Co-variates of Multimodal Accessibility in Canadian Cities

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Abstract

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Accessibility has become one of the predominant ways of understanding the relationship between transportation and land use in urban areas. Traditional measures of accessibility understand it unimodally or comparatively, without consideration of the dynamics of a multimodal transportation system. Multimodal, or mode share weighted accessibility (MWA) measures, take into account observed mode shares of the underlying geographic units and apply them to the accessibility to employment provided by that mode share. The individual MWA values are then added to give a singular MWA value. In this research MWA models are created for over 20 Canadian census metropolitan areas. They're presented at regional and census tract levels, where the latter are then used in regression models to understand correlations that exist between MWA and socioeconomic and demographic factors. Inferential statistics are used to estimate differences in means of the socioeconomic and demographic variables of the top and bottom quintiles of MWA in every region. Many of the socioeconomic factors were found to be significantly corelated with MWA, with higher MWA values being associated with higher median household incomes, lower proportions of renters, and typically lower population density and lower proportions of visible minorities and immigrants. This is the first study to use multimodal accessibility models to understand the relationships between accessibility and socioeconomic factors across large- and medium-sized metropolitan regions in Canada.

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1. Introduction

A confluence of factors that include population growth, continued urbanization, shifting planning paradigms, and climate change have given rise to accessibility as the predominant focus of modern transportation planning. Accessibility has risen in importance in the field of urban planning over the 60 years since it was introduced and is poised to continue to shape city-building decisions through transportation plans, official community plans, and growth strategies. Accessibility is best understood as the ability to reach spatially dispersed opportunities through time (Hansen, 1959), (Ewing, 1995), (Cervero, 1995), (Geurs and Van wee, 2004). Unlike mobility, which measures the ease of movement from a “Point A” to a “Point B”, accessibility cares about how many “Points" or opportunities you can reach from an initial location. In this way accessibility incorporates land with transportation, offering deeper understandings into the workings of cities and the dynamics of the land-use and transportation system than mobility measures can. Recently accessibility has come into the centre of mainstream city-building, in both academic (Bocca, 2021), (Birkenfeld, et al., 2023), (Khavarian-Garmsir et. al, 2023) and public circles (Gomez, 2022) (Kemp, 2023), with the concept of the “15-minute city”, an idea that your day-to-day trips should be achievable in 15 minutes by walking, by transit, or by bike (Moreno et al., 2021), taking centre stage in the discourse in the past few years. While hardly a novel idea, the popularization of the concept in the mainstream in recent years has spread accessibility beyond the realm of transportation planners, and rightfully into broader civic discourse.

In Canada 73.7% of the population now lives in large urban centres, and 9 in 10 immigrants to Canada settle in one of these census metropolitan areas (Statistics Canada, 2022), reflecting the growth in both population and physical size of the urbanized areas of these regions. Canadians are also commuting longer times than they historically have (at least pre-pandemic), reflecting the growing distances between people and their work (Statistics Canada, 2019). Increasing numbers of flexible working arrangements in some professions, rising and uncertain energy prices, and growing inequality are among the most recent possible disruptors to how we move around, making conversations on accessibility as relevant as ever.

At the same time as the principal focus of transportation planning has shifted from mobility to accessibility (Cervero, 2005), equity has become a mainstream filter for conversations surrounding the distribution of resources, including in transportation planning (Manaugh et al., 2015). Transportation, and more specifically, accessibility in this lens can be seen as a resource. Certain groups having greater or less accessibility to employment, greenspaces, healthy foods, or amenities. Viewing accessibility through the idea of equity is essential to understanding not only the spatial disparities of access, but socioeconomic ones as well.

Accessibility is an oft-used measure of equity. Accessibility to employment and access to public transit are important determinants in one’s probability of being employed (Duarte et al., 2023) (Jin & Paulson, 2018), whereas accessibility to health care services and greenspace are important factors in health outcomes (Neutens, 2015). Accessibility shapes and in some ways defines our world. By determining where we can go and what opportunities we can interact with, the day-to-day bounds of our social and economic interactions are limited by the bounds of our accessibility.

In order to properly understand the genesis of the modelling and methods contained in this thesis, the most significant shortcoming in accessibility must be understood: The overwhelming majority of the research in accessibility has used unimodal accessibility measures. This means that accessibility is measured by a singular mode of travel, and the accessibility values (e.g. number of jobs accessible by *car* in 60 minutes) are accordingly unimodal. This made sense given the origins of accessibility as a tool to help understand residential location and commuting patterns in a time of rapid American suburbanization and the development of the interstate. In more modern times though unimodal accessibility measures are not always the right tool for understanding cities, as transit, cycling, and walking have increased in popularity in many Canadian urban areas, necessitating an approach that analyzes multiple modes of travel. This is particularly relevant when discussing accessibility across different socio-demographic groups, as automobile ownership has several barriers to it, such as the cost of owning or leasing a vehicle, the maintenance costs, and the availability of parking. Many people are beholden to public transit or active modes of transportation, while many also choose these modes of travel for environmental, health, or lifestyle reasons. The rise in popularity of these other modes of transportation has necessitated that these other modes of transport be considered in accessibility analyses.

This increase in popularity of alternative modes of transport has in turn led to more research in accessibility by transit, by bicycle, and by foot. While this addressed the issue of automobile-dominance in the early accessibility research, this research was still conducted either unimodally, examining accessibility by a single mode, or comparatively, by contrasting the accessibility by two different modes. While these kinds of analyses are well-suited for certain scenarios, they are incomplete in the context of interventions that involve the expansion of infrastructure of one mode at the expense of another – that is they do not convey information on changes in *overall* accessibility of a city or a region. Accessibility measures that incorporate multiple modes of travel into a single measure have been proposed and tested with good success. The Multimodal Accessibility Indicator, or MAI, is a measure that I helped create and refine, along with colleagues in Dr. Zachary Patterson's lab. This measure applies mode-share weights for each mode of transportation used to the respective number of jobs accessible by each respective mode. These products are then added together to give a global "multimodal" accessibility value. The name of this measure has led to some understandable confusion, as the term "multimodal trips" in transportation planning typically refers to using multiple modes of travel in the same trip. To alleviate any confusion regarding the name of the methods being used I will refer to it as "mode-share weighted accessibility" or MWA for short.

The concept of a mode-share weighted accessibility measure is important as it portrays a more global picture of in cities and regions. One of the issues with unimodal place-based accessibility measures is that the measure, unless applied for an area in which only one mode of travel is used, is incomplete. It is situationally useful to comprehend accessibility values by a single mode of travel, but without an understanding of what proportion of people use that mode, the cumulative and average accessibility, and proportion of people using other modes of travel, the picture is incomplete. For example, knowing the accessibility to employment by automobile values for a lower-income neighbourhood is not particularly useful if not many people in the neighbourhood have access to a car, while it may be very important to understand in a car-dependant, wealthier suburb. By the same token, understanding accessibility to employment by walking in a suburb might not be useful, while in the central business district of a large city it could be integral to understanding the accessibility of its residents. Understanding how accessibility is realized for populations across different neighbourhood typologies can help decision makers better understand how transportation access as a resource is distributed across sub-populations.

The special position accessibility holds at the union of the transportation and land use systems allows for it to be used as a lens to study both systems simultaneously. The importance of accessibility to employment and its previous uses in understanding the spatial distribution of access to opportunities led to the idea that mode-share weighted accessibility could be used to understand accessibility to employment in Canadian regions across multiple modes of travel. By examining accessibility through this cross-modal lens, we will see which social and economic groups have the greatest levels of accessibility, which groups lack accessibility, and how accessibility is distributed spatially in Canadian metropolitan regions. All of these will help answer the overarching questions of this research: Which socioeconomic factors are correlated with greater and lower levels of mode-share weighted accessibility? Which socioeconomic groups have the greatest and lowest levels of accessibility? How are these groups and factors spatially distributed in large Canadian metropolitan areas?

By using the MWA as a framework for understanding transportation, a more complete picture of accessibility can be uncovered. This picture respects the multi-modal nature of the transportation systems in contemporary cities, evaluates the overall accessibility of neighbourhoods, and provides a novel view of the distribution of accessibility to employment. This thesis will examine the MWA of different Canadian regions, examining at a Census Tract (CT) level the number of mode-share weighted jobs that are accessible to the average individual living there. Once this has been completed demographic and socioeconomic factors of the census tracts will be considered against the accessibility values to examine for trends in how accessibility is distributed both spatially and demographically. While this is certainly not the first instance where accessibility has been used as a lens to understand these issues, the four modes of travel of automobiles, transit, cyclists, and pedestrians are rarely considered together, and to my knowledge and research have not been used together with mode-share weights. In this view both the understanding of mode-share weighted accessibility, and of varying levels of accessibility across different socioeconomic groups and neighbourhood across Canada are novel. To best understand the mode-share weighted methods and the impetus to create and use them in this setting to understand inequities in transportation and land use we will first start with a review of the relevant literature.

2. Literature Review

Accessibility, as we commonly define it now in transportation planning and geography, is the potential for interactions with spatially dispersed opportunities that can be reached within a given time (Hansen, 1959), (Wachs & Kumagi, 1973), (Geurs & van Wee, 2004). Practically put, accessibility is the potential to reach destinations, whatever they may be. Accessibility is an integral aspect of the transportation and land use systems in cities and regions, as it bridges the two realms in ways that are quantifiable. This led to the creation of a variety of different methods that each calculate accessibility in their own ways.

This research focuses on a relatively unexplored realm of accessibility, where mode-share weights are applied to accessibility values across four distinct modes of travel then subsequently summed to give an overall multimodal or mode-share weighted number of job accessible. To understand why this embodies a departure from the earlier approaches to understanding transportation and land use systems, it is helpful to rewind, to the birth of the concept.

2.1. *A Brief History of Accessibility*

The idea of accessibility originated in academic planning literature in 1959 with the frequently cited *How Accessibility Shapes Land Use* (Hansen, 1959). Hansen was seeking a way to operationalize the concept of accessibility to develop a growth model for land development. By taking the idea of "population-potential", an equation used to calculate future demographic changes and population growth and applying the concept to land use, travel times and distances the first prototypical gravity-based accessibility model was created, although the first operationalized accessibility model would not appear for over a decade. Gravity-based models are a type of location-based accessibility model that produces accessibility values for distinct spatial areas, where opportunities are graded along a decay function which lowers the value of opportunities that are farther from the origin. Gravity models made up many early accessibility models.

Accessibility models were gradually improved upon over the following years, notably Kain's accessibility model which incorporated accessibility to employment, land-rent theory, and a marginal transportation cost curve to explain residential location (1962). Like many other accessibility models in the 1960's and 1970's it contained incremental improvements, but was unfortunately non-operational and theoretical in nature, limiting its usefulness to professional practice. Kain's model was the target of a critical refutation by Stegman (1969), who argued that perceptions of the quality of a neighbourhood played larger roles in determining residential location than accessibility to employment. With the growth of the suburbs and the interstate system in 1960's America, even though distances to employment downtown were growing for those moving to the suburbs, the development of amenities and commercial space in the suburbs combined with the domination of the automobile meant that accessibility decreases were minimal in many domains of life. By many of Stegman's activity categories accessibility improved in the suburbs, especially the suburbs of large metropolitan areas.

The first operationalized accessibility model was built by Ingram, who constructed a gravity model of accessibility with a realistic decay function so that the model may be used in professional practice. This marked an important step in bringing the concept of accessibility to practice, blending the academic and practical planning worlds.

Another early accessibility model of interest, and one of the earliest operational models, came when Turner (1972) created his accessibility model and framework to be explicitly used in planning analysis and evaluation. This model not only included accessibility to employment, but included accessibility to other urban resource types too, while assigning different population groups and segments different relative accessibility values in an attempt to make the model as comprehensive and true to the observed mobility and accessibility conditions. This was the first operationalized accessibility model to apply the concept of accessibility outside of employment and residential location choices, by introducing accessibility to other urban resources that Turner recognized as affecting lifestyle and preferences.

Some evidence that accessibility was gaining importance in academic circles by the early 1970's comes from Wachs and Kumagai (1973) who stated that accessibility was the most defining and important concept in explaining regional form and function. This paper was important in many facets and is one of the key early accessibility papers. Their paper was the first to discuss inequities in accessibility at length, where they state that although equity had been talked about in both theory and practice, there was little data available to substantiate claims either way. Spatial mismatch, a recurring concept in planning and accessibility literature, is explicitly mentioned as a possible limit in the usefulness of accessibility, and the paper also deals with not only accessibility to employment, but also to health care services, becoming one of the earliest papers to measure access to a non-employment opportunity.

Another seminal early accessibility paper reviewed the research that had been done in accessibility, identifying that nearly every early accessibility model used a gravity-based or cumulative-opportunity based measurement (Burns & Golob, 1976). Concerned by the lack of economic and utility theory involved in these models, the authors attempt to go beyond the traditional location-based accessibility measures and incorporate utility's role in determining travel behaviour into an accessibility model. Ultimately, this was accomplished using a logit multinomial function to calculate utility functions, which served as the basis for the accessibility measure. This paper set precedent for a new type of accessibility model, which is now referred to as a utility-based model.

The 1960's and 70's saw many important theoretical and practical contributions to accessibility, the topic stayed relatively relegated to niches of regional economic and land use modelling during this time, despite recognition of its potential. Hampered by the lack of computational power of their time, the exercises remained highly theoretical. Coupled with the autocentric paradigm at that time, the research focused nearly exclusively on access by automobile. It would not become a central focus of either academic or professional transportation planning until a combination of paradigm shifts and advances in GIS and computing improved spatial modelling in the early 1990's.

Precipitating this paradigm shift was the development and acceptance of a group of related ideas that are now referred to as "New Urbanism". Building off numerous environmental and urban design movements of the past, New Urbanism came to the forefront of planning, city building, and community design in the late 1980's and has only grown in importance and acceptance since then, to the point where the ideas dominate mainstream academic and professional circles. The general tenets of New Urbanism include focusing development on the intensification of existing urban areas, promoting a diversity of land uses, and fostering sustainable and active transportation with the goals of creating healthier, happier, and more sustainable communities (Kelbaugh, 1997), (Congress For The New Urbanism, 2001). These principles serve to curb sprawl and conserve natural environment, while promoting prosperity in communities. The paradigm of accessibility fits well within New Urbanism, as accessibility measures favour non-automobile modes of travel significantly more than mobility measures do, by incorporating land uses and rewarding their density and diversity. This helped balance the scales between the lower mobility modes of walking and transit with the higher mobility mode of driving, especially in dense, mixed-use urban areas. As the two agendas overlapped considerably and new urbanism was gaining favour with urban planners, academics in transportation planning were calling for a shift towards accessibility and away from mobility in the field (Cervero, 1995), (Ewing, 1995). This paradigm shift was followed by a greater focus on justice in transportation (Sanchez & Brenman, 2007) and has led to accessibility being used as a tool to understand differences accessibility according to socio-economic and demographic categories (e.g. Cui et al, 2019), which will be explored more thoroughly after we examine which qualities and inputs are needed to make an accessibility measure.

In the decades since, accessibility has been used to study everything from access to health care (e.g. Neutens, 2015) to access to green space (e.g. Reyes et al., 2014), to access to employment by disadvantaged groups (e.g. McLafferty & Preston, 2019, Hu, 2017). It has also been studied in different ways, with multimodal or mode share weighted methodology applied (e.g. Levinson and Wu, 2020, Patterson et al., 2024). Applying mode share weights to accessibility values of a single mode of travel and then summing the totals of each mode is a relatively recent approach to modelling transportation and land use interactions. The application of mode share weights allows for accessibility to be compared across modes of travel, permitting accessibility to be calculated cumulatively rather than comparatively, enabling interactions between accessibility of different modes of travel to be understood.

2.2. Qualifying Accessibility Measures

Advances in technologies like GIS and transportation simulation software that were happening around this time made calculating accessibility significantly less time-intensive, allowing for accessibility to be calculated in new and different ways. The four predominant types of accessibility measures that exist now are infrastructure-based measures, location-based measures, person-based measures, and utility-based measures (Geurs & van Wee, 2004). Each of these measures has shortcomings and strengths, which make them better suited for some purposes, and ill-suited for others. Infrastructure-based models generally use level-of-service or other performance-based metrics to calculate accessibility. The performance measures are either simulated using transportation simulation software or calculated using observational data from the real world. These types of accessibility measures are commonly used in transportation modelling and typically have weak or no links to land-use, making them primarily function as mobility models (Geurs & van Wee, 2004).

Location-based measures are the most common in the planning literature and in practice, and for good reason. They involve both transport and land use intrinsically, are often the simplest to understand, and can be easily represented visually, making location-based measures the easiest to relay to public audiences. These measures, which include the two most commonly used accessibility measures in the cumulative opportunity measure and gravity measure, produce accessibility values for distinct origin areas, detailing the number of opportunities that can be reached within a given time allotment. This can be done at as fine of a level as the job and travel time data allows for. Gravity measures are slightly more complicated than their cumulative opportunity counterparts, as they require a decay function to act as the "gravity" in the model, giving lower value to opportunities which are farther away. Also housed within this type of accessibility measure are "dual" accessibility measures, which instead of calculating how many opportunities can be reached in a given timeframe, calculates the time frame needed to reach a given number of opportunities (Cui and Levinson, 2020). This has advantages for certain opportunity types where there is a sharp decrease in the marginal utility of access to more opportunities. To use an example, you might not care about how many oncologists you can access in an hour as much as you would care about the travel time to the closest oncologist.

Person-based accessibility models disaggregate accessibility to the individual level. Through the use of "space-time prisms", a geometric representation of an individual's travel paths throughout a day, person-based accessibility models accessibility at a very detailed level, making it useful in certain applications but difficult to aggregate such data at the level needed for some analyses with current computational limitations (Miller, 1991), (Miller, 1999).

Utility-based models, the final of the four types, are based in the economic theory of utility. In these models, trips and therefore accessibility are determined based on a utility function. The most notable and one of the more frequently used utility models is the logsum model, which uses a multinomial logit function to create aggregate accessibility values for cities. These types of models are firmly rooted in utility theory but also quite calculation-intensive and are not typically intuitive or easy to relay to wider audiences.

As seen above, there are many different ways to measure accessibility that have been developed, each with strengths and drawbacks each which is better suited to different scenarios or goals. There have been many attempts historically to classify accessibility measures as well as proposed criteria for what constitutes a good accessibility measure. Morris, Dumble, and Wigan (1979) suggest four principal criteria for selecting an accessibility measure: The accessibility measure should integrate spatial separation that is sensitive to changes in the transportation system, the accessibility measure should have some basis in the travel behaviours and decisions of people, the measure needs to be both technically viable while remaining operationally simple, and the measure needs to be easy to interpret. Another comprehensive accessibility review from Geurs and van Wee (2004) identified four fundamental components of accessibility. These components are land-use, transportation, time, and the individual. The land-use component reflects the quantity and quality of opportunities, while also defining their spatial distribution. It is also where the supply and demand of these opportunities interact in space. The transportation component refers to the transportation systems that connect areas of space together, and their associated costs, speeds, and physical infrastructure. The temporal component includes the temporal impedances and restrictions on travel, opportunities, and on individuals. The individual component refers to the differing needs, abilities, and opportunities that individuals have (Geurs & van Wee, 2004). These tenets and components are foundational when creating accessibility models and are largely consistent with and included in the modelling that is used for this thesis.

Looking at the four criteria set out by Morris, Dumble, and Wigan, we can see that all four criteria are met by the mode-share weighted accessibility models used here. The spatial separation that is sensitive to changes in the transport system is present in the form of the census tracts, which as noted in previous papers using these methods (Patterson et al., 2021, Hermanson & Patterson, 2022, Patterson et al., 2024) are sensitive to changes in the transportation system. As the model uses mode-share weights it retains a strong link to the travel behaviours of people within the system, while being technically viable and operationally simple thanks to the GIS and Python coding which allow for complex calculations to be performed relatively simply. Finally, the measure needs to be easy to interpret. This qualification has proven more challenging to achieve. A few reviewers of previous papers I have co-authored using these methods have noted a lack of clarity around our use of the term “multimodal”, while others have misunderstanding conceptually what is being done. In an attempt to alleviate some of this confusion I refer to the concept as mode-share weighted accessibility, as previously mentioned in the first chapter.

Examining the four criteria set out by Geurs and van Wee (2004), we see that these models will satisfy the four fundamental components. The land-use is accounted for in the spatially dispersed employment data, the transportation and time components are satisfied by the zone-to-zone travel times and the 60-minute limit on one-way commuting times, while the individual component is present through the use of census tract-weighted mode-shares.

The MWA measure used in this thesis is a cumulative opportunity measure, as the accessibility values are calculated from origin areas to all the other accessible areas in their respective regions. The accessibility values are straightforward to convey through numbers alone but will also be mapped to convey greater detail of how mode-share weighted accessibility is distributed spatially throughout the regions. By creating a cumulative opportunity measure whose results can be conveyed with a single measure, like average number of mode-share weighted jobs, a number of demographic and socioeconomic factors can be compared against the measure's values. In the case of this thesis, it will be to understand how accessibility is distributed across different groupings of people in society. This way of calculating and understanding accessibility addresses some of the issues presently in accessibility, while opening new doors in how MWA can be used to describe the connection between accessibility and equity.

2.3. Empirical Findings and Applications of Accessibility Measures

Although accessibility was originally prescribed in an effort to understand land values and future urban growth potential, the most common application of accessibility analyses has been in the examination of accessibility to employment. As accessibility is a versatile paradigm for understanding cities, its original intended function of determining land values and growth is very much still within the realm of what accessibility can help us uncover.

Proximity to rail transit has been found to be correlated with housing market resiliency (Welch, Gehrke, & Farber, 2018), with multifamily dwellings in close proximity to rail transit stations retaining their value better than multifamily dwellings that were farther away from transit. Other studies have found the positive connection between accessibility and real estate or land values in contexts around the globe (Cordera et. al, 2019), (Mulley, 2014), (Guan & Peiser, 2018), (Munshi, 2020), and (Iacono & Levinson, 2017). The increased value of real estate around transit might also help explain one aspect of spatial mismatch, where low-income residents (who presumably are less able to afford higher rents) live farther from jobs and spend longer on their commutes (Kain, 1968), (Blumenburg, 2004), (Lyons & Ewing, 2021). This will be important to keep in mind when interpreting the results of this model. Will we see that areas with higher multimodal accessibility have lower proportions of low-income residents? Will these areas have a lower proportion of people with long commutes?

Spatial agglomeration, or clustering, is a well-studied phenomena where similarly focused businesses locate near each other due to the plethora of advantages it brings. These advantages include the pooling of labour, lower transportation costs, and knowledge spillover (Rosenthal and Strange, 2020). A 2017 paper examined this clustering through the lens of accessibility and found that within high-tech manufacturing and the knowledge economy in Toronto, proximity to the labour market, major transportation infrastructure, and the core of the City were all found to be explanatory in the agglomeration of these firms (Lopez & Paez, 2017).

Another common application of accessibility measures is to the field of accessibility to health. Measuring accessibility as it relates to health reveals some of the disparities in accessibility according to socio-economic or demographic groups to primary care as well as factors affecting the social determinants of health. Examples include investigating which groups have different levels of access to health care (Pagano et al, 2007), (Mattson, 2011), (Neutens, 2015), access to healthy and affordable foods (Paez et al, 2010), (Borja & Dieringer, 2019), and access to greenspaces (Liu et al., 2021), (Xu et al., 2018), (Reyes et al., 2014). Generally, papers examining "health equity" and accessibility have examined how either the population, or a specific group, has access to the subject opportunity of the paper. Some papers look at health through multiple economic or demographic lenses, like a study that examined access to COVID-19 health care in Brazil, which found that poorer neighbourhoods and neighbourhoods with more black people had worse access to treatments, ICU beds, and equipment than wealthier, less black areas did (Pereira et. al, 2021).

While the volume and variety of accessibility research has no doubt grown considerably in the past few decades, accessibility to employment remains the most popularly used accessibility metric, and for good reason. Employment data is easy to gather at different geographic levels, and importantly functions as a proxy for other services and amenities. While a person may only require access to a job or two, they benefit from high levels of accessibility because it means there are greater levels of services and amenities accessible, reducing the time spent traveling. This again highlights the importance of assessing accessibility across differing modes of travel, as urban centres, which experience greater levels of automobile congestion and consequently reduced levels of automobile accessibility, are often transit-rich, walkable, and bikeable environments. Accessibility is one of the factors that determines the potential for social interaction. Consequently, accessibility to employment can also be used as a proxy measure for the potential for social interaction in an area, although this proxy is less ideal as it ignores aspects of urban design and the daily habits of the individual, both of which are connected to but not determined by, accessibility.

Accessibility to employment is also used to evaluate differences in accessibility according to socio-demographic groups, as accessibility has been positively associated with both income and employment rates, as well as overall productivity (Melo et al., 2017) (Garcia-Lòpez & Muñiz, 2013) (Du & Zheng, 2020). Improving accessibility with a focus on improving access in areas of lower accessibility should consequently be of interest to planners and politicians alike. MWA presents an opportunity to use observed travel behaviours to better understand accessibility as it pertains to differences across groups because of its incorporation of non-automobile modes of travel, which disadvantaged and/or lower-income groups may rely on in greater proportions than the overall population. Numerous papers have shown the existing disparities in accessibility, and the benefits of improving accessibility to employment for different groups including low-income groups (Hu, 2017), (Antipova, 2020), those on welfare (Alam, 2009), women (Matas et al, 2010), visible minorities, and immigrants (McLafferty & Preston, 2019). A considerable body of research exists that investigates the phenomenon of spatial mismatch by group, where low-income households tend to have residential locations farther away from their place of employment (Ermagun et al., 2023). The prevalence of this phenomena makes a strong case for the examination of accessibility across modes of travel (made possible for example with the MWA), to understand where the areas of lower accessibility are, and how they relate to socioeconomic factors. Spatial mismatch can also be investigated using this tool, as areas with high proportions of people commuting more than an hour each way to work (as tabulated in the census) can be compared to income and demographic factors to determine which areas are experiencing the longest commutes.

Finally, we arrive on the frontiers of accessibility research. Recently there have been attempts to unify different components of accessibility theories and models to create a universal theory of accessibility (Levinson and Wu, 2020), incorporating person-weighting, and not only time costs but both internalized and external costs too. Additional factors like time of day and mode-share weighting were explored here as well. Other advances in the field, such as modelling the full cost of accessibility (Cui and Levinson, 2018 & 2019), the incorporation of a satisfaction measure into accessibility (Chaloux et al., 2019), and better integration of individual perceptions (Cascetta et al., 2013) and behaviour (Cascetta et al., 2016) into accessibility models.

2.4. Accessibility According to Socio-Demographic Groups

The unique position of accessibility at the juncture of transportation and land use, makes it a valuable tool to understand the people who use these systems. Beyond its humble origins as a conceptual tool used to understand how cities and regions may grow, it has become an excellent framework for understanding how different people and groups of people interact with the built environment and the opportunities within it.

Understanding how accessibility and differences in it between groups affects different groups of people and their quality of life has become one of the principal foci of transportation accessibility in recent years. With the advances in the field of GIS over the past few decades it has become possible to model and understand accessibility and the relationships between people, transportation, and the built environment in ways that were not possible before. While by no means is this an exhaustive list of all of the cases where accessibility has been used to understand equity, it is meant to illustrate a handful of examples where differing levels of accessibility has been shown to affect quality of life for different social groups differently. After some international examples, I will discuss several Canadian examples and how they relate to my research.

Calculating accessibility to employment is undoubtedly the most common and arguably most important use of accessibility indicators in recent times. Over and over again studies have shown the positive impacts of higher levels of accessibility to employment on a number of employment and quality of life fronts, especially in disadvantaged groups. Women in Barcelona and Madrid, Spain who lived in areas of higher employment accessibility by public transit were more likely to be employed than those living in lower accessibility areas (Matas et al, 2010). This effect was more pronounced for women with lower levels of education, who benefited the most from higher accessibility levels and who were also more likely to live in lower accessibility areas. While differences existed between the two cities, the increased likelihood of employment and more significant improvement for women with less education was noted in both cities. While gender proportions are not compared against accessibility values in my research, education levels, race, immigration status, household tenure, and commute length are. My research does not look at employment probabilities, but it will examine how accessibility is distributed across areas with varying levels of education within their populations. It will be interesting to note whether lower educated populations have less accessibility across the Canadian regions in this research.

Hu (2017) found that in Los Angeles, California, a similar trend for low- and medium-income earners (25k-75k per annum) and automobile accessibility. Those who lived in higher accessibility areas were more likely to be employed. This effect was found to have no significance on higher-income (150k +) earners or the lowest (< 25k) earners. It is suggested that the lowest-income earners likely have aspatial barriers and that the high-income earners can overcome accessibility barriers. Despite this, those who earned over 150k a year had significantly higher average automobile accessibility than the other groups which had similar levels of accessibility in each income range, except for the under 25k group, which had slightly lower levels of accessibility to employment. Median household income is one of the CT level variables that is used to evaluate the equity of access to employment, and it will be revealing to see the variation in accessibility across median incomes, especially with mode-share weights and other non-automobile modes of travel considered.

Spatial mismatch and accessibility to employment has also been examined through a racial lens. Early research into racial differences in accessibility to employment found that the accessibility differences between people of different races were most apparent in larger American cities and decreased as city size shrunk (Greytak, 1974). More recent work on the topic found that in one of the US's most diverse cities, New York, non-white people in New York had longer commutes to work and lower accessibility levels than white counterparts (McLafferty & Preston, 2019). This paper included a gender-based analysis as well, which concluded that black and Hispanic women had even worse spatial mismatch from their employment. It should be noted that the findings on spatial mismatch, while pervasive, are not universal. There is also a suggestion that spatial mismatch is worse in New York City because of the cost of renting apartments close to the major employment areas. This may be happening in Canadian cities as well, as rents in both Vancouver, Toronto, and other Canadian regions continue to increase possibly creating spatial mismatch as workers seek a lower cost of living.

Other research, however, has found the opposite: non-white workers in Minnesota had higher accessibility to employment by automobile and by transit (Carlson and Owen, 2021). Antipova (2020) found that lower-income workers in Memphis tended to live about 30% closer to work than other income groups but were still overrepresented in the proportion of people commuting long distances to work. Finally, accessibility to employment by public transit was found to be the single largest factor in reducing the amount of time individuals spent on welfare, in a study examining welfare recipients in Florida (Alam, 2009).

Inequality is prevalent in different groups' access to employment. Living in areas of high automobile and transit accessibility has been shown to be beneficial to one's livelihood through increased employment opportunities. We also see that higher income groups tend to have better accessibility to employment and that visible minorities and women tend to have lower accessibility levels and benefit more from greater levels of accessibility. Before making too many inferences based on the research from these American case studies, we should be cognizant of mode-share. While many of the studies examined accessibility to employment by public transportation, none of these studies included walking or cycling as mode shares in their research. Further to the point, very few studies have examined accessibility to employment by bike or by foot, possibly because these modes are less commonly used. None of these studies considered mode-share weighted accessibility, preferring to focus on one mode. This research, with its mode-share weights across four modes of travel, must be understood in its own context then. While still heavily auto centric, many of the regions that are examined in this research have considerable mode-shares by transit and many census tracts parts of these regions have higher bicycle and walking mode-shares as well. With the differences in methodologies in mind, this body of research suggests that we could see that higher-income areas have higher levels of accessibility, and that areas of lower-income and higher proportions of visible minorities might have lower accessibility.

Turning our attention to the Canadian context of accessibility according to different socio-economic groups, we find an extensive body of research into the benefits of accessibility and how accessibility is distributed, but again, a lack of studies examining cumulative, cross-modal accessibility.

Highlighting the spatial mismatch between disadvantaged groups and their employment, a study found disabled Canadians, with both mild and very severe disabilities were more likely to commute longer distances to work if they were employed (Farber & Paez, 2010). A paper looking at Hamilton, Ontario's CMA found that older people tended to travel shorter distances in their daily lives, raising questions about accessibility as people try and age in place (Mercado, Paez, & SEDAP, 2007). As the likelihood of driving decreases with age and older people make shorter trips in non-automobile modes, it is evident that many elderly people experience a world that is shrinking. This effect appears to be stronger in elderly women who may be less likely to drive than elderly men. With many suburban areas lacking a diversity of land use, comfortable walking facilities, and frequent transit, it is evident that the quality of life must be dropping for the elderly in these lower density, car-dependent areas as their accessibility worsens.

A study examining access to public transit in the Greater Toronto and Hamilton Area created models that found accessibility to public transit benefited low-income groups who owned cars the most, as they were the most sensitive to changes in transit accessibility (Barri et. al, 2021). The study also found low-income individuals were much less likely to take transit if they owned a car compared to low-income individuals who did not. This paper suggests that improvements to transit accessibility benefit lower-income groups disproportionately as the need for a vehicle is reduced where accessible public transit exists.

Increases in accessibility of labour from origins has been found to improve travel times for lower-income earners more than higher income earners, although with caveats regarding increased competition for low-income employment (Cui et al., 2019).

Accessibility to employment for single parents was examined in Toronto, where it was found that although single parents did not experience significantly longer travel times, single women benefited highly from owning an automobile, something that is consistent with other spatial mismatch research (Paez et al, 2013).

A relevant contemporary study with a comparable cross-country scope investigated differences in accessibility to employment according to socio-demographic groups in 11 of Canada’s largest regions (Cui et al, 2020). The paper compared the average accessibility to all jobs to the average accessibility of low-income residents and the average accessibility to low-income jobs for low-income residents. This finer-grain analysis found that in most of the study regions low-income workers had higher accessibility to low-income jobs than the average accessibility to employment by public transit. However, when comparing low-income worker accessibility to all jobs versus their accessibility to low-income jobs there were large discrepancies. As this was examining accessibility to employment by public transit, Census Tracts that had rapid transit had some of the highest accessibility levels, with accessibility dropping with an increase in distance from the CTs with rapid transit.

While not directly comparable because of the unimodal nature of the study, this research provided an in-depth look at how low-income workers travel to low-income jobs and how their accessibility varies compared to all workers. This provides an interesting comparative opportunity, as while my research investigates how workers reach all jobs, it does so across four modes of travel. This presents an opportunity to research low-income workers' accessibility across differing modes of travel, to see if the findings that low-income residents have higher accessibility to all employment opportunities are consistent when the cross-modal, mode-share weighted measure is used.

High levels of accessibility are associated with a number of better outcomes across many indicators, just as lower levels of accessibility are associated with worse outcomes. Understanding these inequalities in accessibility is important for understanding where investments need to be made to improve accessibility, either by improving transportation mobility or by changes in land use through development. Despite the large offering of accessibility studies, few have examined accessibility across multiple modes of travel, instead preferring to focus on accessibility by a single mode of travel, or occasionally comparing disparities in access between modes. However, some research other than the work I have participated in has examined mode-share weighted accessibility.

2.5. Mode-share Weighted Accessibility

Much of the work involving accessibility and multiple modes of travel has been in the comparison of accessibilities of different modes. Automobile accessibility has been frequently compared to transit accessibility in a number of different geographic contexts. This is typically done with the purpose of highlighting differences in travel times and the accessibilities of each respective mode, and occasionally with additional socio-demographic group analyses (e.g. Allen & Farber, 2019). These comparisons occasionally include walking and cycling modes in addition to transit and driving (e.g. Wu et al, 2021). The idea of a mode-share weighted accessibility has been independently proposed at least three times, with different purposes and goals in mind, but all with the commonality of adding a mode-share weight to an accessibility model. Patterson et al, a paper which I co-authored, focused solely on what we at the time referred to as the "multimodal accessibility benchmark" in an attempt to formulate a multimodal accessibility modelling method that would address the shortcomings that have historically existed in accessibility. The essence of the argument in favour of using mode-share weights is that they allow for the actual accessibility potential of a neighbourhood to be calculated. By accurately capturing the mode splits for each area, a clearer and more accurate description of the relationship between land use and transportation, as experienced by the areas being examined can be obtained. Our idea drew inspiration from Alain Bertaud's book *Order Without Design* (2018), where he proposed what he calls the City Mobility Index, or CMI. The CMI, despite its name, is not a mobility measure, but rather a measure of accessibility, representing the population-weighted average number of jobs accessible by a given mode of travel for a region. By applying mode-share weights to the CMI for each mode and adding the resulting values together, we calculated the population-weighted average mode-share-weighted number of jobs available in Montreal. We used the metric in scenario evaluation to determine the accessibility changes that resulted from the implementation of a new BRT route and the associated travel time changes to transit and automobiles. Accessibility has been used as the framework for understanding cities in the literature because of its ability to put the thumb on the scales in favour of non-automotive modes of travel, even though automotive accessibility remains higher in most cases. By adding mode share weights to accessibility, we are able to more accurately depict how accessibility is being realized and remove some of the turbidity that may exist when interpreting an accessibility model.

Levinson and Wu (2020) on their way to a general theory and formulation of accessibility, consider mode use and the idea of a multimodal accessibility measure. While the authors recognize why the inclusion of multiple modes of travel would be important in firming up a general theory of access, they also highlight a somewhat paradoxical aspect of using mode-share weights. In the critique they provided, they illustrate a scenario where an increase in the number of jobs accessible by transit that is accompanied by an increase in transit mode-share will lead to a decrease in the overall accessibility of the area, despite the increase in transit mobility and accessibility. This is called a paradox by the authors, as modal shifts from automobile to transit would be expected to lead to an overall decrease in accessibility, as you trade a higher-mobility mode (automobiles) for a lower-mobility mode (transit). It was seen to be paradoxical because of the assumption people switching from driving to transit would still have the ability to drive to work. This is not necessarily true, as the increase in transit accessibility might influence those switching their commute modes to relieve themselves of the financial burden of automobile ownership and could incentivize or disincentivize residential location choices based on the accessibility changes by mode. Importantly, adding mode-share weights helps to accurately describe the changing accessibility in this hypothetical scenario. As Levinson and Wu point out, travel time costs are not the only costs that go into mode choice, as slower modes of travel have lower personal and social costs as compared to the automobile. The methods I am using to model accessibility do not account for this "full-cost" accessibility. There is no inclusion of the personal cost of owning and driving an automobile, nor is there inclusion of any societal costs associated with the provision of infrastructure for any of the modes. The only cost that is considered is the travel time cost. While there is legitimacy to the criticism that it is deficient in understanding transportation costs holistically, mode-share weighted or multimodal accessibility metrics are useful in understanding the realized accessibility of areas, and specifically how changes in infrastructure, residential and employment location, and mode-share influence this realized accessibility.

