10-5-2017

EXCESS COMMUTING AND ITS RELATION TO URBAN FORM IN ONTARIO, CANADA

Laura J. Ash
University of Windsor

EXCESS COMMUTING AND ITS RELATION TO URBAN FORM IN ONTARIO, CANADA

By

Laura J. Ash

A Thesis
Submitted to the Faculty of Graduate Studies
through the Department of Civil and Environmental Engineering
in Partial Fulfillment of the Requirements for
the Degree of Master of Applied Science
at the University of Windsor

Windsor, Ontario, Canada

2017

EXCESS COMMUTING AND ITS RELATION TO URBAN FORM IN ONTARIO, CANADA

By

Laura J. Ash

APPROVED BY:

W. Anderson
Department of Political Science

C. Lee
Department of Civil and Environmental Engineering

J. Tofflemire, Special Member
Department of Civil and Environmental Engineering

H. Maoh, Advisor
Department of Civil and Environmental Engineering

September 12, 2017

DECLARATION OF ORIGINALITY

I hereby certify that I am the sole author of this thesis and that no part of this thesis has been published or submitted for publication.

I certify that, to the best of my knowledge, my thesis does not infringe upon anyone's copyright nor violate any proprietary rights and that any ideas, techniques, quotations, or any other material from the work of other people included in my thesis, published or otherwise, are fully acknowledged in accordance with the standard referencing practices. Furthermore, to the extent that I have included copyrighted material that surpasses the bounds of fair dealing within the meaning of the Canada Copyright Act, I certify that I have obtained a written permission from the copyright owner(s) to include such material(s) in my thesis and have included copies of such copyright clearances to my appendix.

I declare that this is a true copy of my thesis, including any final revisions, as approved by my thesis committee and the Graduate Studies office, and that this thesis has not been submitted for a higher degree to any other University or Institution.

ABSTRACT

The objectives of this research are to examine the relationship between urban form and excess commuting for 10 different occupation types in 12 different Census Metropolitan Areas (CMA) across Ontario, Canada and to provide insights that could help inform the planning process.

The results suggest the following: 1) that two cities with the same type of urban form may not necessarily exhibit the same level of commuting efficiency; 2) the size of the CMA and the amount of spatial interaction activities are key factors with respect to commuting efficiency; 3) certain occupations were found to have higher excess commuting than the CMA-wide measure; therefore, planners could channel land use development to attract those occupational classes; 4) some patterns of urban form could benefit from a reliable transit system, in which case planners could focus on building transit systems that connect these workers to their places of work; and 5) planners could also utilize the Brotchie's urban triangles to evaluate if the current urban form is associated with an efficient commuting pattern and identify what types of urban form could give rise to more commuting efficiency.

Future research may expand on this thesis by comparing urban land development and commuting efficiency changes for a particular city over time. Other opportunities may include performing similar analysis with a larger sample of CMAs across Canada, or comparing the three largest CMAs in Canada (i.e. Toronto, Montreal and Vancouver). Future research may also consider allowing workers who live in the CMA to commute to jobs outside the CMA, or live outside the CMA and commute inwards.

DEDICATION

To my beloved husband and best friend, Steven, for supporting and encouraging me every step of the way.

ACKNOWLEDGEMENTS

To my advisor, Dr. Hanna Maoh, thank you for believing in me and providing an incredible amount of dedication and support. I could not have completed this without your help. I will never be able to thank you enough for the time, encouragement and dedication you have given me over the past couple of years. You are an incredible professional with remarkable expertise in your field and I have nothing but respect for you. I will miss working with you and wish you all the best.

To the committee members, Dr. Chris Lee, Dr. William Anderson and Mr. John Tofflemire, thank you for the direction, support and consideration you have provided to help me produce this thesis. Thank you Dr. Yong Hoon Kim for supporting me as the chair of my defence. I would also like to extend sincere gratitude to Dr. Bozena Budkowska, Dr. Sreekanta Das, Dr. Shaohong Cheng and Dr. Faouzi Ghrib for introducing me to the M.A.Sc. program, inspiring me to pursue it and encouraging me to complete it. To Shakil Khan, Kevin Gingerich, and Terence Dimatulac, thank you so much for providing constant and dependable academic and technical support.

On a more personal note, my husband and children deserve special recognition and thanks for their patience, support and motivation while I pursued this goal. There is no greater achievement than the love of my family.

Laura J. Ash, P.Eng.

August, 2017

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF APPENDICES

CHAPTER 1: INTRODUCTION

1.1 Overview

Land use patterns, transportation modes and the level of spatial interaction have been continuously changing since the beginning of civilization. We have evolved from small, close-knit communities, dependent on man and horse power to get around, to the development of large, diverse cities that are connected by complex road networks. In Canada, the form of cities has changed over the past century and like many developed countries people exodus from city centers became a common pattern over time (Maoh et al. 2010). The decentralization of Canadian cities has been associated with suburbanization where people started moving further away from the core to enjoy spacious, private residences while still being able to reasonably travel to and from work and other destinations. The evolution of this transformation from monocentric cities to what is known as sprawling pattern has led researchers to analyze and attempt to classify urban form to identify patterns with respect to current commuting behaviour. The work in this thesis contributes to these efforts by focusing on 12 Census Metropolitan Areas (CMAs) in Ontario, Canada. While the province of Ontario consists of 19 CMAs, we opted to focus on the 12 shown in Figure 1.1 given their population size (i.e. over 100,000 but less than 1 million)[1].

The current breakdown of transportation mode for the 12 CMAs targeted in this thesis demonstrates that auto (defined as car, truck or van, as a driver or passenger) is the dominant mode choice (87%) for commuters age 15 and over (2011 National Household Survey). Reasons for this choice may include independence and reliability (no bus

[1] While Branford CMA falls also within the targeted population size range with a size of 135,501 in 2011, it was not included in the analysis due to lack of commuting data for this CMA.

schedule/delays), convenience of a direct route as opposed to changing buses on route, waiting for other patrons, etc., weather protection, having quick access to a vehicle during the day (during lunch break, emergencies, etc.), feasibility of running errands and shopping on-route, perception of time savings, privacy, household structure transforming into families with multiple adults in the workforce needing to transport children to/from school, daycare and other activities, and higher household income resulting from more adults in the workforce, which allows more affordability for personal travel.

Despite the advantages brought on by the automobile, the wide spread of personal vehicles can also be associated with a number of social, environmental and economic challenges and consequences. The cost associated with owning a vehicle can be seen as an economic burden given the amount of out-of-pocket money that needs to be allocated towards vehicle purchase, insurance, maintenance, fuel, parking and so on. Also, driving on congested roads on a regular basis could lead to frustration and stress (e.g. road-rage), which has a negative impact on the driver and the general public. Traffic accidents leading to injuries and fatalities is also a result of more vehicles on roadways. Air pollution due to idling and longer commutes is another environmental concern that has negative impacts on health. Also, the provision of suitable roads by local and provincial governments to facilitate the movement of people requires dedicated infrastructure budgets to not only construct roads and bridges but also to maintain and operate them. For instance, governments must ensure proper lighting, signal systems, drainage and availability of parking areas. Eventually, the construction of more roads also consumes green space and prime agricultural land.

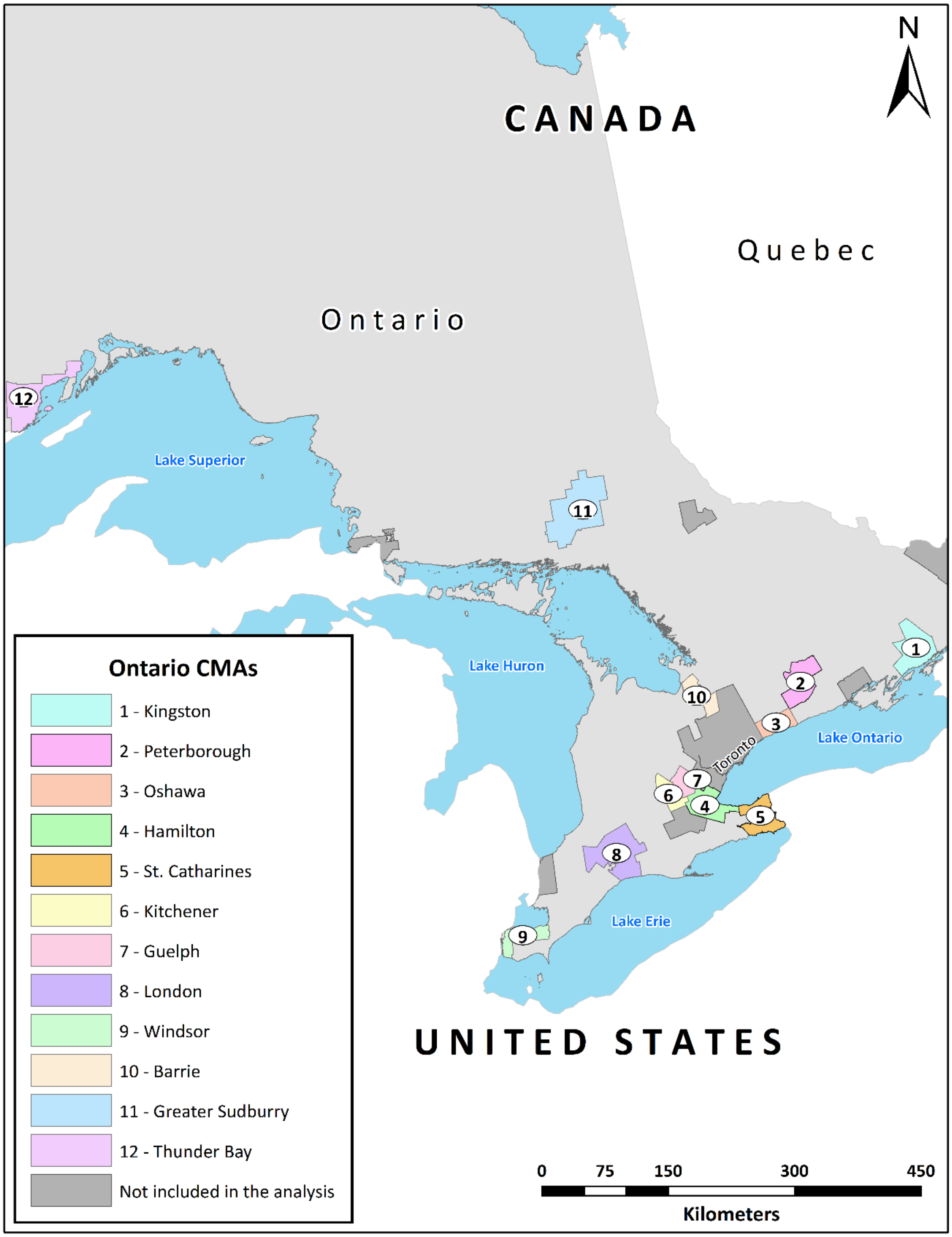


Figure 1.1 – Targeted CMAs Within Ontario, Canada

In addition to the highly auto-driven transportation mode breakdown in the study area, there is an indisputable growing demand on road networks and travel systems due to steady population increases and community development expanding outward from the Central Business District (CBD), especially in metropolitan areas with more development. Increasing travel demand inherently results in undesirable increases in pollution, consumption of natural resources and traffic congestion, which consequently leads to increased travel time. Most Canadian workers depend on road networks to get to their workplaces. Regardless of the mode of transportation, the road networks must be available and functioning to allow transit of workers to the workplace. When increased demand results in higher congestion, the travel times experienced may be longer than actually required.

One way sought to relieve commuting congestion and plan the future of land use and transportation in cities has been to evaluate the spatial relationship between a worker's place of residence and the location of their workplace. Previous studies tried to assess the observed average commute in cities based on the spatial distribution of workers and jobs to determine if the observed commuting trends could be shortened if workers were reassigned to jobs closer to home, or workplaces located closer to the residences (Kanaroglou et al. 2015). The general idea is to calculate the observed average commute and compare it to a hypothetical minimum average commute. The hypothetical minimum value is based on optimizing the spatial interaction pattern (i.e. trip flows) while constraining for the observed number of workers and jobs found in the different zones where work trips originate and end. The difference between the observed and minimized average commute is referred to as "wasteful" or "excess" commuting. The term implies that part of the experienced commute is reducible. To date, research has evaluated this concept for cities in various countries. However, all of the existing efforts have been lacking one major constraint: that the workers be reassigned to jobs within their same occupation. In Figure 1.2 below, for example, the reassignment based on shorter commuting distance alone might relocate a doctor to work in a restaurant, or a cook to work in a manufacturing plant. This obviously is an erroneous assumption that probably will lead to erroneous conclusions.

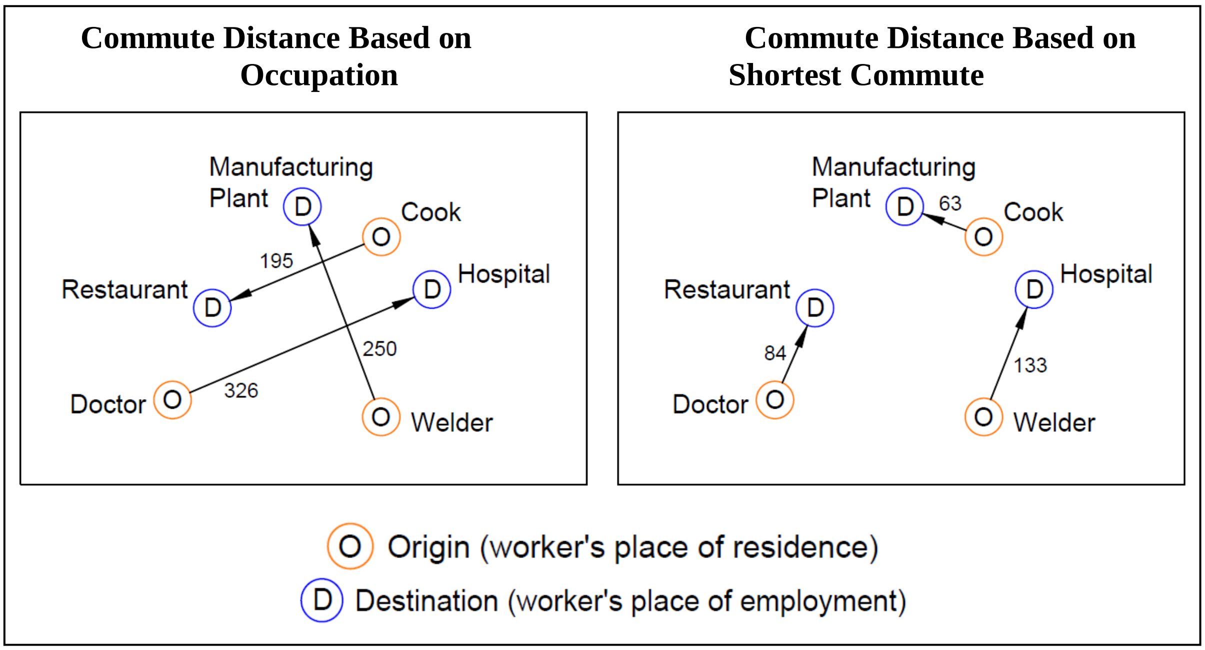


Figure 1.2 - Effect of Assigning Workers to Jobs Randomly Based on Distance

The calculation of the minimum average commute has benefited from the transportation problem, which optimises flow patterns between origins and destinations based on travel costs (Hitchcock, 1941). White (1988) was the first to use the transportation problem to calculate the theoretical minimum average commute. She introduced the idea that commuting costs were directly related to the distance between centroids of the origin/destination census tracts. Another measure, referred to as the maximum commute, was postulated to gauge the observed commute over a scale of the two extremes, since comparing to the minimum alone may not reveal the entire picture when comparing several cities. Horner (2002) postulates this range as “commuting potential”. Finally, a random variable was introduced by Hamilton (1982) and utilized by Charron (2007) which is defined by the average of randomly reassigned home and workplaces within the same metropolitan area. The idea here is to create a random origin-destination (OD) trip matrix that conforms to the observed spatial distribution of workers and jobs in the zones where trips start from and end at. An average random commute can then be calculated using the random OD matrix. If the creation of a random OD matrix is performed *n* times (e.g. n = 1000), then a total of n random commute values could be calculated. The mean of these n random commutes could then be obtained as will be discussed in the next two chapters.

