weather/ca/vancouver
Weier, J., & Herring, D. (n.d.). *Measuring vegetation (NDVI & EVI)[Internet]. 2000 [cited 2013 Dec 30]*.
Where Matters: Health & Economic Benefits Study. (n.d.).
(WHO), W. H. O. (2022). *Mental health*. https://www.who.int/news-room/fact-sheets/detail/mental-health-strengthening-our-response
WHO (World Health Organization). (2017). Other common mental disorders: Global health estimates. *Geneva: World Health Organization*, *24*.
WHO (World Health Organization). (2018). *mhGAP operations manual- Mental Health Gap Action Programme*.
Wilson, J., Spinney, J., Millward, H., Scott, D., Hayden, A., & Tyedmers, P. (2013). Blame the exurbs, not the suburbs: Exploring the distribution of greenhouse gas emissions within a city region. *Energy Policy*, *62*, 1329–1335. https://doi.org/10.1016/j.enpol.2013.07.012
World Health Organization (WHO). (n.d.). *Obesity*.
World Health Organization (WHO). (2016). *GLOBAL REPORT ON DIABETES*.
World Health Organization (WHO). (2018). *Global Action Plan on Physical Activity 2018-2030*.
World Health Organization (WHO). (2022). *Global status report on physical activity 2022*.
World Health Organization (WHO). Mental health action plan 2013–2020. (2013).
World Resources Institute (WRI). (2014). *Policy and Action Standard | Greenhouse Gas Protocol*. https://ghgprotocol.org/policy-and-action-standard
World Resources Institute (WRI). (2015). *Scope 2 Guidance | Greenhouse Gas Protocol*. https://ghgprotocol.org/scope_2_guidance
Wu, X., Tao, T., Cao, J., Fan, Y., & Ramaswami, A. (2019). Examining threshold effects of built environment elements on travel-related carbon-dioxide emissions. *Transportation Research Part D: Transport and Environment*, *75*, 1–12. https://doi.org/10.1016/j.trd.2019.08.018
Wyly, E. K., & Hammel, D. J. (1998). Modeling the Context and Contingency of Gentrification. *Journal of Urban Affairs*, *20*(3), 303–326. https://doi.org/10.1111/j.1467-9906.1998.tb00424.x
Xiao, Z., Lenzer Jr., J. H., & Chai, Y. (2017). Examining the Uneven Distribution of Household Travel Carbon Emissions Within and Across Neighborhoods: The Case

DRAFT

of Beijing. *Journal of Regional Science*, *57*(3), 487–506. https://doi.org/10.1111/jors.12278

Xu, J., Saleh, M., Wang, A., Tu, R., & Hatzopoulou, M. (2019). Embedding local driving behaviour in regional emission models to increase the robustness of on-road emission inventories. *Transportation Research Part D: Transport and Environment*, *73*, 1–14. https://doi.org/10.1016/j.trd.2019.05.011

Xu, L., Cui, S., Tang, J., Yan, X., Huang, W., & Lv, H. (2018). Investigating the comparative roles of multi-source factors influencing urban residents' transportation greenhouse gas emissions. *Science of The Total Environment*, *644*, 1336–1345. https://doi.org/10.1016/j.scitotenv.2018.07.072

Yang, L., Wang, Y., Han, S., & Liu, Y. (2019). Urban transport carbon dioxide (CO2) emissions by commuters in rapidly developing Cities: The comparative study of Beijing and Xi'an in China. *Transportation Research Part D: Transport and Environment*, *68*, 65–83. https://doi.org/10.1016/j.trd.2017.04.026

Zeileis, A., & Hothorn, T. (2002). Diagnostic Checking in Regression Relationships (lmtest). *R News*, *3*(2), 7–10.

Zhang, Y., Liu, N., Li, Y., Long, Y., Baumgartner, J., Adamkiewicz, G., Bhalla, K., Rodriguez, J., & Gemmell, E. (2023). Neighborhood infrastructure-related risk factors and non-communicable diseases: A systematic meta-review. *Environmental Health: A Global Access Science Source*, *22*(1), 1–15. https://doi.org/10.1186/s12940-022-00955-8

Zhao, E., Walker, P. D., & Surawski, N. C. (2022). Emissions life cycle assessment of diesel, hybrid and electric buses. *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, *236*(6). https://trid.trb.org/view/1937361

Zlatinov, A., & Gillette, R. (2018). *Implementation of California's AB1837 Pay for Success Initiative and Opportunities for Expanded Impact* (p. 4). Harvard Kennedy School.

Zwiers, M., Kleinhans, R., & Van Ham, M. (2017). The Path-Dependency of Low-Income Neighbourhood Trajectories: An Approach for Analysing Neighbourhood Change. *Applied Spatial Analysis and Policy*, *10*(3), 363–380. https://doi.org/10.1007/s12061-016-9189-z

DRAFT