Another paper that uses multiple modes of travel, with mode-share weights additively examined the changes in accessibility to emergency and community food sources during the COVD-19 pandemic. The paper, examining Hamilton, Ontario found that although access decreased city-wide due to closures of emergency and community food services, many of the greatest accessibility decreases occurred in the suburbs of the city, which lack the same level of transit accessibility as parts of the central city do (Higgins et. al, 2021). The paper applied mode-share weights for driving, walking, and transit to the parcels, allowing for a mode-share weighted accessibility analysis for each spatial zone in the city. While the destinations, travel time derivation, and temporal threshold are all different, the mode-share weighted cumulative opportunity measure is similar to both the work I have co-authored before and what I am doing in this thesis. The revelation that transit-poor areas suffered the greatest reductions in accessibility fits with the understanding that the suburbanization of poverty has led to worsening accessibility outcomes for disadvantaged groups. It also confirms that mode-share weighted accessibility metrics can be sensitive to small changes in inputs, in this case the closure of a handful of emergency and community food services.

We may be able to predict to some degree how the number of mode-share weighted jobs accessible might look in different regions given the findings of these two papers, as well as an additional study that examined commuting mode-share and access to employment. Wu et al., (2021) found that transit accessibility accounted for the majority of the variation in transit mode-share (61%) across the nearly 50 metropolitan regions examined, with income and automobile accessibility having small effects as well. Understanding the outsized role transit accessibility plays on transit mode-share choice, it would follow that the areas with the highest transit accessibility would have the highest transit mode-shares, resulting in lower levels of mode-share weighted accessibility from the reduction in the number of jobs accessible by transit compared to automobiles. I would expect to see this effect in all of the regions, but with more pronounced effects in larger regions with more developed transit systems and higher transit mode-shares.

The paper that serves as the inspiration for this thesis applied equity lenses to a mode-share weighted accessibility evaluation of the pre- and post-implementation of a new BRT line in East Montreal. The changes in mode-share weighted accessibility by census tract were examined against socioeconomic data from those census tracts. Census tracts were grouped into quintiles based on income, proportion of low-income, proportion of visible minorities, proportion of immigrants, and proportion of indigenous population. While the changes in accessibility resulting from this BRT generally benefited the most disadvantaged groups the most proportionately, they were also found to benefit the most advantaged areas. Despite similar gains in absolute accessibility, the gains were relatively more significant for the less advantaged areas, which tended to have much fewer mode-share weighted accessible jobs than the more advantaged areas did. This prompted thought into how accessibility, and in this case mode-share-weighted accessibility, is distributed geographically and demographically in Canadian regions. This kind of quantification of accessibility, cumulatively, across different modes of travel, with the purpose of examining its distribution within groups has not, to my knowledge, been completed.

My ambition for this thesis was to build off of my previous research in two principal ways. First, by expanding the accessibility analysis from one CMA to 20 CMAs, which includes CMAs of different sizes, in a number of different geographic contexts across the country. Second, by evaluating a greater variety of social and economic census variables in an attempt to determine what other variables correlate to higher or lower levels of accessibility. By adding new CMAs and new CT level variables, I will attempt to answer the questions of how accessibility is distributed geographically and socially across Canada.

3. Case Study Areas and Background

Rather than focusing on a single CMA, or the classic Big 3 Canadian CMAs (Toronto, Montreal, and Vancouver) CMAs of various sizes were chosen for the study areas of this research. Officially, Statistics Canada draws a line at a regional population of 100,000 people and considers it a Census *Metropolitan* Area, which meant 35 regions qualified for this in 2016. CMA status is important here, as CMAs are divided into census tracts, while Census Agglomerations (CA's) are not. The census tracts are an integral component of this research, as they are the fundamental geographic unit to which the job, socioeconomic data, and travel time data are linked. This disqualified any CA from inclusion in these models.
While there were 35 CMAs to choose from, not all of the areas were well suited for this kind of mode-share weighted, multimodal analysis. There were two principal factors that made many of the smallest unsuitable: a high automobile mode share, and a small geographic size. As the methodology will detail, very high automobile mode-shares in a region would not make for an interesting mode-share weighted accessibility analysis. In these cases, accessibility by automobile would be a suitable metric on its own, with other modes of travel only marginally affecting the model. The small geographic regions are also not well suited for the parameters used in these models, like the 60-minute temporal threshold, which this model uses as its temporal boundary of what is considered accessible. In a physically larger region this might be towards the upper limit of a reasonable commute, but in a smaller region the longest driving commutes within the region would be much shorter than that. This would result in every job in a region being accessible for automobiles, and in some regions a majority by bicycle or transit as well, leading to less interesting and dynamic results than in larger regions, or regions with interesting or atypical geographies.

The population cut-off I chose was 250,000 people. This reduced the number of CMAs to 17, which was further reduced by the consolidation of the CMAs of Hamilton, Kitchener-Waterloo-Cambridge, St. Catherine's-Niagara, Oshawa, Barrie, Guelph, and Brantford with Toronto. The municipalities that were consolidated into a greater commuter-shed have a significant population commuting to each other in some way. Oshawa, Barrie, Kitchener-Waterloo-Cambridge, and Hamilton all have strong ties to Toronto, while Hamilton additionally shares strong ties with Brantford and St. Catherine's-Niagara. Guelph was included as it has commuting ties with Toronto and Kitchener-Waterloo-Cambridge. The same consolidation was done for Abbotsford-Mission, which has a large population commuting to Vancouver's CMA. Greater Montreal was not included in this analysis as much of my previous research had examined mode-share weighted accessibility in Greater Montreal and accordingly interesting connections between mode-share weighted accessibility and socioeconomic factors in the Montreal context have been explored.

With these criteria in mind the CMAs that were selected for this analysis, in order from largest population to smallest were Toronto (and its interwoven commuter-shed, as discussed in the previous paragraph), Vancouver (which contains the Abbotsford), Calgary, Ottawa-Gatineau, Edmonton, Quebec, Winnipeg, London, Halifax, Windsor, Victoria, and Saskatoon. This cross-section of Canadian regions provides a number of different geographic contexts, with different urban forms, including dwelling typologies, location and concentration of employment, different levels of transit service, different levels of wealth, and different physical constraints. This allows for the MWA to be put to the test in a variety of contexts which will hopefully provide interesting insight into whether people from similar economic or social contexts in different regions have differing levels of accessibility. The combined populations of the CMAs included in this research was over 18.4 million, which represented about half of the population of Canada from the 2016 Census.

***Table 1**: Summary statistics of CMAs*

	Region / CMA	Population	Active Population	Percentage Active Population	Jobs	Area (in km2)	Active Population Density	Employment Density
Greater Toronto		8,468,647	5,768,350	68.1%	3,737,300	13,234.75	435.85	282.39
*	Toronto	5,928,040	4,083,860	68.9%	2,784,840	5,905.84	691.50	471.54
*	Hamilton	747,545	491,415	65.7%	298,670	1,371.89	358.20	217.71
*	Waterloo	523,894	355,640	67.9%	245,210	1,091.16	325.93	224.72
*	Niagara	406,074	258,545	63.7%	155,750	1,397.49	185.01	111.45
*	Oshawa	379,848	255,120	67.2%	117,350	903.69	282.31	129.86
*	Barrie	197,059	133,625	67.8%	73,345	898.02	148.80	81.67
*	Guelph	151,984	103,155	67.9%	83,740	593.51	173.80	141.09
*	Brantford	134,203	86,990	64.8%	51,740	1,073.15	81.06	48.21
Greater Vancouver		2,643,949	1,831,760	69.3%	1,173,955	3,489.81	524.89	336.40
*	Vancouver	2,463,431	1,714,000	69.6%	1,111,395	2,882.68	594.59	385.54
*	Abbotsford - Mission	180,518	117,760	65.2%	62,560	607.13	193.96	103.04
Calgary		1,392,609	978,145	70.2%	640,155	5,110.21	191.41	125.27
Edmonton		1,321,426	915,490	69.3%	592,340	9,438.86	96.99	62.76

Table 1 continued: *Summary statistics of CMAs*

Region / CMA	Population	Active Population	Percentage Active Population	Jobs	Area (in km2)	Active Population Density	Employment Density
Ottawa	1,323,783	896,765	67.7%	642,330	6,767.41	132.51	94.92
Winnipeg	778,489	525,570	67.5%	362,675	5,306.79	99.04	68.34
Quebec City	800,296	522,170	65.2%	399,240	3,408.70	153.19	117.12
London	494,069	328,480	66.5%	215,525	2,665.62	123.23	80.85
Halifax	403,390	279,630	69.3%	194,585	5,496.31	50.88	35.40
Windsor	329,144	217,360	66.0%	133,855	1,022.30	212.62	130.93
Saskatoon	295,095	201,505	68.3%	136,510	5,890.71	35.74	23.17
Victoria	367,770	241,740	65.7%	166,625	696.15	347.25	239.35

3.1. Data

A number of data sources were used for inputs, to create the models in this research. The travel time data was collected through two streams: the Open Source Routing Machine and Distance Matrix API. The driving, walking, and cycling travel time data came from the Open Source Routing Machine, a free-to-use routing engine which uses OpenStreetMap to calculate travel times and distances between the centroids of the census tracts from the 2016 Canadian Census. Unfortunately, this service does not include public transit data, which was instead purchased from Distance Matrix API and again used to gather centroid to centroid travel times. These centroid-to-centroid travel times were calculated for a weekday morning at 8am to best represent the morning commuting peak. With the travel times calculated, the accessibility models could then be created with the addition of the employment location data and the mode-share weights, both of which came from the 2016 Canadian Census and were retrieved at a Census Tract granularity. Finally, the socioeconomic data, used to evaluate the mode-share weighted accessibility model through equity factors also comes from the 2016 Canadian Census and was retrieved at a Census Tract level.

3.2. Methods

The purpose of this research is to understand and describe the distribution of mode-share weighted accessible jobs in large and medium sized Canadian CMAs. Specifically, I am creating models that will examine the demographic covariates of accessibility at the census tract level, to see how they compare. These models would show which areas and consequently which factors are correlated with the highest and lower accessibility to employment across the country. In the following section I describe the equations and calculations used to create the model. All calculations and much of the GIS was performed in Google Colab, using Python and the PANDAS and GEOPANDAS frameworks.

First, the cumulative opportunity model was created for each mode of travel. Employment data was joined to the census tract layer, giving the number of jobs in each census tract. Travel time data between the centroids of the census tracts was then pivoted by census tract, summed by jobs, and joined, so that only the number of jobs that are accessible within 60 minutes are tied to each census tract. This is subsequently repeated for each of the other three modes of travel, so that each census tract has their respective number of jobs accessible by each mode. This is represented in the Equation 5.3 from Bertaud (2018) below. This equation is Bertaud's CMI equation, which was the inspiration and a foundational piece in the original mode-share weighted accessibility research presented in Patterson et al. 2024, which this section closely follows in methodology.

$$M = \frac{\sum_{i=1}^{n} A_i P_i}{P} \qquad \text{(Eqn. 5.3 from [Bertaud, 2018])}$$

In the CMI equation M is equal to the sum of the number of jobs accessible from a particular area, by a particular mode of travel (A_i) multiplied by the population of that area (P_i), for each area in a region, divided by the total population of the region (P).

These accessibility models are cumulative opportunity models; however, they are still unimodal in nature. The mode share-weighted accessibility model requires mode-share weights (W_m) to be added to them to reflect how residents of each specific census tract travel to work.

Once the mode share weights have been applied to Bertaud's M, the resulting mode share-weighted M's for each mode of travel are summed to give the MWA, or the average number of mode-share weighted jobs accessible to a person in this region, described in the following equation:

$$MWA = \sum_{m=1}^{n=1} MWm \qquad \text{(Equation 1)}$$

Knowing the average number of mode-share weighted jobs a region has is useful for understanding the region's labour market's access to employment. However, it is less useful for a direct comparison of the MWA values of different regions, as they vary in population and in employment numbers. Comparing the absolute number of jobs accessible for the average person in Victoria and Toronto is not meaningful because of the differences in employment opportunities in the cities. Rather, another term needs to be added to the equation for it to be useful in comparative analyses. The MWA can be divided by the total number of jobs in the region, to calculate the Mode-share-weighted Accessibility Target (MAT), as seen below:

$$MAT = \frac{MAI}{J} \qquad \text{(Equation 2)}$$

In previous works I have referred to this equation, MAT as the Multimodal Accessibility Target. In light of the usage of the nomenclature of multimodal to refer to trips that use multiple modes of travel within the same trip, and the ability to describe this kind of accessibility as mode-share-weighted, a renaming was in order. The MAT can be seen as the mode-share-weighted average ratio of the total jobs accessible within a given time in a given region. The MAT is a unitless measurement, it is a ratio between 0 and 1, where a value of 1 would indicate that every job in the region is accessible multimodally to the average person within the given timeframe and a value of 0 would signify that no jobs are accessible to the average person within the given timeframe.

The MAT equation and concept in this research will be primarily used at a CT level, not at the aggregated regional level. This is so the socioeconomic variables, which exist at a census tract level can be viewed through this MWA lens. As this analysis is comparing the accessibility levels of different census tracts, not at a regional level, the inputs to Bertaud's equation must be changed. The total population, P, under the dividing sign becomes equal to the population of the area P_i, and the two terms thereby cancel each other out. Because n=1 for each individual census tract, no summation is required, and Bertaud's M becomes equal to the number of jobs accessible for a given mode, within a given time, for a given census tract. The MWA equation does not need to be changed, as it only adds the mode-share weights and subsequently sums together the mode-share weighted employment opportunities. The MAT equation similarly does not need to change, as the MWA equation has already been altered by the changes to Bertaud's equation. Resultantly, each census tract gets its own M value for each mode of travel, thereby giving each census tract its own MWA and MAT. The census tract level MAT values allow for comparison against other census tracts within their region as well as more meaningful comparison against census tracts in other regions.

With the formulation of the equations thoroughly explained, a detailed description of the process can be made. As mentioned in the data section, the travel time calculations between centroids of census tracts within a region were completed using two different travel time calculating APIs, and these travel times were pivoted by census tract, summed by the number of jobs accessible in the census tracts that were less than 60 minutes away, and joined, so that only the number of jobs that are accessible within 60 minutes are tied to each census tract, for each mode. The mode-share weights of each census tract are then applied to these totals, and the products are summed together to give the MWA. The MWA is then divided by the total number of jobs to give the MAT. This was done for every census tract in each of the CMA's.

Multiple linear regression models were made for each region, testing the relationships between a number of demographic and socioeconomic factors and MWA value at a census tract geography. The variables that were tested are described in the following table:

Table 2: *Socioeconomic and demographic variables*

Variable	Description
Population Density	The number of people living in the census tract divided by the area of the census tract. Measured in people per square kilometre.
Median Household Income	The median sum of the total incomes from all household members in a given census tract. Measured in Canadian dollars.
Unemployment Rate	The percentage of the labour force who were unemployed in a given census tract, the week of May 1 to 7, 2016.
Participation Rate	The total labour force, divided by the total population in a given census tract, the week of May 1 to 7, 2016.
Renter	The percentage of households where no member of the household owns their dwelling unit.
Indigenous	The percentage of people identifying as “First Nations people, Métis, or Inuit”.
Immigrant	The percentage of people who are or who have ever been a landed immigrant or permanent resident.
Visible Minority	The percentage of people who are non-indigenous and non-caucasian.
Without Post-Secondary	The percentage of people who have not completed post-secondary education.
Long Commute	The percentage of people who commute over 60 minutes to work.

These independent variables were tested for their explanatory power of the MWA, or number of mode share weighted accessible jobs accessible by census tract, for each region. The independent variables were chosen either because of they helped characterized different socio-demographic groups or because they were believed to be related to levels of accessibility, as described in the accessibility literature (McLafferty & Preston, 2019, Hu, 2017, Cui et al., 2019, Cui et al., 2020). Much of the research into factors that are related to, or affect, accessibility involves the use of regression models to determine which socio-economic, or demographic factors are influential and significant (e.g. Borja & Dieringer, 2019, Cui et al., 2020, Hu 2017, Wu et al., 2021). While this kind of analysis has been done, it has not been done with mode share weighted accessibility values, nor has it been done comprehensively, across large and medium sized metropolitan areas in Canada.

Regressions, like ordinary least squares, spatial, and binomial regressions, are often used to understand accessibility’s place in urban systems and dynamics, both as an independent and as a dependent variable. The choice of OLS regression here to investigate the relationships that exist between MWA and the independent variables is an atypical use of a regression but is not without precedent. Regressions are usually used to understand how a dependent variable is influenced by the independent variables it's tested against, or in other words how the independent variables affect the resulting dependent variable. This is not what takes place in this research. The disaggregated MWA by census tract is after all, not determined by the socioeconomic or demographic variables that are used in the regression, but rather the transportation network that traverses the region, the location of employment within the region, and the mode shares of each mode of travel at the particular unit of geography. In this sense, the regression is being used to determine how these factors, which are not directly related to the accessibility model's inputs, are related to MWA, allowing for an understanding of the socioeconomic patterns and trends that emerge from viewing an urban region through this lens.

By using a regression in this manner, we can gain an understanding of the correlations that exist between MWA and the many variables, granting an understanding of how MWA at a census tract level is related to factors like income, the percentage of households renting, or the education of a household. These methods are similar to Maharjan et al. (2024), where the gap in accessibility to employment between transit and automobile were examined against a number of socioeconomic variables across 45 American metropolitan areas using regression. Zinia et al. (2023) used regression to examine transit accessibility against a number of socioeconomic variables at a block level to determine which were significantly related to accessibility. Both of these papers used accessibility as their dependent variable to examine neighbourhood or and block level socioeconomic characteristics respectively. Others have used regressions to examine socioeconomic characteristics of neighbourhoods against factors that are similar or related to MWA, such as commute time (Cui et al., 2019) or mode share (Cut et al., 2020).

The intent of the regressions was to determine which variables were significantly correlated with varying levels of MWA, which would then reveal social and economic dimensions to realized accessibility. As these regressions were completed for a number of large and medium-sized Canadian metropolitan areas the regressions could then be compared between the regions to find consistencies of significant variables between regions as well as variables that were only significant in specific regions. To facilitate the interpretation of the results, the MWA values in the regressions were multiplied by 1000. This helped bring many of the estimates from very small numbers to more meaningful and digestible values.

Population density was included in this model to serve as a traditional proxy for accessibility. It was included because densely populated areas often have high accessibility across modes of travel, with higher transit mobility and accessibility and higher non-automobile accessibility than lower density areas due to the greater concentration of services and employment near densely populated areas and better transit service. This in theory means accessibility is correlated with population density within a region, but population density is not endogenous. Mode-share weighted accessibility is calculated differently than a traditional unimodal cumulative opportunity measure, so while greater levels of population density are associated with higher accessibility, determining if this is consistent for MWA is important. Given that MWA is calculated using the observed mode-share weights, mode-share weights for transit, walking, and cycling are higher in areas of greater density, and the inequalities in the mobility of non-automobile modes, we would expect population density to have a negative relationship with MWA. The lower levels of jobs accessible by transit, and significantly lower levels accessible by walking and cycling should mean that the realized levels of mode-share weighted accessibility in the CTs with higher proportions of non-auto mode-share (and higher density) are lower than in the CTs with higher proportions of auto mode-share, all else being equal.

Median Household Income was included in this statistical model as a representation of economic status. As a proxy for economic status, measuring MWA against the median household income of census tracts provides the clearest depiction of how accessibility is distributed among different socioeconomic classes, and how it changes in the contexts of different Canadian regions. Based on the accessibility and spatial mismatch literature, I would predict that median income would be positively associated with MWA, and that the areas with the lowest MWA have considerable overlap with the areas of the lowest median household incomes.

Continuing with the theme of spatial mismatch of disadvantaged communities, the unemployment and participation rates were included to understand their connection to MWA. Again here, the accessibility and spatial mismatch research suggests that lower mode-share weighted accessibility levels would be associated with higher unemployment rates and lower participation rates. We would similarly expect to see some correlation with the proportion of people who commute longer than 60 minutes to work, which was added to this model as an important equity indicator which aids in the detection of spatial mismatch. I expect again, if there is correlation between income, or the unemployment and participation rates and MWA, to find correlation with the percentage of long commutes as well.

Education levels are a commonly used socioeconomic indicator, as higher-paying jobs can necessitate higher levels of education, while minimum-wage jobs often do not. The percentage of people who did not complete any post-secondary was used for this measure, which is composed of those who completed secondary school but did not complete further education, as well as those who did not complete secondary school. If this variable is correlated with MWA I would expect it to be negatively correlated, where areas with a higher proportion of individuals that have not done post-secondary school would have lower MWA levels than those with higher education.

The final economic indicator that was included was the percentage of households renting. While a majority of Canadian households own their residence, a sizable minority, about a third, do not (Evans, 2022). As owning housing typically requires upfront capital in the form of a down payment and housing costs have escalated considerably in recent years, home ownership has fallen farther out of reach of many. The percentage of households renting acts as a proxy for the overall wealth of a neighbourhood as households that own tend to have more capital.

The percentage of immigrants, indigenous peoples, and visible minorities were all included in this model as well. The accessibility literature has painted a contradictory picture, ranging from some research suggesting strongly that immigrants and visible minorities have worse access to employment, to other research not finding statistically significant differences in accessibility levels. Which, if any, of these variables are significant will likely be region-specific, as the region's included in this research have various proportions and distributions of each of these groups, with factors beyond (but possibly including) accessibility affecting residential location.

The initial models were run with all the variables described above included, and subsequently improved by excluding variables that were either not significant or had high levels of multicollinearity. This was often the case for variables like percent immigrant and percent visible minority, or median household income and percent renter. This left the regression for each CMA with different combinations of dependent variables from the pool in Table X. In running these regression models, I came to see that there were some significant outliers. While some of these low MWA outlier values were explained by their high walking mode-shares, others were not. Oftentimes these CTs were in airports or rurally located, leading to their centroids not being located on or near road networks, which presented challenges to the APIs creating the travel time matrices. These CTs were therefore excluded from the models. Still, after the removal of the outliers with obvious errors, there were still outliers in the data, typically in downtown areas of regions, in census tracts with higher proportions of transit, cycling, and walking.

The regression models used to determine relationships between the MWA of census tracts and the independent variables took the following form:

$$\begin{aligned} MWA_i = \beta_0 + \beta_{1Density_i} + \beta_{2Income_i} + \beta_{3Unemployment_i} + \beta_{4Participation_i} \\ + \beta_{5Tenure_i} + \beta_{6Indigenous_i} + \beta_{7Immigration_i} + \beta_{8Minority_i} \\ + \beta_{9Education_i} + \beta_{10Commute_i} \end{aligned}$$

Where:

MWA is the mode share weighted number of jobs accessible from census tract i
Density is the population density in census tract i
Income is the median household income in census tract i
Unemployment is the unemployment rate in census tract i
Participation is the particiaption rate in census tract i
Tenure is the percentage of renters in census tract i
Indigenous is the percentage of indigenous peoples in census tract i
Immigration is the percentage of immigrants in census tract i
Minority is the percentage of visible minorities in census tract i
Education is the percentage of people without post-secondary education in census tract i
Commute is the percentage of people commuting over 60 minutes to work i

Individual models were created for each CMA, where variables that were found to be either insignificant, or multicollinear with other variables in the regression, were excluded.

In addition to the regressions, aimed at finding associations between MWA and the various socioeconomic variables, another set of statistical tests, t-tests and Wilcoxon Rank Sum tests were performed. These tests aimed at discerning differences in the independent variables between low MWA CTs and high MWA CTs. Based on the literature review's links between socioeconomic status and accessibility, as well as unemployment and accessibility, I had anticipated these variables were going to be significantly different between the two groups in all of the regions. I had less conviction that the other variables will be significantly different, although I anticipated that the percentage of renters and the population densities would likely be different too.

Census Tracts with MWA values in the top 20% of values, or top quintile, were grouped together, as were CTs with MWA values in the bottom quintile of values.
While normality is traditionally a condition of the t-test, numerous papers have suggested that t-tests handle non-normal data well, given that the sample size is not too small (n = > 25) and there are not too many significant outliers (Lumley et al., 2002). The t-tests are preferable to the Wilcoxon Rank Sum tests because the t-tests are able to produce estimated means for both groups and distinguish a significant difference in means, allowing for more meaningful

comparison when dealing with the socioeconomic variables in this study. Wilcoxon Rank Sum tests can only differentiate if the rank sum of the groups is meaningfully different.

Abiding by the n = < 25 suggestion meant that only some of the CMAs could have all their variables examined through t-tests. The CMAs with fewer than 125 CTs, or 25 per quintile, could only use t-tests for variables that were not significantly different than a normal distribution. Groups with significant outliers could also not have t-tests performed. For these variables the rank sum test was used.

Finally census tracts were examined for spatial autocorrelation of MWA. Univariate global Moran's I tests were performed to determine how spatially autocorrelated MWA was. Moran's I tests were run using the univariate Moran's I test in GeoDa. The significance of these tests was determined by running a randomization of 999 permutations to generate a pseudo p-value. A high degree of spatial autocorrelation is expected, especially in large regions. The non-mode-share weighted accessibility values do not often change drastically from one census tract to another, especially in dense regions where census tracts have physically smaller footprints. Transportation systems exist in networks, and the number of jobs accessible from one CT to its neighbour regardless of mode tends to be more similar than a CT and a distant CT elsewhere in the region. The same is true for modal splits, where areas that are near each other tend to be more similar than areas that are farther away. For example, the suburbs of Toronto will have similar mode-shares that lean towards driving and accessibility values given their urban form, transportation options available, and location within the regional transportation network. The same could be said about CTs downtown Toronto and its proximity to employment, and mode-shares favouring transit and active modes, both of which will be similar among the CTs located there.

3.3. Model Decomposition

MWA models may present accessibility results that are counterintuitive to those familiar with the typical isochrone maps of accessibility by a single mode of travel. Typically, these maps show accessibility to employment being highest in the areas most proximate to the highest employment densities, which are usually downtowns, for walking, cycling, transit, and sometimes driving. MWA models differ in that areas with higher automobile mode shares, especially those closer to employment areas or infrastructure that provides access to employment areas, had the highest access. To help illustrate how the mode shares and the number of jobs accessible by each mode interact within the model, I have decomposed the models cartographically, showing both these inputs for each mode of travel in one CMA, Vancouver. These maps show the unimodal access to employment by each of the four modes of travel, with each map displaying access for its respective mode, in quintiles. The quintiles vary significantly in absolute terms by mode. Walking had by far the fewest jobs accessible, even in the areas with the high-access by foot, compared to the transit, bicycle, and automobile accessibility for those areas. Transit and cycling had comparable numbers of jobs accessible within their quintiles, and often-times census tracts belonging to the a certain quintile of transit access would be in the same quintile of access by bicycle, with some variation along the rapid transit corridors of the region. Access by driving had the highest accessibility, with four of the five quintiles having access to a similar number of jobs, and even some of the census tracts in the lowest quintile having access to most of the opportunities within the region. As a result, while the difference in automobile accessibility is rather striking on the map, it's not significant in magnitude.

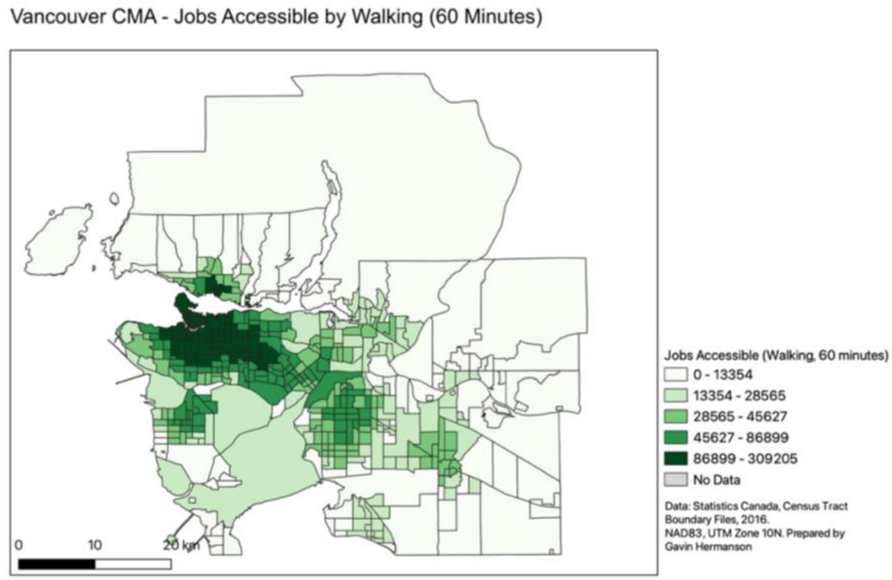

Figure 1*: Jobs Accessible by Walking, Vancouver CMA*

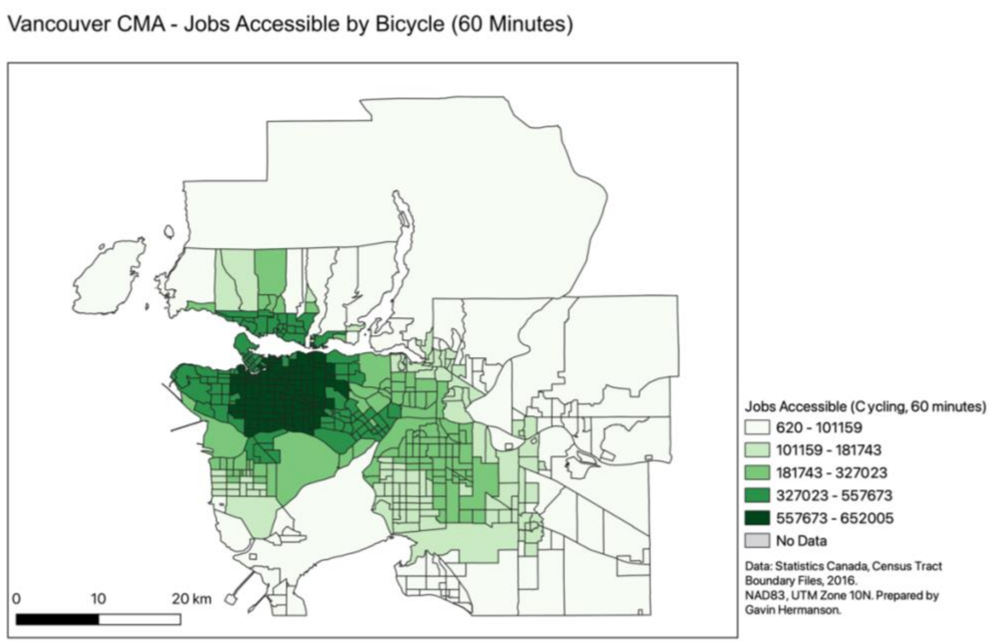

Figure 2*: Jobs Accessible by Cycling, Vancouver CMA*

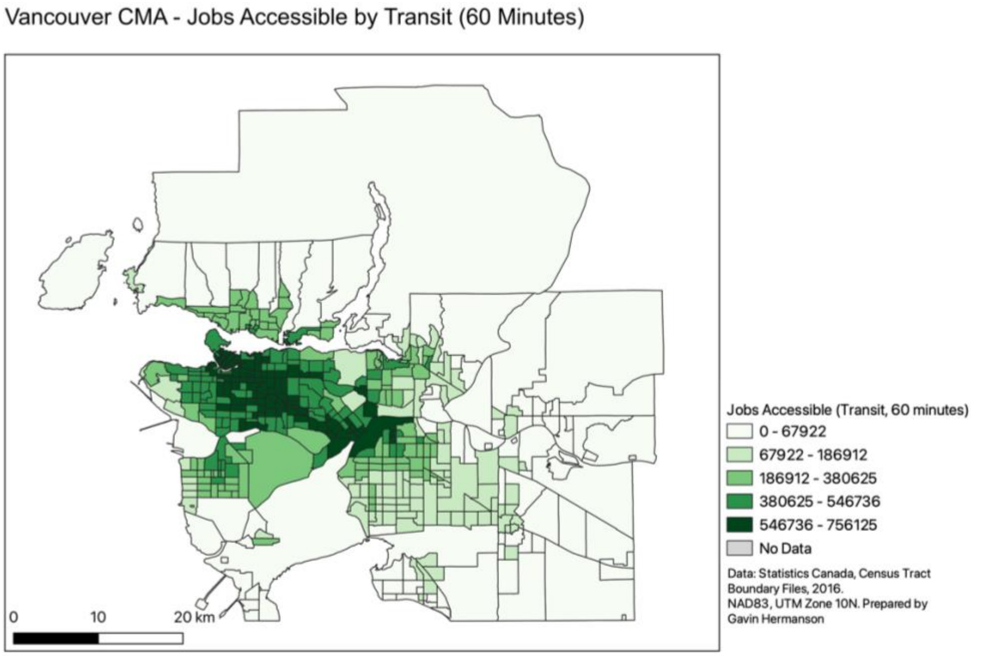

Figure 3: *Jobs Accessible by Transit, Vancouver CMA*

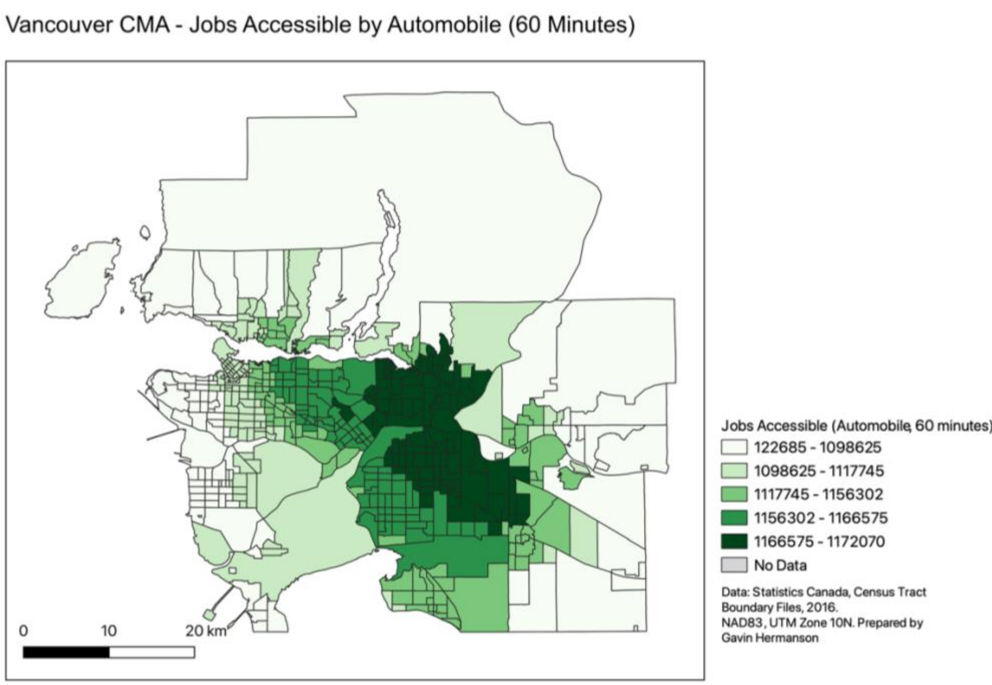

Figure 4: *Jobs Accessible by Automobile, Vancouver CMA*

Access to employment by walking (Figure 1) was highest in the downtown and central parts of the City and was generally lowest in the exurban and rural census tracts, farthest from the higher employment densities. Access to employment by bicycle (Figure 2) was not dissimilar to access by foot, but was shifted slightly away from Downtown, and to the southeast, towards Burnaby and Surrey. Access to employment by Transit (Figure 3), while high Downtown, was also high along the SkyTrain network, with census tracts on the Expo, Millennium, and Canada lines having greater access to employment. Finally, access to employment by automobile (Figure 4) was highest in census tracts nearest to Highway 1, where the freeway infrastructure provides higher levels of accessibility to employment as a result of the greater mobility it allows. The highway also provides automobile access to Abbotsford-Mission, which was modeled as one contiguous region, and its employment areas, explaining why access to employment by automobiles was highest in the census tracts closest to the freeway and away from Vancouver's core.

The other component of MWA models, the mode shares, for each mode are displayed in the four maps below. Again, here, the census tracts are grouped into quintiles based on the percent of people commuting using each mode of travel.