The analysis of commuting patterns cannot be dealt with in isolation of considering the nature of urban form. The latter refers to the way land use activities are distributed over space (Maoh et al. 2010). As will be discussed in Chapter 2, a number of urban forms have been identified in past research. Those include monocentric, polycentric and decentralized or sprawled urban forms. While the configuration of fixed elements (i.e. buildings) determine the nature of urban form, the activities associated with these buildings (i.e. land uses) are equally important. In this thesis, we employ a spatial statistics technique known as the *Moran’s I* statistic to quantify the nature of urban form in the studied CMAs based on the spatial distribution of population and employment. Tsai (2005) describes how the *Moran’s I* statistic can be used to quantify the nature of urban form. The work performed in this thesis will try to establish an association between urban form and the observed commute to assess which types of cities exhibit more or less wasteful commuting.

Each of the 12 CMAs analyzed in this thesis are divided into a finite number of sub-areas called census tracts, or traffic analysis zones (TAZ). The set of TAZs includes a wide variety of metropolitan sizes, populations and land uses. The data used in this thesis was acquired from the 2011 Canadian Census conducted by Statistics Canada. The records include population, density and trip rates separated by mode. Job data was also collected from Statistics Canada's 2011 National Household Survey (NHS) for 10 different occupation types: management; business, finance and administration; natural and applied sciences; health; education, law and social, community and government services; art, culture, recreation and sport; sales and services; trades, transport and equipment operators; natural resources, agriculture and related production occupations; and, manufacturing and utilities. These datasets are used to further analyze the commuting patterns of each CMA according to occupation.

1.2 Research Objectives

The conducted research will help refine our understanding of the connections between urban form and commuting patterns in Ontario. The comparative analysis for the 12 CMAs should also provide a strong basis to guide planners and travel demand modellers with their future master plans to accommodate future development and urbanization. The specific objectives of this research are to:

1) Apply well established spatial measures such as the *Moran's I* statistic to classify the nature of urban form (i.e. monocentric, polycentric or dispersed) for 12 targeted CMAs across the province of Ontario.
2) Measure the level of excess commuting while considering employment classification. The work will also compare the results to the more conventional approach that does not differentiate jobs by occupation type.

3) Quantify the association between the observed urban form and the average commuting patterns observed in the studied CMAs.

1.3 Thesis Outline

Chapter 1 provides an introduction to the research topic, a description of the specific objectives and an outline of the thesis. Chapter 2 provides a review of the current state of knowledge on the subject matter based on the current literature dealing with urban form and excess commuting. Chapter 3 describes the methods of analysis used to classify the urban form of the CMAs, calculate the specific commuting measures for each CMA and 10 occupation classes, and compare the results. The chapter also describes the data utilized in the analysis. Chapter 4 presents the results of the analysis, including the types of urban form and commuting patterns for each CMA, as well as commuting patterns for each occupation type in the CMAs. This chapter also provides an illustration of the relation between commuting and urban form for each CMA using Brotchie's urban triangles. Finally, the last section, Chapter 5, provides a conclusion of the thesis by highlighting the novelty and key contributions of the conducted research. The chapter will also discuss limitations presented in the study and the policy implications on the identified relationships exhibited by the data. Recommendations and directions for future research will also be provided in the last chapter.

CHAPTER 2: LITERATURE REVIEW

The transformation of urban form and its impact on the spatial interactions between residential and workplace locations has been studied for several decades. The changes in urban form have resulted in an increase of commuting levels at alarming rates, which led researchers to analyze the relationship between the two and question the sustainability of the ongoing urban development patterns. This chapter reviews the existing literature on urban form and commuting patterns, more specifically, methods to classify urban form and calculate commuting levels over space.

2.1 Urban Form

2.1.1 Types of Urban Form

In order to create connections between urban form and excess commuting, it is important to have an understanding of the land use within the metropolitan area being studied. Urban form is defined as the spatial pattern of human activities (Anderson et al., 1996), and has been classified into three archetypal metropolitan forms: monocentric, polycentric and sprawl. Monocentricity refers to the characteristic of having one, compact, dense city centre where majority of the activity occurs. Historically, this has been the form characterizing most cities until the automobile became one of the key facets of urbanized households. In contrast, polycentricity refers to an urban form that is associated with multiple centers. In general, a polycentric urban form is one that still enjoys a main core but also has well connected nuclei that are serviced by transit. Here, each centre could be assumed to be more self-dependent where people living in one centre do not need to travel to the core for their shopping needs for instance. Over time, some of the nuclei will grow to become major employment centres. Relative to the first two urban form types, a sprawled city refers to a situation where population growth happens outside the urban area and can be defined by four characteristics: low density, scattered development, commercial strip development or leapfrog development (Ewing, 1997). Low-density growth can be characterized by the wide spread of single and segregated land use across large areas of private properties. Scattered development, on the other hand, refers to random growth that does not have a clear pattern over peripheral urban space (Maoh et al. 2010). Commercial strip development characterizes growth that occurs mainly along the two sides of a major corridor, far away from the urban core. Finally, leapfrog development is a growth that escapes the inner suburbs to occur at the edge of the city on vacant agricultural land or in areas that are not well development but has the potential to become more developed in the near future.

Many studies have related urban form transformation to the effect it has on sustainability. According to recent evidence, urban development in developed countries has been leaning towards sprawled patterns as opposed to the conventional monocentric form. A few possible reasons for this change in development include a decrease in environmental quality near the dense core due to traffic congestion, pollution, degradation of public spaces and reduction of safety; more spacious and private residences (possibly due to higher household incomes); changes of land use in the city centre from residential to other uses; and the cost to build new in the undeveloped areas along the outskirts compared to repairing an aging property within the city centre (Camagni et al, 2002).

As summarized by Camagni et al. (2002), this phenomenon can be simplified into two perspectives: (1) optimistic "neo-free market", where controlling urban sprawl or restricting the mobility and location preferences of individuals is viewed as pointless, impossible, socially undesirable and unacceptable; and (2) pessimistic "neo-reformist", which focuses on more empirical analysis and case studies, demonstrating the negative impacts on social, economical and environmental factors caused by persistent urban sprawl. The first perspective represents positive/neutral views of natural sprawling where intervention and/or interference through the planning process is limited and discouraged. The second view insists that intervention is essential to maintain urban sustainability and promotes policies that control the development of urban sprawl.

Behan et al. (2008) provide a comprehensive description of sprawl and reasons to be concerned about excess commuting based on a case study of Hamilton, Ontario. The authors identify characteristics of sprawl which include unlimited outward extension of development, low-density residential developments, leapfrog development, dominance of transportation by private vehicles, lack of centralized planning or control of land uses, widespread strip commercial development and the segregation of types of land use in different zones. The conclusion remains that decentralization and suburbanization leads to increased automobile dependency, commuting distances, traffic congestion, vehicular emissions, energy consumption and large-scale absorption of open space.

2.1.2 Quantifying Urban Form

The transformation of urban form has been discussed thoroughly, however there is a lack of conclusions regarding how to calculate/measure urban form. Camagni et al. (2002) studied land consumption maps for a given area over a period of 10 years and applied a descriptive/intuitive approach to identify five types of urban expansion (infilling, extension, linear development, sprawl and large-scale projects). Although visual representations of development are helpful, a more statistical approach is desirable.

Tsai (2005) investigated four quantitative variables (see Table 2.1) in an attempt to characterize urban form, and described them using the four figurative examples provided in Figure 2.1 below. The first dimension, metropolitan size, was considered as an indicator of sprawl since sprawling requires larger portions of land (Hess et al, 2001); however, greater land area is more associated with population than urban development. The second dimension, metropolitan density, can provide insight about the level of land consumption per capita and overall activity intensity, but does not provide insight into the pattern of activity distribution within a metropolitan area. The third dimension, degree of distribution, is useful to measure development concentration in specific areas of the metropolitan whole; however, it has been concluded to lack measures involving spatial relationships such as size, shape and number of sub-areas, and is therefore not ideal for identifying sprawl. The fourth dimension, degree of clustering, appears to be an acceptable method for characterizing the degree of centralization/decentralization and distinguishing between monocentric, polycentric and sprawl. This method will be investigated further in this thesis.

Table 2.1 - Proposed Variables to Characterize Urban Form

Metropolitan-Form Dimension	**Variable**	**Data Source**
Metropolitan Size	Population	Statistics Canada 2011
Metropolitan Density	Population Density	Statistics Canada 2011
Degree of Distribution	*Gini coefficient	Statistics Canada 2011
Degree of Clustering	**Moran's I* coefficient	Statistics Canada 2011

*population or employment based

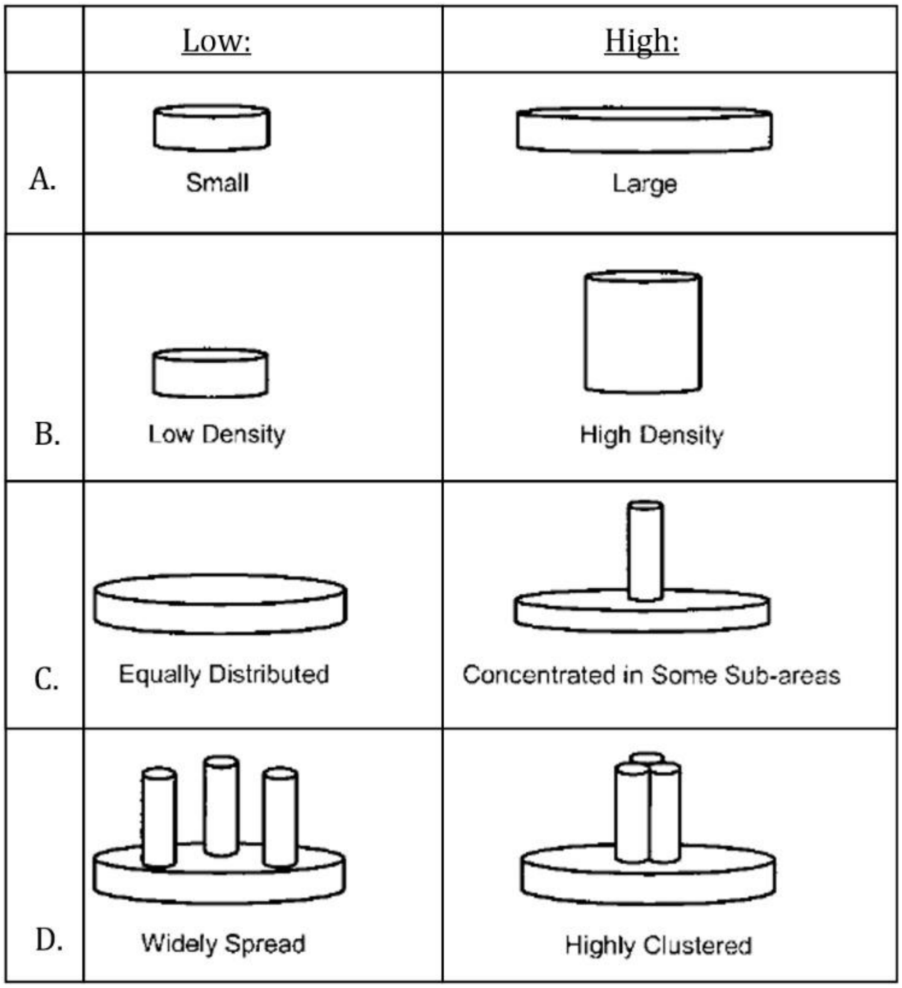
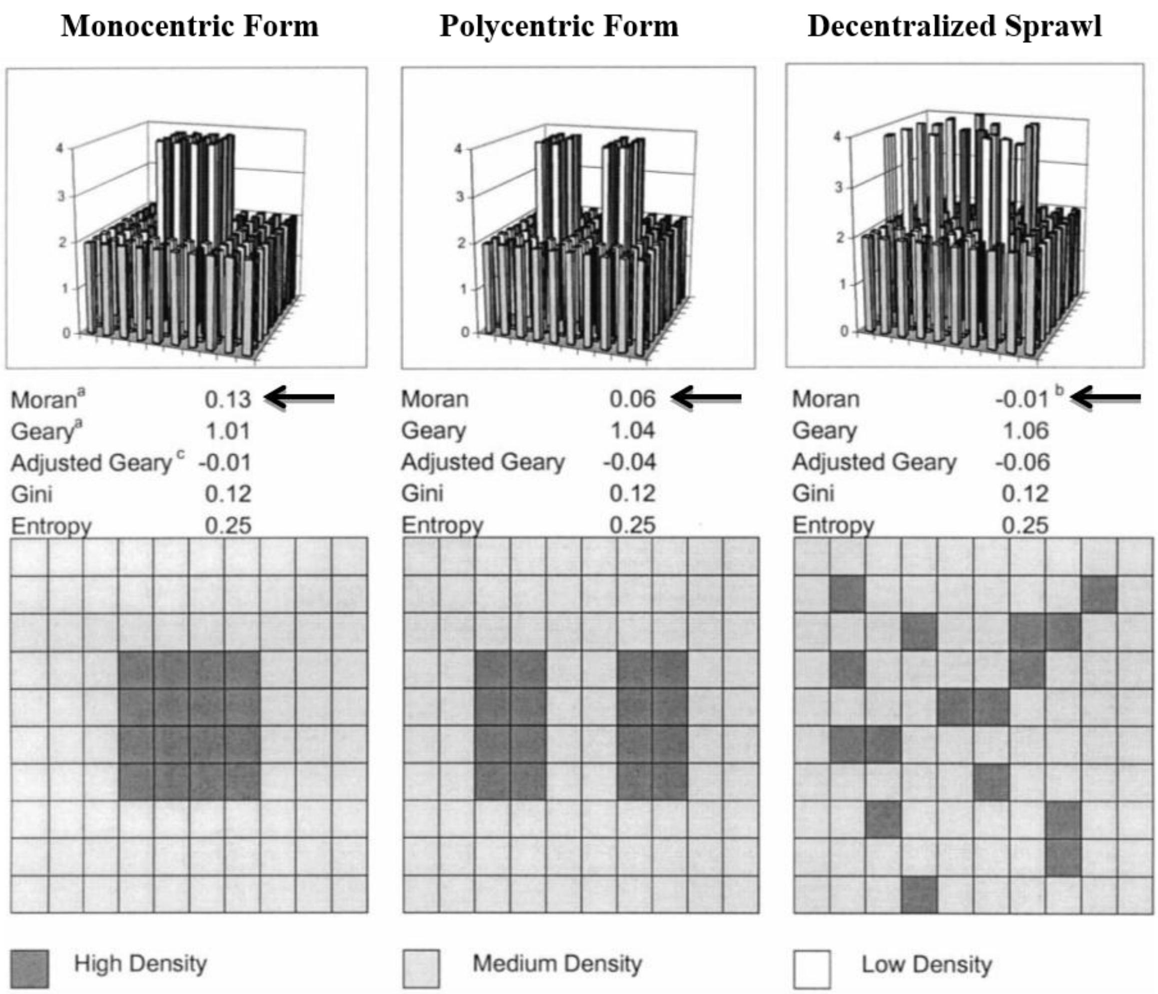


Figure 2.1 - Four Figurative Examples Illustrating Metropolitan Form (*Source: Tsai, 2005)*

Tsai (2005) concluded that the *Moran's I* coefficient, which is a valid measure of spatial autocorrelation, may be used to estimate the degree of land clustering. The typical range of values for a *Moran's I* coefficient are 1 to -1. As shown in Figures 2.2 to 2.4 below, a high value of *Moran's I* (approximately equal to 1) indicates a high correlation between land uses (i.e. clustering) and thus characterizes a monocentric urban form from the perspective of overall metropolitan structure. Intermediate (slightly greater than 0) and low values (less than or approximately equal to 0) represent polycentric and decentralized sprawling forms respectively (further lowered for strip development and discontinuity).