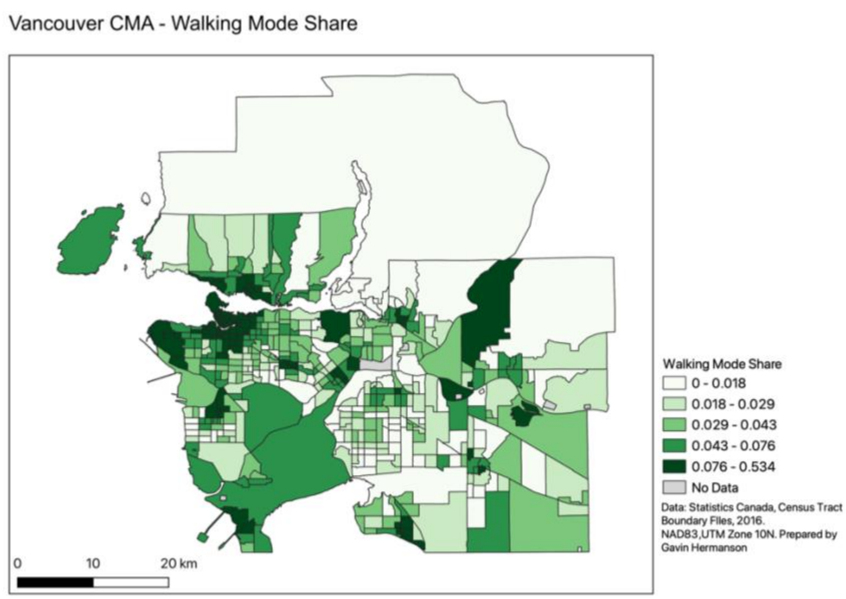

***Figure 5**: Walking Mode Share, Vancouver CMA*

Vancouver CMA - Cycling Mode Share

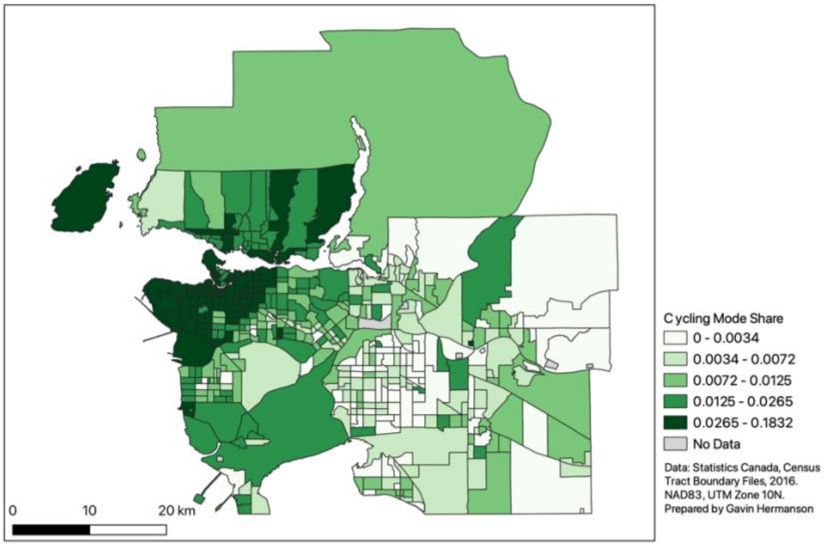

Figure 6: *Cycling Mode Share, Vancouver CMA*

Vancouver CMA - Transit Mode Share

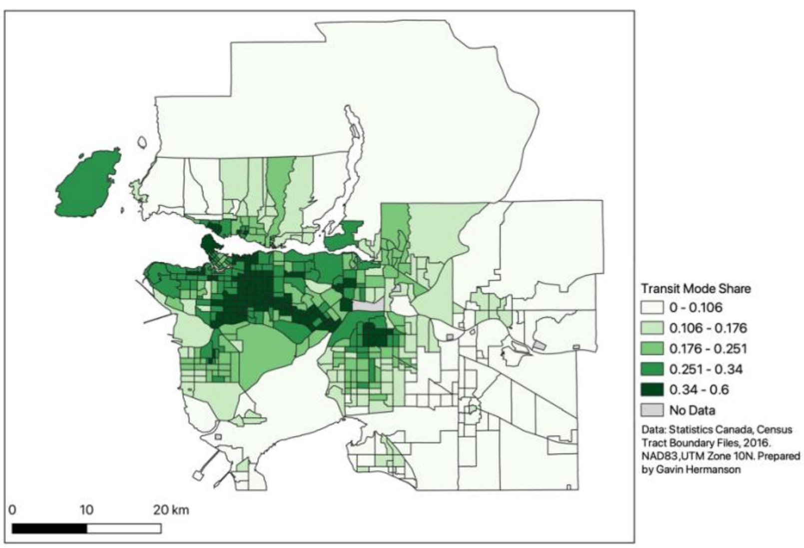

Figure 7: *Transit Mode Share, Vancouver CMA*

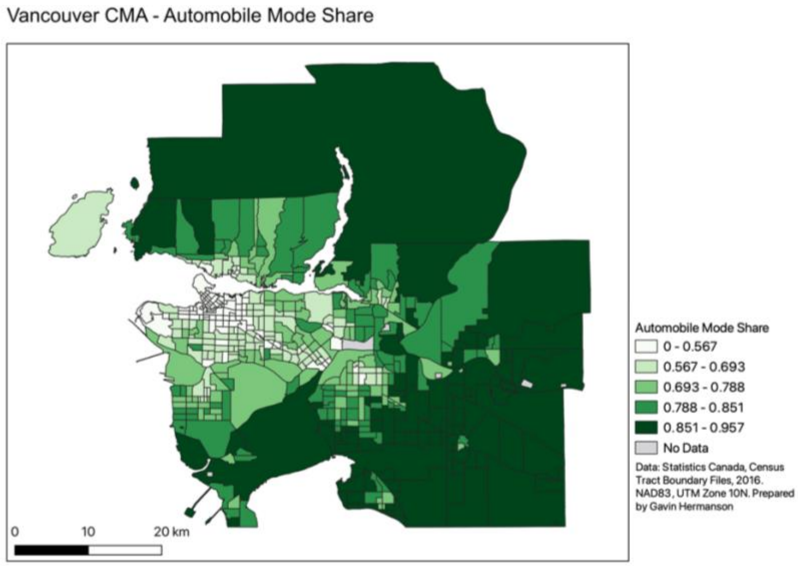

***Figure 8**: Automobile Mode Share, Vancouver CMA*

Walking mode shares (Figure 5) were highest in the various downtowns throughout the region and the universities. Cycling mode shares (Figure 6) were highest downtown, on the west side of Vancouver, and on the east side north of the SkyTrain. Transit mode shares (Figure 7) were highest along the SkyTrain lines in Vancouver. Automobile mode shares (Figure 8) were the highest in the suburban, exurban, and rural parts of Metro Vancouver.

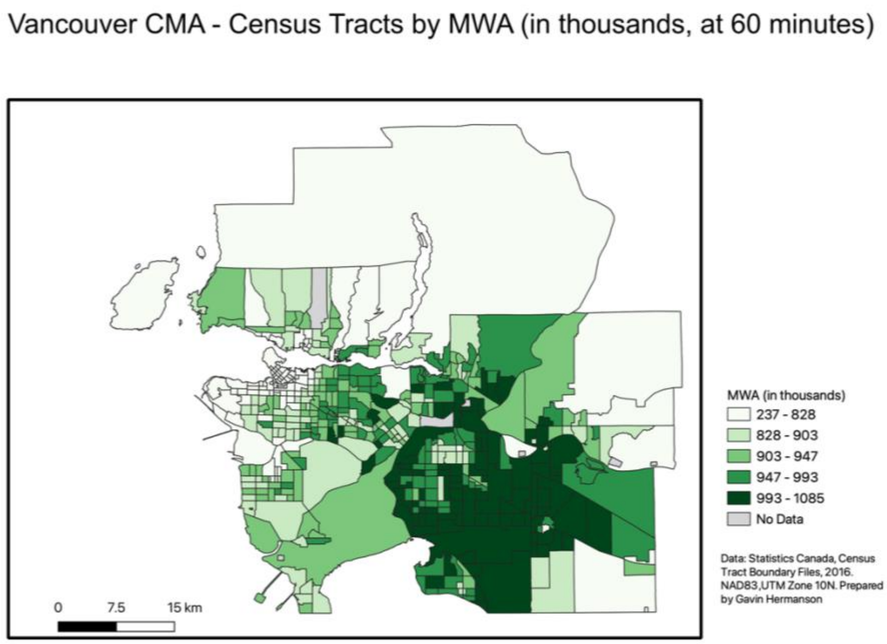

***Figure 9**: Mode-share weighted accessibility (in thousands) by census tract, Vancouver CMA*

By decomposing the MWA into the accessibility to employment by each mode and the observed mode shares from the census, I hope to make clear why the MWA maps, such as Figure 9 for Metro Vancouver, present MWA results that may seem unintuitive. To aid in the visual presentation of this data I've included a table, below, which contains the mode share and accessibility to employment data for each mode for a handful of census tracts from around the region. The appendix to this thesis contains this data for the entire Metro Vancouver region.

Table 3*: Accessibility (60 Minutes), Mode Shares, and MWA for Select Vancouver CMA Census Tracts*

Census Tract Unique ID	MWA	Jobs Accessible by Foot	Walking Mode Share	Jobs Accessible by Bike	Cycling Mode Share	Jobs Accessible by Transit	Transit Mode Share	Jobs Accessible by Automobile	Auto Mode Share
9330029	797,453	247,170	14.68%	588,865	9.11%	613,450	33.39%	1,102,360	45.60%
9330066	622,954	280,435	48.46%	545,195	2.04%	683,855	17.66%	1,102,940	32.20%
9330119	800,454	39,220	5.49%	358,795	4.95%	297,015	16.14%	1,103,670	73.63%
9330146	916,984	18,315	2.48%	199,730	0.73%	245,385	17.97%	1,104,420	78.86%
9330170.05	852,883	21,265	11.90%	51,840	0.95%	64,010	14.77%	1,113,610	73.81%
933206	916,493	38,090	5.14%	339,695	1.03%	705,395	53.8%	1,161,605	45.76%
9330232	941,738	57,485	1.79%	322,890	2.15%	316,850	24.90%	1,169,175	73.18%
9330503.06	991,039	30,420	4.81%	110,490	0.46%	107,945	9.37%	1,147,380	85.32%

3.4. Limitations

There are several limitations that restrict various aspects of the mode-share weighted accessibility model in different capacities. We will start with the issue of granularity with the geographic areas that were used as the spatial element for the origins and destinations in the model. Census Tracts are relatively small, geographic areas that typically contain 2,500 – 8,000 individuals, and together make up Census Metropolitan Areas, which they are the physically largest subdivided level of. They are not as fine or accurate as the dissemination areas that CTs are comprised of, which typically contain 400-700 people, and are a collection of blocks rather than entire neighbourhoods or communities. While much of the socioeconomic data that was required to undertake the demographic analysis component of this research was also available at a dissemination area level, the journey to work data which is essential in forming the mode-share weights, are not available for the dissemination areas. The employment data, another essential input, was also not available at a dissemination area level, making the use of census tracts necessary to complete this research. Additionally, creating the travel time matrices for the dissemination areas would have meant considerably larger and more costly and time-consuming matrix creation because of the larger number of dissemination areas compared to Census Tracts. As it was, the transit travel time calculations had a total of just under 3,000,000 origin-destination pairs. Calculating travel times at the dissemination area level would have led to a number of OD pairs an order of magnitude higher, which would not have been feasible financially. However, the downside is that census tract to census tract travel times lack the precision of travel times between dissemination areas. Census tracts are much larger geographic areas, and their centroid-to-centroid travel times become less representative of the actual travel times than the same travel time calculations between dissemination areas would be. This loss of travel time precision should be marginally consequential to the results of the model. A handful of geographic areas on the periphery of what is accessible in 60 minutes would be excluded because the centroid of their census tract is greater than 60 minutes away, despite the centroid of their dissemination area being less than 60 minutes away. The reverse would also be true, where the dissemination area centroid would not be accessible within 60 minutes, but because the census tract centroid was accessible it would be counted as accessible in the accessibility equations. As this issue of the modifiable area unit and its effect on accessibility values would both increase and decrease the number of jobs accessible the effects are likely marginal.

The next limitation with the methodology used here concerns the travel times themselves, and specifically the paths taken by the pedestrians, cyclists, and cars. Most consequently, free-flow automobile travel times were used for this research, as there was insufficient budget to obtain automobile travel time data with traffic congestion incorporated. Automobile travel times are likely underestimated and as a result, automobile accessibility is overestimated. Further, the open-source routing machine that was used to gather this travel time data assumes individuals take the most efficient routes of travel, and while this might be true, it is not a certainty. Different routes might present faster travel time options on different days depending on traffic volume, and consequently route efficiency in the real world is subject to some variability. As a result, this might underestimate vehicular, pedestrian, or cyclist route efficiency and travel times. While at a census tract level this is unlikely to affect whether an area is accessible or not, it is conceivable that in certain circumstances it might marginally affect accessibility values for these three modes. Transit that is not grade-separated is susceptible to changes in travel times as well, but the travel paths are unchanged.

Another shortcoming of this model is its lack of accounting for the time it takes to park an automobile or a bicycle. The benefits of walking trips and transit trips that begin and end with a walk is the absence of required time to park your vehicle or bicycle. While either bicycle parking may be available near your destination, it is not guaranteed, and often results in parking near, but not at your destination. This adds travel time for both walking and driving modes, which is not accounted for in this model. While some accessibility models have added time "penalties" for the assumed parking and walking times, with a lack of precise knowledge of these time costs to form the basis of additional travel time for driving, it is simply not included in this model. This inevitably makes driving appear to have a greater level of accessibility than it would, but at census tract level travel times it would likely have a marginal effect.

While spatial autocorrelation was tested for in each CMA's model, the regression models were not adjusted for spatial autocorrelation. This means that in the CMA's where spatial autocorrelation was detected (which is noted in the results of each CMA), the regression estimates and their associated p-values may be unreliable, as the presence of spatial autocorrelation suggests that observations are not independent of each other. This is a common problem in spatial analysis, and one to be expected when dealing with data aggregated at a geography like a Census Tract. While there are sometimes

Finally, I would be remiss if I did not mention full cost accessibility. Full cost accessibility is an accessibility framework that seeks to account for costs beyond travel time, which are the only cost most accessibility measures use. I have not attempted to quantify other external or internal costs (pollution, noise, cost of travel inputs like gas or car ownership) for this model, as I believe the mode-share weighted accessibility methods used in these applications are already novel applications from an alternative way of viewing accessibility. Nonetheless it is important to note this "incompleteness" of traditional location-based accessibility metrics. Travel times are an important cost, but understanding the externalities from automobiles is necessary to evaluate the impacts of mobility and accessibility on society as a whole. Private automobiles have better mobility and accessibility than any other mode of transportation, but come at large costs to society, which are not reflected in models such as my own. This deserves recognition as the results of any accessibility model that uses automobiles as a mode of travel but does not account for their externalities runs the risk of unjustly favouring automobiles and its results should be interpreted with that in mind.

4. Results

The overall MWA and MAT values by region are presented here. Smaller regions tended to have higher MATs, as expected, because physically smaller regions have a greater proportion of their census tracts accessible by all modes and tend to have greater proportions of people using automobiles for their journey to work.

Table 4: MWA and MAT by Census Metropolitan Area

Region	Jobs	MWA	MAT
Greater Vancouver	1,173,955	847,104	0.7216
Greater Toronto	3,737,300	1,782,691	0.4770
Calgary	640,155	483,156	0.7547
Edmonton	592,340	497,093	0.8392
Ottawa	642,330	494,135	0.7693
Winnipeg	362,675	232,313	0.6406
Quebec City	399,240	334,906	0.8389
London	215,525	160,958	0.7468
Halifax	194,585	157,452	0.8092
Windsor	133,855	125,109	0.9347
Saskatoon	136,510	125,653	0.9205
Victoria	166,625	139,001	0.8342

The CMAs with the smallest populations tended to have higher MAT values, suggesting a greater proportion of people in these regions have access to all jobs across all of the used modes. This likely comes from both the smaller physical area over which the jobs are dispersed, meaning a greater proportion of the jobs can be reached within an hour regardless of mode of travel, and the propensity of smaller CMAs towards autocentrism. The medium-sized and larger CMAs had lower MWA values, being driven by greater usage of transit, walking, and cycling, while the largest CMAs had physical areas too large for all jobs to be reached within an hour, even by car.

Table 5*: Minimum, Maximum, Median, and Interquartile MWA values by CMA*

Region	Jobs	Lowest MWA	25th Percentile	50th Percentile	75th Percentile	Highest MWA
Greater Vancouver	1,173,955	206,358	827,577	915,728	978,158	1,085,187
Greater Toronto	3,737,300	43,840	1,195,459	1,940,877	2,283,118	3,021,982
Calgary	640,155	398,858	539,775	557,061	573,435	609,287
Edmonton	592,340	299,823	499,635	516,923	528,841	587,195
Ottawa	642,330	268,141	499,388	518,596	538,482	598,282
Winnipeg	362,675	236,322	318,088	326,351	332,102	349,994
Quebec City	399,240	229,612	324,905	347,496	360,366	377,891
London	215,525	157,245	192,221	196,867	201,891	209,733
Halifax	194,585	112,899	160,210	171,021	175,218	184,660
Windsor	133,855	100,671	123,253	128,123	130,273	132,172
Saskatoon	136,510	105,564	124,463	127,772	129,335	131,614
Victoria	166,625	91,533	138,827	145,831	150,976	159,082

Table 6: *Minimum, Maximum, Median, and Interquartile MAT values by CMA*

Region	Jobs	Lowest MAT	25th Percentile	50th Percentile	75th Percentile	Highest MAT
Greater Vancouver	1,173,955	0.17578	0.70495	0.78004	0.83322	0.92439
Greater Toronto	3,737,300	0.01173	0.31987	0.51933	0.61090	0.80860
Calgary	640,155	0.62307	0.84319	0.87020	0.89578	0.95178
Edmonton	592,340	0.50617	0.84349	0.87268	0.89280	0.99131
Ottawa	642,330	0.41745	0.77746	0.80737	0.83833	0.93143
Winnipeg	362,675	0.65161	0.87706	0.89984	0.91570	0.96503
Quebec City	399,240	0.57512	0.81381	0.87039	0.90263	0.94653
London	215,525	0.72959	0.89187	0.91343	0.93674	0.97313
Halifax	194,585	0.58020	0.82334	0.87890	0.90047	0.94899
Windsor	133,855	0.75209	0.92079	0.95718	0.97324	0.98743
Saskatoon	136,510	0.59699	0.91175	0.93599	0.94744	0.98789
Victoria	166,625	0.5494	0.83317	0.87520	0.90609	0.95473

When looking at the MWA and MAT results by quartiles we see a distinct trend emerge, which was particularly strong in the smaller and medium-sized CMAs. The spread between the 25^{th}, 50^{th}, 75^{th}, and 100^{th} percentile MWA and MAT was relatively small, with a substantial gap down to the lowest values. In every region examined, except Greater Toronto, the difference in MWA between the maximum value and the 25^{th} percentile value was less than the difference between the minimum value and the 25^{th} percentile. This tells us that most census tracts within these regions have relatively similar mode-share weighted accessibility to employment, but that the census tracts with the worst accessibility had significantly worse access.

4.1. MWA Multiple Linear Regression model and inferential statistics

One of the challenges presented by working with geographic socioeconomic data is the lack of normality at times in real-world data. While the data used in these models were linearly related to each other, not all of the data were normally distributed, as was to be expected in working with population data separated spatially. While removing some of the outlying MWA values improved the normality of the model residuals, they were only normally distributed in a handful of the CMAs in Southern Ontario. The rest of the CMAs, while largely normal, except for some left skewness as confirmed by QQ plots and density plots, did not pass the Shapiro Wilks test of normality. There was multicollinearity in many of the regression models, but by removing variables with higher VIF values (>3) I was able to remove most of the multicollinearity in the models. Finally, while there was no autocorrelation in the traditional sense, there was spatial autocorrelation present in many of the CMAs. Spatial autocorrelation is difficult to avoid in urban planning applications, where the transportation system and access do not change much from CT to CT, and populations of a census tract more often than not tend to have similar demographic characteristics as their neighbours. Nevertheless, this spatial autocorrelation violates the independence of the residuals. There was some degree of heteroskedasticity in many of the variables, leading to unreliable standard errors. The interpretation problems imposed by the spatial autocorrelation, normality challenges and moderate heteroskedasticity make it difficult to put too much weight into the results of the linear models. T-tests and rank sum tests were performed on the first and fifth quintiles of MWA to determine if meaningful differences in the socioeconomic variables existed, and to confirm if the significant variables in the regression had meaningful differences.

4.1.1. Vancouver

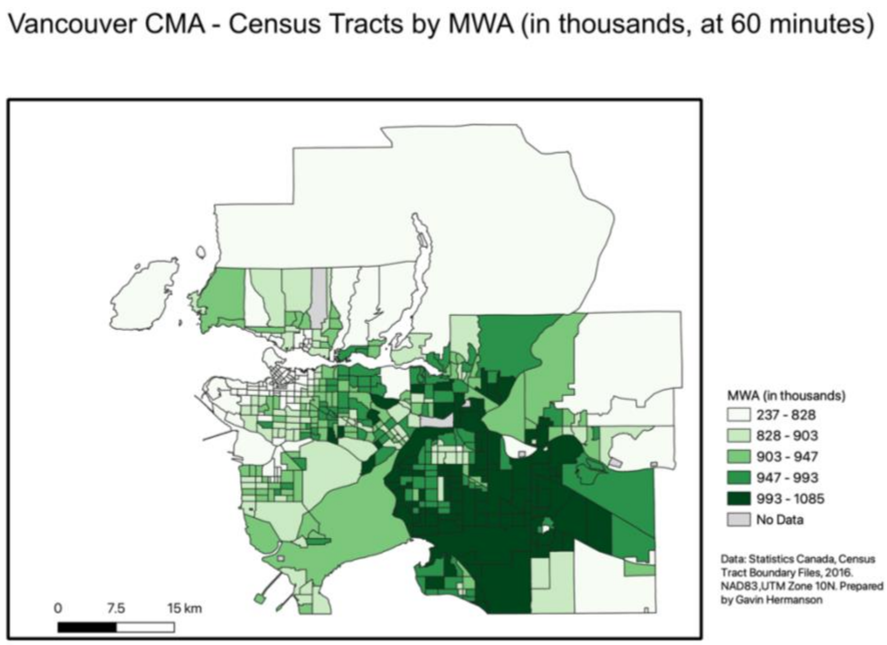

Figure 9: *Mode-share weighted accessibility (in thousands) by census tract, Vancouver CMA*

In Greater Vancouver the CTs with the highest MWA values were primarily located in Surrey, Delta, and Langley, because of their relatively high automotive mode-shares and locations near highways and towards the centre of the region. The lowest MWA values were located at UBC, in Downtown Vancouver, and in False Creek, South of Downtown. These areas, despite being employment rich, tended to have lower MWA's due to the higher active mode-shares and high transit use. Pockets of lower MWA areas exist along the Expo Line corridor traveling Southeast from Downtown towards Central Surrey. The limited accessibility of the North Shore is reflected here, where despite relatively high automobile mode-shares, the CTs were almost exclusively in the bottom half of CTs by MWA because of the travel time delays caused by traffic. There was a moderate degree of spatial autocorrelation in Vancouver's MWA values by census tract. The global Moran's I value was 0.3820, and when randomized 999 times returned a z-value of 14.6576 and pseudo p-value of 0.001.

***Table** 7: Regression model for Vancouver CMA*

Predictor	Estimates	Confidence Interval	*p*
(Intercept)	600.26100	518.63221 – 681.88978	**<0.001**
Population Density	-0.00266	-0.00429 – -0.00103	**0.001**
Median Household Income	0.00080	0.00030 – 0.00131	**0.002**
Unemployment Rate	-6.15606	-10.42931 – -1.88282	**0.005**
Participation Rate	1.98962	1.02717 – 2.95208	**<0.001**
Percentage Renter	-1.91889	-2.51133 – -1.32646	**<0.001**
Percentage Indigenous	-1.36147	-2.42959 – -0.29334	**0.013**
Percentage Visible Minority	0.58281	0.27390 – 0.89172	**<0.001**
Without Post-Secondary	4.04680	3.27583 – 4.81777	**<0.001**
Long Commute	2.90889	1.56447 – 4.25331	**<0.001**

Residual standard error: 63.06 on 452 degrees of freedom (16 observations deleted due to missingness)
Multiple R-squared: 0.6508, Adjusted R-squared: 0.6438
F-statistic: 93.59 on 9 and 452 DF, p-value: < 2.2e-16

There were a number of highly significant variables in Vancouver. While the residuals were nearly normal, the QQ plot revealed that there is some negative skewness to the residuals, entirely on the negative theoretical quantile side of the plot. These census tracts were almost exclusively from two areas: UBC and Downtown Vancouver. Despite the high number of nearby jobs in these areas, their MWA is lowest due to the highest proportions of walking, cycling, and transit trips that were made. I chose to not remove these CTs from the data for the sake of improving the normality of the residuals, as the lower MWA values in these areas are an important conversation piece for this kind of mode-share weighted analysis. Their inclusion however necessitates a degree of caution when interpreting the significance of these variables accordingly.

In Vancouver, nine of the ten examined variables were included in the final model, with only the percentage of immigrants excluded due to a high degree of multicollinearity. Population density, the unemployment rate, the percentage of renters, and the percentage of indigenous peoples were all found to be negatively correlated with MWA. Median household income, the participation rate, the percentage of visible minorities, the percentage of people without post-secondary education, and the percentage of people commuting over an hour to work were found to be positively correlated.

When interpreting the regression coefficients two things should be kept in mind. The first is that MWA in the regressions was multiplied by 1000 for easier interpretation of many of the variables and the second being that many of the variables are percentage measures of an aspect of a census tract. Accordingly, each of the estimates is measured in 1000 mode-share weighted accessible jobs, and a one percent increase in a variable like the unemployment rate means the difference between an 8% unemployment and 9%, not 8% and 8.08%.

The coefficient of median household income suggests that for every dollar increase in the median household income of a census tract, there are 0.8 more mode share weighted jobs accessible. Other coefficients of note include the unemployment rate, where an increase in the unemployment rate of 1% (with all other variables unchanging) corresponds to a decrease of 6,156 jobs, the percentage of renters, where an increase of 1% corresponds to a decrease of 1,919 jobs, the percentage of indigenous people, where an increase of 1% corresponds to a decrease of 1,361 accessible jobs. The full results of the regression and coefficients can be found in table x.

Table 8: *T-tests for Vancouver CMA*

Variable	*t*	*p*	Fifth Quintile Estimate	First Quintile Estimate
MWA	31.21	**<0.001**	1028	741.9
Population Density	-7.53	**<0.001**	2385.55	8616.55
Median Household Income	9.85	**<0.001**	93056.99	65504.91
Unemployment Rate	-1.63	0.106	5.59	6.15
Participation Rate	0.30	0.764	66.64	66.23
Percentage Renter	-11.27	**<0.001**	20.72	50.00
Percentage Immigrant	-0.85	0.396	34.17	35.92
Percentage Indigenous	-2.26	**0.026**	3.14	7.59
Percentage Visible Minority	2.75	**0.007**	43.81	34.76
Without Post-secondary	8.557	**<0.001**	48.29	34.62
Long Commute	12.267	**<0.001**	13.05	6.81

italicized variable indicates Welch's t-test (unequal variance)

Vancouver's quintiles were sufficiently large for t-tests to be performed on every examined variable. The first and fifth quintiles of MWA were grouped together and t-tests were performed to determine if their means were significantly different and what their estimated means were. Seven of the ten variables and the MWA were found to be significantly different between the two groups. The unemployment rate, participation rate, and percentage of immigrants were not found to be significantly different between the first and fifth quintiles, while the rest of the variables were.

The differences in accessibility were significant and pronounced; the MWA t-test produced the highest t-value in the table, suggesting a mean MWA of the fifth quintile of 1,028,000 jobs, but only a mean MWA of 714,900 for the first quintile. There appears to be some economic component to the inequality of access, as the fifth quintile's estimated mean median household income was \$93,056.99, compared to just \$65,504.91 for the first quintile. There is certainly a spatial component to the inequality as well, with population density differences being highly significant. A mean of 2385.55 people live in every square kilometre of the census tracts in the fifth quintile, while 8616.55 people per square kilometre in the first quintile, over three and a half times the density of the fifth quintile. Related to both the economic and spatial component is the percentage of renters, which was estimated at 20.72% in the fifth quintile, and 50% in the first quintile.

The differences in the percentages of indigenous peoples in the first and fifth quintiles was also significant, with the first quintile's mean of 7.59% coming in at over double the fifth quintile's 3.14%. This suggests that some level of inequality of access exists for indigenous people in Vancouver. Differences in the percentages of visible minorities were also found to be significant, but somewhat surprisingly the highest accessibility areas had a greater proportion of visible minorities than the lower accessibility areas did, 43.81% in the fifth quintile against 34.76% in the first.

Nearly half of the people living in the fifth quintile of MWA (48.29%) did not have post-secondary education, compared to 34.62% in the first quintile. While it at first may seem unintuitive, the number of people commuting more than 60 minutes to work was higher in the higher accessibility census tracts than in the lower, with 13.05% of the fifth quintile commuting over an hour, compared to 6.81% in the first quintile. This was the greatest disparity, either proportionally or absolutely, between the percent of people commuting over an hour between the first and fifth quintiles of any CMA studied. In Vancouver's context this is understandable in light of where the low accessibility areas are, and why they have lower access. The proportion of people biking and walking to work in Vancouver's lowest MWA areas (UBC and downtown) is significantly higher than the rest of the city as many people are accessing nearby jobs that do not require an automobile to access. This is in contrast to the higher MWA areas, which tended to have fewer jobs in nearby CTs and were much more heavily reliant on automobiles to access jobs. It should not be too surprising then that people commuting longer distances to work are more likely to do so by automobile and that they would tend to live more in areas of higher automobile accessibility, but the degree to which this happens in Metro Vancouver was surprising.

4.2. *Abbotsford*

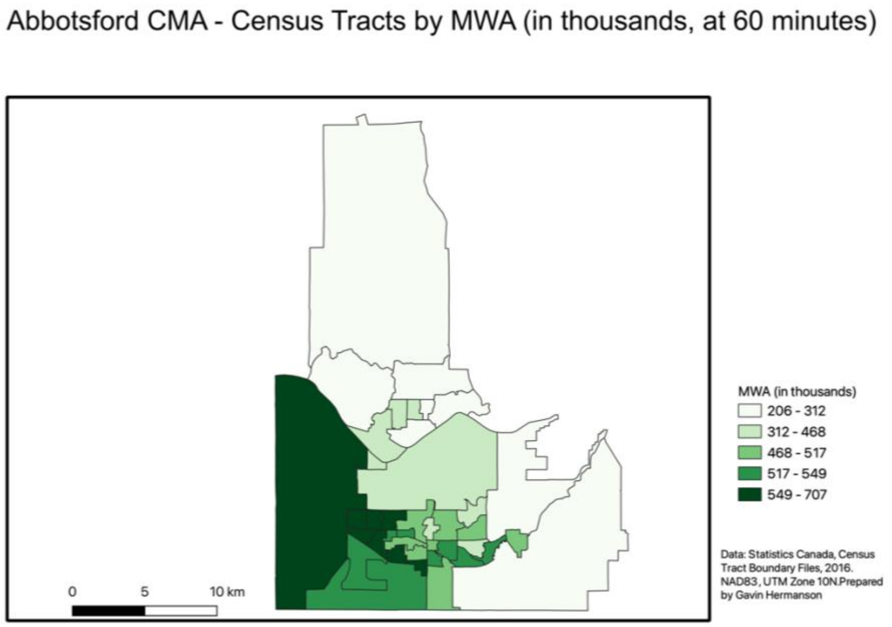

Figure 10: *Mode-share weighted accessibility (in thousands) by census tract, Abbotsford CMA*

Abbotsford's MWA results by CT are heavily influenced by the presence of Metro Vancouver next door. Western parts of Abbotsford, especially along the highway, had the highest MWA values. The CTs north of the Fraser River have lower MWA, as do the rural CTs in the East of the region, likely due to their increased travel times to the employment centres in Vancouver, Burnaby, and Surrey. Abbotsford had a moderately high amount of spatial autocorrelation, with a global Moran's I value of 0.5988, a z-value of 6.9001 on 999 randomizations, and a pseudo p-value of 0.001.

Table 9: *Regression model for Abbotsford CMA*

Predictor	Estimates	Confidence Interval	*p*
(Intercept)	626.21	540.96734 – 711.46153	**<0.001**
Long Commute	-14.43	-21.49027 – -7.37618	**<0.001**

Residual standard error: 104 on 36 degrees of freedom (2 observations deleted due to missingness)
Multiple R-squared: 0.3234, Adjusted R-squared: 0.3046
F-statistic: 17.21 on 1 and 36 DF, p-value: 0.0001954

Only one variable was found to be significant in Abbotsford's regression. The percentage of people commuting over an hour to work was negatively correlated with MWA, meaning that areas with a higher proportion of people commuting over 60 minutes had less accessibility overall.

Table 10: *T-tests for Abbotsford CMA*

Variable	*t*	*p*	Fifth Quintile Estimate	First Quintile Estimate
MWA	12.875	**<0.001**	611.3294	271.8475
Median Household Income	-0.845	0.412	78687.75	85644.38
Participation Rate	-0.291	0.778	66.6125	67.0875
Percentage Renter	2.236	**0.042**	32.09824	20.83634
Percentage Immigrant	5.430	**<0.001**	38.85887	14.50170
Percentage Indigenous	-1.485	0.160	4.387916	6.682902
Percentage Visible Minority	5.719	**<0.001**	55.18164	11.82674
Without Post-Secondary	4.011	**0.001**	61.79511	51.65407

italicized variable indicates Welch's t-test (unequal variance)

Four of the socioeconomic and demographic variables that were t-tested were found to have significant differences in their estimated means between the fifth and first quintiles of MWA in Abbotsford. The fifth quintile had a higher percentage of renters than the first, which broke trend with most of the other regions. The fifth quintile also had a significantly larger percentage of immigrants and visible minorities than the first quintile did. Finally, there were more people without post-secondary education in the fifth quintile than in the first.

Table 11: *Rank sum tests for Abbotsford CMA*

Variable	W	*p*
Population Density	52	**0.041**
Unemployment Rate	55	**0.018**
Long Commute	0	**<0.001**

All three of the variables put through the Wilcoxon rank sum tests were found to have significant differences in the rank sums of the variables. The population density, the unemployment rate, and the percentage of people commuting over an hour to work were all significantly different between the fifth and first quintiles of MWA.

4.3. *Calgary*

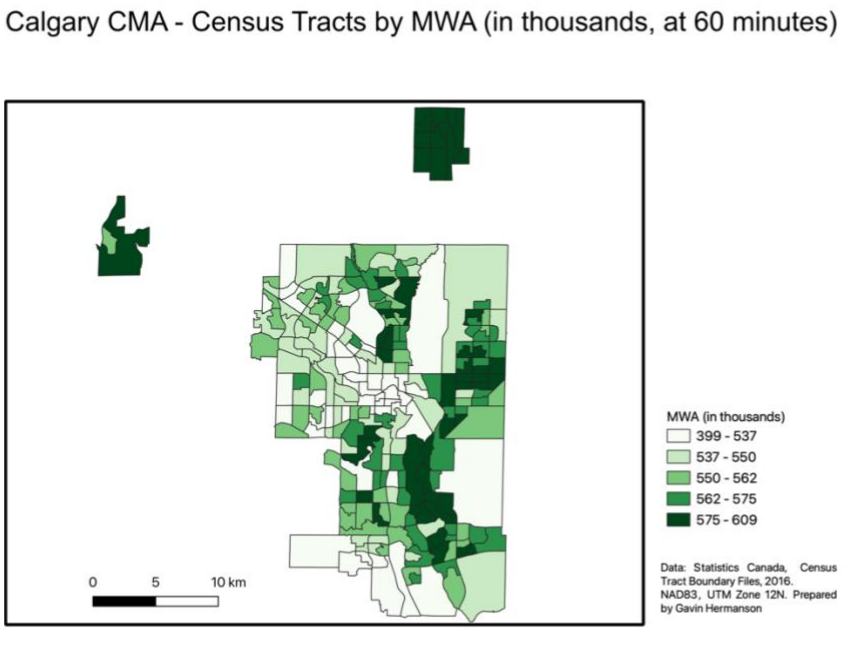

Figure 11: *Mode-share weighted accessibility (in thousands) by census tract, Calgary CMA*

Calgary's map of CTs by CMA at first appears to be a bit of a dog's breakfast. There is certainly a lower MWA cluster downtown Calgary, and along the Red Line LRT, but low MWA areas also exist in the South, Northeast, and Northwest. The high MWA areas were clustered in the Southeast along Highway 2 (and the Bow River), in East Calgary, south of the Airport, and in Airdrie, North of the city. Calgary had a moderately high degree of spatial autocorrelation, with a global Moran's I of 0.5871, a z-value of 16.4545, and an associated pseudo p-value of 0.001.

Table 12: *Regression model for Calgary CMA*

Predictor	Estimates	Confidence Interval	*p*
(Intercept)	527.04042	516.13411 – 537.94674	**<0.001**
Population Density	-0.00223	-0.00410 – -0.00036	**0.020**
Percentage Renter	-0.88687	-1.04154 – -0.73220	**<0.001**
Percentage Immigrant	-0.73909	-0.99612 – -0.48207	**<0.001**
Without Post-secondary	1.90664	1.65411 – 2.15916	**<0.001**

Residual standard error: 19.83 on 227 degrees of freedom (8 observations deleted due to missingness)
Multiple R-squared: 0.6277, Adjusted R-squared: 0.6212
F-statistic: 95.7 on 4 and 227 DF, p-value: < 2.2e-16

Again, in Calgary there is some skewness in the residuals of this model, skewing left as there were some outlying CTs with much lower MWA values than the rest of the region. Four variables were found to be significant in the regression: population density, percentage renter, percentage immigrant, and without post-secondary. Of these, only without post-secondary was positively correlated, where the model suggests an area with an increase of 1% of the percentage of people without post-secondary education would have 1907 more jobs accessible, all else remaining equal. Again, density was negatively correlated, at a similar magnitude to many of the other regions observed. The percentage of renters were negatively correlated with MWA, as were the percentage of immigrants, where an area with a 1% increase in each variable would have on average 887 and 739 fewer jobs accessible, respectively.

Table 13*: T-tests for Calgary CMA*

Variable	*t*	*p*	Fifth Quintile Estimate	First Quintile Estimate
MWA	14.154	**<0.001**	585.3339	505.8253
Population Density	-2.755	**0.008**	2426.721	3556.530
Median Household Income	1.4439	0.152	104291.7	95780.3
Unemployment Rate	-1.273	0.206	9.157447	9.597872
Participation Rate	-0.637	0.526	72.47447	73.34255
Percentage Renter	-4.586	**<0.001**	21.02703	38.54371
Percentage Immigrant	-2.209	**0.030**	23.86446	29.04556
Percentage Indigenous	3.859	**<0.001**	3.728679	2.451189
Percentage Visible Minority	-1.241	0.218	27.44049	31.92542
Without Post-secondary	9.027	**<0.001**	46.28197	30.94968
Long Commute	1.980	0.051	5.44	4.64

italicized variable indicates Welch's t-test (unequal variance)

Calgary's quintiles were sufficiently large to allow for t-tests to be performed on each variable and the MWA. While the MWA's were significantly different between the groups, the inequality of access is proportionally less than in any of the other large regions included in this research. The fifth quintile estimated mean MWA was 585,339 jobs, compared to 505,825 jobs in the first quintile. A meaningful difference was found in the population densities of the highest and lowest accessibility areas, with estimated means of 2426.72 people/km2 in the fifth quintile compared to 3556.53 in the first. While the difference is significant, it is proportionally much less than many of the other large Canadian regions examined here. The differences in median household incomes between the highest and lowest accessibility CTs was not statistically significant, the only large Canadian region to not have a significant difference in the median household income of the CTs in its fifth and first quintiles of accessibility. The unemployment rates and participation rates of these groups were also not significantly different. While the estimated differences in the percentage of renters was significantly different between the groups, the differences were less than in many of the other regions studied. Similarly, the estimated mean percentage of immigrants, while significantly different between the groups, was only estimated at just over a 5% difference, much less than in many other regions.

Uniquely, the estimated mean percentage of indigenous peoples was found to be significantly higher in the fifth quintile (3.73%) than the first quintile (2.45%), the only region studied to have this quality. The final significant difference of variables was found in the estimated mean percentage of people without postsecondary education, which was 46.28% in the fifth quintile and 30.95% in the first. The estimated mean percentage of visible minorities was not different between the groups, nor was the number of people commuting more than 60 minutes.

Calgary's t-tests reveal that the city has considerably less inequality of access compared to its peers. The differences in accessibility were moderate, the differences in income, unemployment and participation rates, and long commutes were not significant. In the variables that had significant differences, they were often slight, or favouring equity-deserving groups.

4.4. Edmonton

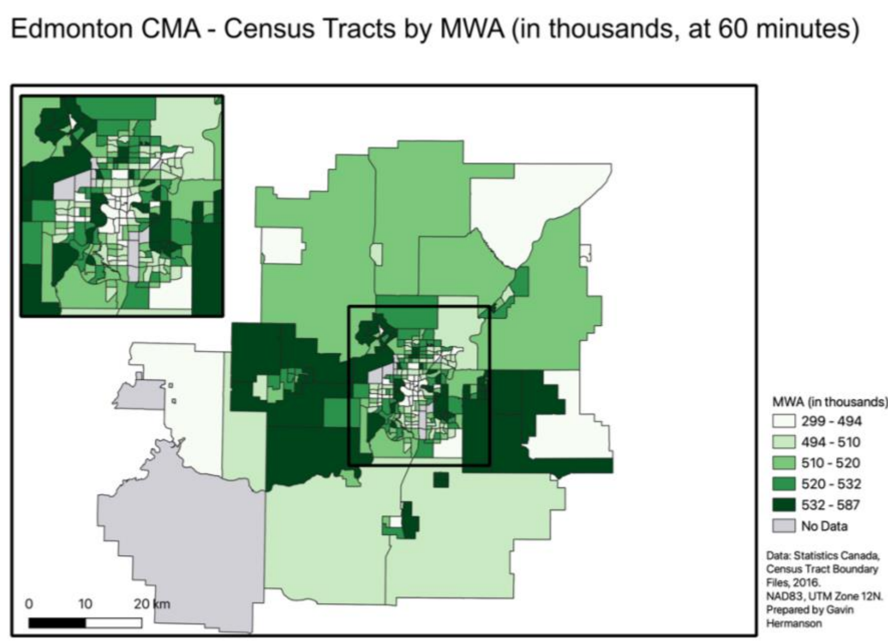

Figure 12: *Mode-share weighted accessibility (in thousands) by census tract, Edmonton CMA*

Edmonton's lowest MWA areas were primarily Downtown and around the University of Alberta South of Downtown, with lower MWA areas to the West and Northeast. The higher MWA areas tended to be dispersed, located in the suburbs to the North and South of the city, as well as some suburban and rural areas to the East and West. Edmonton's LRT seems to have had an effect on the MWA of the region, as the CTs near the LRT tended to have lower MWA values because of the higher transit mode-shares along the corridor. Interestingly, Edmonton's Valley Line LRT west and southeast extensions will be servicing the lower MWA areas in the West and Southeast. Edmonton had some degree of positive spatial autocorrelation, with a Moran's I of 0.2778, a z-value of 8.1408, and an associated pseudo p-value of 0.001.

Table 14: *Regression model for Edmonton CMA*

Predictor	Estimates	Confidence Interval	*p*
(Intercept)	483.33463	439.71868 – 526.95058	**<0.001**
Median Household Income	0.00027	0.00004 – 0.00050	**0.021**
Percentage Renter	-0.51088	-0.80518 – -0.21658	**0.001**
Without Post-secondary	1.00134	0.54930 – 1.45337	**<0.001**
Long Commute	-4.63771	-6.09584 – -3.17958	**<0.001**

Residual standard error: 25.2 on 251 degrees of freedom (16 observations deleted due to missingness)
Multiple R-squared: 0.3835, Adjusted R-squared: 0.3737
F-statistic: 39.04 on 4 and 251 DF, p-value: < 2.2e-16

Edmonton's regression contained four significant variables that together explained just over 38% of the variation of MWA. These variables were median household income, percentage renter, without post-secondary, and long commute. In this model, a $1 increase to the median household income would lead to an increase of 0.27 jobs accessible, all other variables holding equal. A one percentage increase in the percentage of renters was associated with a decrease in accessibility of 511 jobs. The percentage of people without post-secondary education was positively correlated, with a one percent increase being correlated with an increase in accessibility of 1,001 jobs. Finally, the percentage of people commuting over an hour was negatively correlated, with a one percent increase associated with a decrease in accessibility of 4,638 jobs.

Table 15: *T-tests for Edmonton CMA*

Variable	*t*	*p*	Fifth Quintile Estimate	First Quintile Estimate
MWA	12.992	**<0.001**	542.2822	466.1153
Population Density	-4.052	**<0.001**	1638.198	2993.263
Median Household Income	8.829	**<0.001**	119345.73	76432.83
Unemployment Rate	-2.415	**0.018**	8.001923	9.638462
Participation Rate	0.4285	0.669	71.57308	71.05769
Percentage Renter	-9.010	**<0.001**	15.31945	48.61383
Percentage Immigrant	-6.518	**<0.001**	14.32528	27.40500
Percentage Indigenous	-1.605	0.114	5.204920	8.149855
Percentage Visible Minority	-6.153	**<0.001**	14.09056	32.35229
Without Post-secondary	0.042	0.967	42.24914	42.17671
Long Commute	-4.062	**<0.001**	4.601756	6.719807

italicized variable indicates Welch's t-test (unequal variance)

All but three of Edmonton's variables had significant estimated mean differences between the fifth and first quintiles of MWA. The mean estimated population density in the fifth quintile was 1,638.20 people per square kilometre, compared to the denser first quintile estimate of 2,993.26 people per km2. The difference in the estimated means of median household incomes was notable as well, a difference of greater than $50,000 between the groups. The fifth quintile had an estimated mean of $119,345.73, compared to $76,432.83 in the first quintile. The unemployment rates were found to be significantly different as well, with an estimated mean of 8% in the fifth quintile, compared to 9.64% in the first quintile. The percentage of renters, unsurprisingly, was also different between the groups, with an estimated mean of 15.32% in the fifth quintile and 48.62% in the first quintile.

The percentage of immigrants was also found to be different, with 14.33% of the fifth quintile comprised of people born outside Canada, compared to 27.41% of the first quintile. The percentage of visible minorities was similarly different between the groups, with an estimated mean of 14.09% in the fifth quintile compared to 32.35% in the first quintile. Finally, the percentage of people commuting over an hour to work was different, with a mean of 4.60% of the people in the fifth quintile commuting over an hour and 6.72% of people in the first quintile.

While not quite significant, the estimated mean percentage of indigenous peoples in the fifth quintile was 5.2%, compared to 8.15% in the first quintile. Despite the differences in income and unemployment rate between the groups, the participation rates were virtually identical, at 71.57% in the fifth quintile and 71.06% in the first. The percentage of people without post-secondary education was also quite similar between the groups, with 42.25% of people not having post-secondary education in the fifth quintile and 42.18% of people in the first quintile.

4.5. Ottawa

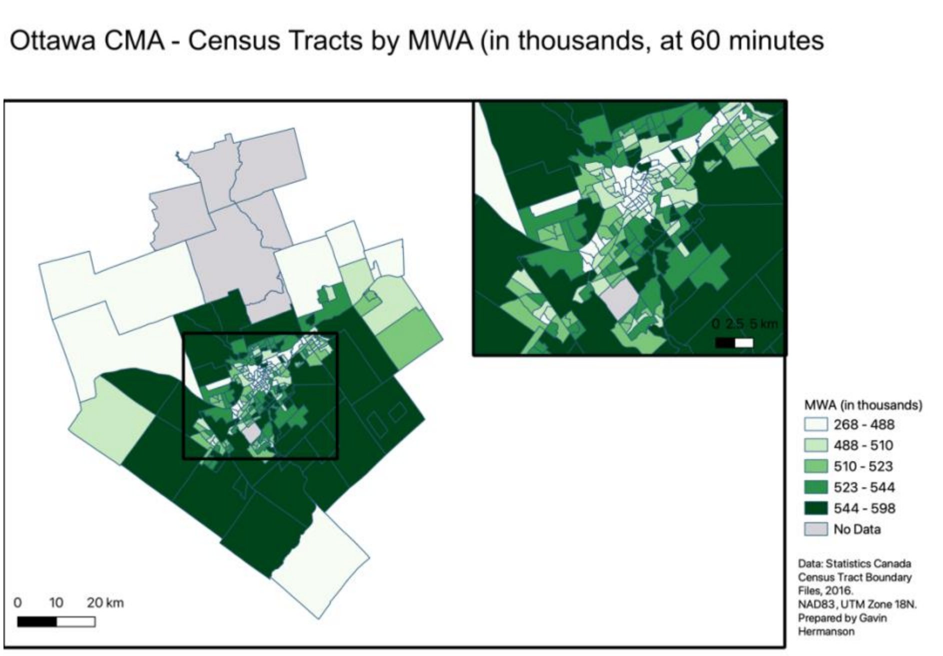

Figure 13: *Mode-share weighted accessibility (in thousands) by census tract, Ottawa CMA*

Ottawa's MWA values reflect the automobile-oriented nature of the region. The rural and suburban areas tended to have the greatest MWA values, which generally fell towards the centre of Ottawa. The West side of Urban Ottawa had some CTs with lower MWA values, coinciding with lower socioeconomic status areas and lower automobile mode-shares. This was also true to the East of downtown Ottawa, with lower MWA values and lower median household incomes. On the Quebec side of the border, a similar pattern emerges with lower MWA values in Hull, gradually rising with distance to Downtown. MWA in Ottawa had a high degree of spatial autocorrelation, with a global Moran's I of 0.6117, a z-value of 18.3776, and an associated pseudo p-value of 0.001.

__Table 16__: Regression model for Ottawa CMA

Predictor	Estimates	Confidence Interval	*p*
(Intercept)	386.11373	350.87825 – 421.34922	**<0.001**
Population Density	-0.00595	-0.00788 – -0.00402	**<0.001**
Median Household Income	0.00088	0.00070 – 0.00106	**<0.001**
Without Post-secondary	2.56290	2.01124 – 3.11456	**<0.001**
Long Commute	-4.32865	-5.51749 – -3.13981	**<0.001**

Residual standard error: 29.54 on 263 degrees of freedom (9 observations deleted due to missingness)
Multiple R-squared: 0.5087, Adjusted R-squared: 0.5013
F-statistic: 68.09 on 4 and 263 DF, p-value: < 2.2e-16

Ottawa's regression model again comes with the caveat of a non-normal distribution of the residuals. As with many of the regression models in this research the lower tail on the Q-Q plot exhibits downward deviance from the normal line, skewing to the left. Four variables were found to be significant: Population Density, Median Household Income, Without Post-secondary, and Long Commute. Density, again, was found to be negatively associated with MWA, with an estimate predicting that every increase of 1 person per square kilometre, would be correlated with 5.95 fewer mode-share weighted jobs accessible. Similar to other regions, Median Household Income was positively associated with MWA, as was Without Post-secondary. An increase of $1 of median household income was associated with an increase of 0.88 jobs accessible, while an increase of 1% of the percentage of people without post-secondary education was associated with 2,563 more jobs. Long Commute was found to be negatively associated, where an increase of 1% of the percentage of people commuting over an hour was associated with 4,329 fewer jobs accessible.

Table 17: *T-tests for Ottawa CMA*

Variable	*t*	*p*	Fifth Quintile Estimate	First Quintile Estimate
MWA	19.833	**<0.001**	562.6949	449.6138
Population Density	-6.679	**<0.001**	1053.524	4283.709
Median Household Income	7.287	**<0.001**	105900.69	66501.04
Unemployment Rate	-4.306	**0.018**	6.025926	8.279630
Participation Rate	-0.146	0.884	67.14444	67.34630
Percentage Renter	-9.722	**<0.001**	17.42857	55.62245
Percentage Immigrant	-2.629	**0.010**	15.84723	20.56341
Percentage Indigenous	-1.940	0.055	2.620360	3.189954
Percentage Visible Minority	-3.333	**0.001**	13.57436	21.36963
Without Post-secondary	1.485	0.141	37.98091	35.18141
Long Commute	-0.601	0.550	6.220173	6.640273

italicized variable indicates Welch's t-test (unequal variance)

Ottawa's quintiles were large enough for t-tests to be performed on the variables of the fifth and first quintiles. The estimated differences in mean MWA were significant; the estimated mean CT in the fifth quintile had 562,695 jobs accessible, while the mean CT in the first had 449,614. The contrasts in the population densities were also stark, with the estimated mean density of the fifth quintile at 1053.53 people per km2 in the fifth quintile, and 4283.71 in the first quintile, over four times greater. Median Household Incomes were found to be significantly different too, at $105,900.69 for the fifth quintile, compared to $66,501.04 for the first. The unemployment rates were found to be significantly different, though the participation rates between the two groups had no significant difference.

The disparity in the percentage of renters was quite large and significant, with the t-tests suggesting renters making up on average 17.43% of the households in CTs in the fifth quintile, but 55.62% of households in the first quintile. While the percentage of immigrants was also significantly different, the difference between the groups was less severe, 15.85% in the fifth quintile against 20.56% in the fifth quintile. Although Percentage Indigenous was not significant, it fell just outside of the 0.05 significance level, the fifth quintile had a slightly lower percentage of indigenous peoples than the first quintile. Differences in the percentage of visible minorities was also found to be significant. Neither the estimated means of Without Post-secondary nor Long Commute were significantly different in Ottawa, despite the regression identifying the Long Commute variable as significant.

4.6. Winnipeg

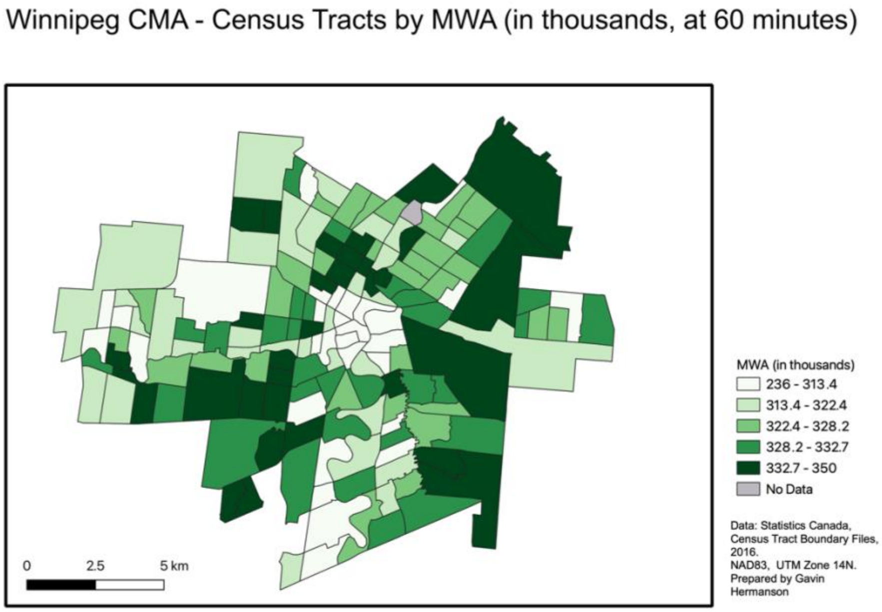

***Figure 14**: Mode-share weighted accessibility (in thousands) by census tract, Winnipeg CMA*

Winnipeg's CMA had the most dispersion of its high and low MWA CTs. While Winnipeg, consistent with other CMAs, had many of its lowest MWA values in its Downtown, it had low CMA values in other parts of the city, like the South, West, and some parts of the North. The high MWA CTs were quite dispersed, with the first two quintiles of MWA values being located around all areas of the city except for Downtown. Winnipeg did not have much spatial autocorrelation, with a global Moran's I of just 0.0577, with an associated z-value of 1.9663, and corresponding p-value of 0.043.

***Table 18**: Regression model for Winnipeg CMA*

Predictor	Estimates	Confidence Interval	*p*
(Intercept)	279.94108	270.03927 – 289.84288	**<0.001**
Median Household Income	0.00046	0.00036 – 0.00056	**<0.001**
Percentage Indigenous	0.77368	0.50830 – 1.03906	**<0.001**

Residual standard error: 11.52 on 149 degrees of freedom (2 observations deleted due to missingness)
Multiple R-squared: 0.3662, Adjusted R-squared: 0.3577
F-statistic: 43.05 on 2 and 149 DF, p-value: 1.75e-15

As is the case with many of these regressions, the residuals were not normal, skewing to the left. The same degree of caution should be used in interpreting the results of the regression. The only two variables that were found to be significant were Median Household Income and Percentage Indigenous, which were both found to be positively correlated and highly significant. The regression model suggests that for every dollar increase in median household income the MWA increases by 0.46 jobs, while for every percent increase in indigenous population, the MWA increases by 774 jobs.

Table 19: *T-tests for Winnipeg CMA*

Variable	*t*	*p*	Fifth Quintile Estimate	First Quintile Estimate
MWA	13.919	**<0.001**	338.8668	301.6309
Population Density	-2.745	**0.008**	2704.665	4331.884
Median Household Income	5.6061	**<0.001**	88047.68	50990.68
Unemployment Rate	-1.581	0.120	6.732258	8.135484
Participation Rate	1.3839	0.172	67.17097	64.06452
Percentage Renter	-6.881	**<0.001**	23.71712	61.41024
Percentage Immigrant	-1.738	0.087	22.38260	27.87983
Percentage Indigenous	-0.189	0.850	14.16568	14.65064
Percentage Visible Minority	-1.901	0.062	23.89	32.47
Without Post-secondary	-0.358	0.721	46.99617	47.98968
Long Commute	-2.124	**0.038**	3.562113	4.643336

italicized variable indicates Welch's t-test (unequal variance)

Winnipeg's quintiles were sufficiently large enough for t-tests to be run on the variables. While the MWAs of the first and fifth quintiles were different, they were proportionally less unequal than many of the large CMAs. Population densities of the two quintiles were significantly different, at 2704.67 people per km2 in the fifth quintile and 4331.88 in the first quintile. These differences again, while not insignificant, were proportionally much smaller than many of the other large CMAs. Median household incomes of the two groups were also different, with an estimated mean of $88,047.68 of the fifth quintile, compared to $50,990.68 of the first quintile. While the unemployment rates and participation rates were not significantly different, the estimated means suggest that the unemployment rate is lower and participation rate is higher in the CTs of the fifth MWA quintile. The percentage of renters was significantly different between the groups, (23.72% vs 61.41%). The final significant variable was long commute, which had a significantly higher estimated first quintile mean.

Despite the percentage of indigenous people being significant in the regression, the means of the first and fifth quintiles were not significantly different. When this seeming contradiction was investigated further, a bifurcation was revealed within the fifth quintile. There were many higher MWA CTs with a high percentage of indigenous people, while the other of the highest MWA CTs had a very low indigenous population. The highly indigenous CTs tended to have higher MWAs, leading to the positive regression coefficient, but the cluster of high MWA CTs with very low indigenous population kept the estimated mean of the fifth quintile similar to that of the first.

4.7. Quebec City

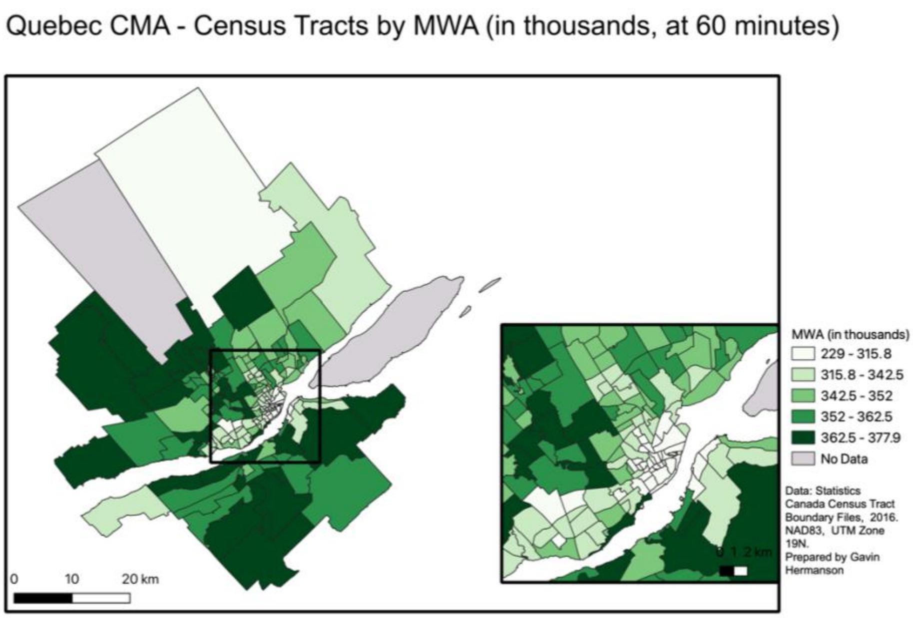

***Figure 15**: Mode-share weighted accessibility (in thousands) by census tract, Quebec CMA*

Quebec's low MWA values were primarily contained to Old Quebec and the surrounding neighbourhoods. These areas had a much higher proportion of active modes of travel as well as transit, and correspondingly much lower automobile mode-shares. The south shore (Levis) generally had a higher MWA values, except for the older parts of the city, which were further from the bridge connections to Quebec City and its jobs and had higher active and transit mode-shares in their own right. The suburbs to the North and West of Quebec City tended to have high MWA values as well, as they had high auto mode-shares as well as good access to the south shore. Quebec had a moderately high amount of spatial autocorrelation, with a global Moran's I of 0.4757. On a randomization of 999 permutations, a z-value of 11.0482 and associated pseudo p-value of 0.001 were returned.

Table 20*: Regression model of Quebec CMA*

Predictor	Estimates	Confidence Interval	*p*
(Intercept)	207.16163	181.78674 – 232.53653	**<0.001**
Population Density	-0.00221	-0.00345 – -0.00097	**0.001**
Median Household Income	0.00101	0.00081 – 0.00120	**<0.001**
Without Post-secondary	2.01728	1.63328 – 2.40127	**<0.001**

Residual standard error: 19.45 on 175 degrees of freedom (2 observations deleted due to missingness)
Multiple R-squared: 0.639, Adjusted R-squared: 0.6328
F-statistic: 103.3 on 3 and 175 DF, p-value: < 2.2e-16

Quebec's regression model needed just three independent variables to explain 63.9% of the variation of the data: Population Density, Median Household Income, and Without Post-secondary. The population density was negatively correlated with MWA, the median household income was positively correlated, as was the percentage of people without post-secondary education. In this regression an increase of 1 person per square kilometre would be associated with a decrease of 2.21 mode-share weighted jobs, an increase of median household income of $1 would be associated with an increase of 1.01 jobs, and an increase of 1% to the percentage of people without post-secondary would translate to an increase of 2017 jobs.

Table 21*: T-test for Quebec CMA*

Variable	*t*	*p*	Fifth Quintile Estimate	First Quintile Estimate
MWA	10.522	**<0.001**	366.6718	275.2318
Population Density	-6.538	**<0.001**	916.1028	5982.8861
Median Household Income	10.553	**<0.001**	83113.97	48246.83
Unemployment Rate	-5.204	**<0.001**	3.738889	6.047222
Participation Rate	4.047	**<0.001**	71.75000	66.05833
Percentage Renter	-11.121	**<0.001**	22.65940	65.45497
Percentage Immigrant	-7.708	**<0.001**	3.411234	9.442649
Percentage Indigenous	-0.597	0.553	1.287829	1.404795
Percentage Visible Minority	-5.439	**<0.001**	2.665508	7.814300
Without Post-secondary	1.094	0.279	32.64975	30.47772
Long Commute	0.770	0.444	3.353437	3.122364

italicized variable indicates Welch's t-test (unequal variance)

Quebec's first and fifth quintiles have significantly different mean MWA's, with the fifth quintile's 366.67 over 30% greater than the first quintile's reading of 275.23. The population densities were significantly different as well, 916.10 in the fifth quintile, compared to 5982.89 in the first. Continuing with the general trend of an economic component to the distribution of access, the fifth quintile had an estimated mean median household income of $83,113.97, significantly higher than the first quintile's $48,246.83.

The unemployment and participation rates were both significantly different, with the fifth quintile's estimated mean unemployment rate sitting at 3.74%, while the first quintile had an estimated mean of 6.05%. The fifth quintile similarly enjoyed a higher estimated mean participation rate (71.75%) than the first quintile (66.06%) did. The percentage of renters in the groups was also estimated to be significantly different, 22.65% in the fifth quintile and 65.45% in the first, nearly three times higher.

The percentage of immigrants and visible minorities were both significant, with the fifth quintile having a much smaller proportion of each (3.41% and 2.67% respectively) than the first quintile (9.44% and 7.81%). Percentage Indigenous, Without Post-secondary, and Long Commute were not significantly different between the two groups in Quebec City.

4.8. London

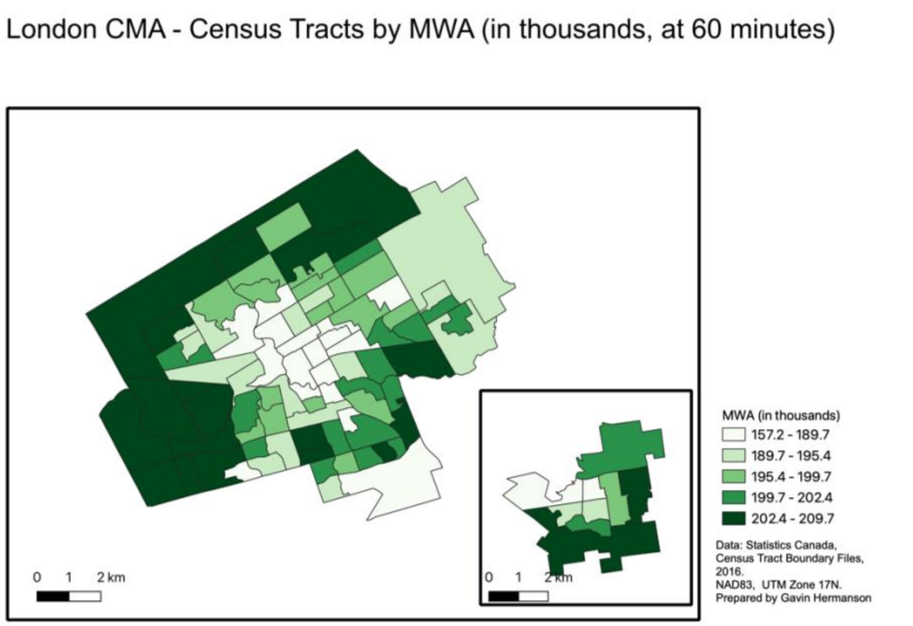

Figure 16: *Mode-share weighted accessibility (in thousands) by census tract, London CMA*

London's census tracts had a pretty clear bifurcation between the high and low MWA areas. Downtown London, as well as some CTs just west and south of Downtown had the lowest MWA values, typically in the bottom two quintiles, while the higher MWA areas tended to be located in the suburbs in the North and West, as well as pockets of the South. St. Thomas, a town located a twenty-minute drive South of London, and included in its CMA had CTs in each of the quintiles. London CMA's MWA results by CT are heavily influenced by the mode-shares of the underlying CTs, as the areas with a higher proportion of active modes and transit had lower MWA values. London had a moderate, positive degree of spatial autocorrelation, with a global Moran's I value of 0.4139, with a z-value of 7.0434, and an associated pseudo p-value of 0.001.

Table 22: *Regression model for London CMA*

Predictor	Estimates	Confidence Interval	*p*
(Intercept)	238.43011	221.23961 – 255.62060	**<0.001**
Participation Rate	-0.58515	-0.83488 – -0.33543	**<0.001**
Percentage Renter	-0.34757	-0.41998 – -0.27516	**<0.001**
Long Commute	1.37379	0.29683 – 2.45076	**0.013**

Residual standard error: 6.9 on 88 degrees of freedom
Multiple R-squared: 0.5185, Adjusted R-squared: 0.5021
F-statistic: 31.59 on 3 and 88 DF, p-value: 5.946e-14

London's regression model needed just three variables to explain 51.85% of the variation of MWA: The participation rate, the percentage of renters, and the percentage of people commuting over an hour to work. The participation rate and percentage renters were both negatively correlated, while the percentage of people commuting over an hour was positively correlated. This model suggests that every one percent increase in the participation rate is associated with a decrease of 585 jobs accessible, a one percent decrease in the percentage of renters is associated with 348 fewer jobs accessible, and a one percent increase in the percentage of people commuting over an hour is associated with 1,374 more jobs accessible.

Table 23: *T-tests for London CMA*

Variable	*t*	*p*	Fifth Quintile Estimate	First Quintile Estimate
MWA	11.776	**<0.001**	204.5430	179.4753
Population Density	-0.649	0.520	1872.805	2130.868
Percentage Renter	-7.909	**<0.001**	16.80931	57.85939
Percentage Immigrant	1.128	0.267	20.56612	17.73103
Percentage Indigenous	-3.299	**0.003**	1.518576	2.732138
Percentage Visible Minority	-0.743	0.463	15.36824	17.95312
Long Commute	-1.201	0.238	4.504201	4.960965

italicized variable indicates Welch's t-test (unequal variance)

London's quintiles were not sufficiently large for t-tests to be performed on the non-normal data. As a result, t-tests were run for the 6 variables that were normal. While the estimated mean MWA's were significantly different, the proportional differences were not as pronounced, in contrast to what many of the large regions exhibited. The population densities of the first and fifth quintiles, breaking with the trend of most regions examined in this research, were not significantly different, with an estimated mean of 1,872.81 people per km2 in the fifth quintile and 2,130.87 in the first quintile. The percentage of renters in the two groups was significantly different, 16.81% in the fifth quintile and 57.86% in the first quintile. The percentage of indigenous peoples was the other significant variable, comprising an estimated mean of 1.52% of the population in the fifth quintile and 2.73% in the first quintile. The other variables were not significantly different.

Table 24: *Rank sum tests for London CMA*

Variable	W	*p*
Median Household Income	167	0.7043
Unemployment Rate	6	**<0.001**
Participation Rate	173.5	0.8495
Without Post-secondary	136	0.1989

The Wilcoxon rank sum tests were performed on the remaining variables, of which only the unemployment rate was found to have significantly different rank sums between the two quintiles.

4.9. <u>Halifax</u>

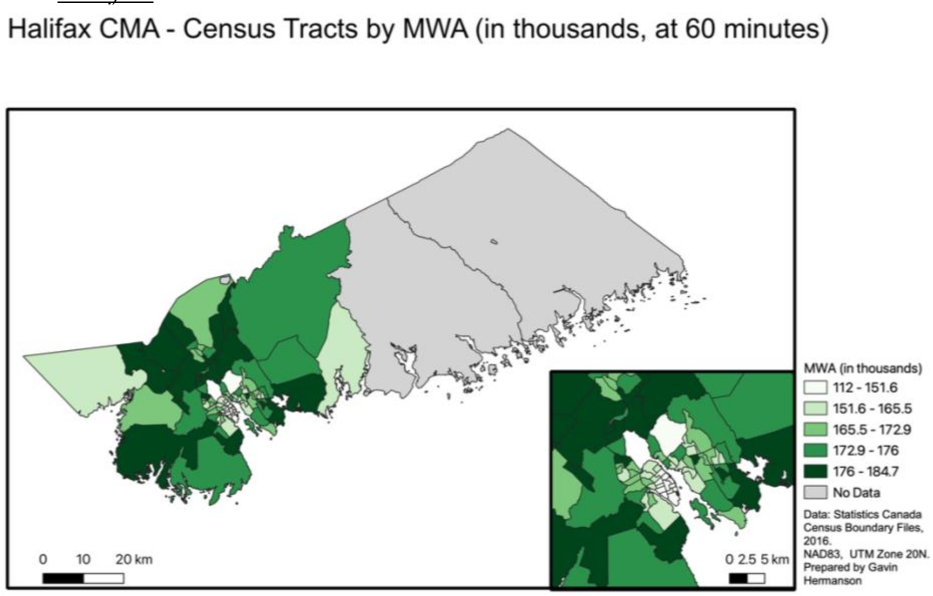

Figure 17: *Mode-share weighted accessibility (in thousands) by census tract, Halifax CMA*

Halifax's CMA had the typical distribution of lower MWA CTs being located in the core of the city and higher MWA areas being located in the suburbs. There were, however, some 2nd and 3rd quintile CTs located in the rural areas around Halifax. These areas had lower MWA values because of the marginally lower accessibility to employment by automobile. While a CT around Bedford may be able to access all the jobs in the region by automobile in an hour, other CTs that were further away from the core could not.

Halifax had a moderately high amount of spatial autocorrelation in its MWA, as it had a global Moran's I of 0.5529. On 999 randomizations, a z-value of 9.155, and associated pseudo p-value of 0.001 were returned.

Table 25: *Regression model for Halifax CMA*

Predictor	Estimates	Confidence Interval	*p*
(Intercept)	184.35898	175.37519 – 193.34277	**<0.001**
Population Density	-0.00280	-0.00444 – -0.00117	**0.001**
Unemployment Rate	-2.47184	-3.65609 – -1.28759	**<0.001**
Percentage Renter	-0.19106	-0.32041 – -0.06171	**0.004**
Percentage Immigrant	0.63966	0.14074 – 1.13858	**0.013**
Percentage Indigenous	1.60721	0.44961 – 2.76482	**0.007**

Residual standard error: 10.35 on 85 degrees of freedom (7 observations deleted due to missingness)
Multiple R-squared: 0.5897, Adjusted R-squared: 0.5655
F-statistic: 24.43 on 5 and 85 DF, p-value: 3.648e-15

In Halifax five of the variables were found to be significant and together explained 58.97% of the variation of MWA in the region. Three of the variables were negatively correlated with MWA: population density, unemployment rate, and percentage renter. Two were positively correlated, percentage immigrant and percentage indigenous. The unemployment rate had the largest effect on the model, where a one percent increase in the unemployment rate was correlated with a decrease in accessibility of 2,472 mode-share weighted jobs. A one percent increase in the percentage of renters was correlated with a decrease of 191 jobs accessible in this model. A one percent increase in the percentage of immigrants was associated with an increase in accessibility of 640 jobs, while a one percent increase in the percentage of indigenous peoples was correlated with an increase in MWA of 1,607 jobs.

Table 26: *T-tests for Halifax CMA*

Variable	*t*	*p*	Fifth Quintile Estimate	First Quintile Estimate
MWA	11.899	**<0.001**	179.3604	139.9058
Participation Rate	1.753	0.090	69.64211	66.15789
Percentage Indigenous	-0.551	0.587	3.335957	3.620853
Long Commute	0.301	0.765	4.410761	4.216276

italicized variable indicates Welch's t-test (unequal variance)

Due to the small sample sizes and non-normal data, only three of the variables had t-tests run, and none of them suggested significant differences in the means between the fifth and first quintiles. While the estimated mean participation rates were slightly different, they were not significantly so. The percentage indigenous and percentage commuting over an hour were virtually identical. The lack of meaningful difference in the percentage of indigenous peoples between the groups is incongruent with the regression model, which had indicated that we would expect to see a higher proportion of indigenous peoples in the higher MWA areas because of its positive correlation.

Table 27: *Rank sum tests for Halifax CMA*

Variable	W	*p*
Population Density	41	**<0.001**
Median Household Income	333	**<0.001**
Unemployment Rate	33	**<0.001**
Percentage Renter	19	**<0.001**
Percentage Immigrant	107	**0.033**
Percentage Visible Minority	56	**<0.001**
Without Post-secondary	204	0.5019

The Wilcoxon rank sum tests were performed on the remaining variables, where six of the seven were found to have significantly different rank sums between the two quintiles. These were population density, median household income, unemployment rate, percentage renter, percentage immigrant, and percentage visible minority. Only the percentage of people without post-secondary education was not found to be significantly different.