Notes: a. The weighting is the inverse distance between the centroids of two cells; b. (–1/number of cells) = randomly scattered. In this case, the Moran coefficient = –0.01 means randomly scattered; c. The scale of the Geary coefficient is adjusted to become similar to the Moran coefficient. That is, values close to +1 mean high clustering; values close to zero mean random scattering; and negative values mean a chessboard pattern.

Figure 2.2 - Monocentric, Polycentric and Decentralized Sprawl *(Source: Tsai, 2005)*

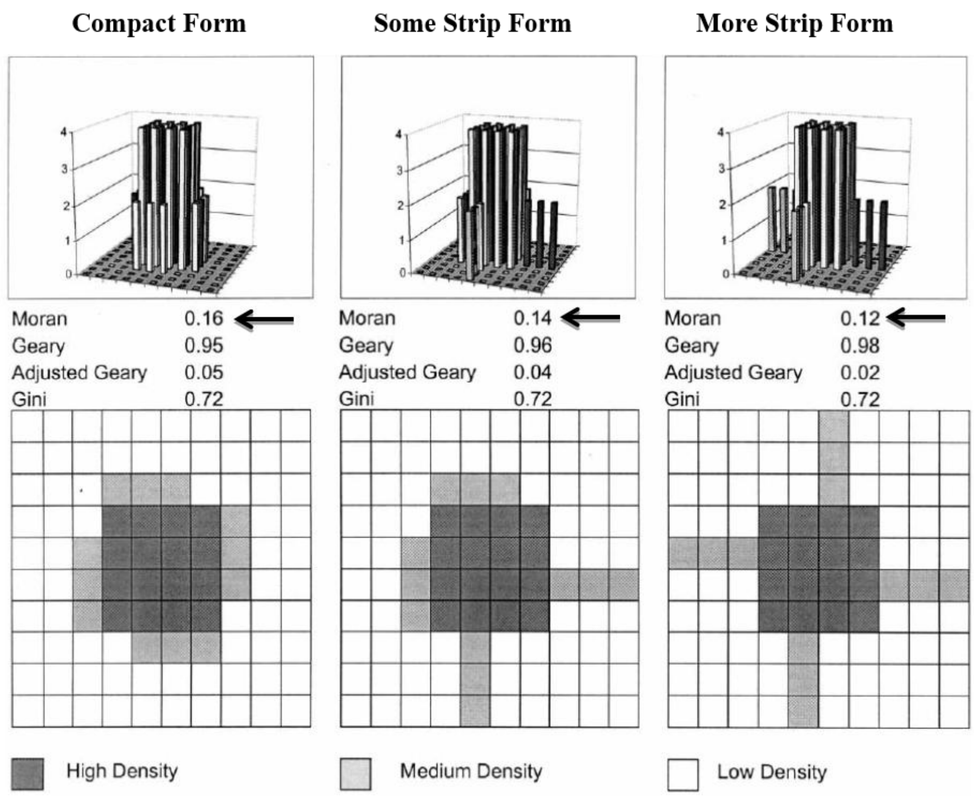


Figure 2.3 - Types of Strip Form *(Source: Tsai, 2005)*

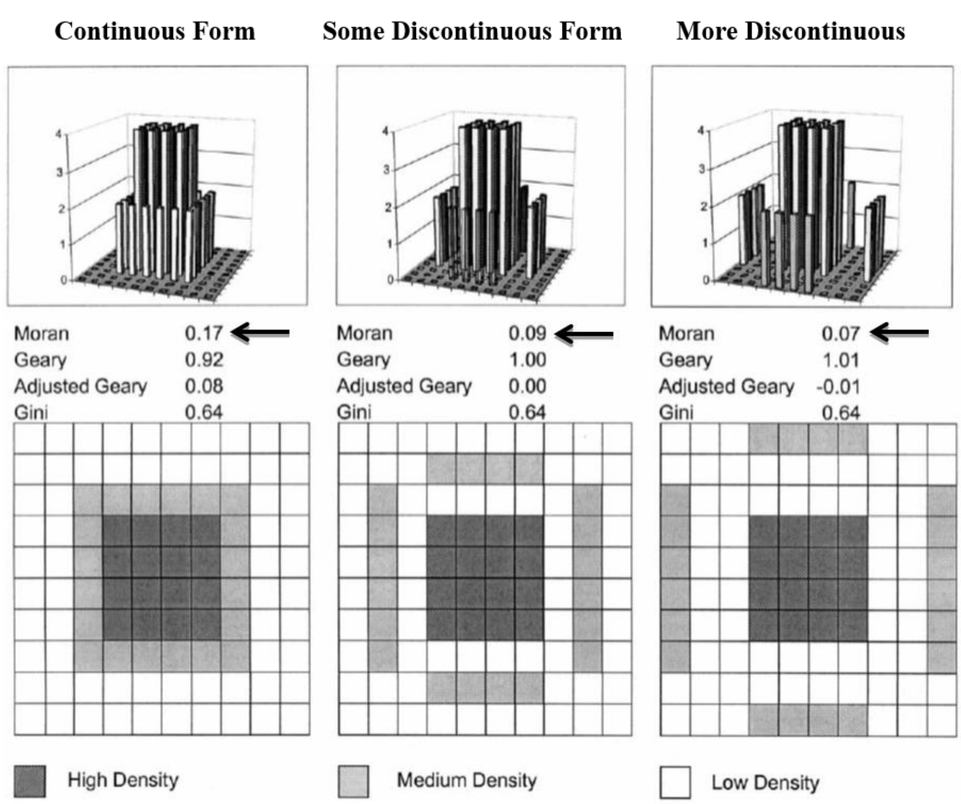


Figure 2.4 - Continuous Form *(Source: Tsai, 2005)*

A summary of the hypothesised *Moran's I* coefficients identified by Tsai (2005) is included in Table 2.2 below based on the theoretical definitions for each urban form classification. The formula to calculate the *Moran's I* coefficient is provided in Section 3.1.1, and the nature of urban form for each CMA exhibited in this study has been characterized based on the *Moran's I* calculation and summarized in Section 4.1. It should be noted that the *Moran's I* values listed in Table 2.2 are based on hypothetical urban form structures in which space is divided into a finite number of equal grid cells. Therefore, the application of *Moran's I* to irregularly shaped traffic analysis zones might not translate into the same outcome as in the case of equal grid cells.

Table 2.2 - Theoretical Moran's I Coefficients for Urban Form Classification

Urban Form	**Moran's I Value**
Decentralized Sprawl	Less than 0.03
Polycentric	0.03 to 0.069
Compact	0.07 (centrality with discontinuous outer suburban 0.09 (centrality with discontinuous inner suburban 0.12 (centrality with more strip form) 0.13 (average centrality) 0.14 (centrality with some strip form) 0.16 (compact with non-contiguous diffusion on the central 0.17 (compact with contiguous diffusion on the central edge)
Highly Compact	Greater than 0.20

Chu (2002) used employment and residential densities to define the mixed density index (MDI) as a way of quantitatively measuring mixed land use patterns. The MDI is also an indicator of the jobs-housing balance. A high MDI indicates a greater degree of land use mixing, which is associated with shorter commuting distances, decreased congestion and reductions in the number of trips (Giuliano and Small, 1993). Besides the

MDI, the concept of entropy has been used in the past to quantify if land uses within a given zone are homogeneous (i.e. belong to the same land use type) or heterogeneous (i.e. fairly mixed) (Cervero and Kockleman, 1997). The calculation of entropy, as will be shown in Chapter 3, relies on the land use coverage in the study area. Typically, the entropy value will range between 0 and 1, with 0 suggesting total homogeneity and 1 suggesting the presence of a high mix in land uses within the zone.

2.2 Excess Commuting

2.2.1 Early Work on Wasteful Commute

Wasteful commuting (or excess commuting) is the difference between the average actual observed commute and the theoretical average minimum commute, expressed as a percentage of the average observed commute. Hamilton (1982) introduced the concept of excess commuting, postulating that there was a theoretical minimum commute (C_{min}) that workers should experience based on the regional urban form, assuming that every worker was employed at the nearest job location from home, and the difference between the minimum and the actual observed commute (C_{obs}) was wasteful. Although this was a major advancement, Hamilton incorporated the assumption of a monocentric city, which limited the use of this model.

A new method of calculating the theoretical minimum commute was introduced by White (1988). This method reassigns residential and workplace locations using an iterative optimization algorithm commonly known as the transportation problem (Hitchcock, 1941). The outcome resulted in a much lower excess commuting estimate (11%) than Hamilton's method (87%). As such, the model by White has been used in numerous applications and studies since then. White's method to calculate C_{min} is introduced in Section 3.2.2.

2.2.2 Approaches to Examine Excess Commuting

In addition to calculating an average theoretical minimum commute, Horner (2002) introduced the calculation of an average theoretical maximum commute (C_{max}) in order to gauge the observed commute between a best case (minimum) and worst case (maximum) scenario. The range between C_{min} and C_{max} represents the commuting potential, or capacity, that a particular urban area would provide. Figure 2.5 provides an illustration of how comparing the observed average commute (C_{obs}) to this range provides a useful measure to compare commuting efficiencies between different cities. Horner proposed that the degree to which cities approach their upper commuting limit is a valuable approach to benchmarking commuting efficiency and termed this index the commuting potential utilized.

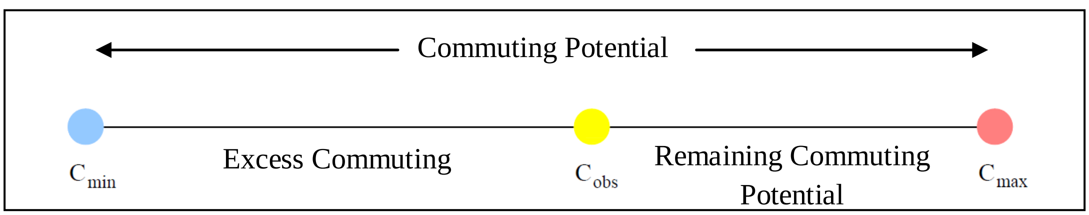


Figure 2.5 - Commuting Potential

Horner (2002) illustrated the significance of C_{max} by comparing two cities, City A and City B. Figure 2.6 illustrates the commutes for each of these two cities. Although City B appears to have less excess commuting from the original definition by comparing the observed commute to the theoretical minimum commute, it consumes more of its commuting potential than City A and therefore may have less efficient commuting.

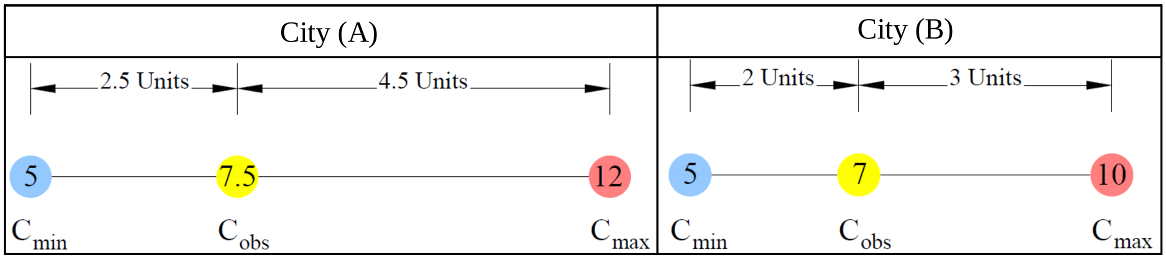


Figure 2.6 - Comparison of C_{obs} with C_{max} and C_{min}

Another measure, proposed by Hamilton and first utilized by Charron (2007), is the average random commute (C_{rnd}), which is calculated by reassigning workers to workplaces randomly within the same metropolitan area without consideration of commuting distance. The assumptions are such that the commuting distance is irrelevant within a labour market, and that labour markets operate at the metropolitan scale. The formula used to calculate the random average commute is provided in Section 3.2.2. The random commute assumes that the same urban form is applicable in terms of the spatial distribution of houses (i.e. workers) and workplaces (i.e. jobs). Given that the number of random assignments could be large (i = 1, 2, …, n), an average commute per random distribution i (i.e. $C_{rnd}(i)$) could be calculated and the mean of these average commutes $C_{rnd} = \frac{\sum_{i=1}^{n} C_{rnd}(i)}{n}$ could be obtained. In fact, if one generates enough random assignments (i.e. set n to a fairly large number), then a frequency distribution could be derived from the calculated $C_{rnd}(i)$ values. Here, the Monte Carlo simulation technique is used to generate a large number of randomly assigned possibilities to form the frequency distribution. Figure 2.7 below illustrates the relationship between the four excess commuting measures (C_{rnd} can be greater, equal to or less than C_{obs}). If C_{obs} falls within the C_{rnd} distribution then commuters do not consider commuting distance when travelling to work. Alternatively, if C_{obs} is outside the C_{rnd}

distribution (as in Figure 2.7), then commuters take advantage of the nature of urban form and place an importance on the commuting distance travelled.

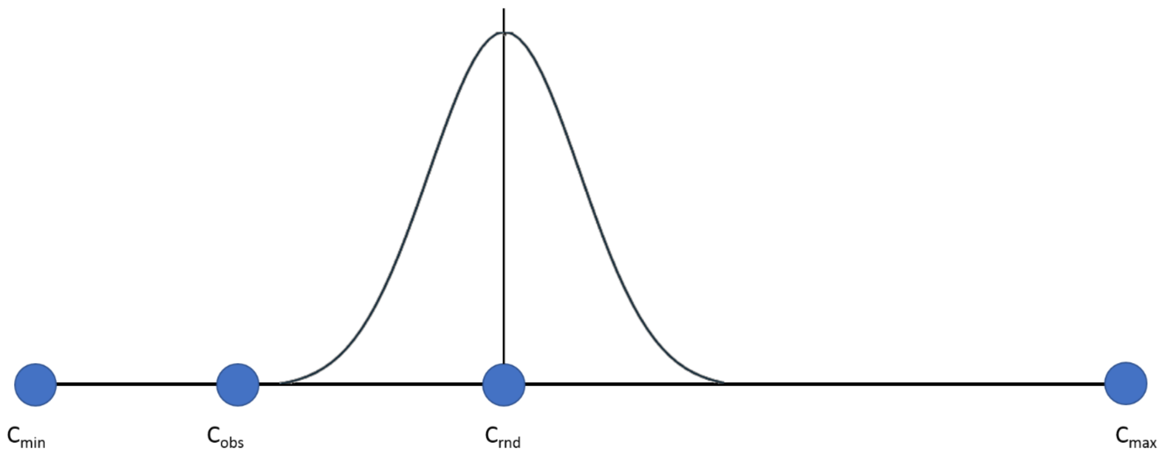


Figure 2.7 - Excess commuting measures: C_{min}, C_{max}, C_{obs} and C_{rnd}

2.3 Relation between Urban Form and Travel Patterns

2.3.1 Interaction between Land Use and Travel

The relationship between land use and travel patterns operates in both directions in that a well-developed transportation network may support development further from the urban centre, while sporadic development outside the city centre encourages further development of the transportation network to enhance connections between locations. Wegener (1995) described the traditional land use modeling proverbial 'land-use transportation feedback cycle' based on Figure 2.8 below, such that land use and transportation interact in a pattern of circular causation.

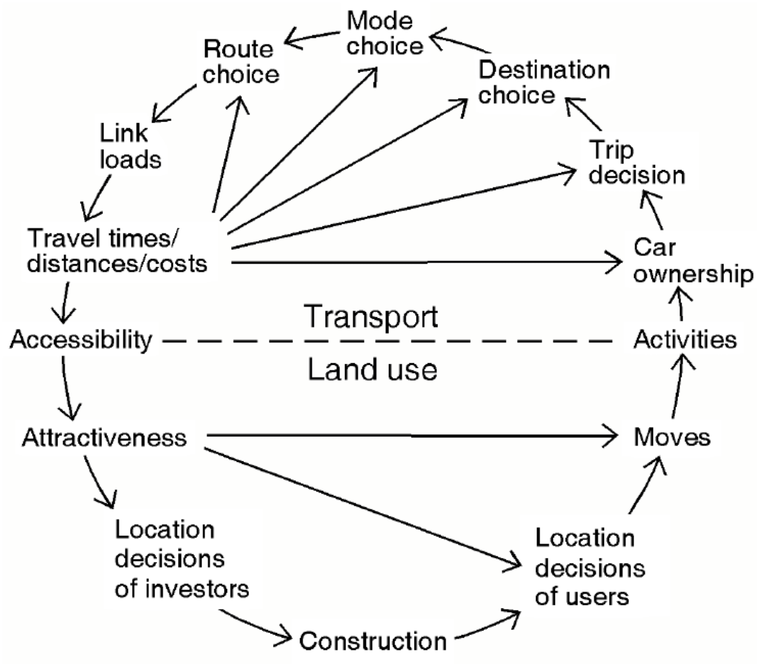


Figure 2.8 - The 'land-use transportation feedback cycle' *(Source: Wegener, 1995)*

To understand the inter-relation between the land use and transportation systems based on Figure 2.8, let us assume the availability of a vacant land parcel at a distant location in the suburbs. Naturally, if no road infrastructure is available to lead to that land parcel, then the parcel is said to be inaccessible. The construction of a new highway in proximity to the vacant land parcel will provide accessibility to that land. Consequently, the land will become more attractive for development. Attractiveness will trigger the decision of investor to develop the parcel for residential and/or commercial use. The outcome is a construction process that translates into introducing new buildings on the once vacant land parcel. Eventually, new development that has high accessibility is attractive for both households and firms. As such, the construction of new buildings will trigger a location decision by users (i.e. households and/or firms) who are looking to relocate within the urban area. The outcome of such process is a series of moves that places people in the suburbs.

The movement of people from the traditional central locations to the newly developed suburbs will have a direct impact on travel demand since people need to engage in activities such as driving to work, shopping or leisure. Therefore, people will be more prone to own one or more vehicles to enable them to engage in travel activities. The availability of a vehicle in itself could lead to new trip decisions to various destinations. If the latter are not accessible by public transit, then people will be more likely to choose auto as their mode of travel. The presence of more vehicles on roadways (i.e. road link loads) will have a direct effect on travel time (i.e. more vehicles lead to more congestion), which in turn will have an impact on accessibility over time. The key point here is that land use and transportation are inter-connected and therefore there is a need to study both systems to be able to make reasonable and meaningful conclusions about commuting in the urban context.

In line with the conceptualization given in Figure 2.8, Handy (2005) explored four common propositions regarding the relationship between land use and transportation, and their role in smart growth. The author examined the following hypotheses: 1. building more highways contributes to more sprawl; 2. building more highways leads to more driving; 3. investing in light-rail transit systems increases densities; and 4. adopting new urbanism design strategies (i.e. smart growth) will reduce automobile use. Despite encountering insufficient data and research to fully resolve the propositions, Handy concluded that new highway capacity will influence growth patterns and could slightly increase travel, light-rail transit may encourage higher densities under certain conditions and new urbanism strategies do enable less travel.

2.3.2 Brotchie's Urban Triangles

Another model previously used to analyze the relationship between urban form and travel patterns is Brotchie's urban triangles (Chowdhury et al. 2013; Ma and Banister, 2007). Figure 2.9 represents this framework. Point A on the triangle represents a monocentric city, where all jobs are located in the city centre. Point B represents a completely dispersed city, where all jobs and population are equally dispersed and workers chose their work locations without consideration of the distance from home. Point C also represents a completely dispersed city, where the supply of a transportation network is minimal, therefore travel is minimal. According to Ma and Banister (2007), when using the Brotchie triangle for relating journey-to-work trip length vs. land dispersal, line AB on the figure represents a large number of cross-commuters and longer commuting distances, whereas line AC represents minimal commuting and residents finding work close to home. The more dispersed a city is, the more flexible it is to reduce or increase the average commuting distances by relocating residences. The difference between the theoretical minimum and theoretical maximum commute for a given city becomes greater as the level of dispersal increases.

Ma and Banister (2007) use the example of City I and City II in Figure 2.9, where City I has shorter trip lengths and therefore a more efficient commuting pattern. City II exhibits a longer commute (i.e. pertains to an excess commuting situation) although it has the same land dispersal as City I. This signifies that City I has benefited by dispersing from the monocentric city model, whereas City II has achieved the opposite and has longer trip lengths than a monocentric city. Another useful diagram used by the authors to illustrate the effect of cross-commuting and dispersal is found in Figure 2.10 for four different trip patterns (Bertaud, 2002). Cities A and D are both considered monocentric cities, however City D has more cross-commuting and usually represents a larger city. Cities B and C are both considered polycentric cities and are more dispersed. This is a good example of how two cities with the same urban form could have different commuting patterns, which is likely due to economic, political, geographical or sociodemographic factors.

Chowdhury et al. (2013) dwelled on the Brotchie triangle method to examine the relationship between urban form and commuting efficiency in three Canadian metropolitan areas: Hamilton, Halifax and Vancouver. They performed comparative analysis between the three cities and over three points in time: 1996, 2001 and 2006. The study found that the Brotchie triangle approach is more reliable in quantifying the relationship between urban form and commuting efficiency. They concluded that the method is more promising when compared to the more conventional approach that utilized the commuting range to quantify whether the commuting pattern is efficient or wasteful. The advantage of using the Brotchie triangle method relies in its ability to work without the need for more data. In this thesis, the Brotchie triangle framework will be applied to the 12 CMAs as will be shown in the results included in Section 4.3.

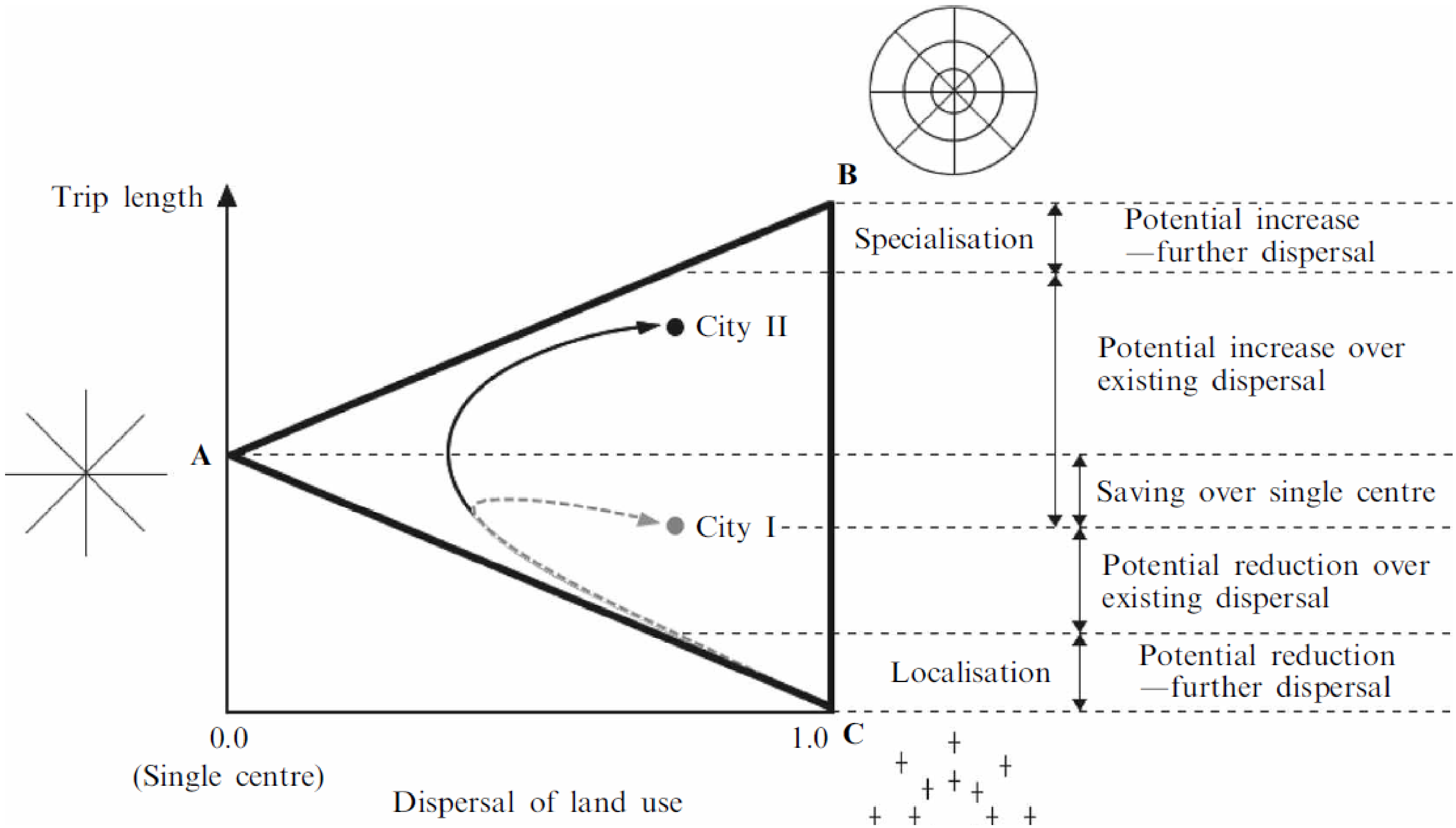


Figure 2.9 - Framework of Brotchie's Triangle Using Trip Length and Land Dispersal *(Source: Ma and Banister, 2007)*

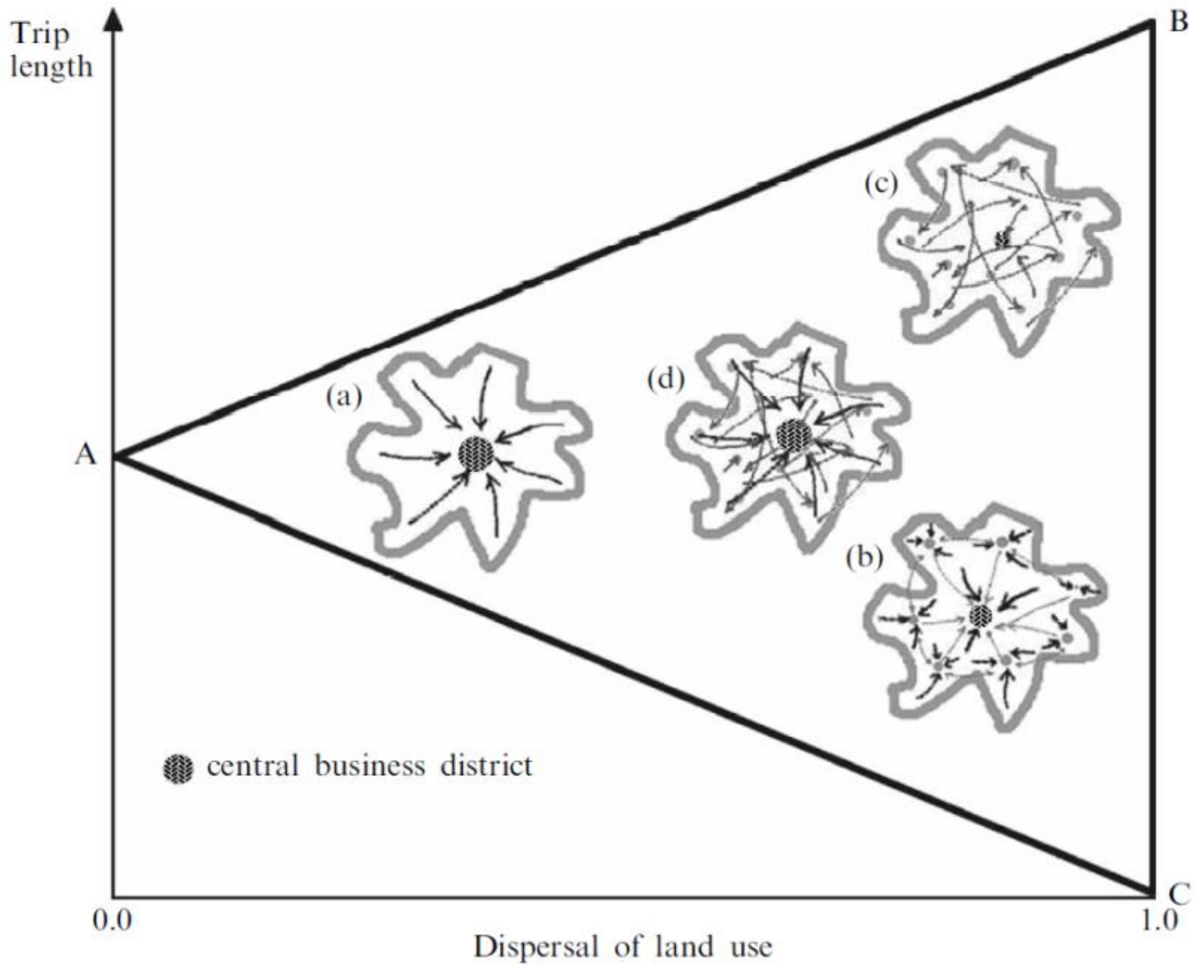


Figure 2.10 - Effect of Cross-Commuting and Dispersal with Four Different Trip Patterns *(Source: Ma and Banister (2007) and Bertaud (2002))*

CHAPTER 3: METHODS OF ANALYSIS

The purpose of this chapter is to discuss the methods and techniques used in the analysis of the 12 CMAs listed in Chapter 1. The chapter will also describe the datasets used to implement the described methods. Given our interest in both urban form and excess commuting, the chapter is organized into two major sections that are dedicated to discuss the techniques and data employed for (1) measuring urban form, and (2) calculating excess commuting. As will be seen, each section starts by describing the various methods and then moves to describe and highlight the datasets used in the analysis.