4.10. *Windsor*

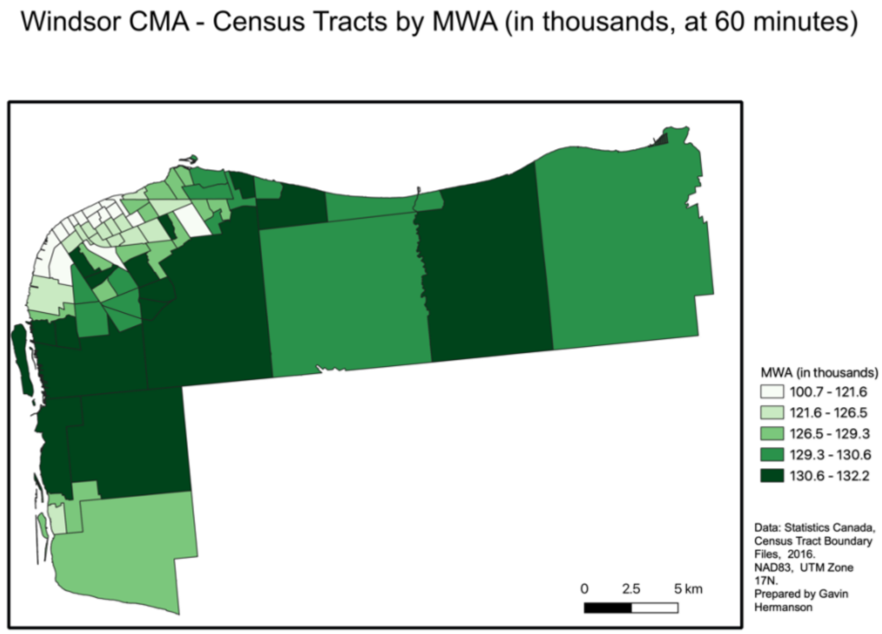

Figure 18: *Mode-share weighted accessibility (in thousands) by census tract, Windsor CMA*

Windsor's MWA values were sharply divided between the older, urban city, and newer suburbs and rural areas. Along the Detroit River, near the industrial lands, downtown, and connections to Detroit the CTs had the highest proportions of transit use and active mode-shares, as well asl the lowest MWA values. Conversely, the newer suburban parts of Windsor in the South and East had higher MWA values. Windsor had a moderately high degree of spatial autocorrelation, with a global Moran's I of 0.5344, a z-value of 7.8412, and a pseudo p-value of 0.001.

Table 28: *Regression model for Windsor CMA*

Predictor	Estimates	Confidence Interval	*p*
(Intercept)	137.40635	135.38746 – 139.42523	**<0.001**
Unemployment Rate	-0.86709	-1.08418 – -0.65000	**<0.001**
Long Commute	-1.93760	-2.46499 – -1.41021	**<0.001**

Residual standard error: 3.568 on 70 degrees of freedom
Multiple R-squared: 0.7124, Adjusted R-squared: 0.7041
F-statistic: 86.68 on 2 and 70 DF, p-value: < 2.2e-16

Incredibly, in Windsor just two variables explain 71.24% of the variation in MWA: the unemployment rate and the percentage of people commuting over an hour, both of which were negatively correlated with MWA. The unemployment rate coefficient suggests that a 1 percent increase to the unemployment rate is correlated with a decrease in access of 867 jobs, while an increase of one percent to the percentage of people commuting over an hour is correlated with a decrease in access of 1938 jobs.

***Table 29**: T-tests for Windsor CMA*

Variable	*t*	*p*	Fifth Quintile Estimate	First Quintile Estimate
MWA	10.272	**<0.001**	131.3045	115.0603
Median Household Income	10.514	**<0.001**	96823.87	36594.80
Unemployment Rate	-4.59	**<0.001**	6.006667	13.080000
Percentage Immigrant	-0.782	0.441	22.75890	26.21503
Without Post-secondary	-4.323	**<0.001**	43.52710	55.52683

italicized variable indicates Welch's t-test (unequal variance)

Windsor had four variables with normal distributions in each of the quintiles, allowing for t-tests to be performed. The median household income was significantly different, and proportionally more unequal than any other region, with estimated means of $96,823.87 for the fifth quintile and $36,594.80 for the first quintile. The unemployment rates were also significantly different, and proportionally more unequal than other regions. The fifth quintile had an estimated mean unemployment rate of 6.01%, compared to 13.08% in the first quintile, over twice as high. The percentage of people without post-secondary education also differed between the quintiles, suggesting that the fifth quintile had a more highly educated population.

***Table 30**: Rank sum tests for Windsor CMA*

Variable	W	*p*
Population Density	52	**0.01282**
Participation Rate	380.5	**0.005104**
Percentage Renter	4	**<0.001**
Percentage Immigrant	92	0.4068
Percentage Indigenous	14	**<0.001**
Percentage Visible Minority	63	**0.04211**
Long Commute	2	**<0.001**

The Wilcoxon rank sum tests were performed on the remaining variables, where population density, participation rate, percentage renter, percentage indigenous, percentage visible minority, and long commute were all found to have significantly different rank sums.

4.11. Saskatoon

Saskatoon CMA - Census Tracts by MWA (in thousands, at 60 minutes)

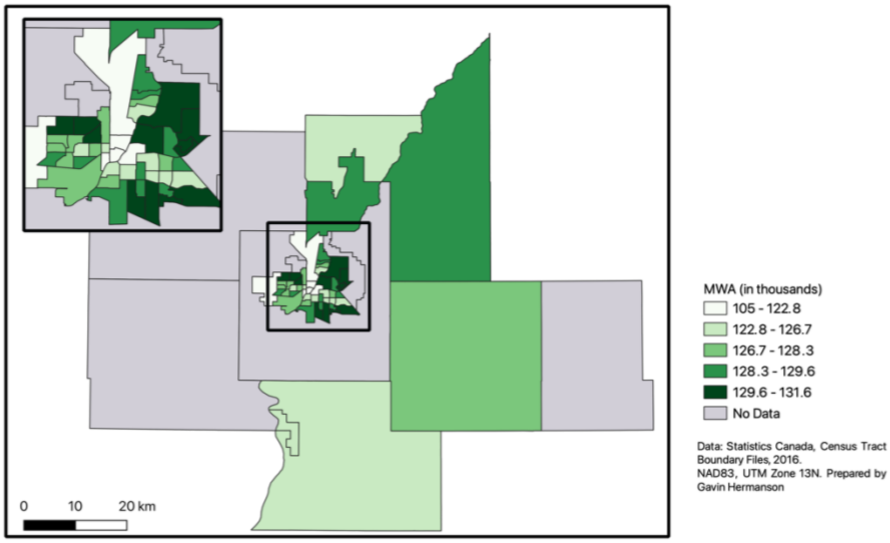

Figure 19: *Mode-share weighted accessibility (in thousands) by census tract, Saskatoon CMA*

The quintiles of Saskatoon's CTs were fairly evenly dispersed around the region. There was very little difference in the MWA values of most of the CTs, with 80% of all CTs falling within 122,800 jobs and 131,630 jobs. The lowest quintile of MWA values came Downtown Saskatoon and the West end of the city, while the higher values tended to be located in the Northeast and Southeast. Saskatoon's MWA values had a low amount of spatial autocorrelation, with a global Moran's I of 0.1646. On 999 permutations the z-value was 2.4738, giving it a pseudo p-value of 0.03.

Table 31: *Regression model for Saskatoon CMA*

Predictor	Estimates	Confidence Interval	*p*
(Intercept)	126.82892	118.26224 – 135.39559	**<0.001**
Percentage Renter	-0.20309	-0.28961 – -0.11658	**<0.001**
Percentage Indigenous	-0.17974	-0.32571 – -0.03377	**0.017**
Without Post-secondary	0.38237	0.15662 – 0.60813	**0.001**
Long Commute	-2.94719	-3.88398 – -2.01041	**<0.001**

Residual standard error: 4.762 on 49 degrees of freedom (5 observations deleted due to missingness)
Multiple R-squared: 0.5003, Adjusted R-squared: 0.4595
F-statistic: 12.26 on 4 and 49 DF, p-value: 5.511e-07

Saskatoon's regression found four significant variables: percentage renter, percentage indigenous, without post-secondary, and long commute. Of these, only without post-secondary was positively correlated. The coefficients estimate that a one percent increase of the percentage of renters would be associated with a decrease in accessibility of 203 jobs, a one percent increase in the percentage of indigenous peoples would be associated with a decrease in accessibility of 180 jobs, and an increase in one percent of the percent of people commuting over an hour would lead to a decrease in access of 2972 jobs. A one percent increase to the percentage of people without post-secondary education would be associated with an increase in accessibility of 382 jobs.

***Table 32**: T-tests for Saskatoon CMA*

Variable	*t*	*p*	Fifth Quintile Estimate	First Quintile Estimate
MWA	4.680	**<0.001**	130.5889	116.9282
Population Density	1.894	0.072	2188.764	1366.791
Median Household Income	3.039	**0.006**	100848.82	70048.82
Participation Rate	1.981	0.062	74.50000	69.01818
Percentage Renter	-2.738	**0.013**	20.94392	42.71826
Percentage Immigrant	0.581	0.570	17.69039	16.00324
Percentage Visible Minority	0.824	0.424	20.71205	17.47379
Without Post-secondary	- 0.231	0.820	41.11697	41.85123

italicized variable indicates Welch's t-test (unequal variance)

T-tests were performed on the normally distributed variables of the fifth and first quintiles of MWA. The estimated mean MWA of the two quintiles, while significantly different, was smaller than many of the regions examined. The population density, while outside the cusp of significance, suggested the fifth quintile had a higher mean population density, contrary to the other CMAs researched. The estimated mean median household income was higher in the fifth quintile ($100,848.82) than the first quintile ($70,048.82). While the participation rate was also just outside the 0.05 significance level, it suggested a higher participation rate in the fifth quintile than the first. Consistent with the findings of other CMAs, the percentage of renters was lower in the fifth quintile (20.94%) than the first quintile (42.72%). The percentage of immigrants, visible minorities, and people without post-secondary education were all not significantly different between the groups.

__Table 33__: Rank sum tests for Saskatoon CMA

Variable	W	*p*
Unemployment Rate	44.5	0.3081
Percentage Indigenous	43	0.2643
Long Commute	57	0.8438

Wilcoxon rank sum tests performed on the remaining variables did not find significant differences in the rank sums of the groups for the unemployment rate, percentage indigenous, or long commute.

4.12. Victoria

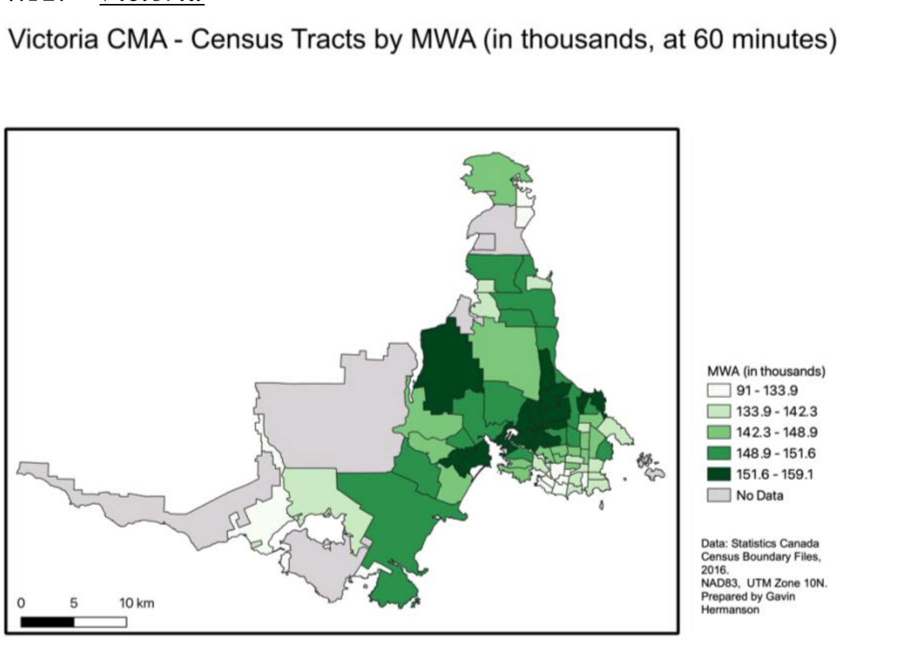

***Figure 20**: Mode-share weighted accessibility (in thousands) by census tract, Victoria CMA*

Victoria's CMA had some interesting results, largely shaped by its unique geography. Downtown Victoria and James Bay, with their high transit and active mode-shares had the lowest MWA values in the region. Parts of Oak Bay and Saanich which had slightly less automobile use for the commute to work were also in the 2nd and 3rd quintiles. The highest MWA areas were in Saanich, View Royal, and Langford, which were positioned near the highway, relatively centrally in the region, and had higher automobile mode-shares. The northern tip of the Saanich peninsula, as well as the West end of the region, out in Sooke, were void of CTs in the top two quintiles as the travel times to the other ends of the region, even by automobile, were greater than an hour. Victoria's MWA by CT had a moderate amount of spatial autocorrelation, with a global Moran's I of 0.2401. On 999 permutations a z-value of 3.6737 was returned, with an associated pseudo p-value of 0.006.

Table 34*: Regression model for Victoria CMA*

Predictor	Estimates	Confidence Interval	*p*
(Intercept)	102.60631	88.93399 – 116.27863	**<0.001**
Median Household Income	0.00023	0.00015 – 0.00032	**<0.001**
Unemployment Rate	-1.12847	-1.92423 – -0.33271	**0.006**
Percentage Visible Minority	0.30615	0.10127 – 0.51103	**0.004**
Without Post-secondary	0.71314	0.47121 – 0.95507	**<0.001**
Long Commute	-0.48618	-0.93777 – -0.03459	**0.035**

Residual standard error: 6.662 on 67 degrees of freedom (5 observations deleted due to missingness)
Multiple R-squared: 0.5218, Adjusted R-squared: 0.4861
F-statistic: 14.62 on 5 and 67 DF, p-value: 1.116e-09

Just over 52% of the variation in MWA was explained by the five variables in the regression. The median household income of a CT, its percentage of visible minorities, and percentage of people without post-secondary education were all positively correlated with MWA. The unemployment rate and percentage of people commuting over an hour were negatively correlated.

Table 35*: T-tests for Victoria CMA*

Variable	*t*	*p*	Fifth Quintile Estimate	First Quintile Estimate
MWA	15.753	**<0.001**	154.9375	129.8626
Population Density	-2.147	**0.045**	1833.287	3346.200
Median Household Income	2.839	**0.008**	79941.80	60653.87
Participation Rate	1.255	0.220	64.74000	61.00667
Percentage Immigrant	-0.909	0.372	18.11054	20.05592
Percentage Visible Minority	1.947	0.061	16.02632	10.48322
Without Post-secondary	1.724	0.096	44.24160	38.22434

italicized variable indicates Welch's t-test (unequal variance)

T-tests were performed on the six normally distributed variables in Victoria. Significant differences in estimated means were found for the population density and median household income. The estimated mean population density in the fifth quintile of accessibility was 1833.29 people per square kilometre, compared to 3346.2 people per square km in the first quintile. The mean median household income was estimated to be $79941.80 in the fifth quintile compared to $60,653.87 in the first quintile. While the percentage of visible minorities was just outside the 0.05 significance level, it suggested that the fifth quintile has a higher percentage of visible minorities than the first quintile. The other variables did not have estimated means that were significantly different.

Table 36*: Rank sum tests for Victoria CMA*

Variable	W	*p*
Unemployment Rate	76.5	0.1403
Percentage Renter	77	0.1466
Percentage Indigenous	112	1
Long Commute	102	0.6783

The Wilcoxon rank sum tests performed on the remaining variables did not find any significant differences in the rank sums of the variables.

4.13. Barrie

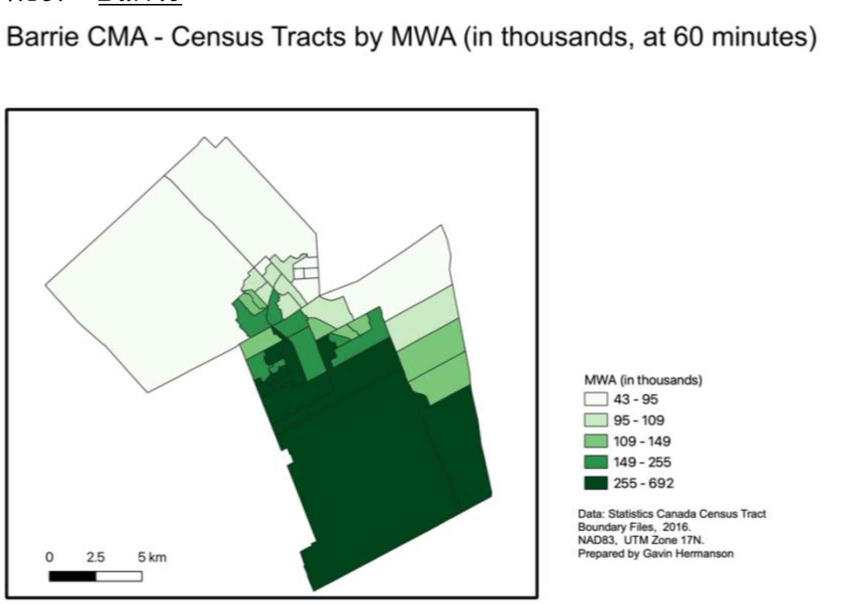

Figure 21*: Mode-share weighted accessibility (in thousands) by census tract, Barrie CMA*

It appears as if Barrie's MWA values were impacted by its proximity to Toronto and the high number of jobs in Toronto's CMA more than any other factor. The CTs in the South of Barrie's CMA, by Highway 400 had the highest MWA values, as they could reach more of the employment-rich CTs in the GTA in an hour by automobile than the CTs in Barrie proper or to the North. The CTs in Barrie's core had marginally higher transit and active mode-shares as well, further lowering their MWA relative to the more auto-oriented areas in the South. Barrie had a moderate degree of spatial autocorrelation, with a global Moran's I of 0.3975, a z-value of 5.0677, and an associated pseudo p-value of 0.001.

Table 37*: Regression model for Barrie CMA*

Predictor	Estimates	Confidence Interval	*p*
(Intercept)	263.01924	199.10210 – 326.93637	**<0.001**
Population Density	-0.04402	-0.07251 – -0.01553	**0.003**

Residual standard error: 105.4 on 36 degrees of freedom (4 observations deleted due to missingness)
Multiple R-squared: 0.2143, Adjusted R-squared: 0.1925
F-statistic: 9.818 on 1 and 36 DF, p-value: 0.003429

In creating Barrie's regression model, only one variable, population density, was found to be significant. The coefficient of population density was negatively correlated with MWA, although it should be noted the confidence interval does not exclude a positive correlation with MWA, lowering the confidence of the prediction.

Table 38*: T-tests for Barrie CMA*

Variable	*t*	*p*	Fifth Quintile Estimate	First Quintile Estimate
MWA	12.64	**<0.001**	715.3340	437.6126
Median Household Income	1.9569	0.071	88448.0	74584.5
Percentage Renter	-2.128	0.052	20.13081	32.99955
Percentage Visible Minority	0.768	0.455	8.056666	9.929580
Percentage Immigrant	1.228	0.240	14.38057	13.00832
Percentage Indigenous	-2.349	**0.034**	2.962412	4.677942
Without Post-secondary	2.238	**0.042**	51.76314	46.41074

italicized variable indicates Welch's t-test (unequal variance)

The t-tests of the first and fifth quintiles of MWA in Barrie found a significant difference in just two of the variables, percentage indigenous, and without post-secondary. The fifth quintile had a lower estimated mean for the percentage of indigenous peoples and a higher estimated mean percent of people without post-secondary education. While the median household income and percentage renter were just outside of the 0.05 significance level, they suggested a wealthier fifth quintile with fewer renters, consistent with the other regions in this research.

Table 39: *Rank sum tests for Barrie CMA*

Variable	W	*p*
Population Density	54	**0.02395**
Unemployment Rate	40	0.4302
Participation Rate	15	0.0829
Long Commute	15	0.08312

The Wilcoxon rank sum test for the remaining variables did find a meaningful difference in the rank sums of the population densities of the fifth and first quintiles, providing evidence that the regression's identification of population density as significant is likely meaningful.

4.14. Brantford

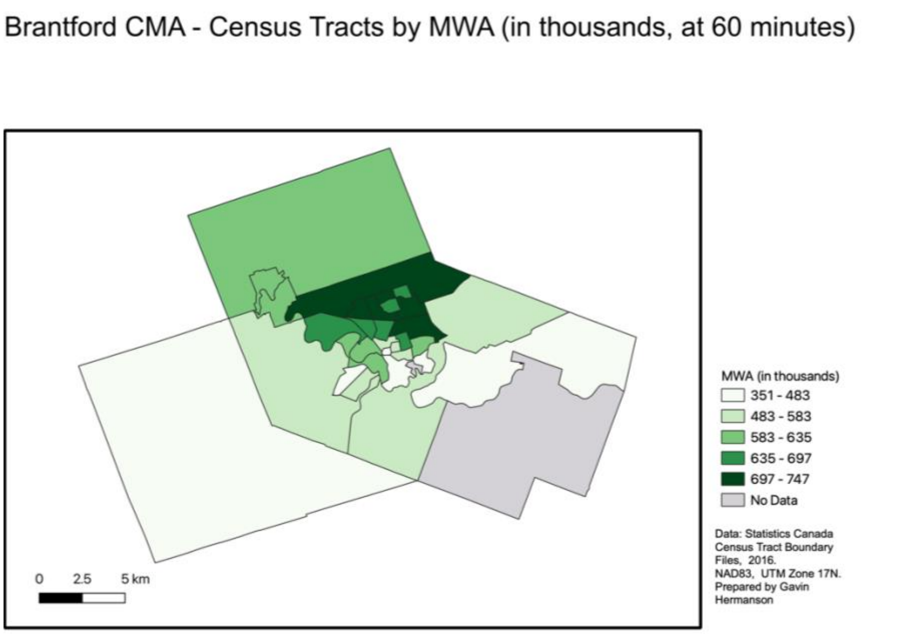

Figure 22: *Mode-share weighted accessibility (in thousands) by census tract, Brantford CMA*

Brantford's CTs, similar to Barrie, had MWA values influenced by a highway (Highway 403) connecting and providing high mobility to Hamilton, Toronto, and Niagara and the higher number of jobs in these regions. Brantford's MWA decreased moving Southwest, away from the employment centres in Toronto and Hamilton. Brantford has a moderate amount of spatial autocorrelation, with a global Moran's I of 0.4059, with a z-value of 4.5555, and a pseudo p-value of 0.001.

Table 40*: Regression model for Brantford CMA*

Predictor	Estimates	Confidence Interval	*p*
(Intercept)	1318.96832	716.33960 – 1921.59704	**<0.001**
Participation Rate	-9.79800	-18.53905 – -1.05694	**0.029**
Percentage Indigenous	-16.20884	-28.86452 – -3.55317	**0.014**

Residual standard error: 94.98 on 26 degrees of freedom (1 observation deleted due to missingness)
Multiple R-squared: 0.2419, Adjusted R-squared: 0.1836
F-statistic: 4.148 on 2 and 26 DF, p-value: 0.02732

In the creation of Brantford's regression model, it was found that only two variables were significantly correlated to MWA: the participation rate and the percentage of indigenous peoples. Both of these relationships with MWA were negatively correlated. A one percent increase in the participation rate was associated with a decrease in accessibility of 9,798 jobs, while a one percent increase in the percentage of indigenous peoples was associated with a decrease in accessibility of 16,209 jobs.

Table 41*: T-tests for Brantford CMA*

Variable	*t*	*p*	Fifth Quintile Estimate	First Quintile Estimate
MWA	12.64	**<0.001**	715.3340	437.6126
Population Density	0.426	0.679	1398.7	1121.3
Median Household Income	0.054	0.959	76859.17	76146.83
Unemployment Rate	-1.178	0.266	4.966667	7.283333
Participation Rate	-1.099	0.298	64.83333	68.15000
Percentage Visible Minority	0.291	0.777	11.161138	9.594119
Percentage Immigrant	0.853	0.414	15.02253	12.19227
Percentage Indigenous	-1.252	0.265	3.776875	5.483533
Without Post-secondary	-0.699	0.501	49.58482	52.20459

italicized variable indicates Welch's t-test (unequal variance)

Despite the participation rate and percentage of indigenous peoples turning up as significant in the regression model, the t-tests examining the differences in the variables between the CTs in the fifth and first quintiles of MWA did not find significant differences in their means, nor the means of any other variables.

Table 42: *Rank sum tests for Brantford CMA*

Variable	W	*p*
Percentage Renter	25	0.298
Long Commute	9	0.1735

The two variables with non-normal distributions had the Wilcoxon rank sum tests performed on them, where no significant differences in the rank sums of the two groups were found for either variable.

4.15. Guelph

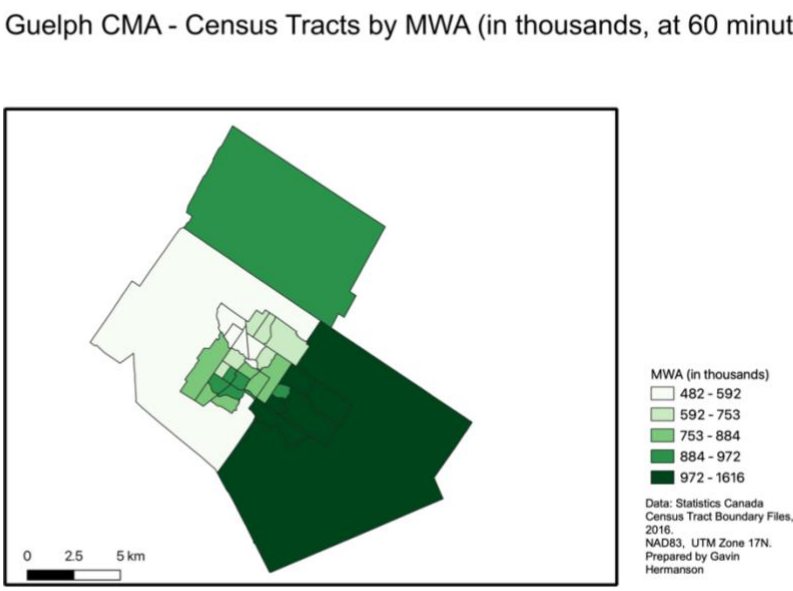

Figure 23: *Mode-share weighted accessibility (in thousands) by census tract, Guelph CMA*

Guelph, like so many of the CMAs around Toronto, had its highest MWA values located near highways providing access to Toronto. In Guelph's case this was Highway 401, located in the South of Guelph's CMA. Guelph's North and East had the lowest MWA as a result of their increased distance to the highway and other employment centres compared to the South of the CMA and their higher transit mode-shares. These CTs had much lower median household incomes than the South of Guelph did. Guelph had a high degree of spatial autocorrelation, at 0.5474, with a z-value of 6.0369, and a pseudo p-value of 0.001.

Table 43*: Regression model for Guelph CMA*

Predictor	Estimates	Confidence Interval	*p*
(Intercept)	350.98362	0.44216 – 701.52508	**0.050**
Median Household Income	0.00613	0.00192 – 0.01034	**0.006**

Residual standard error: 230.6 on 27 degrees of freedom (1 observation deleted due to missingness)
Multiple R-squared: 0.2487, Adjusted R-squared: 0.2208
F-statistic: 8.935 on 1 and 27 DF, p-value: 0.005899

Only one variable was included in the regression for Guelph as the other variables lacked significance. Median household income had an estimated coefficient of 0.00613, meaning a $1 increase in the median household income of a CT was associated with an increase of 6.13 jobs.

Table 44*: T-tests for Guelph CMA*

Variable	*t*	*p*	Fifth Quintile Estimate	First Quintile Estimate
MWA	7.724	**<0.001**	1243.8467	549.5793
Population Density	-2.743	**0.021**	1096.55	2135.45
Median Household Income	3.271	**0.008**	101799	72702.17
Unemployment Rate	-0.173	0.866	5.933333	6.066667
Participation Rate	-0.071	0.945	69.46667	69.73333
Percentage Renter	-1.612	0.138	16.71451	35.68497
Percentage Immigrant	2.835	**0.018**	23.90893	16.44781
Percentage Indigenous	-3.198	**0.010**	0.9926651	1.7146577
Without Post-secondary	-2.169	0.055	38.32062	43.79649

italicized variable indicates Welch's t-test (unequal variance)

The t-tests for Guelph, however, reveal that there are meaningful differences in the mean values of certain variables between the fifth and first quintiles of MWA. The population densities were significantly different, with the fifth quintile having an estimated mean of 1096.55 people per square kilometre, compared to 2135.45 in the first quintile. The mean median household incomes were significantly different between the groups, as the fifth quintile had a mean estimate of $101,799 per year, compared to $72,702.17 per year.

The percentage of immigrants and percentage of indigenous peoples were both found to be significantly different between the first and fifth quintiles. The fifth quintile's estimated mean percentage of immigrants was 23.91%, while the first quintile's estimate was 16.45%, while the estimated mean percentage of indigenous peoples in the fifth quintile was 0.99%, compared to 1.71% in the first quintile.

The unemployment rate, participation rate, percentage renter, and without post-secondary did not have significant difference, although without post-secondary was just outside of the cusp of significance and suggested that the fifth quintile had a marginally lower percentage of people without post-secondary.

Table 45: *Rank sum tests for Guelph CMA*

Variable	W	*p*
Percentage Visible Minority	31	**0.04533**
Long Commute	27	0.1735

Guelph's Wilcoxon rank sum tests on the non-normal variables found a significant difference in the rank sums of the percentage of visible minorities between the two quintiles. The difference in the rank sums of the percentage of people commuting more than an hour was not found to be significant.

4.16. Hamilton

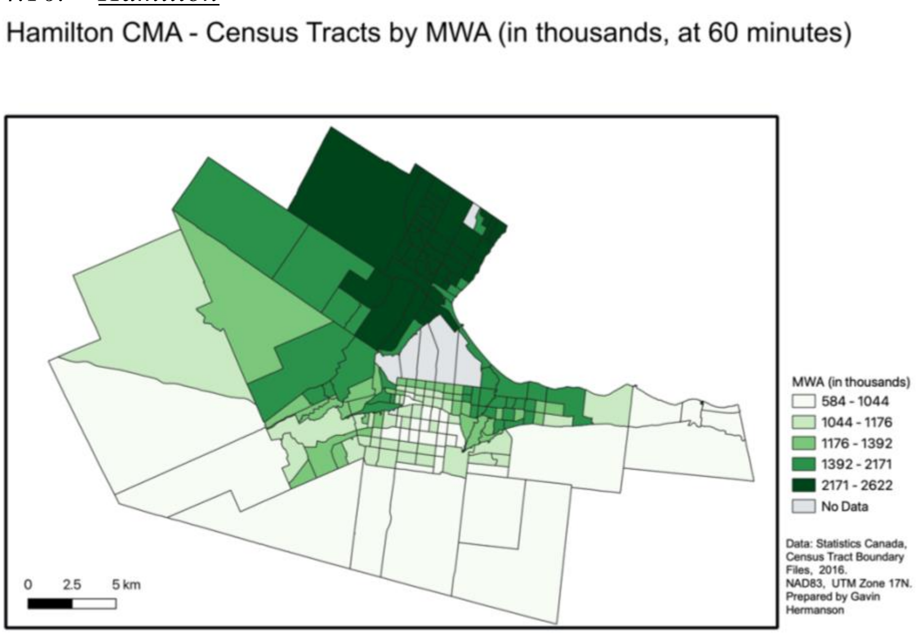

Figure 24: *Mode-share weighted accessibility (in thousands) by census tract, Hamilton CMA*

The MWA of Hamilton's CTs was again influenced by both highways and their proximity to Toronto. Burlington, located in the North of Hamilton's CMA is much closer to Toronto, allowing for many more jobs to be accessed by both automobile and transit in an hour than in other parts of Hamilton. Similarly, the parts of Dundas, to the west of Downtown, and lower Stoney Creek, to the East, had higher MWA values because of their proximity to highways which provide access to Toronto. Hamilton's lowest MWA CTs were located at the periphery of the region, furthest from Toronto, as well as Hamilton's "upper-city", on the Niagara escarpment, South of Downtown. Despite the access to highways traversing the upper-city, the travel times to employment-rich areas and higher transit reliance led to their lower MWA values. These areas were often among Hamilton's lowest income areas, as were many of the CTs in the 2nd quintile. Hamilton had a high degree of spatial autocorrelation of MWA, with a global Moran's I of 0.7995, with a z-value of 19.8910, and a pseudo p-value of 0.001.

***Table 46**: Regression model for Hamilton CMA*

Predictor	Estimates	Confidence Interval	*p*
(Intercept)	92.34669	-269.90637 – 454.59975	0.616
Median Household Income	0.00623	0.00379 – 0.00867	**<0.001**
Long Commute	75.04671	48.01736 – 102.07606	**<0.001**

Residual standard error: 466.7 on 183 degrees of freedom (5 observations deleted due to missingness)
Multiple R-squared: 0.2559, Adjusted R-squared: 0.2478
F-statistic: 31.47 on 2 and 183 DF, p-value: 1.798e-12

Hamilton's regression was composed of two significant variables: the median household income and the percentage of people commuting over an hour. Both variables were positively correlated. A one percent increase in the participation rate was associated with an increase in access of 23,894 jobs, while a one percent increase in the percentage of immigrants was associated with an increase of 23,926 jobs. The percentage of people commuting over an hour was positively correlated with MWA, suggesting that a one percent increase in the percentage of people commuting over an hour is associated with an increase in access of 83,666 jobs.

Of note, Hamilton's intercept was not significant, differing from the other regions in this research, and has a confidence interval that includes negative values, which as we know is not realistic, making it difficult to rely on the outcomes of the regression and its predictive power.

Table 47*: T-tests for Hamilton CMA*

Variable	*t*	*p*	Fifth Quintile Estimate	First Quintile Estimate
MWA	56.163	**<0.001**	2383.7872	932.7603
Population Density	-1.244	0.218	2261.157	2695.939
Median Household Income	5.405	**0.013**	103672.76	75410.74
Unemployment Rate	-2.58	**0.018**	5.389189	6.636842
Participation Rate	3.614	**<0.001**	69.12432	63.93947
Percentage Renter	-3.130	**0.003**	15.94649	28.30751
Percentage Immigrant	-0.477	0.635	21.80562	22.45846
Percentage Indigenous	-4.129	**<0.001**	1.153832	1.923114
Percentage Visible Minority	-1.429	0.158	14.09347	17.31113
Without Post-secondary	-8.830	**<0.001**	38.40774	49.85457
Long Commute	5.438	**<0.001**	13.84328	11.01973

italicized variable indicates Welch's t-test (unequal variance)

Hamilton's quintiles were sufficiently large enough for t-tests to be performed on each variable. The fifth and first quintiles had large differences in their estimated mean MWA, with CTs in the fifth quintile of accessibility enjoying more than double the mode-share weighted access to employment as the first quintile did. The population densities were not significantly different between the two groups and the estimates were only about 500 people per square kilometre different, much less than many of the other large regions studied.

The differences in median household income were significant, with the fifth quintile estimated mean at $103,672.76 and the first quintile estimated mean at $75,410.74. The unemployment rate (5.39% and 6.64%) and the participation rate (69.12% and 63.94%) were also found to be meaningfully different between the fifth and first quintiles respectively. The percentage of renters was (15.94% and 28.31%), percentage without post-secondary education (38.41% and 49.86%) and percentage of people commuting over an hour (13.84% and 11.02%) were found to be significantly different between the two groups as well. Finally, the percentage of indigenous peoples, at 1.15% in the fifth quintile and 1.92% in the first quintile were found to be meaningfully different between the two groups as well. The percentage of immigrants and visible minorities were not found to be significantly different.

4.17. <u>Niagara</u>

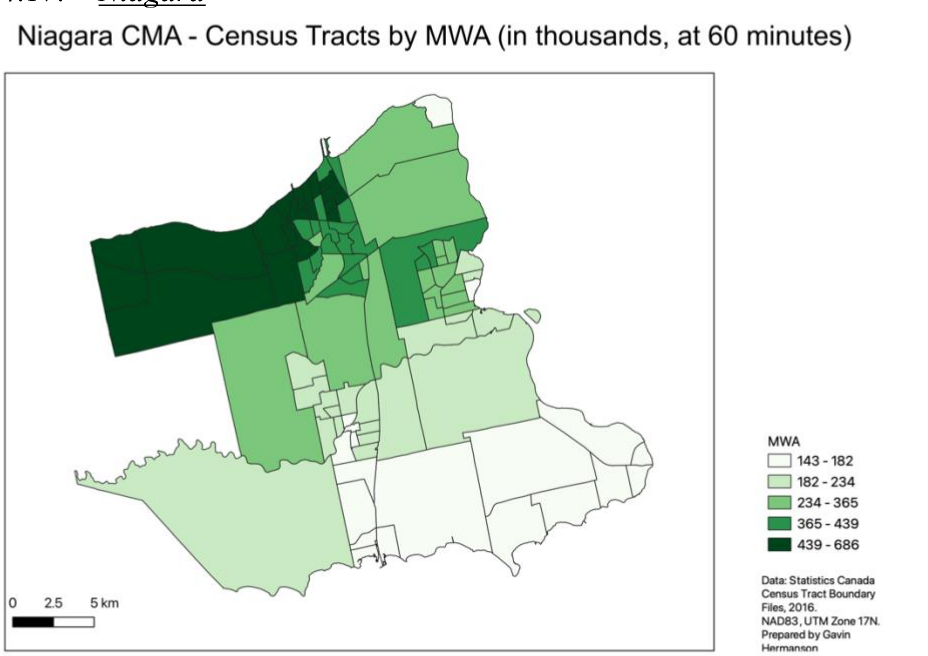

Figure 25*: Mode-share weighted accessibility (in thousands) by census tract, Niagara CMA*

Continuing the trend in the regions surrounding Greater Toronto, the closest CTs to Toronto in the Niagara region had the highest MWA value. These CTs in West Niagara and St Catherine's were closest to Hamilton and Toronto, and consequently had many more employment-rich CTs accessible within an hour by automobile. Conversely, Fort Erie and South Niagara, furthest from Hamilton and Toronto had the lowest MWA values. In between these two regions was a clear gradient of MWA by CT from the lower towards the higher values. Niagara had an extremely high degree of spatial autocorrelation, with a Moran's I of 0.8685, a z-value of 13.6026, and a pseudo p-value of 0.001.