3.1 Measuring Urban Form

3.1.1 Moran's I Statistic

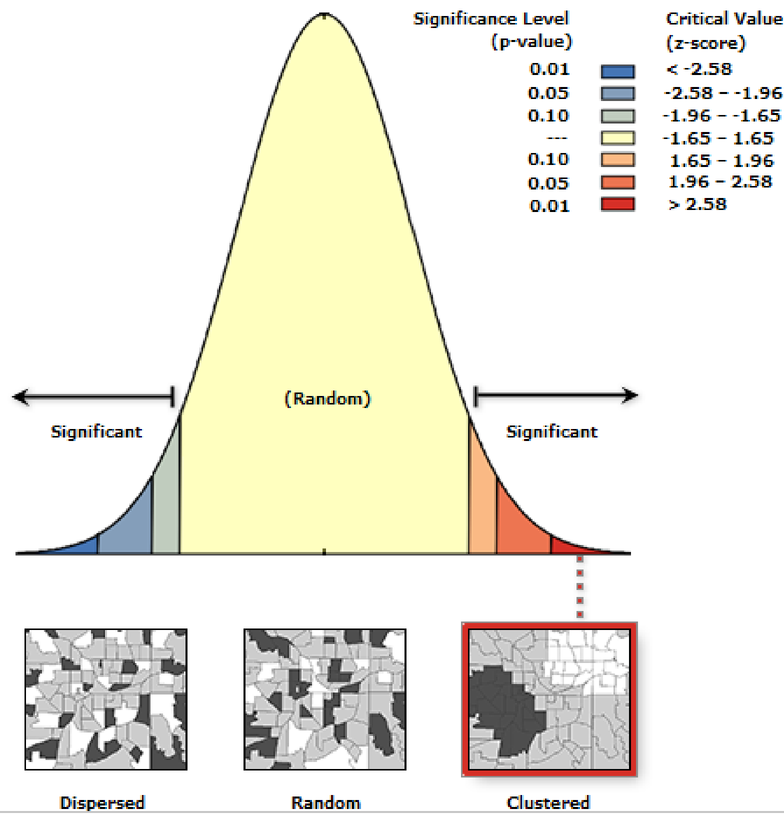
As discussed in Chapter 2, the *Moran's I* coefficient has been used in the past to classify an urban form as monocentric, polycentric or sprawled. As shown in Tsai (2005), the *Moran's I* coefficient is calculated for each of the 12 CMAs using the following equation:

$$I = \frac{\mathrm{N} \sum_{\mathrm{i}=1}^{\mathrm{N}} \sum_{\mathrm{j}=1}^{\mathrm{N}} \mathrm{W_{ij}} (\mathrm{X_i} - \overline{\mathrm{X}})(\mathrm{X_j} - \overline{\mathrm{X}})}{(\sum_{\mathrm{i}=1}^{\mathrm{N}} \sum_{\mathrm{j}=1}^{\mathrm{N}} \mathrm{W_{ij}})\ (\mathrm{X_i} - \overline{\mathrm{X}})^2} \quad \text{... (3.1)}$$

where N represents the total number of zones in the CMA, X_i and X_j represent the population (or employment) of zone i and its neighboring zone j, respectively, $\overline{X}$ represents the mean of the population (or employment) and W_{ij} is a weight that equals 1 if zones i and j are neighbors, 0 otherwise. The calculation of the *Moran's I* is performed in ArcGIS 10.1. Population (or employment) data is imported into ArcGIS in the form of a shapefile that consists of a set of polygons (i.e. TAZs). The software calculates the weight elements

W_{ij} based on the adjacency of the TAZs. It then utilizes equation 3.1 to calculate *Moran's I* based on the X_i values associated with the TAZs. To determine if clustering is present in the data, we test the null hypothesis that the data exhibits no spatial autocorrelation and are randomly distributed over space. A positive and significant *Moran's I* value leads us to reject the null hypothesis. Accordingly, the data is said to exhibit clustering over the study area. As shown in Figure 3.1, ArcMap GIS (key mapping module of ArcGIS) assumes that the *Moran's I* statistic follows the normal distribution and as such calculates the z-score and p-value associated with the calculated *Moran's I* coefficient to infer its significance.

Moran's Index: 0.136957
z-score: 3.136117
p-value: 0.001712



Given the z-score of 3.14, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

Figure 3.1 – ArcMap's Spatial Autocorrelation Report

The *Moran's I* statistic is calculated for all 12 CMAs using both the population and employment, as will be shown in the next chapter.

Table 3.1 provides summary information about the 12 targeted CMAs. As can be seen, the CMAs vary in terms of their total land area and population size. As noted in Chapter 1, only CMAs in the population size range of 100,000 – 1,000,000 were considered. The Toronto and Ottawa regions were excluded from the analysis since both are considered mega cities with well above 1 million inhabitants. Their large size was thought to introduce too much complexity when it comes to assessing the nature of their land use and commuting patterns. Therefore, these two CMAs should be studied separately and compared to other large CMAs across Canada (e.g. Montreal, Vancouver, Calgary and Edmonton). On the other hand, four CMAs in Ontario (namely, Belleville, Sarnia, Sault Ste. Marie and North Bay) housed less than 100,000 inhabitants. Those were also excluded since they were deemed too small for the conducted analysis. It is worth noting that although Brantford housed a total of 135,501 inhabitants in 2011, it was not included in the analysis due to lack of trip data for the year 2011.

As shown in Table 3.1, the smallest CMA considered in the analysis is Peterborough with a population size of 118,975. On the other hand, Hamilton stands as the largest CMA in the analysis with a population size of 721,053. The CMAs are ranked based on their land area, population and job sizes, and population and employment densities (i.e. PD and ED). Table 3.2 provides the ranking along with the identified trend per group of CMAs. Figure 3.2 is used to visually depict the identified patterns in the data.

Table 3.1 - Demographic Data by Metropolitan Area from 2011 Statistics Canada

CMA ID	CMA Name	Area (km^2)	# of Census Tracts	Population	Jobs
521	Kingston	2,147	40	159,561	75,572
529	Peterborough	1,637	28	118,975	51,497
532	Oshawa	908	74	356,177	112,641
537	Hamilton	1,404	188	721,053	282,776
539	St. Catharine's	1,425	94	392,184	154,324
541	Kitchener	840	101	477,160	232,281
550	Guelph	604	30	141,097	76,580
555	London	2,679	109	474,786	214,707
559	Windsor	1,032	73	319,246	123,470
568	Barrie	967	39	187,013	67,938
580	Greater Sudbury	3,850	42	160,770	69,090
595	Thunder Bay	2,640	35	121,596	51,591

Table 3.2 - CMA Rankings by Land Area, Population and Employment

CMA ID	CMA Name	Land Area Rank	Population Rank	Job Rank	PD Rank	ED Rank	*Trend
580	Greater Sudbury	1	8	9	12	12	(1)
521	Kingston	4	9	8	9	9	
529	Peterborough	5	12	12	10	10	
595	Thunder Bay	3	11	11	11	11	
537	Hamilton	7	1	1	2	2	(2)
541	Kitchener	11	2	2	1	1	
532	Oshawa	10	5	6	3	4	
568	Barrie	9	7	10	7	8	(3)
539	St. Catherines	6	4	4	5	7	
559	Windsor	8	6	5	4	7	
550	Guelph	12	10	7	6	3	(4)
555	London	2	3	3	8	7	(5)

*Trend:
(1) Large area, small population/employment, low density
(2) Small area, high population/employment, high density
(3) Similar rank for land area, population and employment
(4) Small land area, population and employment; however, large density
(5) Large land area, population and employment; however, small density

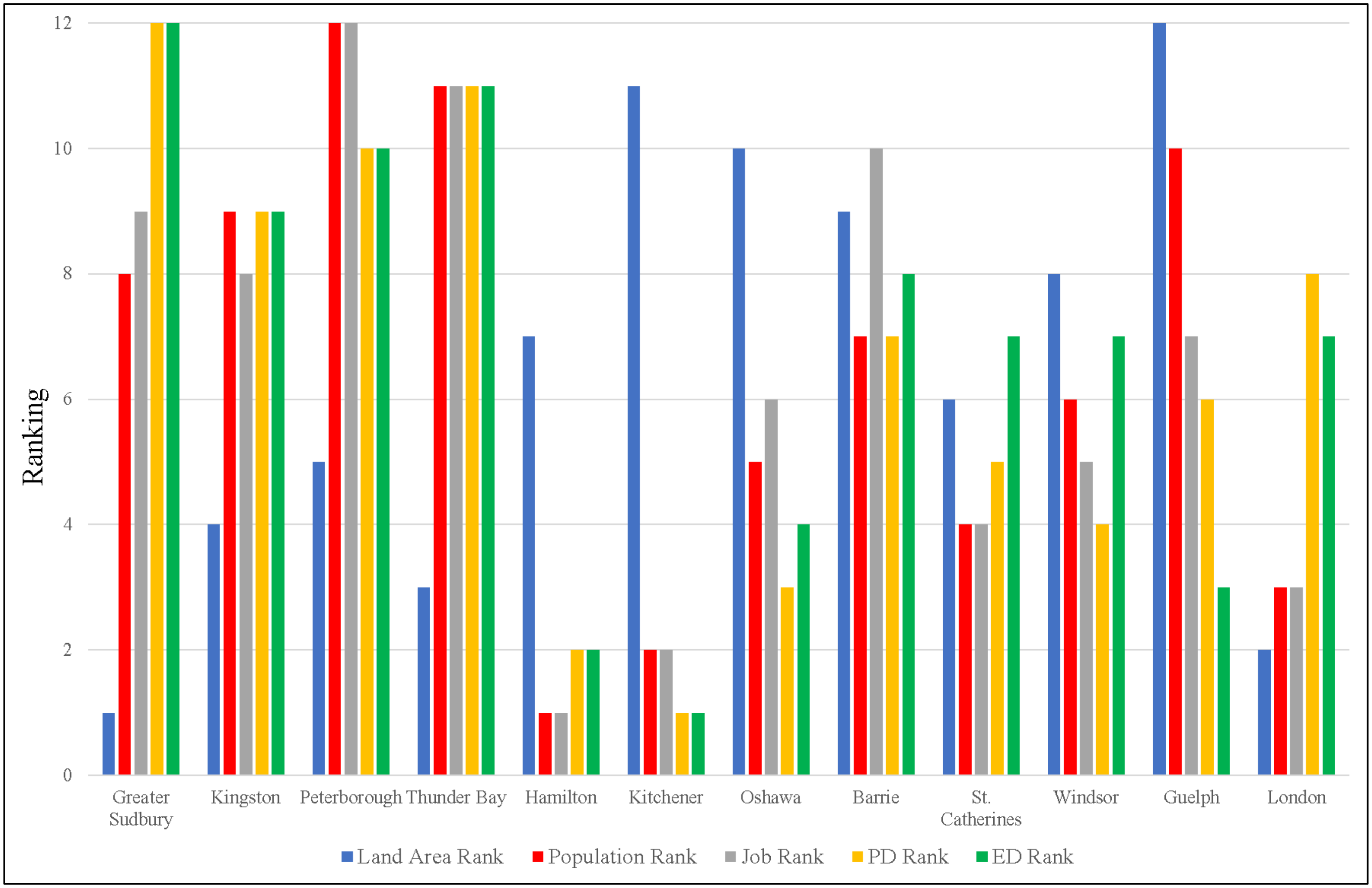


Figure 3.2 - Land Area, Population and Employment Size and Density Ranks between CMAs

3.1.2 Mixed Density Index and Entropy Index

Urban areas with a higher balance of jobs to housing tend to have less commuting. The same could be said about areas that exhibit a higher level of land use mix or heterogeneity. The mixed density index (MDI_i) for a given TAZ *i* is a useful measure to quantify the jobs to housing balance. According to Behan et al. (2008), the index could be calculated using the following equation:

$$\mathrm{MDI_i} = \frac{1}{2}\left(\frac{\mathrm{PD_i} \times \mathrm{ED_i}}{\mathrm{PD_i} + \mathrm{ED_i}}\right) \qquad \text{... (3.2)}$$

where PD_i represents the population density for zone i and ED_i represents the employment density for zone i. An average mixed density index per CMA (MDI) can then be obtained by averaging the values calculated in equation 3.2 over all the TAZs forming the CMA. Typically, a large MDI suggests a higher level of job-housing mix in the metropolitan area, whereas low values tend to be associated with a single type of density. The MDI is calculated for each city to estimate the jobs-housing balance and gauge how that can be connected to excess commuting. Population and employment totals per TAZ within the 12 CMAs were obtained from Statistics Canada for the year of 2011 to calculate the MDI indices. Those data were also used to calculate the *Moran's I* coefficients highlighted in the previous section.

Besides the MDI, the land use entropy index (EI_i) is calculated for each TAZ i to evaluate the level of land use mix (i.e. homogeneity vs. heterogeneity) in each CMA. An entropy index value approaching 0 represents homogeneity, while a value approaching 1 signifies heterogeneity. The land use entropy index for a given TAZ i can be calculated using the following equation:

$$EI_i = \frac{1}{K}\sum_{k=1}^{K} -P_k \times \ln P_k \qquad \text{... (3.3)}$$

where P_k represents the proportion of land use type k in census tract or TAZ i and K represents the number of land use classes in TAZ *i*. An average entropy index per CMA (EI) can be calculated by taking the mean of the EI_i values calculated from equation 3.3 for all the TAZs forming the CMA.

In this thesis, the variable P_k is generated using data obtained from the Desktop Mapping Technology Inc. (DMTI) GIS database. More specifically, the land use cover map from the 2013 Route Logistics GIS data library is used. Land uses in the data are broken-down into the following seven classes: Commercial; Government & Institutional; Open Area; Parks & Recreation; Residential; Resource & Industrial; and Water Bodies. The data was processed in ArcGIS 10.1 to generate the P_k values required to calculate the EI_i for the different TAZs.