Table 48*: Regression model for Niagara CMA*

Predictor	Estimates	Confidence Interval	*p*
(Intercept)	-348.94199	-661.75939 – -36.12459	**0.029**
Population Density	0.06714	0.04477 – 0.08952	**<0.001**
Unemployment Rate	-13.93450	-23.69433 – -4.17467	**0.006**
Participation Rate	7.69640	3.79219 – 11.60061	**<0.001**
Percentage Immigrant	5.09004	1.74911 – 8.43098	**0.003**
Long Commute	21.42959	8.84255 – 34.01663	**0.001**

Residual standard error: 93.98 on 88 degrees of freedom
Multiple R-squared: 0.4781, Adjusted R-squared: 0.4484
F-statistic: 16.12 on 5 and 88 DF, p-value: 2.945e-11

Niagara's regression model accounted for nearly half of the variation of MWA, 47.81%, and consisted of five variables: the population density, the unemployment rate, the participation rate, the percentage of immigrants, and the percentage of people commuting over an hour to work.

Niagara's intercept is negative, suggesting that if the value of the variables in the regression were all 0, there would be negative access to employment. This is not practical and should suggest a degree of caution be used in interpreting the variables. The population density in Niagara was positively correlated, breaking with the trends of most of the regions that were examined in this research. The regression coefficient for population density suggests that every additional person per square kilometre is associated with an increase in MWA of 67.14 jobs. The unemployment rate was negatively correlated with MWA. In this model a one percent increase in the unemployment rate was associated with a decrease of 13,935 accessible jobs. Participation rate in the labour market in Niagara was positively correlated with MWA, where an increase in the participation rate of one percent was associated with an increase in access of 7,696 mode-share weighted accessible jobs. The percentage of immigrants was positively correlated with MWA, as was the percentage of people commuting over an hour.

Table 49: *T-tests for Niagara CMA*

Variable	*t*	*p*	Fifth Quintile Estimate	First Quintile Estimate
MWA	22.215	**<0.001**	480.6408	160.8262
Median Household Income	3.182	**0.003**	75281.42	57948.95
Unemployment Rate	-2.587	**0.018**	6.852632	8.805263
Participation Rate	2.635	**0.012**	61.16842	56.27895
Percentage Indigenous	-5.013	**<0.001**	1.889958	4.443901
Without Post-secondary	-2.531	**0.016**	47.01587	53.22042
Long Commute	1.416	0.165	6.949938	6.219074

italicized variable indicates Welch's t-test (unequal variance)

The MWA of the first and fifth quintile were significantly different, with the mean CT of the fifth quintile having mode-share weighted access to nearly 3x the jobs of the mean CT of the first. Population densities were significantly different as well, but broke with the trend of most regions and had a higher mean population density in the highest MWA homes. Median household incomes were significantly different between the two groups too, with estimated means of $75,281.42 in the fifth quintile compared to $57,948.95 in the first quintile.

The unemployment rates were meaningfully different between the groups as well, with an estimated mean of 6.85% in the fifth quintile, against 8.81% in the first quintile. The participation rates were similarly different between the quintiles, at 61.17% in the fifth quintile and 56.28% in the first quintile. The percentage of renters was not significantly different between the groups, one of the only CMAs where it was not.

The percentage of indigenous peoples was also significantly different, with estimated means of 1.89% in the fifth quintile and 4.44% in the first quintile. The percent of people without post-secondary education was different between the groups, with an estimated mean in the fifth quintile of 47.02% compared to 53.22% in the first quintile. The percentage of people commuting over an hour was not significantly different.

***Table 50**: Rank sum tests for Niagara CMA*

Variable	W	*p*
Population Density	252	**0.03819**
Percentage Renter	155	0.4655
Percentage Immigrant	267	**0.01205**
Percentage Visible Minority	256	**0.02855**

Three of the four variables that were run through the Wilcox rank sum tests were found to have significantly different rank sums between the first and fifth quintiles. While the rank sums of the percentage of renters were not significantly different between the groups, the CTs in the first and fifth quintiles of MWA were found to have significantly different population densities, percentage of immigrants, and percentage of visible minorities.

4.18. <u>Oshawa</u>

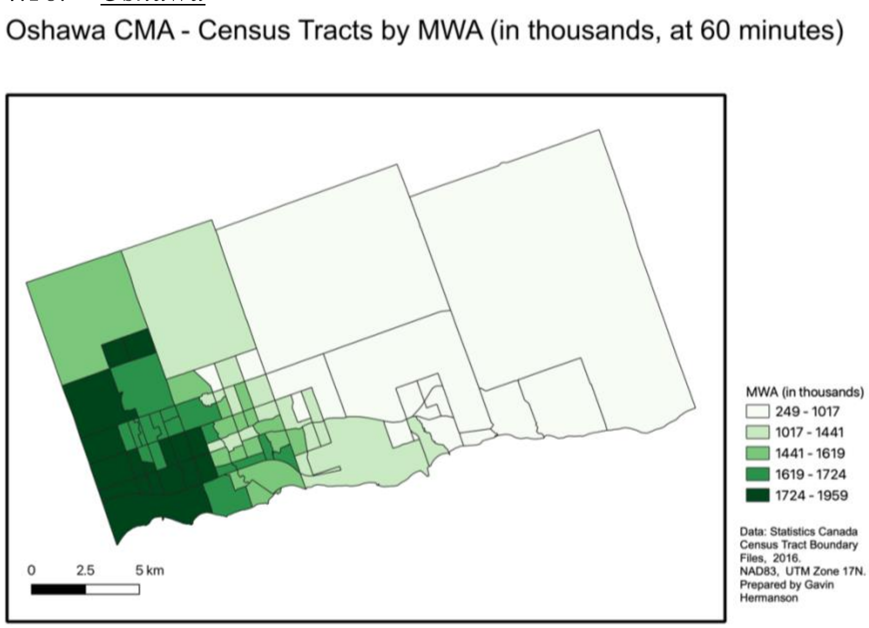

***Figure 26**: Mode-share weighted accessibility (in thousands) by census tract, Oshawa CMA*

Given what we have seen so far in the other CMAs around Toronto, it should be of surprise to nobody that Oshawa followed the same pattern as other CMAs surrounding Toronto. The CTs in the West of Oshawa, closest to Toronto and the myriad of jobs and employment-dense CTs had the highest MWA values. As distance, and accordingly travel times, to Toronto increased the MWA decreased. Again, proximity to the 401 helped increase the values further, as Central and Eastern Oshawa CTs closer to the 401 had consistently higher MWA values. Oshawa had a very high degree of spatial autocorrelation, with a global Moran's I of 0.8468, a z-value of 14.0002, and a pseudo p-value of 0.001.

***Table 51**: Regression model for Oshawa CMA*

Predictor	Estimates	Confidence Interval	*p*
(Intercept)	783.06523	515.36773 – 1050.76274	**<0.001**
Percentage Renter	6.07771	1.71639 – 10.43903	**0.007**
Percentage Immigrant	27.82153	15.45411 – 40.18896	**<0.001**

Residual standard error: 369.5 on 81 degrees of freedom
Multiple R-squared: 0.2211, Adjusted R-squared: 0.2019
F-statistic: 11.5 on 2 and 81 DF, p-value: 4.03e-05

Only two variables were found to be significant in Oshawa's regression, and together explained 22.11% of the variation of MWA. The percentage of renters was significant and had an estimated coefficient suggesting a one percent increase in the percentage of renters was associated with an increase in mode-share weighted accessible jobs of 6,078. The percentage of immigrants was also significantly positively correlated, with an estimated coefficient of 27,822 jobs.

***Table 52**: T-tests for Oshawa CMA*

Variable	*t*	*p*	Fifth Quintile Estimate	First Quintile Estimate
MWA	20.72	**<0.001**	1831.3643	705.8082
Median Household Income	0.096	0.924	93322.35	92582.88
Unemployment Rate	-0.244	0.808	7.658824	7.811765
Percentage Indigenous	-0.670	0.508	2.070778	2.282636
Without Post-secondary	-1.022	0.316	44.70567	46.68138

italicized variable indicates Welch's t-test (unequal variance)

None of the t-tested variables, median household income, unemployment rate, percentage indigenous, or without post-secondary were significantly different between the first and fifth quintiles of MWA. Median household income being virtually identical between the two groups broke with the trend in most of the CMAs where the difference in estimated mean median household income between the groups was significant.

Table 53: *Rank sum tests for Oshawa CMA*

Variable	W	*p*
Population Density	186	0.1579
Participation Rate	112	0.2702
Percentage Renter	178	0.2557
Percentage Immigrant	244	**<0.001**
Percentage Visible Minority	243	**<0.001**
Long Commute	235	**0.002**

The Wilcoxon rank sum tests were performed on the remaining variables, where it was found that the percentage of immigrants, percentage of visible minorities, and percentage of people commuting over an hour all had significantly different rank sums.

4.19. <u>Toronto</u>

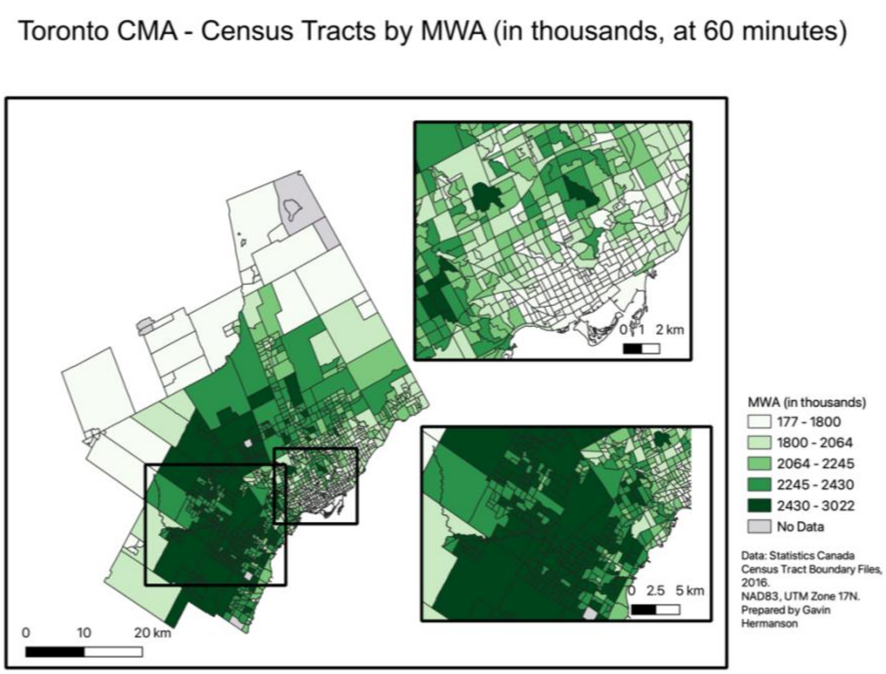

Figure 27: *Mode-share weighted accessibility (in thousands) by census tract, Toronto CMA*

Toronto's CMA, including Toronto and many of the suburban cities, had a similar pattern to many of the other regions in this research, where the downtown CTs had much lower MWA values due to their higher transit and active mode-shares. Within Toronto proper the fourth and fifth quintiles of MWA were located predominantly in wealthy CTs that had high median household incomes. Many CTs in Mississauga, Brampton, and Halton, to the West of Toronto, were in the fourth or fifth quintile of MWA, as they had high automobile mode-shares, were within an hour by car of many employment-rich CTs in Toronto's CMA but also Hamilton, and Waterloo Region. The North of Toronto's CMA, in the far reaches of York Regional Municipality, had lower MWA values because of the longer travel times into areas with larger numbers of jobs. MWA in Toronto had a very high degree of spatial autocorrelation, with a Moran's I value of 0.7613, and a z-value of 45.789, giving it a pseudo p-value of 0.001.

Table 54*: Regression model for Toronto CMA*

Predictor	Estimates	Confidence Interval	*p*
(Intercept)	2081.13938	1877.15733 – 2285.12143	**<0.001**
Population Density	-0.01066	-0.01438 – -0.00694	**<0.001**
Median Household Income	0.00193	0.00086 – 0.00301	**<0.001**
Percentage Renter	-5.10437	-6.43774 – -3.77099	**<0.001**
Percentage Indigenous	-124.36148	-153.40364 – -95.31932	**<0.001**
Percentage Visible Minority	3.14349	2.15004 – 4.13693	**<0.001**
Without Post-secondary	6.58358	4.33000 – 8.83716	**<0.001**
Long Commute	-15.28660	-19.23296 – -11.34024	**<0.001**

Residual standard error: 321.3 on 1135 degrees of freedom (8 observations deleted due to missingness)
Multiple R-squared: 0.3979, Adjusted R-squared: 0.3942
F-statistic: 107.2 on 7 and 1135 DF, p-value: < 2.2e-16

Toronto's model contained seven highly significant independent variables, which together explained nearly 40% of the variation of MWA. The population density was negatively correlated, with an estimate suggesting MWA would decrease by 10.66 jobs for every additional person per square kilometre. The median household income was positively correlated with MWA. It had a coefficient of 1.93 jobs per $1 increase of median household income in a CT. The percentage of renters was negatively correlated, as was the percentage of indigenous peoples. The percentage of visible minorities was positively correlated, as was the percentage of people without post-secondary education. Finally, the percentage of people commuting over an hour to work was negatively correlated. Of all the variables measured as a percentage of the population, the percentage of indigenous peoples had the greatest impact on MWA, as a one percent increase in the percentage of indigenous peoples was estimated to decrease accessibility of 124,361 jobs. An increase in the percentage of people commuting over an hour was estimated to decrease accessibility by 15,287 jobs.

Table 55: *T-tests for Toronto CMA*

Variable	*t*	*p*	Fifth Quintile Estimate	First Quintile Estimate
MWA	44.251	**<0.001**	2577.477	1477.771
Population Density	-10.496	**<0.001**	3390.231	10824.944
Median Household Income	16.552	**<0.001**	103746.87	67763.73
Unemployment Rate	-4.0183	**<0.001**	7.050655	8.048035
Participation Rate	-0.946	0.345	67.76245	68.42664
Percentage Renter	-23.066	**<0.001**	13.49979	52.95650
Percentage Immigrant	6.919	**0.042**	46.41391	36.91789
Percentage Indigenous	-10.991	**<0.001**	0.5824415	1.3515562
Percentage Visible Minority	4.707	**<0.001**	50.68304	39.41701
Without Post-secondary	5.808	**0.016**	44.10299	38.31123
Long Commute	0.709	0.479	15.3335	14.9397

italicized variable indicates Welch's t-test (unequal variance)

In Toronto all but two of the variables were significantly different between the fifth and first quintiles of MWA. The estimated mean population density of the fifth quintile was a third of the estimate of the first quintile, at 3390.23 people per km2 compared to 10824.94. The median household income estimate of the fifth quintile was $103,746.87, compared to $67,763.73 in the first quintile. The unemployment rates were significantly different, with an estimated fifth quintile rate of 7.05%, compared to 8.05% in the first quintile.

The percentage of renters was significantly different between the groups, with only 13.50% of households renting in the fifth quintile, compared to 52.96% in the first quintile. The fifth quintile was composed of a greater percentage of immigrants, with an estimated mean of 46.41%, compared to 36.92% in the first quintile. The fifth quintile had a lower proportion of indigenous peoples, estimated to be 0.58%, compared to 1.35% in the first quintile. The percentage of visible minorities was also significantly different, with an estimate of 50.68% in the fifth quintile, compared to 39.42% in the first. Finally, the percentage of people without post-secondary education was also found to be meaningfully different, comprising 44.10% of the adult population in the fifth quintile, compared to 38.31% in the first quintile. Neither the participation rate nor the percentage of people commuting more than an hour were significantly different between the groups.

4.20. Waterloo

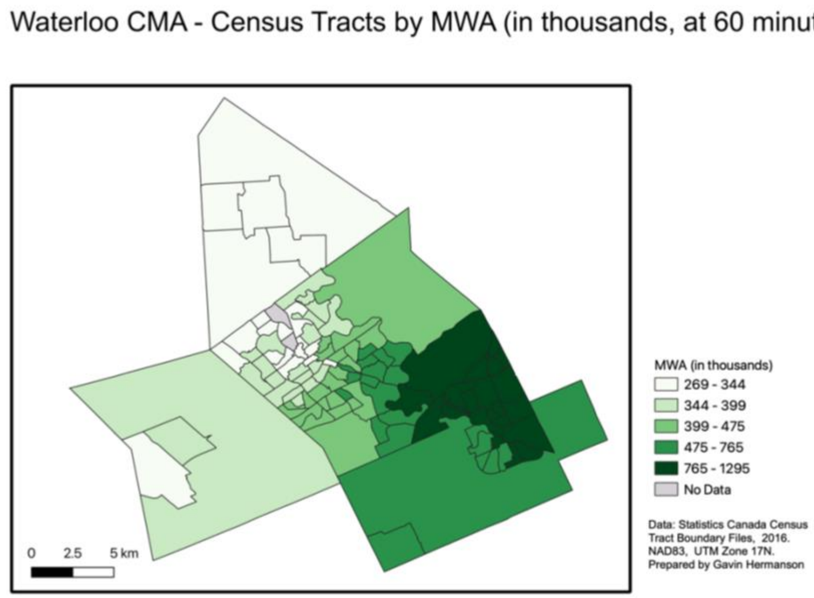

***Figure 28**: Mode-share weighted accessibility (in thousands) by census tract, Waterloo CMA*

Waterloo Region, on the same track as the other CMAs around Toronto, had the familiar pattern of its highest MWA areas near a highway (Highway 401) with good access to the jobs in Toronto and Hamilton. The CTs in the fourth and fifth quintiles were found in South Kitchener, Cambridge, and North Dumfries, in the Southeast, closer to other CMAs in and around Toronto. Conversely, in the North and West of Waterloo Region, the MWA values were lower, due in part to the longer travel times to CTs containing more employment. The exception here is around the universities in Waterloo, where CTs had lower MWA because of the greater proportions of people taking active modes and transit to school and work. Waterloo had an extremely high Moran's I of 0.9007, with a z-value of 16.4165 and a corresponding pseudo p-value of 0.001.

***Table 56**: Regression model for Waterloo CMA*

Predictor	Estimates	Confidence Interval	*p*
(Intercept)	-793.16979	-1147.08624 – -439.25333	**<0.001**
Median Household Income	0.00332	0.00150 – 0.00515	**<0.001**
Without Post-secondary	14.93103	9.71050 – 20.15156	**<0.001**
Long Commute	54.70008	37.42717 – 71.97298	**<0.001**

Residual standard error: 194.8 on 103 degrees of freedom (1 observation deleted due to missingness)
Multiple R-squared: 0.4662, Adjusted R-squared: 0.4507
F-statistic: 29.99 on 3 and 103 DF, p-value: 5.111e-14

Waterloo’s regression, similar to Niagara’s and Hamilton’s, produced a negative intercept. The regression model explained 46,62% of the variation of MWA using three variables: median household income, without post-secondary, and long commute. All three of these variables were positively correlated, with an $1 increase in median household income increasing accessibility by 3.32 jobs, a one percent increase in the percentage of people without post-secondary education increasing accessibility by 14,931 jobs, and a one percent increase in the percentage of people commuting over an hour increasing accessibility by 54,700 jobs.

Table 57: *T-tests for Waterloo CMA*

Variable	*t*	*p*	Fifth Quintile Estimate	First Quintile Estimate
Unemployment Rate	-0.437	0.666	6.440909	6.827273
Percentage Renter	-0.736	0.466	30.43085	35.98830
Percentage Immigrant	0.471	0.640	20.89492	19.73132
Percentage Indigenous	3.407	**0.001**	2.066304	1.198706
Percentage Visible Minority	-0.986	0.330	16.43074	20.74787
Without Post-Secondary	3.215	**0.003**	53.83904	43.39573
Long Commute	5.311	**<0.001**	8.427018	4.832937

italicized variable indicates Welch's t-test (unequal variance)

Waterloo’s quintiles were not large enough for non-normally distributed variables to have t-tests performed. Seven of the ten independent variables were normally distributed in both quintiles and could have t-tests performed on them. The three variables with significant differences between the quintiles were the percentage of indigenous peoples, the percentage of people without post-secondary education, and the percentage of people commuting over an hour to work. These three variables had larger estimated mean values in the fifth quintile than the first.

Table 58: *Rank sum tests for Waterloo CMA*

Variable	W	*p*
Population Density	298	0.1927
Median Household Income	247	0.9159
Participation Rate	290	0.2648

None of the three variables that were subjected to the Wilcoxon rank sum test were found to have significantly different rank sums.

4.21. Comparison between regions

***Table 59**: Comparison of Estimated Means of Economic Variables, 5th and 1st Quintile of MWA*

Region	5th to 1st Quintile MWA ratio	5th to 1st Quintile Population Density Ratio	5th to 1st Quintile Median Household Income Ratio	5th to 1st Quintile Unemployment Ratio	5th to 1st Quintile Percentage Renter Ratio	5th to 1st Quintile Percentage Without Post-Secondary Ratio	5th to 1st Quintile Percentage Long Commute Ratio
Toronto	1.74	0.31	1.53	0.78	0.25	1.15	1.03
Vancouver	1.39	0.28	1.42	0.91	0.41	1.39	1.92
Calgary	1.16	0.68	1.09	0.95	0.55	1.50	1.17
Edmonton	1.16	0.55	1.56	0.83	0.32	1.00	0.68
Ottawa	1.25	0.25	1.59	0.73	0.31	1.08	0.94
Quebec City	1.33	0.15	1.72	0.62	0.34	1.07	1.07
Winnipeg	1.12	0.62	1.73	0.62	0.39	0.98	0.77
Hamilton	2.56	0.84	1.37	0.81	0.56	0.77	1.26

Taking the t-test results one step further, I now offer a comparison of the ratios of estimated means of variables in the fifth and first quintiles and compare these numbers between the nine regions that had all their variables put through t-tests.

Winnipeg, followed by Calgary and Edmonton, had the smallest spreads of MWA between the fifth quintile (highest MWA areas) and the first quintile (lowest MWA areas). While all three of these regions had statistically significant differences between the estimated means of the quintiles, neither proportionally nor in absolute values were they hugely unequal, with the difference in MWA between Winnipeg's fifth and first quintiles at just 12% (338,867 jobs against 301,631). In both Calgary (585,334 against 505,826) and Edmonton (542,282 against 466,116) the fifth quintiles were 16% higher than the first. This level of disparity in MWA values could be more easily remedied than in some of the CMAs with larger differences in their MWAs. While regions like Ottawa, Quebec, and Vancouver had slightly greater inequalities between the first and fifth quintiles it was in Canada's largest urban centre and largest economic driver where the inequalities were the largest. The estimated mean CT in the fifth quintile had access to 74% more jobs in Toronto's CMA than the estimated mean CT in the first quintile. The results in the CMAs surrounding Toronto were even more stark, with the estimated mean fifth quintile CT in Hamilton having an MWA of greater than 150% that of the first quintile, and Niagara's estimated mean fifth quintile CT having access to 200% more jobs than that of the first.

Population densities tended to be much higher in the first quintile than in the fifth quintile. This pattern seemed to emerge because higher density areas tend to be areas that are well supported by transit and close to higher employment densities, facilitating active modes of travel and allowing people to have greater choice in how they travel to work. These areas tended to be located in and around downtowns of regions. This compared to the highest MWA areas, which tended to be less proximate to downtowns, more suburban, and much more automobile reliant for mobility, leading to less density.

Median household incomes were higher in the fifth quintile of MWA in every region than their first quintile. Most regions had a significant degree of inequality here, with the exception of Calgary, where the fifth quintile's estimated mean for median household income was only 9% greater than that of the first quintile. Interestingly, the greatest levels of inequality here were in Ottawa, Quebec, and Winnipeg, three regions that had smaller spreads between the MWA values of their first and fifth quintiles. It appears as while these regions might have larger income inequalities between the quintiles, it may not be as significant as the difference in mode-share weighted jobs between the quintiles is smaller.

The unemployment rate differences between the fifth and first quintiles tended to be slightly smaller than the differences in income between the quintiles. Again here, we saw that the estimated mean unemployment rate was lower in the fifth quintile of MWA than the first quintile, in every region. In many regions they seem to be inversely related to the median household incomes, where the magnitude of the difference in the estimated mean median household incomes is related to the magnitude of difference in the estimated mean unemployment rate. Calgary, which had the lowest amount of income inequality between the two quintiles similarly had the smallest gap in the estimated mean unemployment rates. Conversely, Quebec City and Winnipeg, which had the largest inequalities in median household income between the fifth and first quintiles had the largest inequalities in unemployment rates.

The percentage of renters was lower in the fifth quintile of every region than in the first, sometimes significantly so. Toronto, Edmonton, Ottawa, Quebec City, Vancouver and Winnipeg all had mean proportions of renters near or greater than two and a half times higher in their first quintile of MWA than their fifth. Calgary and Hamilton were not much more equal, with both regions having nearly double the proportion of renters in the first quintile than the fifth.

The percentage of people without post-secondary education did not have a clear trend between the regions. While Calgary and Vancouver had much higher percentages of people without post-secondary education in their fifth quintiles of MWA than their first, Toronto, while significantly different, had a much smaller difference proportionally. Ottawa, Quebec, Edmonton, and Winnipeg did not have significant differences between the two MWA quintiles, while Hamilton had a lower percentage of people without post-secondary education in its fifth quintiles.

While the percentage of people commuting over an hour was significantly different in many of the regions, they were split among those where the percentage was higher in the fifth quintile and those where it was higher in the first. The difference between the quintiles was not significant in Toronto, Calgary, or Quebec City. Vancouver sits as an outlier, with the fifth quintile having nearly double the percentage of people commuting over an hour than the first quintile. The other region to have greater percentages of people commuting over an hour in their fifth quintile were Hamilton with 25% more people in the fifth quintile. Conversely, Edmonton and Winnipeg had a significantly higher estimated mean percentage of people in their first MWA quintiles commuting over an hour, suggesting the possibility of transport poverty in the lower MWA areas in those cities. Something that should be kept in mind with these results is the relatively small proportions of people commuting over an hour can lead to small differences (like Calgary's 5.44% in the fifth quintile and 4.64% in the first quintile, a 17% difference from first to fifth) sound larger than they are.

***Table 60**: Comparison of Estimated Means of Demographic Variables, 5th and 1st Quintile of MWA*

Region	5th to 1st Quintile MWA ratio	5th to 1st Quintile Percentage Immigrant Ratio	5th to 1st Quintile Percentage Indigenous Ratio	5th to 1st Quintile Percentage Visible Minority Ratio
Toronto	1.74	1.25	0.43	1.29
Vancouver	1.39	0.95	0.42	1.26
Calgary	1.16	0.82	1.52	0.86
Edmonton	1.16	0.52	0.63	0.44
Ottawa	1.25	0.77	0.82	0.63
Quebec City	1.33	0.36	0.92	0.34
Winnipeg	1.12	0.80	0.97	0.74
Hamilton	2.56	0.97	0.60	0.81

There were no perfect trends across the racial and immigrant variables between the regions. The percentage of immigrants made up a larger percentage of the fifth quintile than the first in Toronto, while not being meaningfully different in Vancouver or Hamilton. They were a significantly higher percentage of the population in the first quintile in Calgary, Ottawa, Winnipeg, Edmonton, and Quebec City, with the last two regions having large disparities.

The percentage of indigenous people in the population was significantly different for many of the CMAs. Notably, it was only higher in Calgary, where the fifth quintile of MWA had an estimated mean of 3.73% compared to 2.45% in the first quintile. While differences were not significant in Winnipeg or Quebec City, they were significant and large in the other CMAs, with both Vancouver (3.14% compared to 7.59%) and Toronto (0.58% compared to 1.35%) having large inequalities between their fifth and first quintiles of MWA.

The percentage of visible minorities tells a slightly different story than the percentage of immigrants. While many regions had similarities in the proportional differences of percentage of visible minorities as they did for percentage of immigrants, they typically had a lower ratio, indicating a larger difference between the first and fifth quintiles of MWA, and that the lower MWA areas had larger proportions of visible minorities than they did immigrants. While

Vancouver had no significant difference in the percentage of immigrants between its first and fifth quintiles, it had a significant difference in the percentage of visible minorities, with the fifth quintile having a larger estimated mean percentage than the first quintile did.

5. **Discussion**

While there was a fair degree of variability in the MWA results by CT through the different regions examined here, there were a number of trends that were visible across multiple regions. These trends, their causes, and their implications are discussed in the following subsections.

5.1. Spatial Components and disparities of MWA

It was not a great surprise given how it is calculated and what we know about how urban form relates to transportation choices (Bertaud, 2018), but MWA had varied and unequal distributions in all of the regions that were analyzed. Nearly every CMA that was examined followed a pattern where the CTs downtown and near downtown had lower MWA values, which increased with distance from the downtown. Values in some of the physically larger regions decreased towards the peripheries, especially in large rural CTs where the centroid of the CT may not have been near the centre of the population in that CT.

The mechanisms for this are relatively straightforward, but the implications are worth consideration. The areas with the highest active travel and transit mode-shares have mode-share weighted access to fewer jobs by the very nature of the mode-share weights themselves and the higher levels of mobility provided by automobiles. While the number of jobs accessible by transit compared to automobiles is always fractional, the number of jobs accessible by bike and by walking is an even smaller fraction. This consistently led to the areas with the highest active mode-shares having the lowest overall MWA. High transit mode-share areas also had lower MWAs. These areas often had higher active modes of travel as well. The low MWA values in central areas of cities is contrasted with the higher unimodal, cumulative opportunity accessibility values for walking, cycling, and transit from these areas, reflecting the effect of the mode share weights and higher proportion of non-auto commuting from these core areas.

The other half of this logic follows that the CTs with the highest MWA values were ones with the highest automobile mode-shares, which held true nearly universally, with the caveat that CTs with higher automobile mode-shares, but existed on the periphery of a region, would have lower MWA than a CT with a lower auto share that had access to enough additional jobs by car that when mode-share weights were applied it made up the difference in MWA. As a result, the highest MWA areas tended to be in auto-oriented parts of cities and regions, and near highways that provided high levels of mobility towards areas of employment. In practice this meant that there were few high MWA areas in the older parts of cities, but those that existed typically had abnormally high automobile mode-shares compared to nearby CTs.

When the boxplots of MWA were examined by CMA a similar pattern emerged in many of the regions. The box plots of the standalone regions revealed that the interquartile ranges of the MWA were relatively small, with the fourth and especially the first quintiles having a larger range. They typically had a handful of outliers, all with MWA values less than the box plot's first quintile. This pattern was inconsistent however with the smaller CMAs surrounding a larger

CMA, which had their own pattern, visible in those surrounding Toronto. Guelph, Hamilton, Waterloo, Niagara, Brantford, and Barrie all had box plots with larger fourth quartiles, large third quartiles, and smaller second and first quartiles. The MWA in the region was so influenced by Toronto and its employment that CTs nearest to Toronto or to highways connecting to Toronto had substantially higher MWA values.

There was a large amount of variation between regions on the level of inequality in the MWA by CT. As discussed briefly in the previous section, CMAs like Winnipeg, Calgary, Saskatoon, and Edmonton did not have large variance between the high MWA areas and the low MWA areas, outside of a few low MWA CTs with substantially higher transit and active mode-shares. The variation in regions like Quebec City, and especially Vancouver, and Toronto however were much greater, owing to the greater proportion of people walking, cycling, and taking transit to work, and the smaller number of jobs accessible by these modes. The differences were greatest however in the CMAs surrounding Toronto, where the areas with high automobile shares and access to Toronto had significantly higher MWA than areas that were farther from Toronto and had higher non-automobile mode-shares.

One final observation on the spatial component of accessibility through the regions: many of the regions with the smallest differences in the mean MWA of their first and fifth quintiles were just as unequal or more in their respective socioeconomic measures than the regions with the largest differences in their MWAs. Discounting the exception of Calgary, which had the least amount of socioeconomic inequality in its high and low MWA regions, and low inequality of access, there were four CMAs with less inequality in their MWA values, but significant inequalities between these CTs in other variables. Ottawa, Quebec City, Edmonton, and Winnipeg all had less inequality in their MWA values proportionally, and in absolute numbers, but some significant inequalities in other aspects of their respective high and low MWA CTs. Income inequalities were significant between the high and low MWA CTs in all four of these regions and were the largest by proportion and magnitude of any of the larger CMAs. These CMAs similarly had the largest differences in the unemployment rates, and some of the highest proportions of renters and greatest differences in population densities among the regions examined. Finally, they also had some of the greatest disparities of the proportion of immigrants and visible minorities, with Edmonton also having large differences in the percentage of indigenous peoples. Despite the large and obvious differences in these socioeconomic factors between the high and low MWA CTs in these regions, the differences in the MWA were fairly small. This directly contrasts with many of the CMAs surrounding Toronto, which had huge disparities between their high and low MWA areas, but oftentimes smaller (like Niagara or Hamilton, and Guelph) or no (Oshawa and Waterloo) socioeconomic differences between them.

For this I offer a few explanatory factors. Toronto and Vancouver are too large for all of the regional jobs to be accessible within an hour by automobile. The same cannot be said about Edmonton, Quebec City, Ottawa, and Winnipeg, where most jobs in the region (>90%) were accessible from most (>85%) of the census tracts. As not all jobs are accessible by transit, walking, or cycling, in any of the regions, this creates a situation where the highest MWA areas by default are those with some of the highest automobile mode-shares. The MWA values end up acting as a proxy for the percent of automobile mode-shares used to travel to work, which I believe may be the reason for the larger disparities. We know automobiles have capital and operating costs, making it more burdensome for households to have two vehicles, or even sometimes one. By the nature of their cost, poorer areas will have fewer vehicles per capita and less driving to work from those areas. These CMAs have greater proportions of automobile usage for the commute to work than the larger cities, setting a higher floor for MWA values, leading to smaller spreads between the lowest MWA and the highest MWA. As Vancouver and Toronto were physically too large for all jobs to be accessible, and have more comprehensive rapid transit networks, MWA was unable to act as a proxy for automobile usage the same way, leading to less pronounced, but still significant, differences in socioeconomic factors between the high and low MWA census tracts. As these regions were physically quite large and had some CTs with significantly higher non-automotive shares of travel, the ranges of MWA values ended up being larger, despite the smaller economic differences in the high and low MWA CTs. The absence and or reduced socioeconomic differences in the CMAs surrounding Toronto, despite their large spreads between the high and low MWA areas I believe can be attributed to the number of people commuting over an hour to work. While the 60-minute threshold has certainly been a popular one in the literature, it might not be entirely realistic in places like Southern Ontario, where increasing housing prices have squeezed people from Toronto's market to the housing markets in nearby CMAs. While people may move for more affordable housing, or a larger house for their family, they may do so while keeping their employment and lengthening their commute. This phenomenon can be seen in the percent of people commuting over an hour to work, which is above 10% in many CTs in the regions. The limit of the "reasonable" commute might be well over an hour, which could be why despite the large differences in MWA, there are small or no differences in socioeconomic attributes of these census tracts.

5.2. Economic dimensions of access

There was a clear and resounding connection between the MWA and median household income of a census tract in nearly every region examined. These differences were significantly greater in some areas than in others, but they persisted in every region except Oshawa and Waterloo, which both had its MWA results heavily influenced by Toronto. These models reveal a very clear and consistent economic angle of MWA, one that was expected based on the literature of the benefits of accessibility. It was not a surprise that census tracts that had access to more jobs and a greater proportion of the total jobs would have higher incomes. It was similarly unsurprising that these higher income census tracts were more likely to own vehicles and drive as vehicles are expensive assets with high yearly maintenance and operating costs. The greater propensity for driving because of higher household incomes leads to a chicken and egg problem. Do these areas have higher median household incomes because of their greater access to employment by automobile? Or are these areas more auto-oriented because of their greater median household incomes? Additionally, what role does built form, residential location choice, and transportation network play into this?

Although it is likely a multitude of factors influencing each other and ultimately residential location choices and travel behaviour, additional data from the census helps shed some light on the possible answers. The percentage of renting households gives us key insight that high MWA areas tend to have significantly fewer renting households than low MWA areas do. This again reflects the economic means of these census tracts, where high MWA areas have fewer renters, likely as a result of the higher incomes in these areas.

An important consideration in this discussion is the role of the built environment and the transportation system. It is no secret Canada is a suburban nation. A huge amount of the country's population growth has been facilitated through greenfield suburbs since the end of World War Two. This built form has been granted by the mass adoption of the automobile and the expansion of highways and road systems. The auto-oriented nature of these suburbs, subsidized roads and fuel, the limited mobility provided by transit in these areas, and lack of nearby employment density has synthesized a condition that has all but necessitated a vehicle to travel to work. A result of this is the suburban census tracts where transit and active mode-shares are higher, tend to have lower median household incomes. This may be why many of the areas with the highest MWAs, which are a product of the high automobile accessibility of their location and high automobile mode-shares, tended to have higher median household incomes.

Purpose built rentals are less likely to exist in newer, suburban developments and areas located further from transit. Higher land values in higher density areas, zoning, and the preference to trade increased transportation costs for increased residential size have helped contribute to this. At the same time higher MWA CTs, which we know are higher in large part because of their very high automobile mode-shares, facilitated by incomes high enough to afford multiple vehicles per household, are less likely to be census tracts with a large proportion of rentals because the household incomes allow greater proportions of home ownership. These two conditions together are a plausible explanation for why the highest MWA areas have significantly fewer renters than the lower MWA areas do.

Unemployment rates were consistently lower in the high MWA CTs than in lower MWA CTs. In more than half of the CMAs, and the majority of them outside of Toronto's megaregion, had significant differences in the unemployment rates. The unemployment rates in the fifth quintile of MWA tended to be slightly lower or at the regional average, while the unemployment rates in the first quintile of MWA ranged from slightly above the median unemployment rate in places like Toronto, Vancouver, and Calgary to significantly above the median unemployment rate in places like Ottawa, Winnipeg, Quebec, and Windsor. I believe this may be because of the accessibility to employment that rapid transit provides and the high employment density in those cities with less inequality in their unemployment rates. Lower MWA areas, as we have discussed, have fewer people driving to work and likely lower automobile ownership. In Vancouver, Toronto, and Calgary, many of the lowest MWA CTs contain or are near to a rapid transit station, or are near to employment-dense areas, with a significant number of jobs as the regions themselves are three of Canada's biggest four. The unemployment rates in the lower MWA areas are not unreasonably higher because of the number of jobs that can be reached by non-auto modes in these areas. This contrasts with places like Ottawa, where the transitway rapid transit (BRT) was more focused on bringing suburban commuters into the city than in providing accessibility to lower access areas, or places like Winnipeg, Quebec, or Windsor which lacked rapid transit entirely.

Despite the differences in unemployment rates, differences in participation rates were not always present or significant. Some of the same factors mentioned in the previous paragraph on unemployment might have been at play here, as Toronto, Vancouver, and Calgary did not have significant differences in their participation rates in the low and high MWA areas. At the same time, Ottawa and Edmonton, which did have significant differences in their unemployment rates, did not have significant differences in their participation rates. Adding to this, regions like Hamilton and Niagara did have significant differences in both unemployment and participation rates, where the higher unemployment areas tended to have lower participation rates. To complicate things further, Brantford's highest MWA areas had a lower participation rate than their lowest MWA areas. There must be confounding factors playing into these mechanics that are not easily visible, as MWA alone is not reliably related to participation rates in regions across the country.

Lower education levels, measured through the percentage of people without post-secondary education, was largely a non-factor. When the differences between the first and fifth quintiles were significant, they were much more likely to have a larger proportion of people without post-secondary education living in the high MWA areas than a larger proportion in the low MWA areas. The literature available had suggested that lower accessibility areas tended to be worse educated, but this was not true with MWA in the context of most of these Canadian regions.

5.3. <u>Visible minority and Immigrant dimensions of access</u>

In many of the CMAs immigrants had worse access to employment than non-immigrants, although there were some significant exceptions. Toronto, Canada's largest CMA, had a higher proportion of immigrants in its fifth quintile of MWA than its first, with the mean fifth quintile CT having 25% more immigrants than the first quintile. Niagara was the only other CMA where the fifth quintile had a higher proportion. Vancouver and Hamilton's CMAs had no significant difference, while all the other major CMAs had a lower proportion of immigrants in the fifth quintile than the first. Some, like Edmonton and Quebec City, significantly so.

While the percentage of visible minorities typically was similar to the percentage of immigrants in a census tract in many of the regions, there was typically a slightly lower percentage of visible minorities in the fifth quintile and/or slightly higher percentage in the first quintile. This meant there were larger differences in the percentage of visible minorities between the first and fifth quintiles of MWA. A notable difference was Vancouver, where there was no significant difference in the percentage of immigrants in a fifth or first MWA quintile CT, had a significant difference in the percentage of visible minorities, who were a greater proportion of the population than in the first quintile.

The American accessibility literature had suggested that visible minorities and immigrants may have lower levels of accessibility, while in the Canadian context, literature on access to employment had suggested that there would likely not be substantial differences. What this research revealed was that there were large regional variations in the percentage of immigrants in high and low accessibility areas. A possible explanation for the variation is the historical and present immigration patterns and trends in Canada. International cities, like Vancouver and Toronto may be attracting a higher proportion of wealthy immigrants due to their status as world-renowned cities, existing communities of immigrants in these regions, their attractive investment climates because of their size, labour force, or other competitive advantages. This may explain why they are living in areas with higher MWA at greater rates, areas that also had higher median household incomes. Many CMAs had negligible differences in the percentage of immigrants and visible minorities between the high and low MWA areas. Two regions had significantly more visible minorities and immigrants in their low MWA CTs than their high MWA counterparts: Edmonton and Quebec City. These regions, while having some similarities, like smaller relative disparities between the highest and lowest MWA areas and the spatial distribution of high and low MWA areas through their regions, were different in their geographic barriers, transit systems, active mode-share propensities, and distribution of employment.

Nearly universally across the country the highest MWA areas had a lower percentage of indigenous peoples than the lowest MWA areas did. These disparities did not exist in Calgary, where indigenous people made up a larger proportion of the population in the higher MWA census tracts, or in Winnipeg, where they made up nearly equal proportions in the high and low MWA CTs. Outside of these regions there were significant disparities in all of the large CMAs. Vancouver and Toronto, the two largest CMAs in this study, had similar inequalities proportionally. Hamilton and Niagara, located near the largest indigenous reserve in Canada also had large inequalities in access for indigenous peoples. Edmonton also had large inequalities here. While proximity to indigenous reserves of, or the number of indigenous peoples living in Vancouver, Edmonton, Hamilton, Niagara, and Toronto might seemingly suggest that CMAs with more indigenous peoples or near reserves have greater disparities, Winnipeg, the CMA with the highest proportion of indigenous peoples in Canada did not have significant differences. In either case, it is clear that urban indigenous in many regions in Canada have lower levels of accessibility, likely due to the historic and enduring legacies of colonization, systemic, institutional, and individual racism, and the denied economic opportunities that these have caused.

These disparities are layered onto the aspatial barriers to access exist for these groups. Language barriers, conscious and unconscious discrimination of employers and in hiring practices, and systemic barriers to the education and skills needed to work all exist on top of the lower mode-share weighted accessibility in the areas they tended to live in.

5.4. Spatial mismatch and residential location choices

Something I thought I might see in these models was some evidence of spatial mismatch where low MWA areas would have lower incomes and a higher proportion of people commuting over an hour to work. Only two CMAs met these criteria: Edmonton and Winnipeg. Both of these cities had significant differences in the median household incomes of their highest and lowest MWA CTs and in the percentage of people commuting over an hour. Contrary to what I expected, there were more CMAs where the CTs in the 5th quintile of MWA had a significantly higher proportion of people commuting over an hour. Hamilton, Waterloo, and Vancouver all had significantly higher proportions of people commuting over an hour in their higher accessibility areas. Calgary, just outside the cusp of significance, did as well. While evidence for spatial mismatch emerged from two regional models, this phenomenon was local, not global.

5.5. Effectiveness of MWA

MWA modelling effectively picked up on the economic inequalities in access, demonstrating linkages between median household income, unemployment rates, and mode-share weighted accessibility. These links were present nearly universally in the CMAs that were studied, only not clearly visible in CMAs surrounding larger CMAs, suggesting that other interregional dynamics were at play, while being visible and pronounced in stand-alone CMAs. MWA also successfully identified disparities in access by different visible minorities, immigrants, and indigenous peoples.

MWA successfully identified two main types of low MWA areas: the downtowns and inner-cities of regions as well as suburban areas experiencing transport poverty, each with higher mode-shares of non-auto transport and tending to have lower median incomes and higher unemployment.

A challenge with using non-auto mode-shares is that they may be depressing MWA values beyond what the actual mode-share weighted access could be based on the means of an area. While undoubtedly some who walk to work do so because they cannot afford the cost of a monthly transit pass, one would imagine that many of the people commuting by foot choose to walk instead of taking public transit because it is more convenient or faster for them, or because they enjoy the exercise and health benefits. It is likely if you are choosing an active mode of travel to work in an urban setting, you could take transit to work instead. While it is also possible many of these people have automobiles that they choose not to drive to work but could, we'll focus on transit for now. As active modes are being used, the active mode-share weights are applied to the number of jobs that can be reached within an hour by the respective modes, which for cycling tended to be between 1x the number of jobs accessible by transit to 5x, (depending on the CMA and access to transit), while the number of jobs accessible by walking was just a fraction of the transit or cycling-accessible jobs, typically under half the number of those accessible by transit.

As a result, the MWA of areas with high proportions of people walking to work were among the lowest. While this should be seen as a feature, not a bug given that it accurately describes the realized accessibility of a census tract, it would be of interest to see how much the accessibility of low MWA areas would increase if all the walking mode-share was transferred to transit. It would also be of interest to understand how this transformation would affect the estimated mean socioeconomic variable values for the bottom quintile of census tracts. Would the median household incomes change positively or negatively as some of the census tracts with high transit accessibility and high active mode-shares experience large increases in MWA. I examined a handful of census tracts in downtown Toronto that had high (>50%) walking mode-shares, adding the walking mode-share values to the transit mode-share values, and recalculating the MWA to demonstrate how it affects the MWA of an area.

Table 61*: Sample of Census Tracts from Toronto with high walking mode shares*

CT	Median Household Income	Walking Share	Transit Share	MWA	MWA with Walking Share Assigned to Transit	MWA Gain
5350011	$82,950	55.34%	22.22%	1,118,795	1,281,437	162,642
5350014	$110,336	62.22%	18.90%	1,178,219	1,549,023	370,804
5350015	$91,097	55.18%	28.57%	1,100,290	1,410,464	310,174
5350035	$47,671	58.31%	24.83%	1,086,538	1,387,174	300,636
5350036	$49,948	53.15%	26.02%	1,079,389	1,272,887	193,498

Ultimately, from the quintile analysis perspective it would make no difference, as these census tracts would all be in the bottom quintile regardless. Despite this, it may be useful for certain applications of an MWA tool to make the assumption and convert the walking mode-shares to transit mode-shares to give a better comparison of what the maximum realized accessibility could be. Of course, this raises questions on people using transit when they might have a vehicle accessible to them, but if we were only interested in analyzing the vehicle ownership of an area, not its potential accessibility, we could do that in other ways. The caveat in adding the walking mode-share to transit in an attempt to understand what the MWA could be is that monthly transit passes could be a significant economic burden to a large percentage of households in the two CTs used in this analysis with median household incomes under $50,000.

While the inclusion of walking mode-shares materially affects the MWA and may more accurately demonstrate the potential mobility of the labour market, any assumption in future use cases regarding people walking to work being able to afford the trip on transit should be verified.

6. Conclusion

This research succeeded in its objective of describing mode-share weighted accessibility across Canada. In doing so it revealed the large but variable inequalities in mode-share weighted accessibility in cities across the country. By quantifying the mode-share weighted accessibility to employment I was able to evaluate the differences in mode-share weighted access in these census tracts against their socioeconomic differences.

Accessibility is an important determinant of the world you are able to interact with, of the experiences you can enjoy, the friends you can see, the jobs you can work at, and the quality of life you have. Your accessibility is your horizon. Accessibility has traditionally not been examined in a meaningful way across modes of travel, as research has typically focused on accessibility by one mode of travel or comparatively, rather than cumulatively.

Mode-share weighted accessibility models have not been used extensively in the literature, with this being the first study to examine accessibility to employment in this way across the country. As linkages to equity have been increasingly made to accessibility in academic literature, I wanted to examine how these held up against mode-share weighted accessibility. Would the phenomenon of spatial mismatch to employment be evident in this data? Would immigrants and visible minorities have worse access to jobs? Would high accessibility areas have higher incomes and lower unemployment levels? By comparing socioeconomic and demographic data to MWA values I was able to adopt an equity "lens" to gain understanding in how mode-share weighted access is distributed both spatially and demographically across Canada.

By constructing mode-share weighted accessibility models using geographic, employment, mode-share, and population data from the 2016 census, as well as travel time data from routing engines, I was able to accurately describe the realized accessibility experienced by the census tracts. By layering in demographic data from the census I was able to create regression models to determine which variables were correlated with MWA and perform t-tests on the census tracts with the highest and lowest MWA values to see how their socioeconomic makeup differed.

While there certainly was variation in how accessibility was distributed across the country, there were a few trends worth noting. Census tracts with higher MWA values tended to have higher median household incomes. This was nearly universal and oftentimes marked, with large disparities in income appearing between high and low accessibility areas. There was also a clear trend of low MWA census tracts having significantly higher unemployment levels. The third trend, which had both economic, demographic, and built form implications, was the significantly larger percentage of households renting in low MWA areas than high MWA areas.

There were also trends present in many regions relating accessibility levels to visible minority and immigration status. Many regions had significantly higher proportions of visible minorities, immigrants, and indigenous peoples in their lowest MWA census tracts than in their higher MWA divisions. While Toronto and Vancouver bucked this trend for immigrants and visible minorities, they had massive inequalities in access for their indigenous populations. As these are two of Canada's three largest regions the absolute number of people in each of these groups were among the greatest in the study regions. Some regions, like Edmonton and Quebec City had inequitable access for all three groups. These disparities suggest that visible minorities, immigrants, and indigenous peoples are more likely to be reliant on transit or an active mode to get to work, limiting their potential access to employment.

This research adds to the large body that suggests more accessibility to employment is correlated to decreased unemployment and better economic conditions to those in the areas. We know these areas tend to be more economically disadvantaged, with higher unemployment rates, and tend to be overrepresented by some disadvantaged groups. If improving MWA (and achieving an MAT of 1) is the one of the primary goals of transportation planning, and we seek to do so with equity in mind, then the impetus should be to focus transportation infrastructure investments and land use changes in areas and corridors with the greatest potential to improve the lowest MWA areas. This must be done within a regional context, as infrastructure changes improving the MWA in one area, may negatively impact the MWA in other areas because of the trade-offs that result from the interactions between accessibility across modes of travel.

It should be noted there are a few shortcomings in this research that could be addressed in future work in MWA to improve upon what was accomplished here. First and foremost, spatial autocorrelation was not accounted for in these models. This can lead to the regression coefficients and their associated p-values being potentially unreliable and could be addressed using a spatial regression model. If the mode share data became available at a smaller geography, like a dissemination area, the models could be made more precisely, with more accurate travel times between areas of study and with more granular socioeconomic makeups of the areas. Finally, I would suggest that the travel times themselves could be made more accurate. Free-flow automobile travel times were used to calculate the automobile accessibility portion of the MWA equation, which are not likely representative of the peak hour travel times throughout many areas of the regions studied in these models.

I do not believe that anything revealed in this research is new or ground-breaking in a vacuum. We have known for many years that less wealthy areas tend to have lower accessibility, and that in some regions visible minorities and immigrants have lower levels of accessibility to employment. We have also known that automobiles provide a greater level of mobility, and therefore accessibility, than other modes of travel. What this research did is congregate a mode-share weighted accessibility model and socioeconomic data to quantify mode-share weighted accessibility to employment, the levels of inequality of accessibility, and how different socioeconomic variables and their magnitudes were related to accessibility. To my knowledge, no other research has used methods like these to evaluate accessibility cumulatively and weighted by mode across the four principal modes of travel. Consequently, no research has used this novel and innovative approach to understanding how this kind of accessibility relates to socioeconomic variables through space.

There are a few interesting directions that this research could go in the future that were not explored in this thesis. Comparing this research and its 2016 socioeconomic, mode-share, and employment data to its 2021 counterpart would offer insight into how mode-share weighted accessibility changed in the face of the COVID-19 pandemic, changing mode-shares, transportation investments and network changes, as well as how the demographics of high and low accessibility areas have changed. As previously mentioned, an interesting future use case for MWA modelling would be in evaluating how accessibility would change if cities hit their prescribed mode-share targets. An interesting piece of research might be conducting that modelling exercise and quantifying the accessibility that would be lost to achieve these targets without new transportation investments. Finally, the main case and greatest value I see from using MWA is in scenario evaluation, like what was done for the Pie-IX BRT for the MTQ. Understanding the accessibility trade-offs that will result from a project and the potential equity implications of these trade-offs can be a valuable input in a multicriteria analysis.

My hope for MWA is two-fold, one for practicing planners and one for academic planners. I hope that MWA can continue to be a useful tool to planners in assessing the impacts of infrastructure changes in communities. I am hopeful that it will also be used in assessing the impacts of transportation and community plans, and I am hopeful it will be used to understand discrepancies in accessibility between different groups, so that the impacts on vulnerable and disadvantaged groups can be understood. For academic planners, geographers, and those using researching accessibility, I hope that MWA can be used as a modelling framework to understand different urban phenomena. Whether it is the housing market, demographic change, adoption of sustainable modes, or changes of unemployment through recessions to name a few, there are many applications of MWA where traditional accessibility models have been used in the past.

The impetus to create a multimodal accessibility model came from what was observed as a gap in the accessibility literature. When MWA was introduced in 2020, it was met with a degree of apprehension and resistance. New ideas take time to be understood and to be accepted. I am not posturing that MWA is the end of innovations in accessibility, I see its shortcomings alongside the opportunities this kind of modelling brings. Ideas are made to be challenged and iterated on, so what I hope more than anything is that when people look at this research, they see that accessibility can be thought of in a different way, and they contemplate ways accessibility can be thought of in new paradigms. For a concept so fundamental to understanding cities and people, does it not deserve to be looked at in a new light?

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Appendix A

Table A 1: Accessibility (60 Minutes), Mode Shares, and MWA for All Vancouver CMA Census Tracts

Census Tract Unique ID	MWA	WalkJobs60	Walking Mode Share	BikeJobs60	Biking Mode Share	TransitJobs60	Transit Mode Share	DriveJobs60	Automobile Mode Share
9330506.02	920,046	3,370	2.51%	53,135	0.69%	45,570	2.88%	981,135	93.59%
9330506.01	761,019	3,370	3.89%	52,440	0.52%	25,475	3.47%	823,755	92.23%
9330505.04	952,952	6,595	3.31%	30,330	0.92%	0	4.32%	1,050,985	90.63%
9330505.03	988,416	1,215	22.22%	75,010	0.00%	26,395	0.00%	1,111,665	88.89%
9330505.01	978,284	2,470	7.86%	82,820	0.63%	52,730	5.11%	1,127,310	86.48%
9330504.15	1,077,417	24,755	1.34%	119,885	0.00%	64,290	6.20%	1,150,300	93.29%
9330504.14	842,426	11,925	0.00%	94,430	0.00%	13,180	0.00%	1,123,235	75.00%
9330504.13	1,085,187	35,425	2.01%	100,485	0.00%	95,705	5.88%	1,166,795	92.46%
9330504.12	1,063,145	39,620	1.43%	103,675	0.41%	70,455	7.46%	1,166,645	90.59%
9330504.11	1,059,453	22,815	1.19%	96,815	0.63%	66,670	5.84%	1,146,270	92.01%
9330504.1	1,007,325	38,720	8.75%	120,830	0.50%	114,810	4.99%	1,166,795	85.50%
9330504.09	1,041,225	34,700	2.83%	130,750	0.00%	66,135	7.85%	1,170,055	88.46%
9330504.08	1,067,077	15,595	3.62%	99,410	1.11%	63,695	2.54%	1,150,300	92.48%
9330504.07	1,028,708	20,220	3.05%	111,280	0.68%	72,290	7.91%	1,150,300	88.81%
9330504.05	1,018,266	25,570	4.84%	119,530	0.69%	146,285	7.67%	1,170,055	85.89%
9330504.03	1,026,439	1,770	1.84%	74,670	0.46%	10,285	6.36%	1,120,035	91.55%
9330503.09	979,525	34,180	4.76%	101,515	0.87%	97,220	8.12%	1,142,180	84.85%
9330503.08	996,010	35,385	5.78%	115,460	0.00%	127,970	8.24%	1,148,095	85.66%
9330503.07	814,035	34,620	15.20%	103,715	1.17%	98,285	17.08%	1,141,110	69.30%
9330503.06	991,039	30,420	4.81%	110,490	0.46%	107,945	9.37%	1,147,380	85.32%
9330503.03	1,053,501	28,160	1.98%	102,725	0.28%	67,280	5.85%	1,140,680	91.94%
9330503.01	1,057,267	29,135	1.85%	108,315	0.74%	66,910	5.33%	1,141,110	92.22%
9330502.07	1,019,526	14,130	2.20%	90,140	1.20%	54,400	3.92%	1,109,375	91.58%
9330502.06	1,083,335	10,370	1.08%	87,725	1.08%	30,990	1.29%	1,130,865	95.67%
9330502.05	830,910	1,200	5.04%	58,175	1.16%	0	1.41%	911,425	91.09%
9330502.03	1,053,296	16,830	1.04%	101,450	1.88%	72,855	4.65%	1,138,115	92.07%
9330502.02	898,907	2,330	1.66%	84,865	0.66%	38,175	5.13%	959,920	93.38%
9330502.01	1,046,235	5,565	1.43%	97,200	0.71%	61,860	4.24%	1,127,395	92.50%
9330501.03	992,386	1,000	2.85%	35,505	0.85%	0	7.58%	1,055,185	94.02%
9330501.02	1,059,787	5,375	1.63%	68,960	0.00%	4,200	2.63%	1,114,160	95.10%
9330501.01	1,006,336	12,670	3.81%	87,580	0.88%	29,340	5.24%	1,121,995	89.44%
9330500.02	709,789	2,705	4.27%	30,265	0.00%	0	2.99%	775,910	91.46%
9330500.01	617,106	0	0.00%	25,850	0.00%	0	0.00%	651,390	94.74%
9330410.06	1,009,175	13,045	2.46%	111,540	0.41%	66,365	10.40%	1,150,300	87.06%
9330410.05	941,974	8,420	3.49%	98,415	0.73%	86,880	16.41%	1,147,845	80.73%
9330410.04	921,986	555	9.40%	28,675	1.71%	0	5.15%	1,088,980	84.62%
9330410.02	916,023	6,080	3.02%	92,130	0.55%	4,125	14.70%	1,109,545	82.44%
9330404.02	490,036	1,040	1.53%	1,040	0.00%	0	6.51%	530,720	92.33%
9330404.01	568,611	1,510	2.07%	16,165	0.32%	8,870	5.37%	614,005	92.52%
9330403.07	996,357	14,095	4.59%	105,165	0.88%	78,130	7.61%	1,146,890	86.22%
9330403.06	838,981	13,045	16.67%	104,660	11.11%	47,575	0.00%	1,142,555	72.22%
9330403.05	1,008,723	11,160	3.81%	80,805	0.00%	77,545	7.30%	1,134,880	88.35%

Table A 2 Continued: Accessibility (60 Minutes), Mode Shares, and MWA for All Vancouver CMA Census Tracts

Census Tract Unique ID	MWA	WalkJobs60	Walking Mode Share	BikeJobs60	Biking Mode Share	TransitJobs60	Transit Mode Share	DriveJobs60	Automobile Mode Share
9330403.04	981,851	9,940	0.89%	71,850	1.11%	18,700	11.29%	1,132,350	86.44%
9330403.01	941,347	16,445	3.85%	73,110	0.37%	41,945	14.19%	1,114,440	83.85%
9330402.04	918,061	10,320	6.61%	40,110	0.00%	21,335	8.15%	1,092,300	83.83%
9330402.03	889,599	11,410	7.53%	47,810	0.71%	22,020	11.78%	1,100,785	80.47%
9330402.02	943,307	11,105	4.55%	58,780	0.79%	30,045	10.73%	1,102,910	85.15%
9330401.02	864,244	11,805	7.31%	44,555	0.43%	29,550	14.61%	1,093,965	78.51%
9330401.01	898,188	15,225	6.96%	52,065	0.73%	38,625	15.38%	1,110,455	80.22%
9330400.09	512,107	1,920	2.12%	12,725	0.00%	7,395	5.59%	553,900	92.37%
9330400.08	0	0	0.00%	1,275	0.00%	7,395	0.00%	641,350	0.00%
9330400.07	0	1,970	0.00%	20,285	0.00%	1,630	0.00%	939,920	0.00%
9330400.06	981,675	9,330	1.07%	27,350	0.00%	22,020	6.85%	1,061,550	92.32%
9330400.05	928,140	8,225	3.02%	26,795	0.72%	21,980	9.50%	1,061,550	87.19%
9330400.04	852,222	3,550	1.54%	22,170	0.28%	8,170	10.43%	956,990	88.95%
9330292.04	993,748	18,115	2.18%	86,605	1.19%	45,740	14.11%	1,171,445	84.16%
9330292.03	1,012,143	26,500	2.86%	100,965	1.11%	107,555	11.17%	1,171,445	85.21%
9330292.01	981,682	26,275	1.11%	88,005	0.37%	55,020	14.88%	1,149,570	84.63%
9330291.02	995,359	32,235	2.89%	100,045	0.58%	118,840	15.80%	1,171,445	83.24%
9330291.01	906,070	38,450	5.46%	102,990	0.80%	120,675	20.68%	1,171,445	74.97%
9330290.07	994,716	24,675	2.01%	136,425	0.46%	56,860	14.68%	1,171,445	84.10%
9330290.06	0	22,000	0.00%	114,335	0.00%	23,690	0.00%	1,171,445	0.00%
9330290.05	1,011,961	20,320	3.58%	124,665	0.00%	71,690	10.65%	1,171,445	85.67%
9330290.04	1,039,356	13,005	1.20%	170,985	0.40%	57,570	10.57%	1,171,445	88.13%
9330290.02	924,570	26,130	4.28%	125,095	1.18%	100,670	18.53%	1,171,445	77.11%
9330287.16	910,418	40,135	8.15%	128,600	0.63%	414,575	24.63%	1,171,445	68.65%
9330287.15	952,031	24,040	4.71%	103,865	0.59%	277,085	19.66%	1,171,445	76.47%
9330287.14	870,382	2,075	1.03%	52,205	0.00%	34,280	20.29%	1,073,720	80.41%
9330287.13	962,646	20,155	1.95%	85,275	0.28%	119,345	19.61%	1,170,000	80.22%
9330287.12	944,103	22,350	0.63%	85,275	0.63%	99,790	22.10%	1,170,000	78.75%
9330287.11	937,423	27,060	4.69%	117,225	0.39%	275,220	21.15%	1,170,000	75.00%
9330287.1	937,206	19,225	1.26%	83,805	0.00%	101,765	17.76%	1,149,820	79.92%
9330287.09	854,065	28,105	11.35%	123,780	0.00%	310,710	24.85%	1,170,000	66.13%
9330287.06	847,973	27,640	11.33%	110,385	0.55%	176,170	20.56%	1,170,000	69.06%
9330287.02	952,675	1,130	1.16%	33,910	0.27%	0	12.51%	1,099,045	86.67%
9330287.01	940,765	23,735	4.32%	86,575	1.05%	107,620	17.62%	1,170,000	78.62%
9330286.03	995,644	28,620	3.03%	151,615	1.65%	210,375	13.74%	1,169,575	82.37%
9330286.02	988,602	38,715	2.30%	155,130	0.64%	195,830	18.74%	1,171,445	81.10%
9330286.01	978,746	24,390	3.07%	185,120	0.36%	154,080	17.74%	1,170,045	81.19%
9330285.02	986,585	24,520	2.62%	227,530	0.75%	254,070	18.26%	1,169,570	80.19%
9330285.01	866,276	39,175	6.99%	269,540	0.61%	235,300	30.48%	1,171,020	67.48%
9330284.02	1,013,275	32,630	1.84%	260,105	0.53%	500,360	26.63%	1,169,175	75.10%
9330284.01	872,050	43,315	4.14%	276,600	1.33%	360,490	37.37%	1,168,590	62.63%
9330283	903,191	45,675	4.90%	304,225	0.52%	393,095	31.77%	1,170,045	66.19%
9330282.02	936,839	37,690	4.22%	275,555	0.47%	323,215	25.79%	1,171,645	72.60%
9330282.01	956,512	40,860	4.00%	293,800	0.89%	357,395	22.40%	1,171,645	74.44%

Table A 3 Continued: Accessibility (60 Minutes), Mode Shares, and MWA for All Vancouver CMA Census Tracts

Census Tract Unique ID	MWA	WalkJobs60	Walking Mode Share	BikeJobs60	Biking Mode Share	TransitJobs60	Transit Mode Share	DriveJobs60	Automobile Mode Share
9330281.02	1,005,362	34,415	3.28%	250,015	1.25%	271,200	14.07%	1,171,645	82.19%
9330281.01	1,003,312	14,510	1.51%	197,075	0.34%	112,285	14.34%	1,171,020	84.23%
9330280.02	996,511	27,785	1.48%	182,870	0.74%	120,265	15.42%	1,171,445	83.33%
9330280.01	0	13,710	0.00%	165,105	0.00%	66,175	0.00%	1,171,020	0.00%
9330270	0	25,860	0.00%	252,270	0.00%	168,890	0.00%	1,171,445	0.00%
9330260.12	981,970	25,950	3.68%	157,000	0.39%	511,365	26.83%	1,169,575	72.09%
9330260.11	845,835	120	0.00%	40,760	0.00%	15,405	31.25%	1,103,840	76.19%
9330260.1	962,427	28,310	3.88%	132,815	1.14%	322,215	20.16%	1,170,000	76.48%
9330260.08	947,567	18,605	1.53%	101,785	0.00%	106,440	17.41%	1,148,215	80.89%
9330260.07	936,312	27,060	6.02%	116,245	0.43%	193,860	17.23%	1,170,000	76.99%
9330260.06	978,604	11,750	0.85%	98,960	1.41%	40,575	14.19%	1,145,615	84.79%
9330260.05	983,746	24,370	2.03%	181,055	0.68%	244,065	18.07%	1,167,145	80.36%
9330260.04	967,732	12,055	2.88%	179,565	0.52%	280,275	21.05%	1,167,145	77.75%
9330251.02	813,030	0	18.75%	49,880	0.00%	1,635	0.00%	1,084,040	75.00%
9330251.01	0	785	0.00%	61,165	0.00%	785	0.00%	1,115,970	0.00%
9330250.02	338,556	620	1.56%	620	1.04%	0	9.06%	377,905	89.58%
9330250.01	273,085	1,085	6.25%	2,535	2.96%	0	27.35%	410,765	66.45%
9330243.02	792,579	26,480	9.50%	237,500	1.28%	123,615	26.70%	1,160,825	64.96%
9330243.01	956,281	46,035	1.15%	509,445	1.54%	402,265	30.66%	1,158,845	71.15%
9330242	948,684	43,590	2.75%	499,395	0.72%	364,755	25.60%	1,156,295	73.55%
9330241	955,965	59,880	3.86%	559,970	1.93%	448,385	24.13%	1,157,030	72.14%
9330240.02	972,866	78,690	3.18%	586,485	2.06%	488,040	24.57%	1,159,055	72.34%
9330240.01	939,307	89,025	5.92%	582,795	1.08%	578,110	29.08%	1,160,730	65.45%
9330239.02	938,488	78,670	5.17%	577,970	1.62%	576,925	34.68%	1,159,645	62.52%
9330239.01	971,347	71,735	3.54%	566,830	0.79%	485,550	24.89%	1,158,115	72.83%
9330238.02	949,139	56,140	2.10%	549,990	1.46%	461,500	29.40%	1,158,590	69.42%
9330238.01	959,726	63,615	1.73%	556,510	1.45%	573,520	37.05%	1,160,825	63.58%
9330237	964,805	36,160	1.90%	428,190	1.02%	467,020	29.41%	1,160,825	70.85%
9330236	1,012,176	27,665	1.69%	309,425	2.03%	502,805	17.49%	1,161,605	78.98%
9330235.04	877,035	45,615	5.16%	307,880	1.00%	571,890	40.94%	1,169,175	54.52%
9330235.03	938,035	44,210	6.84%	309,130	0.85%	677,150	43.24%	1,169,175	54.70%
9330235.02	929,964	40,055	3.24%	276,090	1.42%	429,185	30.82%	1,168,590	67.81%
9330234	888,507	37,855	3.45%	302,115	0.94%	129,850	24.41%	1,163,050	73.31%
9330233	949,044	44,105	2.18%	353,080	0.95%	421,100	30.53%	1,161,605	70.26%
9330232	941,739	57,485	1.79%	322,890	2.15%	316,850	24.90%	1,169,175	73.12%
9330231	995,753	61,610	2.98%	380,105	1.19%	493,790	22.54%	1,161,605	75.60%
9330230.02	935,391	86,335	3.56%	558,600	1.05%	449,235	31.08%	1,160,825	67.78%
9330230.01	970,466	92,935	3.73%	496,570	2.07%	461,360	22.84%	1,161,605	73.29%
9330229	956,452	97,120	4.07%	590,015	1.51%	519,790	30.78%	1,159,645	67.57%
9330228.04	943,747	99,555	6.39%	583,490	1.13%	664,105	38.83%	1,158,590	58.08%
9330228.03	868,786	95,170	9.07%	570,205	0.47%	719,935	55.94%	1,157,170	39.30%
9330228.02	979,911	101,975	2.90%	587,370	1.29%	566,055	32.57%	1,158,845	67.74%
9330227.02	888,467	74,120	9.02%	563,300	0.82%	694,160	47.80%	1,157,170	47.13%
9330227.01	875,737	89,050	9.29%	576,035	1.09%	738,305	57.26%	1,157,170	37.89%

Table A 4 Continued: Accessibility (60 Minutes), Mode Shares, and MWA for All Vancouver CMA Census Tracts

Census Tract Unique ID	MWA	WalkJobs60	Walking Mode Share	BikeJobs60	Biking Mode Share	TransitJobs60	Transit Mode Share	DriveJobs60	Automobile Mode Share
9330226.04	893,726	90,045	8.06%	509,895	1.21%	657,450	50.74%	1,158,845	47.18%
9330226.03	867,303	91,535	13.71%	555,665	0.50%	680,700	37.76%	1,158,845	51.34%
9330226.02	856,198	91,680	6.60%	565,540	0.99%	470,180	39.47%	1,160,825	56.77%
9330225.02	887,993	65,475	5.10%	444,020	0.48%	509,065	38.75%	1,158,115	59.17%
9330225.01	970,239	72,265	2.65%	403,075	1.02%	460,710	25.00%	1,158,845	73.27%
9330224.02	918,867	79,385	3.58%	359,740	0.55%	493,540	39.41%	1,160,825	61.98%
9330224.01	946,540	84,580	4.79%	396,080	0.66%	638,290	44.49%	1,158,845	56.60%
9330223.02	898,043	79,300	2.44%	341,535	0.81%	490,275	42.27%	1,161,605	59.06%
9330223.01	956,035	67,215	2.71%	356,040	0.24%	652,300	43.03%	1,160,825	57.95%
9330222.02	935,906	58,815	1.79%	350,095	0.89%	667,215	40.77%	1,158,115	56.96%
9330222.01	957,345	60,735	2.65%	434,750	1.12%	565,790	35.24%	1,156,295	64.99%
9330221.04	937,740	78,455	5.84%	525,755	2.02%	630,410	35.79%	1,157,170	60.22%
9330221.03	945,965	60,550	3.49%	512,850	1.45%	442,985	24.83%	1,155,610	71.51%
9330221.01	1,049,222	64,845	1.68%	590,875	2.79%	513,285	19.87%	1,155,610	80.45%
9330220	896,470	46,260	1.57%	333,515	1.57%	249,235	27.68%	1,146,495	71.65%
9330210	900,784	55,860	8.41%	327,435	0.76%	626,465	42.11%	1,170,045	53.82%
9330209	950,174	46,060	4.95%	353,050	0.88%	474,120	23.40%	1,169,175	71.32%
9330208	876,365	48,285	9.44%	359,445	2.24%	405,015	23.29%	1,161,605	66.24%
9330207	902,500	41,450	8.44%	352,340	0.63%	698,255	50.36%	1,163,050	46.88%
9330206	916,493	38,090	5.14%	339,695	1.03%	705,395	53.80%	1,161,605	45.76%
9330205.02	873,178	47,290	11.32%	321,805	0.64%	554,270	32.60%	1,161,605	58.97%
9330205.01	850,328	42,030	7.42%	343,115	0.41%	587,035	50.24%	1,161,605	47.42%
9330204.02	914,514	48,545	4.80%	342,235	0.89%	528,380	40.86%	1,161,605	59.68%
9330204.01	907,494	45,590	7.00%	334,150	0.92%	607,605	38.83%	1,161,605	57.27%
9330203	976,958	57,310	3.64%	334,870	1.82%	626,710	29.26%	1,161,605	67.61%
9330202	889,072	39,705	5.13%	328,020	0.70%	597,630	45.06%	1,160,825	53.02%
9330201	1,037,554	51,775	2.45%	344,400	1.23%	750,595	41.79%	1,159,360	61.96%
9330200	993,223	24,330	2.87%	299,340	1.06%	571,935	23.88%	1,156,295	73.75%
9330192	1,073,592	49,285	1.64%	278,190	1.10%	681,670	26.98%	1,163,050	76.16%
9330191.07	890,657	48,170	5.94%	224,755	0.48%	636,725	58.91%	1,170,670	43.71%
9330191.06	968,356	44,930	2.69%	252,545	0.00%	591,680	42.86%	1,170,045	60.99%
9330191.05	969,085	42,265	2.48%	242,610	0.50%	448,925	33.86%	1,168,590	69.73%
9330191.04	883,631	53,515	6.56%	212,095	0.73%	489,440	39.47%	1,169,570	58.60%
9330191.03	967,419	51,485	3.71%	214,975	0.37%	369,790	29.88%	1,168,590	73.10%
9330190.05	902,404	46,185	2.74%	227,010	1.37%	424,760	41.53%	1,170,670	61.64%
9330190.04	948,047	43,995	1.69%	233,325	0.28%	253,035	26.96%	1,170,670	75.04%
9330190.03	861,956	47,260	4.38%	217,905	0.28%	287,770	36.94%	1,171,645	64.27%
9330190.01	868,995	57,935	7.42%	211,230	0.33%	483,005	41.72%	1,170,670	56.59%
9330189.1	881,668	45,345	5.65%	237,230	0.30%	205,810	27.40%	1,172,070	70.13%
9330189.09	990,699	44,855	2.53%	240,585	0.00%	244,565	18.13%	1,172,070	80.65%
9330189.08	825,072	43,455	8.80%	233,370	0.00%	384,870	38.86%	1,172,070	57.31%
9330189.07	913,189	25,830	6.52%	237,055	0.00%	317,465	25.65%	1,172,070	70.82%
9330189.06	844,764	44,790	3.00%	220,270	0.00%	187,135	39.57%	1,171,645	65.67%
9330189.05	855,708	46,885	6.45%	235,370	0.67%	206,995	26.83%	1,172,070	67.88%