3.2 Measuring Excess Commute

The concept of measuring excess commuting relies on the relationship between the location of a worker's place of residence and the cost to travel to their workplace. The analysis involves measuring the actual observed commute (C_{obs}) and comparing it to several theoretical commuting measures, including an average minimum (C_{min}), maximum (C_{max}) and random commute (C_{rnd}), as discussed in Chapter 2 (Figure 2.7). Excess commuting (C_{ex}) is the difference between the average observed commute and the theoretical average minimum commute. It is calculated using the following formula, expressed as a percent of the observed average commute:

$$C_{ex} = 1 - \frac{C_{min}}{C_{obs}} \qquad \text{... (3.4)}$$

The commuting potential utilized (C_u) is calculated using the following formula, expressed as a percent:

$$C_u = \frac{C_{obs} - C_{min}}{C_{max} - C_{min}} \qquad \text{... (3.5)}$$

The random commute (C_{rnd}) is a relatively new measure that was introduced by Charron (2007) to assess the importance of commuting distance for workers. Typically, workers tend to exploit the nature of urban form to reduce or increase their commuting distances when C_{obs} is significantly different from C_{rnd}.

The transportation data used to calculate excess commuting was collected from the 2011 National Household Survey (NHS) of Statistics Canada. The NHS data represents the main transportation mode used to travel between home and work for employed population aged 15 years and over (both drivers and passengers) with a usual place of work or no fixed workplace address. The data, which is referred to as Journey-to-Work data, provides the number of work trips (by mode) between the different origin-destination TAZs. The data is available for each CMA. The following modes of transportation are provided on record: car/truck/van as auto-driver, car/truck/van as auto-passenger, public transit, walking, bicycling and other. A summary of the modal shares per CMA is presented in Table 3.3 below.

Table 3.3 - Transportation Modal Shares by CMA

CMA ID	CMA Name	Auto[1]	Public[2] Transit	Green[3]	Other
521	Kingston	83%	5%	11%	1%
529	Peterborough	87%	3%	9%	1%
532	Oshawa	87%	8%	4%	1%
537	Hamilton	84%	9%	5%	1%
539	St. Catherines	90%	3%	6%	1%
541	Kitchener	88%	5%	5%	1%
550	Guelph	86%	6%	7%	1%
555	London	85%	7%	7%	1%
559	Windsor	91%	3%	5%	1%
568	Barrie	90%	5%	4%	1%
580	Greater Sudbury	88%	5%	6%	2%
595	Thunder Bay	88%	4%	6%	2%

Note: 1- Auto includes both auto drive and auto passenger
2- Public transit includes bus, subway, elevated rail, light rail, streetcar, commuter train and passenger ferry
3- Green mode includes non-motorized modes (e.g. walking and biking)

It is evident that auto (personal vehicle trips for drivers and passengers) accounts for the majority of all work trips. On average, 87% of work trips in the 12 CMAs were undertaken by the auto-mode. By comparison, the average transit share across the 12 CMAs is only 5%. The Hamilton CMA seems to have a well above average transit share of 9% where as Peterborough, St. Catherines and Windsor have the lowest transit share of only 3%. The cost variable used to calculate excess commuting is assumed to be associated with the distance d_{ij} a worker commutes between his place of residence TAZ i and place of work TAZ j. As in other studies, travel time was not considered due to uncertainties and inconsistencies such as congestion and parking time.

In what follows, the measures used to quantify the nature of commuting in the 12 CMAs will be discussed. A custom program was developed to generate the results for this thesis. The program was designed to read in the trip origin-destination (OD) matrix and the distance matrix as inputs to calculate the various average commute measures (C_{obs}, C_{min}, C_{max}, C_{rnd}). The program also included a routine to calculate the trip entropy (E) of the transportation system based on the provided OD matrix. The trip entropy of the commuting trip matrix with trips T_{ij} between origin TAZ i and destination TAZ j is also a useful measure that could be used to determine how busy a CMA is in terms of its spatial interaction (i.e. the busier the area, the higher the trip entropy). E is calculated using the following equation (Ortuzar and Willumsen 2011):

$$\mathrm{E} = (\mathrm{T} \ln \mathrm{T} - \mathrm{T}) - \sum_{\mathrm{i}} \sum_{\mathrm{j}} \left(\mathrm{T_{ij}} \ln \mathrm{T_{ij}} - \mathrm{T_{ij}} \right) \qquad \dots (3.6)$$

3.2.1 Average Observed Commute (C_{obs})

The average observed commute (C_{obs}) represents the actual average commute experienced CMA-wide and is calculated using the following equation:

$$\mathrm{C_{obs}} = \frac{1}{\mathrm{W}} \sum_{\mathrm{i}=1}^{\mathrm{n}} \sum_{\mathrm{j}=1}^{\mathrm{m}} d_{\mathrm{ij}} \mathrm{T_{ij}} \qquad \dots (3.7)$$

where T_{ij} represents the observed commute trip totals between TAZs i and j provided by the NHS 2011, d_{ij} represents the distance between zones, and W represents the total number of workers (i.e. trips) in the CMA. To create the cost matrix (d_{ij}), the distance between each TAZ was calculated to create a square matrix including all TAZs. ArcMap GIS was used to locate the centroid (X_i, Y_i) of each TAZ i. Pythagorean's theorem was then applied to the coordinate of any two TAZ pairs i and j to calculate the Euclid distance in kilometers as follows:

$$d_{ij} = \frac{\sqrt{(X_j - X_i)^2 + (Y_j - Y_i)^2}}{1000} \qquad \text{... (3.8)}$$

3.2.2 C_{min} and C_{max} Calculation

The calculation of the theoretical minimum commute is based on White's (1998) method, in which C_{min} occurs when workers are reassigned to the nearest job location from home. C_{min} is calculated using an optimal $T_{min,ij}$ OD matrix that is calculated by optimizing the following linear program:

$$\text{Minimize } C_{min} = \frac{1}{W} \sum_{i=1}^{n} \sum_{j=1}^{m} d_{ij} T_{min,ij} \qquad \text{... (3.9.1)}$$

s.t.

$$\sum_{i=1}^{n} T_{min,ij} = W_i \qquad \forall\, i \qquad \text{... (3.9.2)}$$

$$\sum_{j=1}^{n} T_{min,ij} = E_j \qquad \forall\, j \qquad \text{... (3.9.3)}$$

$$T_{min,ij} \geq 0 \qquad \forall\, i, j \qquad \text{... (3.9.4)}$$

where W is the total number of workers (trips) in the entire CMA; W_i is the number of workers in TAZ i; E_j is the number of jobs in TAZ j; n and m are the total number of origin and destination zones, respectively; d_{ij} is the cost of travel (i.e. distance) between zones i and j; and, $T_{min,ij}$ is the number of optimal work trips between zones i and j. $T_{min,ij}$ in equation 3.9.1 represents the decision variables that will be optimized subject to the constraints given in equations 3.9.2 - 3.9.4. The outcome of the optimization problem is an optimal OD matrix $T_{min,ij}$ which assigns the job location of workers as close as possible to their places of residence. This matrix is then used to calculate the C_{min} based on the objective function provided in equation 3.9.1.

The theoretical maximum commute (C_{max}) is calculated in a similar fashion as in the case of the C_{min}. However, the objective function in equation 3.9.1 is maximized instead of being minimized. That is:

$$\text{Maximize } C_{max} = \frac{1}{W}\sum_{i=1}^{n}\sum_{j=1}^{m} d_{ij} T_{max,ij} \qquad \text{... (3.10.1)}$$

s.t.

$$\sum_{i=1}^{n} T_{max,ij} = W_i \qquad \forall\, i \qquad \text{... (3.10.2)}$$

$$\sum_{j=1}^{n} T_{max,ij} = E_j \qquad \forall\, j \qquad \text{... (3.10.3)}$$

$$T_{max,ij} \geq 0 \qquad \forall\, i, j \qquad \text{... (3.10.4)}$$

As in the case of the theoretical minimum commute, the outcome of maximizing the objective function in equation 3.10.1 is an optimal OD matrix $T_{max,ij}$ which assigns the job location of workers as far as possible from their places of residence. This matrix is then used to calculate the C_{max} based on the objective function provided in equation 3.10.1.

3.2.3 C_{rnd} Calculation

The average random commute (C_{rnd}) represents a theoretical commute that does not take into consideration the effect of commuting cost. Since commuting cost is not a factor in this case, one could think of the existence of a large number of commuting possibilities (i.e. trip matrices) that conform to the observed spatial distribution of workers and jobs (i.e. urban form) across the TAZs of the CMA. In any given commuting possibility, workers in an origin zone i could be assigned to jobs in destination zone j in a random fashion regardless of the cost of commuting between zones i and j. According to Charron (2007), a Monte Carlo simulation could be utilized to obtain these randomly assigned commuting possibilities. Each randomly assigned commuting possibility *t* is represented by an OD matrix $T_{rnd}(t)$. The average random commute $C_{rnd}(t)$ can be calculated in the same way the C_{obs} is calculated in equation 3.7 but using the generated $T_{rnd}(t)$ matrix. A frequency distribution characterizing the nature of the commuting possibilities ($C_{rnd}(t)$) could be generated with a sufficiently large number of randomly generated $T_{rnd}(t)$ matrices. The mean of the frequency distribution provides a good benchmark measure of the random average commute C_{rnd}. In this thesis, a total of 1000 Monte Carlo simulations (t) were performed to calculate the mean C_{rnd} value per CMA. Charron (2007) noted that the C_{obs} could be compared to the obtained C_{rnd} by calculating a simple ratio (C_{obs} / C_{rnd}). The latter provides the relative location of C_{obs} on the commuting possibilities frequency distribution. Charron (2007) notes that if C_{obs} is statistically significant compared to C_{rnd}, then commuting distance is an important factor for workers. That is, workers tend to take advantage of the nature of urban form to either reduce or increase their commute.

The calculation of the $T_{rnd}(t)$ in the software utilized in this thesis is performed according to the following steps:

- Step 1: Initialize a matrix to the dimensions of the TAZs comprising the CMA.
- Step 2: Populate the elements of the initialized matrix with randomly generated numbers ranging between 0 and 1. Call this matrix $T0_{rnd}(t)$.
- Step 3: Apply the iterative proportional fitting (IPF) (i.e. Fratar or Furness) method to update the elements $T0_{rnd,ij}$ of matrix $T0_{rnd}(t)$ to create matrix $T_{rnd}(t)$ with elements $T_{rnd,ij}$ such that:

$$\sum_{i=1}^{n} T_{rnd,ij} = W_i \qquad \forall\, i \qquad \ldots (3.11.1)$$

$$\sum_{j=1}^{n} T_{rnd,ij} = E_j \qquad \forall\, j \qquad \ldots (3.11.2)$$

3.2.4 Iterative Proportional Fitting (IPF) Method

As noted in the previous section, the iterative proportional fitting (IPF) method or Fratar method was used to generate a set of OD matrices that represent a range of commuting possibilities that are associated with the urban form of a given CMA. IPF was also used in the treatment of the Journey-to-Work and Occupation raw dataset, as will be discussed in the next section. It was also instrumental in creating the Journey-to-Work OD matrices by type of occupation. IPF was chosen in this research for two reasons: 1) when applied to update the state of an OD matrix, IPF assumes that the transportation cost (i.e. the nature of the transportation network) remains fixed over time; and, 2) IPF is also a robust method for updating two-way tables when the future state of the table does not deviate significantly from the current state.

Ortuzar and Willumsen (2011) note that the method works by calculating a new state of an OD matrix that conforms to known marginal rows and columns using an existing state of that OD matrix, as illustrated in Figure 3.3.

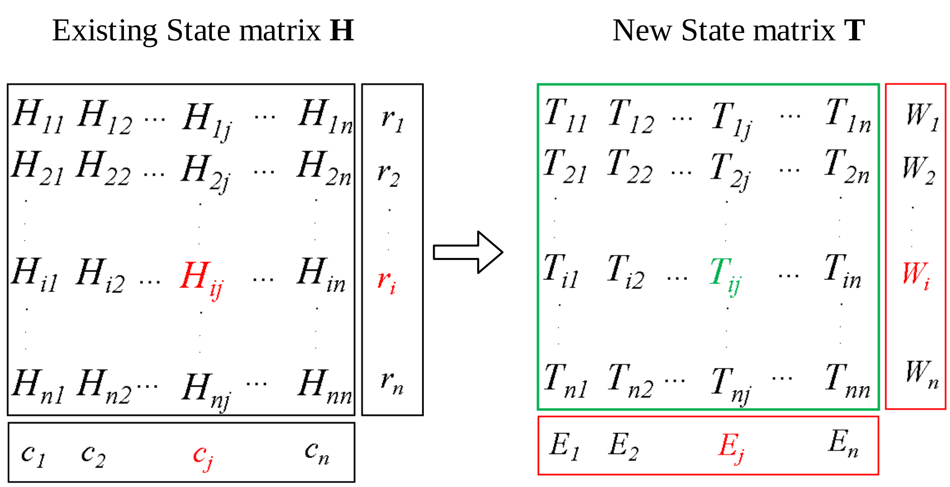


Figure 3.3 – Updating an Existing State of an OD Matrix to a New State

In Figure 3.3, an element H_{ij} in the existing state matrix H represent the randomly generated number obtained in Step 2 in Section 3.2.3 above. The row marginal totals r_i and column marginal totals c_j of matrix H are known for all i and j. Also known are the row marginal totals W_i and column marginal totals E_j of the new state matrix T. The IPF will make use of all these known values to populate matrix T with elements T_{ij} such that the sum of the generated values in a given row i add up to the row marginal total W_i, and the sum of the generated values in a given column j add up to the column marginal total E_j. IPF is an iterative procedure that can be best described according to the flow chart given in Figure 3.4.