Table A 5 Continued: Accessibility (60 Minutes), Mode Shares, and MWA for All Vancouver CMA Census Tracts

Census Tract Unique ID	MWA	WalkJobs60	Walking Mode Share	BikeJobs60	Biking Mode Share	TransitJobs60	Transit Mode Share	DriveJobs60	Automobile Mode Share
9330189.03	975,684	25,325	4.13%	237,820	0.00%	144,595	16.73%	1,171,645	81.12%
9330188.08	1,014,932	15,030	2.35%	227,470	0.00%	161,385	13.49%	1,172,070	84.71%
9330188.07	994,857	8,765	0.90%	218,100	0.00%	74,235	15.68%	1,172,070	83.88%
9330188.06	957,388	8,890	1.46%	151,585	1.46%	47,875	11.30%	1,172,070	81.02%
9330188.05	1,016,988	1,040	2.04%	153,525	0.00%	56,635	13.33%	1,172,070	86.12%
9330188.04	1,009,557	19,910	2.65%	195,295	0.00%	84,700	13.06%	1,172,070	85.15%
9330188.02	992,768	21,150	1.83%	237,425	0.00%	256,680	18.64%	1,172,070	80.59%
9330188.01	959,911	1,040	1.40%	214,740	0.70%	43,295	18.88%	1,171,395	81.12%
9330187.16	977,777	14,055	2.40%	205,295	1.37%	126,825	15.23%	1,172,070	81.51%
9330187.15	986,580	21,985	3.88%	205,840	0.60%	151,135	14.79%	1,172,070	82.09%
9330187.14	932,775	19,365	3.03%	201,795	0.00%	189,735	21.45%	1,172,070	76.06%
9330187.13	977,601	40,905	1.23%	215,335	0.49%	233,115	24.76%	1,171,645	78.38%
9330187.12	925,426	43,555	2.58%	234,315	0.52%	188,255	25.00%	1,172,070	74.74%
9330187.11	933,585	14,485	2.75%	200,960	0.31%	185,550	23.30%	1,172,070	75.88%
9330187.07	1,085,075	10,820	1.03%	198,265	0.00%	154,055	6.29%	1,171,395	91.79%
9330187.06	1,039,227	27,865	1.58%	213,305	0.32%	181,295	13.20%	1,172,070	86.53%
9330187.05	1,025,022	62,940	0.86%	190,480	0.43%	300,145	18.83%	1,170,670	82.61%
9330187.04	1,000,777	63,620	2.92%	206,870	0.00%	290,965	22.94%	1,171,645	79.56%
9330187.03	997,381	56,650	2.18%	222,120	0.54%	337,445	23.79%	1,171,645	78.07%
9330186.08	954,273	67,630	3.55%	192,310	0.32%	268,950	26.44%	1,168,500	75.32%
9330186.07	982,775	61,590	0.92%	189,300	1.10%	289,890	26.84%	1,166,575	77.35%
9330186.06	1,005,293	47,115	4.22%	168,945	0.00%	187,170	15.85%	1,160,415	83.91%
9330186.05	968,760	47,700	1.42%	183,705	0.28%	233,540	25.94%	1,163,050	77.98%
9330186.02	955,372	43,375	1.19%	236,795	0.34%	248,115	27.88%	1,167,250	75.81%
9330186.01	1,010,477	32,250	2.05%	202,900	0.27%	425,360	22.92%	1,161,605	78.49%
9330185.22	987,909	37,670	2.42%	159,480	0.91%	153,520	19.74%	1,158,190	82.48%
9330185.21	1,006,268	34,750	2.37%	180,840	0.00%	219,315	19.17%	1,159,530	83.09%
9330185.2	1,022,702	34,760	1.00%	177,435	0.60%	117,360	15.07%	1,158,190	86.65%
9330185.19	972,342	29,865	1.73%	170,720	0.35%	189,685	19.96%	1,158,190	80.59%
9330185.18	1,036,741	27,005	0.79%	140,095	0.00%	70,160	11.82%	1,158,190	88.78%
9330185.17	1,022,389	26,970	2.44%	163,805	0.00%	121,625	10.57%	1,158,190	87.11%
9330185.16	955,906	49,410	3.36%	167,110	0.00%	144,745	22.36%	1,164,760	79.15%
9330185.15	981,906	60,975	3.17%	173,400	0.37%	179,680	19.34%	1,166,575	80.97%
9330185.12	1,027,556	38,410	0.62%	161,035	0.31%	154,920	15.57%	1,157,780	86.60%
9330185.11	943,559	40,165	3.38%	142,785	0.44%	191,450	22.77%	1,158,190	77.53%
9330185.1	996,579	40,730	2.41%	137,920	1.01%	147,165	17.98%	1,158,970	83.50%
9330185.09	949,385	38,735	2.62%	155,850	0.40%	168,345	22.42%	1,160,310	78.43%
9330185.08	1,081,851	10,235	1.32%	135,355	1.32%	55,770	1.61%	1,155,550	93.38%
9330185.07	1,039,103	32,090	0.99%	151,065	0.44%	154,220	13.55%	1,159,635	87.72%
9330185.05	951,092	38,810	2.03%	164,220	0.37%	186,020	25.19%	1,158,970	77.90%
9330184.16	1,006,891	42,960	1.23%	160,885	0.00%	133,670	19.23%	1,166,575	84.06%
9330184.15	1,045,072	59,825	0.61%	189,920	0.61%	145,630	13.67%	1,169,370	87.54%
9330184.14	1,011,113	12,455	1.96%	184,910	0.22%	140,165	13.80%	1,164,765	85.09%
9330184.13	1,030,148	11,920	1.81%	162,655	0.00%	129,755	12.66%	1,163,315	87.12%

Table A 6 Continued: Accessibility (60 Minutes), Mode Shares, and MWA for All Vancouver CMA Census Tracts

Census Tract Unique ID	MWA	WalkJobs60	Walking Mode Share	BikeJobs60	Biking Mode Share	TransitJobs60	Transit Mode Share	DriveJobs60	Automobile Mode Share
9330184.12	993,312	27,890	1.42%	175,505	0.00%	153,890	17.59%	1,161,500	83.16%
9330184.11	1,025,566	40,110	0.90%	185,465	0.00%	137,010	14.39%	1,167,160	86.15%
9330184.1	1,004,105	44,540	0.39%	192,655	0.00%	131,465	17.34%	1,169,995	83.86%
9330184.09	1,030,600	53,495	0.43%	215,350	0.43%	187,985	15.89%	1,171,645	85.31%
9330184.08	981,411	34,350	2.49%	174,795	0.36%	144,540	17.22%	1,156,330	82.59%
9330184.07	986,893	42,675	2.33%	172,305	0.47%	160,050	18.67%	1,163,570	82.09%
9330184.06	1,022,084	27,725	1.18%	183,855	0.29%	161,285	16.45%	1,166,575	85.27%
9330184.02	897,411	45,755	3.55%	163,635	0.27%	145,505	25.79%	1,166,575	73.53%
9330183.09	1,053,901	37,775	1.79%	149,875	0.62%	68,885	7.37%	1,166,795	89.75%
9330183.08	1,040,281	35,445	2.32%	144,080	0.44%	84,435	8.76%	1,166,795	88.40%
9330183.07	1,081,223	34,415	1.52%	157,960	0.91%	119,205	5.53%	1,166,795	91.93%
9330183.06	1,017,224	37,720	3.08%	132,610	0.77%	93,385	8.84%	1,148,095	87.69%
9330183.05	1,049,202	30,745	1.73%	181,005	0.61%	122,205	9.05%	1,168,865	88.68%
9330183.03	1,027,586	22,675	5.34%	168,775	1.29%	120,605	5.74%	1,166,370	87.22%
9330183.01	1,061,813	16,435	2.82%	185,075	0.63%	144,495	7.36%	1,166,370	89.98%
9330182.06	1,053,943	24,400	5.32%	161,270	2.13%	90,105	2.70%	1,171,395	89.36%
9330182.05	1,060,668	18,780	1.98%	194,590	0.31%	109,670	9.04%	1,171,395	89.62%
9330182.04	1,035,474	9,420	3.57%	180,875	0.00%	85,080	8.88%	1,170,970	87.76%
9330182.03	1,038,186	13,450	1.49%	182,810	0.00%	142,900	12.36%	1,166,575	87.46%
9330182.02	1,073,303	17,740	0.89%	188,205	0.00%	124,845	8.50%	1,166,370	91.10%
9330182.01	1,080,214	7,015	1.09%	131,610	0.44%	5,205	5.56%	1,160,535	93.00%
9330181.16	1,007,843	17,100	2.14%	53,135	0.71%	34,460	9.62%	1,148,350	87.41%
9330181.15	1,010,836	10,220	20.00%	53,825	0.00%	25,995	0.00%	1,120,880	90.00%
9330181.14	938,548	21,195	6.85%	85,010	0.68%	121,530	14.29%	1,151,900	79.79%
9330181.13	989,562	21,940	3.04%	85,985	0.00%	92,765	11.39%	1,153,930	84.78%
9330181.12	1,055,989	19,750	1.09%	90,955	0.00%	50,960	7.93%	1,151,900	91.30%
9330181.11	845,650	22,855	14.20%	62,775	0.00%	66,965	12.50%	1,146,795	72.73%
9330181.1	953,272	23,855	3.44%	64,475	0.57%	42,595	14.95%	1,150,015	82.23%
9330181.09	1,007,081	12,325	2.49%	50,060	0.75%	41,025	6.74%	1,133,680	88.53%
9330181.08	965,354	8,705	3.50%	45,285	0.00%	39,565	12.42%	1,116,435	86.00%
9330181.07	957,398	5,790	3.69%	42,075	0.74%	29,040	9.96%	1,114,350	85.61%
9330181.05	913,156	22,395	9.32%	69,245	1.02%	76,515	11.80%	1,151,055	78.31%
9330181.03	992,251	5,830	3.69%	67,005	0.00%	38,785	8.29%	1,143,325	86.49%
9330180.04	1,011,536	19,920	4.00%	91,730	0.46%	69,255	8.99%	1,156,225	86.84%
9330180.03	1,048,690	7,185	2.43%	74,090	0.40%	52,805	4.94%	1,134,270	92.18%
9330180.01	1,012,470	14,725	3.34%	99,375	0.33%	107,880	9.26%	1,151,900	86.96%
9330170.08	979,275	18,360	7.76%	49,400	0.62%	42,595	6.64%	1,133,060	86.02%
9330170.07	985,779	19,245	7.57%	55,575	0.95%	47,700	7.35%	1,146,685	85.49%
9330170.05	852,884	21,265	11.90%	51,840	0.95%	64,010	14.77%	1,138,610	73.81%
9330170.04	972,159	18,235	5.91%	49,190	0.95%	40,320	7.69%	1,133,680	85.34%
9330170.03	875,795	21,265	15.65%	52,520	0.76%	72,145	8.70%	1,145,645	75.57%
9330163.08	1,001,244	30,480	1.04%	177,545	0.52%	191,765	16.01%	1,159,530	83.59%
9330163.07	995,783	22,125	2.05%	170,885	0.62%	266,555	18.84%	1,160,985	81.31%
9330163.06	998,845	33,715	2.17%	150,450	0.48%	164,305	14.51%	1,158,190	84.06%

Table A 7 Continued: Accessibility (60 Minutes), Mode Shares, and MWA for All Vancouver CMA Census Tracts

Census Tract Unique ID	MWA	WalkJobs60	Walking Mode Share	BikeJobs60	Biking Mode Share	TransitJobs60	Transit Mode Share	DriveJobs60	Automobile Mode Share
9330163.05	986,406	32,455	2.18%	156,270	0.59%	300,760	19.38%	1,160,985	79.80%
9330163.04	1,038,523	12,745	1.07%	208,390	1.25%	366,075	13.95%	1,160,205	84.88%
9330163.01	1,012,744	15,630	1.55%	216,650	0.52%	158,785	13.31%	1,155,955	85.66%
9330162.04	1,010,785	10,775	2.76%	124,035	0.39%	127,435	10.99%	1,158,190	86.00%
9330162.03	982,352	36,015	2.48%	143,115	0.55%	105,035	16.49%	1,159,530	83.08%
9330162.02	1,008,358	28,345	1.24%	166,070	0.31%	148,410	15.88%	1,160,205	84.81%
9330162.01	999,572	28,630	1.76%	147,650	0.00%	68,920	13.75%	1,157,550	85.49%
9330161.09	946,509	27,485	4.89%	43,910	2.17%	34,235	7.09%	1,103,745	85.33%
9330161.08	884,813	3,340	10.20%	38,125	0.00%	10,640	7.89%	1,082,450	81.63%
9330161.07	0	335	0.00%	38,125	0.00%	1,460	0.00%	1,060,225	0.00%
9330161.06	939,284	5,325	3.84%	38,125	1.37%	37,020	9.72%	1,097,300	85.21%
9330161.05	921,452	5,325	4.13%	38,125	2.07%	151,820	13.27%	1,101,215	81.76%
9330161.03	948,364	5,325	5.74%	38,125	0.45%	220,015	11.50%	1,110,460	83.08%
9330161.02	863,754	5,325	5.44%	38,125	1.27%	41,900	15.87%	1,097,300	78.04%
9330160.04	850,259	5,315	8.99%	38,125	0.58%	10,640	13.79%	1,095,850	77.39%
9330160.03	897,803	5,315	5.33%	38,125	1.28%	10,640	9.82%	1,083,035	82.73%
9330160.02	891,661	4,980	6.50%	38,125	0.68%	10,640	9.98%	1,082,450	82.22%
9330160.01	927,344	4,980	2.89%	38,125	2.10%	10,640	8.76%	1,075,010	86.09%
9330151.08	912,732	50,015	3.08%	446,815	0.90%	317,320	20.27%	1,104,420	76.32%
9330151.07	827,312	51,985	12.54%	497,715	1.05%	445,815	25.93%	1,097,825	63.76%
9330151.06	950,250	54,420	2.37%	399,745	1.19%	253,770	16.00%	1,104,420	81.82%
9330151.05	920,707	48,720	5.59%	554,590	0.59%	433,425	22.18%	1,104,420	74.12%
9330151.03	819,574	13,290	2.55%	544,720	2.23%	24,440	22.18%	1,094,455	73.25%
9330150	824,524	19,755	3.49%	250,680	8.14%	0	12.31%	1,046,895	76.74%
9330149.09	896,072	47,275	5.00%	197,960	1.82%	317,540	18.59%	1,081,865	76.82%
9330149.08	919,356	45,095	1.61%	260,795	1.38%	349,755	19.95%	1,085,320	77.88%
9330149.07	934,011	42,220	3.51%	211,075	2.34%	310,165	13.33%	1,082,475	81.87%
9330149.06	907,167	26,805	2.79%	181,915	0.93%	180,285	15.54%	1,072,645	81.73%
9330149.05	903,532	46,095	5.26%	210,050	0.00%	311,840	18.80%	1,085,240	77.63%
9330149.02	879,533	31,850	1.44%	164,130	2.15%	242,215	20.53%	1,075,350	76.79%
9330148	766,638	48,820	13.13%	291,920	0.91%	405,510	30.99%	1,091,825	57.88%
9330147.1	814,886	47,775	4.68%	203,505	1.04%	373,115	34.29%	1,094,975	62.34%
9330147.09	828,983	47,605	6.40%	223,360	2.40%	356,740	25.96%	1,087,605	66.93%
9330147.08	797,852	50,920	10.21%	241,630	1.01%	425,380	30.59%	1,095,110	60.28%
9330147.07	714,287	51,025	14.68%	258,940	0.64%	462,710	40.57%	1,095,415	47.23%
9330147.05	843,502	46,460	7.42%	178,920	0.72%	382,065	28.03%	1,096,195	66.75%
9330147.04	898,448	46,460	2.95%	240,400	1.97%	373,845	23.26%	1,102,790	73.03%
9330147.01	919,969	49,390	3.13%	248,210	0.21%	382,525	21.92%	1,104,420	75.52%
9330146	916,984	18,315	2.48%	199,730	0.73%	245,385	17.97%	1,104,420	78.86%
9330145.02	970,796	48,120	1.38%	201,730	0.69%	368,390	18.25%	1,103,095	81.72%
9330145.01	924,209	46,455	4.00%	174,290	1.00%	402,395	17.56%	1,089,690	78.00%
9330144.06	919,137	24,325	1.98%	175,250	1.98%	258,570	18.83%	1,102,790	78.57%
9330144.05	951,093	31,895	0.90%	167,895	0.90%	337,625	18.46%	1,093,920	81.08%
9330144.04	847,606	24,320	3.78%	148,925	2.39%	264,570	26.54%	1,095,130	70.58%

Table A 8 Continued: Accessibility (60 Minutes), Mode Shares, and MWA for All Vancouver CMA Census Tracts

Census Tract Unique ID	MWA	WalkJobs60	Walking Mode Share	BikeJobs60	Biking Mode Share	TransitJobs60	Transit Mode Share	DriveJobs60	Automobile Mode Share
9330144.03	907,036	17,675	2.03%	158,565	2.03%	200,660	19.28%	1,102,235	78.46%
9330143.04	933,854	34,620	2.38%	171,150	1.19%	351,960	16.01%	1,083,020	80.76%
9330143.03	915,434	44,470	0.57%	155,480	1.13%	338,705	23.41%	1,094,595	76.20%
9330143.02	891,074	35,380	4.36%	200,880	0.00%	349,045	20.99%	1,085,915	75.17%
9330143.01	939,642	29,585	1.35%	151,675	1.13%	335,925	17.54%	1,081,160	81.26%
9330142.03	845,974	28,185	1.79%	148,945	2.39%	182,825	23.17%	1,075,350	74.35%
9330142.02	908,824	12,100	1.61%	147,320	1.84%	178,815	14.68%	1,074,870	81.84%
9330142.01	900,561	11,375	1.81%	142,110	1.45%	170,620	16.91%	1,073,230	81.01%
9330141.02	957,545	7,540	7.27%	98,820	0.00%	74,085	4.17%	1,070,715	89.09%
9330141.01	876,495	7,715	4.99%	98,820	2.83%	178,175	13.77%	1,071,085	79.25%
9330140.04	1,002,982	4,630	0.36%	292,155	0.00%	395,170	19.07%	1,146,495	80.91%
9330140.03	882,504	28,160	5.62%	230,550	0.47%	256,640	20.90%	1,109,385	74.47%
9330140.02	891,533	11,135	2.78%	103,170	2.64%	11,415	12.23%	1,072,380	82.72%
9330135	896,247	2,655	2.21%	110,460	0.95%	2,655	9.85%	1,046,780	85.49%
9330134	796,003	5,360	2.92%	109,170	1.70%	5,360	10.16%	942,500	84.18%
9330133.02	904,855	1,620	1.64%	17,845	0.70%	0	9.92%	1,032,910	87.59%
9330133.01	839,779	1,450	6.17%	17,615	0.97%	150,400	12.69%	1,023,045	80.19%
9330132	908,266	3,420	2.33%	192,800	1.86%	267,865	8.56%	1,047,300	84.19%
9330131	914,195	18,260	5.15%	359,030	3.51%	278,190	10.62%	1,093,990	79.63%
9330130.04	733,295	45,300	14.35%	418,180	2.17%	380,265	36.56%	1,099,975	52.61%
9330130.03	795,875	28,870	11.34%	379,675	2.06%	368,215	28.35%	1,099,975	61.86%
9330130.01	794,294	19,525	12.35%	333,830	1.59%	316,160	19.91%	1,074,720	67.33%
9330122	886,877	4,605	2.04%	203,015	1.75%	24,370	13.59%	1,062,720	82.80%
9330121	944,980	35,470	5.02%	300,390	2.51%	297,890	10.28%	1,101,930	82.13%
9330120	910,890	27,400	3.81%	326,920	2.77%	246,560	13.38%	1,099,975	78.89%
9330119	880,455	39,220	5.49%	358,795	4.95%	297,015	16.15%	1,103,670	73.63%
9330118	846,087	49,055	7.20%	425,240	3.40%	324,475	25.53%	1,103,670	67.53%
9330117	908,973	34,870	3.39%	302,385	1.80%	210,525	17.36%	1,103,740	78.44%
9330116	104,298	5,265	1.97%	50,570	2.19%	0	12.27%	122,685	84.03%
9330115	852,772	3,525	5.77%	88,630	2.23%	19,835	15.67%	1,101,930	76.91%
9330114.02	937,361	21,425	3.04%	245,880	3.24%	257,555	15.35%	1,117,745	79.55%
9330114.01	933,094	9,115	2.36%	138,545	2.36%	224,380	13.79%	1,103,740	81.42%
9330113	934,615	20,505	4.53%	346,795	2.06%	262,140	16.61%	1,127,335	78.33%
9330112	935,395	33,820	2.82%	437,610	2.42%	265,865	19.21%	1,127,335	77.42%
9330111.07	814,672	5,185	4.56%	83,235	3.11%	5,185	20.38%	1,100,845	73.65%
9330111.06	738,590	46,720	0.00%	486,280	0.00%	483,560	22.22%	1,157,075	54.55%
9330111.05	955,515	12,625	5.43%	441,040	4.35%	403,235	15.96%	1,141,870	76.30%
9330111.04	946,934	5,095	5.53%	267,350	2.51%	341,780	11.98%	1,118,135	80.40%
9330111.02	802,020	1,190	1.71%	5,885	2.42%	0	13.77%	965,530	83.05%
9330110.04	905,394	4,785	6.67%	127,790	1.48%	195,460	12.20%	1,102,585	79.75%
9330110.03	714,465	675	3.99%	1,865	2.90%	0	7.59%	853,550	83.70%
9330110.02	931,871	4,785	3.24%	58,845	1.80%	196,525	12.13%	1,100,845	82.37%
9330104	856,767	39,185	6.72%	384,080	2.58%	243,030	21.34%	1,127,335	70.28%
9330103	782,657	42,745	12.86%	397,450	1.84%	235,065	22.26%	1,118,135	64.17%

Table A 9 Continued: Accessibility (60 Minutes), Mode Shares, and MWA for All Vancouver CMA Census Tracts

Census Tract Unique ID	MWA	WalkJobs60	Walking Mode Share	BikeJobs60	Biking Mode Share	TransitJobs60	Transit Mode Share	DriveJobs60	Automobile Mode Share
9330102.02	819,237	104,800	10.33%	413,305	2.54%	287,170	23.22%	1,110,960	65.82%
9330102.01	788,971	192,240	11.36%	433,780	0.00%	391,590	34.29%	1,113,845	56.82%
9330101.06	817,541	205,020	12.52%	439,080	1.96%	500,885	33.18%	1,118,135	55.19%
9330101.05	769,097	160,115	11.81%	432,085	2.29%	290,060	30.43%	1,115,040	58.48%
9330101.04	739,641	156,360	15.73%	432,415	2.37%	328,095	29.06%	1,117,745	54.53%
9330101.03	723,604	186,070	15.13%	444,255	2.18%	382,990	36.04%	1,118,135	48.99%
9330100.02	846,996	39,885	8.39%	448,190	3.50%	360,990	25.07%	1,141,870	64.58%
9330100.01	828,374	98,175	10.88%	438,975	2.39%	244,510	22.15%	1,126,585	66.84%
9330069.02	523,434	32,060	22.45%	380,030	11.02%	142,005	26.58%	1,048,735	41.63%
9330069.01	505,597	25,015	31.27%	358,790	7.73%	370,910	26.43%	1,045,960	35.57%
9330068	600,716	197,530	25.21%	453,420	8.46%	438,650	36.94%	1,101,960	31.81%
9330067.02	650,951	271,545	36.20%	530,695	2.43%	633,350	30.25%	1,102,940	31.57%
9330067.01	575,527	262,920	40.82%	530,920	5.67%	585,255	29.21%	1,101,160	24.26%
9330066	622,954	280,435	48.46%	545,195	2.05%	683,855	17.66%	1,102,940	32.20%
9330065	562,317	287,375	48.31%	553,610	4.48%	640,215	27.09%	1,102,245	20.44%
9330064	572,449	284,440	46.85%	544,110	5.84%	622,225	29.16%	1,102,245	20.50%
9330063	608,284	274,045	34.82%	520,935	8.30%	526,965	29.05%	1,101,160	28.74%
9330062	673,684	247,670	19.61%	500,355	12.32%	491,780	28.88%	1,098,230	38.38%
9330061	656,457	272,740	26.66%	513,715	10.48%	561,225	35.17%	1,101,160	30.20%
9330060.02	621,824	283,735	37.63%	543,725	7.71%	592,265	28.13%	1,102,940	27.79%
9330060.01	612,602	277,360	37.41%	520,300	8.98%	565,620	28.25%	1,102,245	27.43%
9330059.14	691,395	299,715	38.61%	563,850	2.82%	662,235	21.32%	1,116,945	37.48%
9330059.13	633,509	302,180	42.63%	552,715	3.81%	699,060	30.13%	1,116,945	24.44%
9330059.11	597,106	307,890	53.44%	554,510	1.66%	743,100	20.41%	1,107,765	24.53%
9330059.1	611,575	296,375	45.83%	553,330	2.02%	651,965	23.94%	1,103,445	27.96%
9330059.09	631,856	298,440	41.71%	548,760	3.25%	650,740	28.99%	1,107,765	27.16%
9330059.08	770,994	301,990	28.14%	552,000	2.57%	676,220	25.34%	1,110,160	45.08%
9330059.07	752,371	300,120	30.90%	548,535	3.76%	610,930	17.54%	1,102,940	48.23%
9330059.06	616,841	300,505	42.88%	561,805	7.97%	667,210	26.99%	1,116,945	23.56%
9330058	590,642	280,785	31.29%	563,625	11.66%	450,775	34.53%	1,118,845	25.15%
9330057.02	742,778	279,200	17.80%	573,255	18.32%	601,290	26.75%	1,125,450	37.96%
9330057.01	668,203	296,620	31.96%	563,495	12.37%	646,465	35.15%	1,117,335	24.74%
9330056.02	804,116	270,145	10.10%	595,195	16.76%	553,145	35.94%	1,146,495	41.71%
9330056.01	784,430	243,230	10.09%	545,190	17.20%	555,280	38.44%	1,140,785	39.68%
9330055.02	835,620	153,245	8.13%	540,190	9.33%	529,720	36.24%	1,157,075	50.20%
9330055.01	856,202	202,060	6.79%	569,925	12.60%	572,995	39.57%	1,157,030	47.01%
9330054.02	909,090	129,735	4.06%	568,910	6.35%	478,885	29.12%	1,157,030	62.94%
9330054.01	856,785	208,380	5.71%	566,320	13.01%	510,975	31.68%	1,155,370	52.74%
9330053.02	927,947	81,245	3.68%	559,575	3.42%	513,300	33.96%	1,158,180	63.16%
9330053.01	904,792	79,450	3.98%	558,305	5.21%	475,510	32.07%	1,158,115	62.17%
9330052.02	964,716	84,585	3.64%	574,205	3.31%	526,500	27.33%	1,158,915	68.93%
9330052.01	950,125	98,350	3.78%	598,535	2.08%	593,760	40.22%	1,160,000	59.92%
9330051.02	920,217	137,435	4.31%	570,705	3.02%	569,160	37.56%	1,157,095	59.05%
9330051.01	913,566	181,935	4.32%	596,500	12.39%	655,710	35.96%	1,155,370	51.59%

Table A 10 Continued: Accessibility (60 Minutes), Mode Shares, and MWA for All Vancouver CMA Census Tracts

Census Tract Unique ID	MWA	WalkJobs60	Walking Mode Share	BikeJobs60	Biking Mode Share	TransitJobs60	Transit Mode Share	DriveJobs60	Automobile Mode Share
9330050.04	836,421	297,530	10.03%	610,140	9.50%	661,490	44.18%	1,130,545	40.37%
9330050.03	799,441	300,335	13.80%	582,245	15.37%	624,825	31.87%	1,126,795	41.66%
9330050.02	850,961	237,820	7.17%	591,500	12.55%	688,010	47.44%	1,146,495	37.79%
9330049.02	745,634	281,395	18.97%	563,350	6.90%	495,425	30.60%	1,100,580	45.59%
9330049.01	793,637	304,970	20.45%	600,050	6.74%	665,340	30.21%	1,109,075	44.17%
9330048	777,907	287,030	16.09%	582,750	10.69%	596,885	29.63%	1,101,665	44.71%
9330047.02	753,640	266,250	14.05%	556,725	10.81%	553,785	36.82%	1,100,580	41.08%
9330047.01	786,188	255,865	11.06%	540,290	11.53%	509,340	30.13%	1,097,145	49.41%
9330046	705,839	265,715	13.64%	568,550	9.93%	500,000	45.38%	1,097,650	35.19%
9330045.02	697,350	117,930	9.69%	512,990	12.34%	448,620	39.27%	1,090,550	40.94%
9330045.01	743,094	187,635	7.02%	512,710	13.09%	419,765	33.47%	1,087,920	48.01%
9330044	762,255	50,870	7.16%	402,385	10.15%	386,170	26.35%	1,074,810	57.31%
9330043.02	784,260	63,185	5.31%	460,940	11.88%	368,155	29.50%	1,085,845	56.88%
9330043.01	731,686	43,885	8.49%	412,495	9.12%	414,610	32.53%	1,077,035	51.57%
9330042	746,005	90,540	7.39%	515,410	10.04%	398,725	32.74%	1,091,055	51.06%
9330041.02	794,008	259,535	12.96%	577,135	7.75%	493,385	29.05%	1,101,275	51.97%
9330041.01	702,978	285,225	18.78%	582,065	9.94%	542,265	37.58%	1,102,360	35.17%
9330040.02	703,996	294,385	19.53%	585,800	9.26%	505,180	34.22%	1,102,360	38.05%
9330040.01	720,299	299,740	22.38%	594,725	7.28%	571,445	36.83%	1,102,360	36.23%
9330039.02	750,778	302,315	19.46%	599,265	8.54%	574,905	33.92%	1,109,075	40.19%
9330039.01	768,970	307,830	17.72%	622,370	13.09%	606,675	31.84%	1,115,860	39.41%
9330038	787,369	309,205	13.61%	650,720	14.97%	608,345	36.28%	1,125,450	37.96%
9330037.02	852,142	186,715	5.45%	621,920	11.59%	712,015	54.29%	1,147,440	33.41%
9330037.01	867,230	245,590	5.96%	646,040	15.52%	648,490	34.46%	1,139,985	46.39%
9330036.02	934,436	110,295	2.94%	586,335	1.80%	549,555	35.21%	1,158,915	62.75%
9330036.01	909,989	107,920	3.37%	602,810	1.52%	558,465	43.11%	1,157,095	56.73%
9330035.02	916,114	143,395	4.40%	638,150	4.25%	599,825	39.39%	1,157,030	55.87%
9330035.01	964,794	110,765	1.45%	611,685	1.93%	647,820	46.89%	1,155,610	56.04%
9330034.02	935,020	144,440	3.99%	644,695	7.83%	696,760	38.95%	1,139,985	53.28%
9330034.01	908,968	147,525	3.67%	652,005	2.65%	584,565	40.28%	1,126,795	57.76%
9330033.02	863,770	138,655	3.79%	636,940	3.79%	573,705	42.64%	1,117,760	52.76%
9330033.01	913,003	151,795	2.34%	630,945	5.34%	540,160	35.21%	1,115,860	61.44%
9330032	864,943	242,395	4.49%	648,345	8.77%	562,900	36.17%	1,125,450	52.74%
9330031.02	839,211	254,540	10.02%	647,615	9.39%	528,775	31.36%	1,115,860	52.61%
9330031.01	809,544	295,995	10.28%	648,010	12.22%	547,420	33.51%	1,107,230	46.65%
9330030	821,887	166,115	8.38%	643,350	11.51%	528,185	31.76%	1,107,230	51.14%
9330029	797,453	247,170	14.68%	588,865	9.12%	613,450	33.39%	1,102,360	45.60%
9330028	904,926	236,640	7.51%	577,465	5.93%	555,820	21.10%	1,101,275	66.80%
9330027.02	904,476	88,195	2.86%	538,000	2.38%	422,870	22.16%	1,091,750	72.86%
9330027.01	902,358	142,010	2.25%	558,840	6.37%	457,735	23.40%	1,091,750	69.29%
9330026	848,923	84,515	4.48%	513,155	5.37%	423,845	25.68%	1,089,120	65.07%
9330025	816,774	53,990	5.73%	480,175	6.68%	403,775	25.60%	1,080,265	62.79%
9330024	860,346	38,325	4.00%	464,690	6.00%	401,180	20.45%	1,081,440	69.25%
9330023	882,739	64,630	3.91%	496,605	4.89%	437,105	20.51%	1,089,120	70.36%

Table A 11 Continued: Accessibility (60 Minutes), Mode Shares, and MWA for All Vancouver CMA Census Tracts

Census Tract Unique ID	MWA	WalkJobs60	Walking Mode Share	BikeJobs60	Biking Mode Share	TransitJobs 60	Transit Mode Share	DriveJobs60	Automobile Mode Share
9330022	794,729	79,470	7.44%	535,515	3.26%	466,030	33.68%	1,091,750	56.28%
9330021	904,744	143,210	7.31%	566,095	7.76%	449,570	14.00%	1,098,345	71.69%
9330020	874,477	133,070	8.64%	606,950	1.23%	545,710	27.21%	1,101,275	64.20%
9330019	885,060	132,220	2.46%	620,405	5.65%	552,180	34.15%	1,102,360	59.71%
9330018.02	907,063	105,930	2.21%	625,480	4.97%	566,505	38.82%	1,116,250	58.56%
9330018.01	932,007	71,945	3.29%	618,870	2.57%	604,490	40.54%	1,127,870	59.29%
9330017.02	977,695	95,755	3.14%	614,895	1.14%	695,215	44.76%	1,154,570	56.86%
9330017.01	956,910	87,275	1.92%	631,120	1.10%	625,060	40.19%	1,141,970	61.04%
9330016.06	924,344	96,180	2.43%	614,430	1.31%	731,500	55.71%	1,155,675	43.82%
9330016.05	956,904	95,740	3.77%	607,785	0.40%	756,125	59.95%	1,155,610	43.06%
9330016.04	988,920	95,610	1.74%	620,070	1.07%	748,010	49.92%	1,155,675	52.54%
9330016.01	961,650	83,145	2.99%	613,790	0.40%	650,220	40.32%	1,154,570	60.16%
9330015.02	937,662	62,305	2.42%	625,790	1.21%	577,605	34.75%	1,145,220	63.56%
9330015.01	988,211	75,610	1.46%	617,670	0.63%	581,610	36.87%	1,155,610	66.53%
9330014.02	927,157	57,135	2.96%	617,745	0.79%	580,035	38.69%	1,125,450	61.86%
9330014.01	945,615	54,550	2.97%	615,220	0.00%	555,485	32.70%	1,126,795	67.66%
9330013.04	957,564	48,805	1.14%	606,890	0.86%	573,575	42.55%	1,115,860	63.43%
9330013.03	913,659	52,305	2.46%	591,500	1.85%	516,625	38.38%	1,111,780	63.24%
9330013.01	902,489	76,215	2.70%	627,800	2.22%	536,755	42.40%	1,115,860	59.05%
9330012	871,080	100,265	3.01%	617,165	4.97%	559,645	38.66%	1,102,360	56.34%
9330011	855,851	57,435	3.93%	606,355	2.45%	489,670	42.32%	1,102,360	57.28%
9330010.02	900,223	67,790	3.27%	598,740	2.61%	507,575	30.26%	1,103,980	66.01%
9330010.01	904,289	100,445	6.04%	598,290	0.82%	565,330	34.08%	1,103,980	63.46%
9330009	827,201	66,335	5.08%	574,885	4.30%	482,280	32.17%	1,091,750	58.98%
9330008.02	892,994	29,405	4.29%	485,450	3.96%	363,385	15.19%	1,081,440	75.58%
9330008.01	743,982	15,345	11.29%	433,580	4.84%	97,610	19.23%	1,062,315	66.13%
9330007.02	952,352	47,845	2.15%	565,865	5.15%	400,830	14.98%	1,091,750	78.97%
9330007.01	839,605	31,355	4.46%	551,525	2.72%	365,890	30.73%	1,091,825	65.10%
9330006.02	850,978	57,795	3.37%	595,910	1.93%	470,480	37.60%	1,101,050	60.00%
9330006.01	858,745	53,725	5.14%	580,335	1.80%	405,085	30.23%	1,094,455	66.07%
9330005	759,588	22,980	5.51%	568,975	2.99%	459,130	51.93%	1,097,825	45.81%
9330004.02	885,213	40,980	3.22%	592,840	0.85%	559,145	46.64%	1,105,065	55.93%
9330004.01	873,617	32,520	2.73%	609,690	2.98%	535,145	39.39%	1,103,980	58.31%
9330003.02	946,991	40,125	2.15%	601,915	1.08%	557,345	43.54%	1,109,935	62.80%
9330003.01	906,009	43,930	2.65%	601,395	0.80%	517,410	40.58%	1,111,780	62.07%
9330002.04	967,872	33,710	2.16%	596,245	0.96%	572,890	25.82%	1,115,860	72.90%
9330002.03	972,872	38,635	1.36%	603,150	0.00%	533,350	28.75%	1,116,250	73.37%
9330002.01	945,130	23,840	1.68%	608,480	2.02%	439,755	25.68%	1,115,860	73.45%
9330001.02	994,153	50,065	1.57%	606,910	0.98%	482,060	23.21%	1,141,970	76.67%
9330001.01	927,380	76,025	2.37%	614,570	2.20%	478,265	32.38%	1,147,440	65.99%