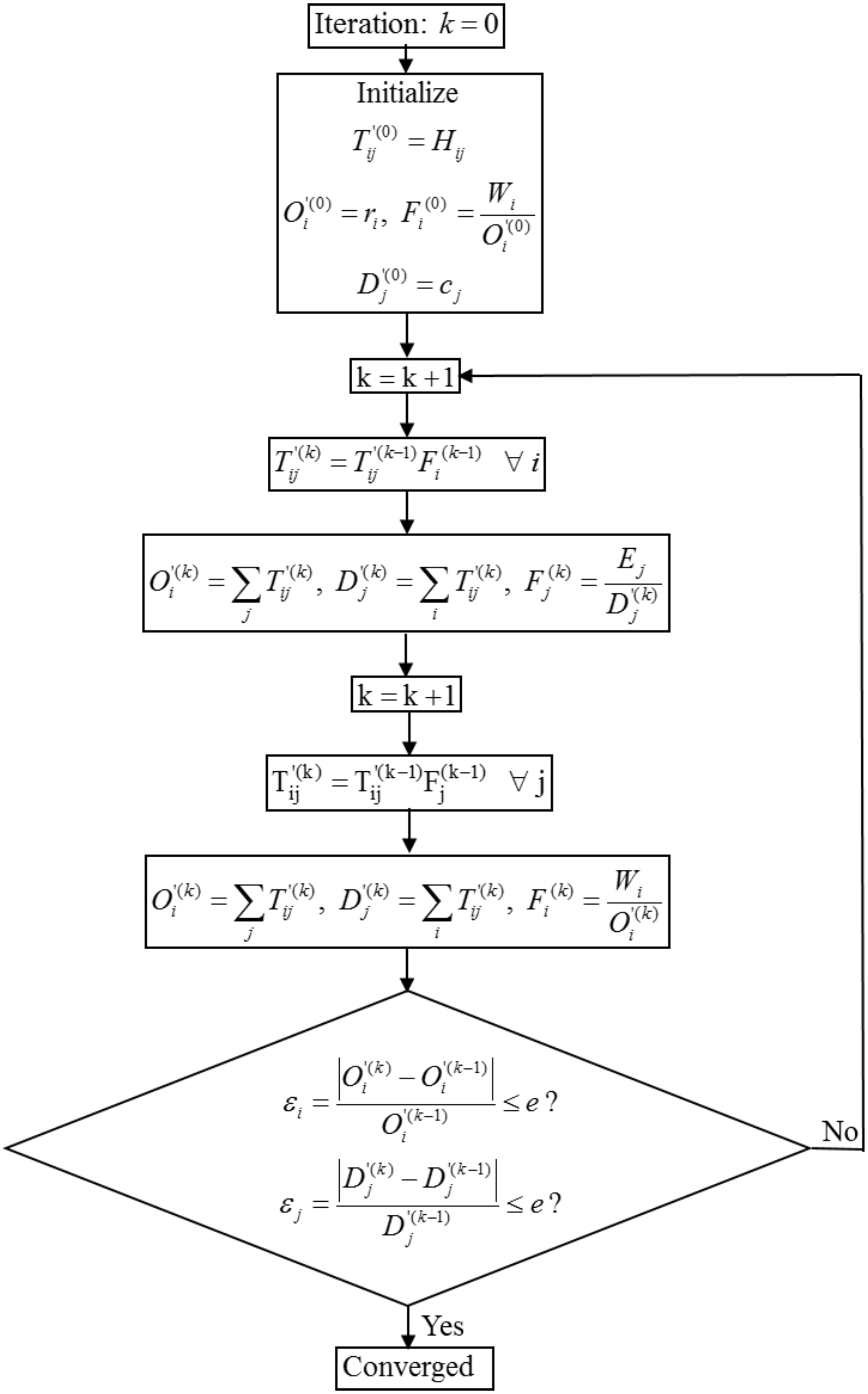


Figure 3.4 – The Iterative Proportional Fitting (IPF) Procedure

The IPF procedure attempts to minimize the error in the row and column marginal totals εi and εj throughout the different iterations. As such, the convergence tolerance *e* is normally set to a very small value (such as 0.05). The IPF method is a practical technique that achieved the desired outputs quickly. It has been used in various transportation studies to update the OD matrix for future years when no major changes are expected to occur in the transportation network (Ortuzar and Willumsen, 2011).

3.3 Extensions to the Brotchie's Triangle

As discussed in Chapter 2, Brotchie's triangle is a method that could be used to examine the effect of cross-commuting and land use dispersal (Ma and Banister, 2007). Chowdhury et al. (2013) adapted the same concept to examine commuting efficiency in Canadian cities. They modified the Brotchie's triangle to include the C_{min}, C_{max} and C_{obs} measures in the triangle, as shown in Figure 3.5.

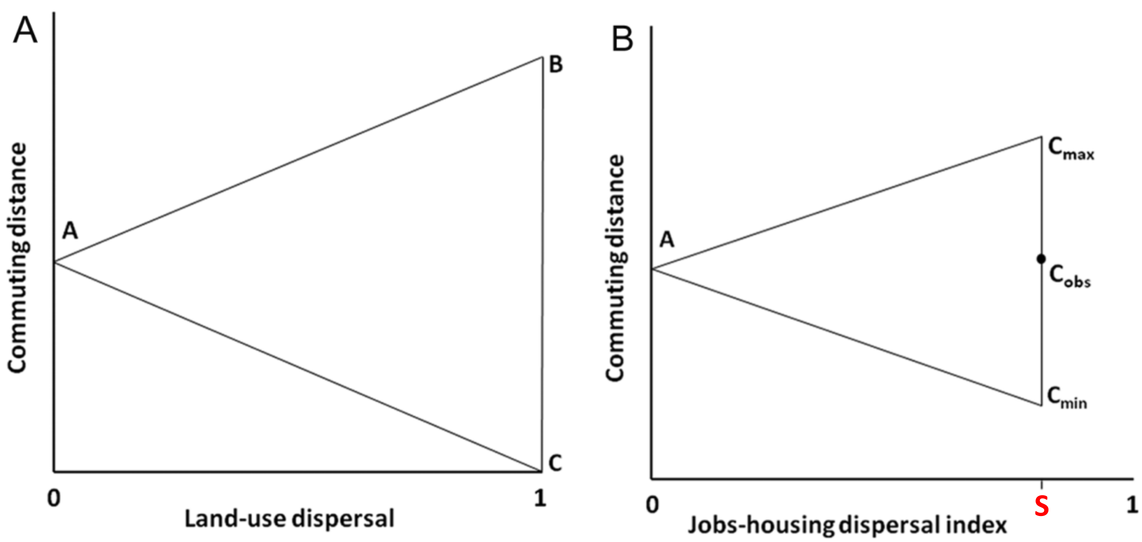


Figure 3.5 – A. Classical Brotchie's Triangle; B. Modified Brotchie's Triangle (*Source: Adapted from Chowdhury et al. 2013*)

According to Chowdhury et al. (2013), the commuting potential measured as the difference between the C_{max} and C_{min} is plotted against the jobs-housing dispersal level. Typically, C_{obs} falls on the line between C_{min} and C_{max}. The jobs-housing dispersal index S for a given CMA is calculated as follows:

$$S = \frac{\text{Job Dispersal (km)}}{\text{Household Dispersal (km)}} \qquad \text{... (3.12)}$$

where

$$\text{Household Dispersal y} = \frac{\sum_{i=1}^{n} \mathrm{d}_{\mathrm{i,CBD}} \times \mathrm{W}_i}{\text{Total Workers in CMA}} \qquad \text{... (3.13)}$$

$$\text{Job Dispersal} = \frac{\sum_{i=1}^{n} \mathrm{d}_{\mathrm{i,CBD}} \times \mathrm{E}_i}{\text{Total Jobs in CMA}} \qquad \text{... (3.14)}$$

where $d_{i,CBD}$ represents the distance from the centroid of TAZ i to the centroid of the TAZ representing the CBD for a given CMA, and n represents the total number of TAZs. ArcMap GIS was used to project the coordinates of the centroids and calculate the distance. Table 3.4 presents the TAZs identified as the CBD in each of the 12 CMAs. As noted by Chowdhury et al. (2013), a perfect monocentric city will yield an S value of 0. On the other hand, if each TAZ has an equal number of jobs and workers, then S will equal 1. Further, an S value greater than 1 reflects a situation where households are located near the CBD, while jobs are sprawled.

To understand how the modified Brotchie's triangle can help us evaluate the relationship between commuting efficiency and urban form, we need to look at its various dimensions. Typically, any given CMA will have a certain jobs-housing dispersal S associated with its urban form. That dispersal is also associated with the observed average commute C_{obs}, and the two theoretical average commuting measures C_{min} and C_{max}. In that sense, one can plot the three pairs of values (S, C_{min}), (S, C_{obs}) and (S, C_{max}) in a two-dimensional plot. Hypothetically, if the city had a monocentric urban form with all jobs located in the centre, then the job dispersal value will be equal to zero. The corresponding commuting distance, which represents the household dispersal y, would be a value located on the vertical axis of the two dimensional plot in which workers living outside the core commute a certain distance to get to work. This point (0, y) represents the tip of Brotchie's triangle (i.e. point A) in Figure 3.5 (B). Typically, a smaller triangle suggests a more efficient urban system.

Table 3.4 – TAZ ID Representing the CBD in Each CMA

CMA #	CMA Name	CBD TAZ ID
1	Barrie	5680006
2	Greater Sudbury	5800005
3	Guelph	5500006
4	Hamilton	5370037
5	Kingston	5210001
6	Kitchener	5410017
7	London	5550022
8	Oshawa	5320010
9	Peterborough	5290007
10	St. Catherines	5390005
11	Thunder Bay	5950014
12	Windsor	5590035

3.4 Data Treatment and Processing

3.4.1 Journey to Work Data

The Journey-to-Work origin-destination matrices used in the analysis are based on the data collected in Statistics Canada's 2011 National Household Survey. The acquired records included the 24-hour work trips for employed population aged 15 years and over (both drivers and passengers) with a usual place of work or no fixed workplace address. Trip flows were provided at the census tract level. The initial processing of the data revealed some discrepancies in terms of the total trips per CMA. In some cases, certain origin-destination pairs were missing and in other cases the total number of workers as provided by the sum of a given row (i.e. census tract) in the OD matrix did not add up to the total number of workers as reported in the 2011 Canadian Census. After careful examination, it became clear that values for many origin-destination pairs were suppressed to maintain data confidentiality. A way around the data suppression issue was to process the records by adding missing census tracts to create square matrices. Further, cells with missing trip values or with 0 trips were populated with a value of 1 as an initial step. Given the worker and job distribution at the census tract level, each of the 12 matrices were processed through the IPF method to update the trip matrix elements such that the row and column sums corresponded to the 2011 worker and job spatial distributions that were separately obtained from Statistics Canada. The total number of work trips in the updated matrices add up to the total number of jobs reported in Table 3.1. These 12 updated ODs are the ones used in the analysis of the 12 CMAs.

3.4.2 Occupation Data

The next steps are to recalculate similar commuting measures to the ones provided above by occupation type to investigate the true nature of linkage between commuting and urban form in the studied CMAs. The job and worker data by occupation is broken down into 10 distinct classes, as shown in Table 3.5. To calculate C_{obs}, C_{min}, C_{max}, and C_{rnd} by occupation, the IPF procedure could be used to create occupation based T_{ij} matrices. A total of 10 matrices will be created per CMA (one for each occupation type). The distribution of the workers and jobs by a given occupation class at the census tract level will be used as the marginal row and column totals for the new state matrix. The adjusted T_{ij} matrix described in Section 3.4.1 will be used to represent the current state.

Two tables were obtained from Statistic Canada to represent the spatial distribution of works and jobs by occupation and census tract for 2011 for each CMA. As in the case of the Journey-to-Work data, census tract × occupation tables exhibited some discrepancies in which information was missing for some census tracts. Also, the total number of occupation based jobs and workers were not equal in some cases. Therefore, the spatial distribution of workers and jobs by occupation were adjusted to produce balanced worker and job census tract × occupation tables. The column marginal totals (i.e. totals by occupation) in each CMA was set to the values shown in Table 3.5 for that CMA.

Table 3.5 – Total Number of Workers (or Jobs) by Occupation Type

CMA ID	CMA Name	Occ. 1	Occ. 2	Occ. 3	Occ. 4	Occ. 5	Occ. 6	Occ. 7	Occ. 8	Occ. 9	Occ. 10
521	Kingston	8,412	12,152	4,757	7,047	14,922	1,987	18,202	6,187	533	1,373
529	Peterborough	5,406	7,981	3,441	4,626	7,201	1,331	13,906	4,600	635	2,370
532	Oshawa	12,606	17,316	5,916	8,446	15,471	2,616	30,026	11,611	1,232	7,401
537	Hamilton	30,767	47,677	16,452	24,817	36,477	7,172	72,417	29,722	3,487	13,788
539	St. Catharines	16,277	23,477	6,917	9,887	16,457	4,047	51,082	16,047	3,417	6,716
541	Kitchener	26,985	40,145	22,580	12,430	25,985	5,220	52,600	25,020	1,971	19,345
550	Guelph	8,300	12,030	5,470	4,280	8,800	1,620	15,070	8,825	1,050	11,135
555	London	22,330	37,160	12,180	18,901	27,901	5,146	54,726	21,431	2,506	12,426
559	Windsor	11,092	18,212	6,412	9,072	14,212	2,416	32,151	15,646	1,161	13,096
568	Barrie	8,009	11,459	3,169	5,114	8,784	1,859	19,269	7,489	532	2,254
580	Greater Sudbury	6,448	12,928	4,218	5,413	9,093	1,323	16,743	8,918	2,688	1,318
595	Thunder Bay	4,606	8,516	3,136	4,791	7,856	946	13,816	6,066	612	1,246

Key:

Occ. 1	Management occupations
Occ. 2	Business, finance and administration occupations
Occ. 3	Natural and applied sciences and related occupations
Occ. 4	Health occupations
Occ. 5	Occupations in education, law and social, community and government services
Occ. 6	Occupations in art, culture, recreation and sport
Occ. 7	Sales and service occupations
Occ. 8	Trades, transport and equipment operators and related occupations
Occ. 9	Natural resources, agriculture and related production occupations
Occ. 10	Occupations in manufacturing and utilities

On the other hand, the row marginal totals in the case of the workers (census tract × occupation) table was set to equal the row marginal total of the adjusted T_{ij} matrix obtained in Section 3.4.1. Further, the row marginal totals in the case of the jobs (census tract × occupation) table was set to equal to the transpose of the column marginal total of the adjusted T_{ij} matrix obtained in Section 3.4.1. As in the case of the Journey-to-Work matrices, missing census tracts were added. Also, missing values as well as values originally set to 0 by Statistics Canada were set to 1 before running the IPF procedure to obtained the balanced census tract × occupation tables for workers and jobs. A total of 24 IPF runs were performed to process the 24 census tract × occupation files (i.e. 12 worker files and 12 job files). The outcome is balanced occupation based tables that could be used to create the trip matrices by occupation type for the 12 CMAs. In each CMA case, the adjusted T_{ij} matrix from Section 3.4.1 was used as input along with the occupation-specific values for workers and jobs that were obtained from the balanced census tract × occupation files. The latter were used as the marginal totals for the new state trip matrix in the IPF procedure. A total of 120 IPF runs were preformed to create 10 occupation-specific trip matrices for each of the 12 studied CMAs. It should be noted that the analysis in this thesis assumes a closed system for each of the studied CMAs. That is, we are only focused on the work trips that originate and end within the same CMAs. Admittedly, there will be workers living in the CMA who work outside of it and at the same time, there will be jobs in the CMA that attract workers from outside the CMA. Those internal-external and external-internal commuters were not part of the conducted analysis in this thesis. It remains, however, that the majority of the workers within the CMA will be associated with jobs within the CMA. Also, the majority of jobs within the CMA will be associated with workers from the same CMA.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Urban Form Types

The nature of urban form has been characterized for each of the 12 CMAs based on the calculated *Moran's I* coefficients, which are presented in Table 4.1. The classification scheme presented in Table 2.2 was adopted to determine the type of urban form for each CMA based on the zoning system and density of land use activities. The *Moran's I* values represented in Table 2.2 (Chapter 2) based on the work of Tsai (2005) set the basis for characterizing the type of urban form. It should be noted, however, that the values shown in Table 2.2 are based on simulating conceptual urban form types. The latter were derived from a regular lattice with cells of equal size all across space. Therefore, these values should only be used as benchmarks for relative comparisons. Tsai (2005) states that:

"*the Moran coefficients of monocentric, polycentric and decentralised sprawling forms are high, intermediate and close to zero respectively; and, the local sprawl, comprising leapfrog and strip developments, will lower the value of the Moran coefficients.*"

Based on the above, the *Moran's I* values for the 12 CMA were sorted in an ascending fashion to characterize the type of urban form. The results are presented in Figures 4.1 and 4.2. As can be seen in Figure 4.1, four CMAs exhibit a decentralized population urban form, two have a polycentric form, while the remaining six are more compact in nature. On the employment side, four CMAs have sprawled employment, five are more polycentric while three have a more compact employment configuration. A cross-classification of urban form based on population and employment spatial structure is provided in Table 4.2. According to the derived classifications, CMAs like Windsor and Hamilton fall into the compact category for both employment and population. These

Table 4.1 – Urban Form Related Measures for Analyzed CMAs

CMA ID	CMA Name	Area (Km^2)	TAZs	Population	Work Trips	X_i = 2011 Population		X_i = 2011 Employment		Land Use Indices	
						Moran's I	z-score	Moran's I	z-score	Mean MDI	Mean EI
521	Kingston	2,147.39	40	159,561	75,572	0.157	1.82	0.067	0.99	402.90	0.1439
529	Peterborough	1,637.35	28	118,975	51,497	-0.194	-1.46	-0.008	0.31	306.69	0.1467
532	Oshawa	907.9	74	356,177	112,641	0.364	5.16	0.066	1.12	356.58	0.1638
537	Hamilton	1,403.77	188	721,053	282,776	0.137	3.14	0.152	3.57	616.48	0.1566
539	St. Catherines	1,424.88	94	392,184	154,324	-0.018	-0.11	0.024	0.58	302.87	0.1560
541	Kitchener	839.81	101	477,160	232,281	0.111	2.06	0.088	1.71	451.74	0.1789
550	Guelph	603.63	30	141,097	76,580	0.094	1.31	-0.117	-1.13	415.49	0.1644
555	London	2,679.06	109	474,786	214,707	0.205	3.79	-0.027	-0.36	413.50	0.1534
559	Windsor	1,032.22	73	319,246	123,470	0.292	4.28	0.127	2.04	440.72	0.1606
568	Barrie	966.96	39	187,013	67,938	-0.032	-0.06	0.042	0.77	317.29	0.1686
580	G. Sudbury	3,850.41	42	160,770	69,090	0.125	1.6	0.036	0.67	222.23	0.1463
595	Thunder Bay	2,640.44	35	121,596	51,591	0.027	0.58	0.187	2.61	332.28	0.1369

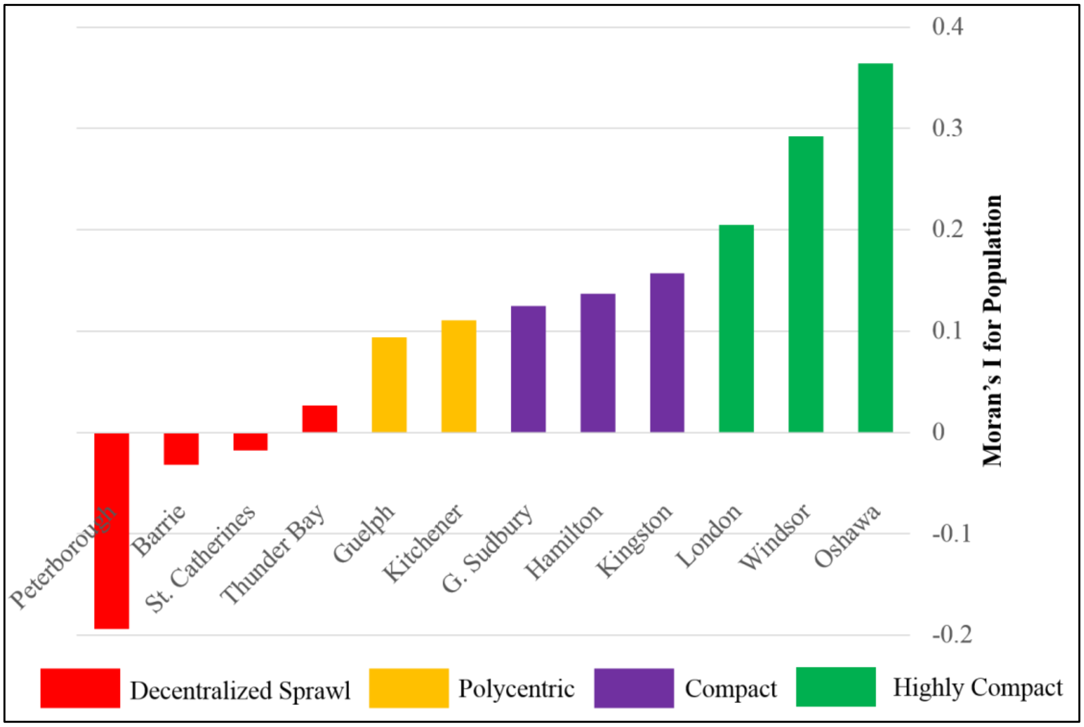


Figure 4.1 – Urban Form Classification based on Moran's I for Population

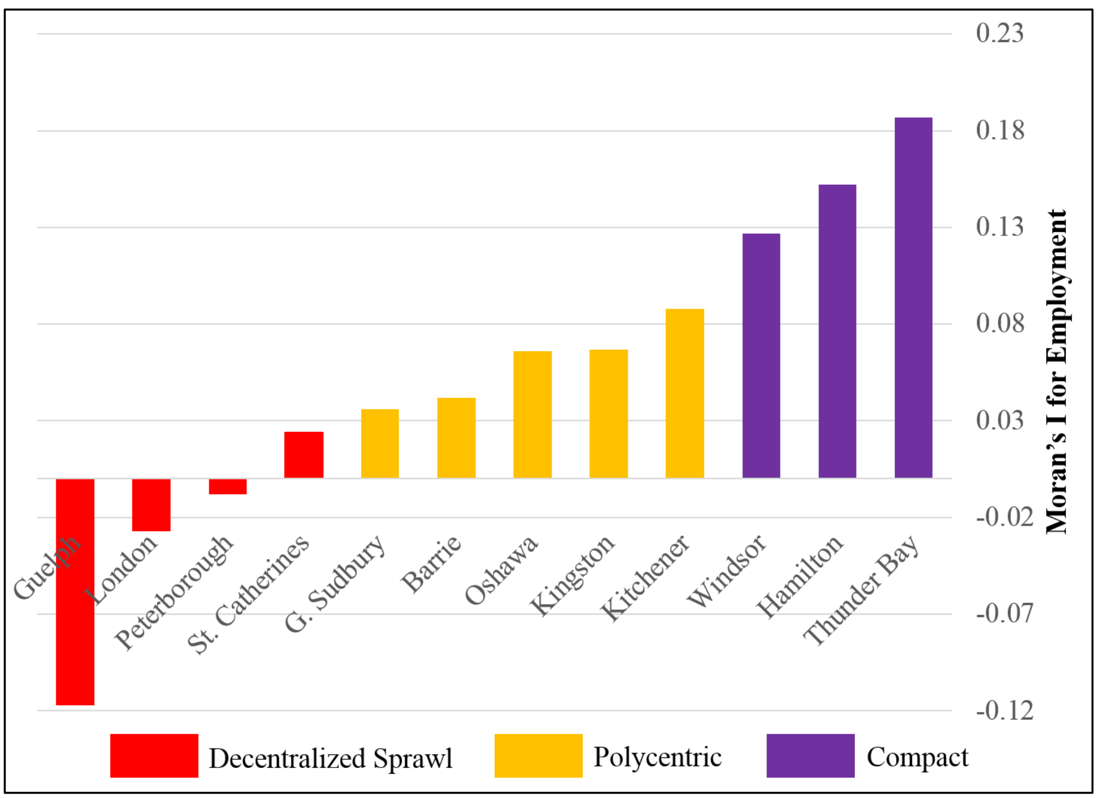


Figure 4.2 – Urban Form Classification based on Moran's I for Employment

Table 4.2 – Cross Classification of Urban Form Based on Population and Employment

Population \ Employment	Compact	Polycentric	Sprawled
Compact	Windsor Hamilton	Oshawa Kingston Greater Sudbury	London
Polycentric	-	Kitchener	Guelph
Sprawled	Thunder Bay	Barrie	St. Catherines Peterborough

findings might come across as surprising given the conclusions reported in Maoh et al. (2010) for Hamilton where sprawl was found to be an emerging trend in this Canadian CMA. The same could be said about Windsor in which urban sprawl is also an emerging trend (Maoh and Tang, 2012). Obviously, the *Moran's I* coefficient tends to capture the dominant spatial clustering trend in the data across the TAZs. As such, it is a measure of density and not size. A closer look at the spatial patterns of population and employment densities could clarify this point. As shown in Appendix A, the mixed density index (MDI) maps for Hamilton and Windsor portray a clear central effect with respect to their population and employment density mix. By comparison, the MDI map for a place like St. Catherines clearly suggests that density is more scattered, which lines up with the *Moran's I* values. The key point here is that while certain CMAs have been progressively moving towards un-wanted sprawled patterns, their population and/or employment densities could still exhibit centrality (see Figure 4.3). Therefore, the *Moran's I* coefficient is more of a global measure that only depicts the dominant spatial pattern.

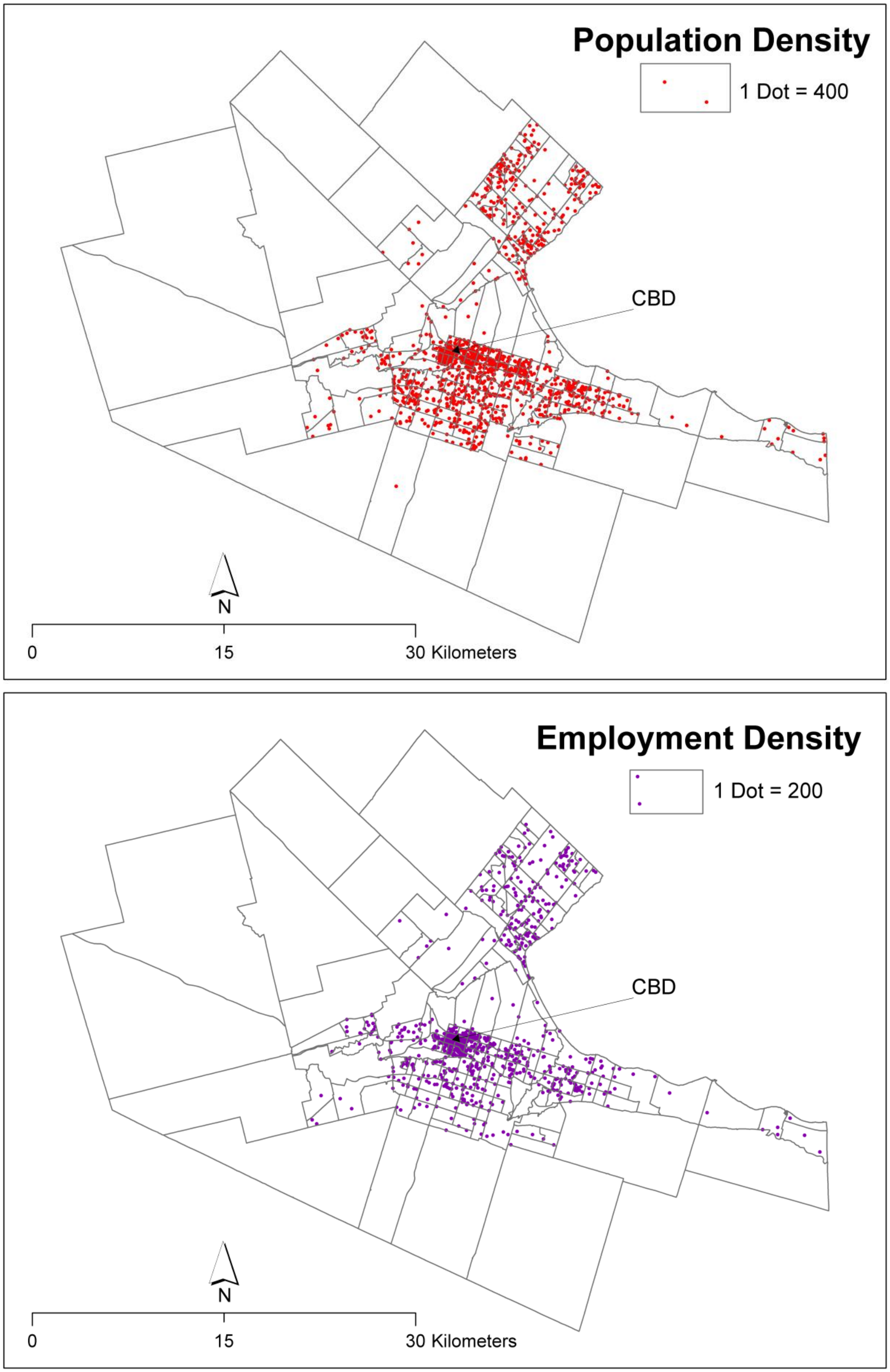


Figure 4.3 – Population and Employment Density Maps for Hamilton CMA

The reader should also note that the size of the zones for each CMA will also impact the values of the obtained *Moran's I* statistic. While Tsai's (2005) work relied on regular grid cells to represent the zones, our analysis is based on irregular zones which tend to be much larger for suburban areas. The latter house a disproportional number of workers and jobs in most metropolitan areas. However, since all 12 CMAs share the same zonal characteristics, the *Moran's I* values are deemed acceptable to use for comparison purposes across the 12 CMAs.

The results from Table 4.1 for London and Thunder Bay are interesting with respect to the *Moran's I* coefficient for population vs. employment. These CMAs are classified as compact with respect to one, but sprawled with respect to the other. London is considered very compact when reviewing the results based on population, but sprawled with respect to employment. Thunder Bay is compact in terms of employment but sprawled with respect to population. When looking at the city sizes, London has the third highest population of the 12 CMAs, whereas Thunder Bay has the second lowest. If considering CMA size by land area, London and Thunder Bay are almost equal to each other. The MDI for London is slightly higher than the average of the 12 CMAs, whereas Thunder Bay is slightly lower than the average. A review of the calculated land use entropy reveals that Thunder Bay has the lowest entropy of all the CMAs in the study, which represents the least interaction between CMAs and therefore would expect less spatial interaction. London is approximately equal to the average of the 12 CMAs. The modal split does not provide any alarming differences between the two cities (provided in Table 3.3). According to the figures in Table 4.1, London has large land area, population and employment; however, small density, and Thunder Bay has large area but small population/employment and low density.

Another notable result may be observed for Windsor, which is a medium sized CMA with respect to land area and population compared to the other 11 CMAs. It also has high land use entropy (ranks 5th in the study area), and is characterized as compact with respect to population and employment (highly compact with respect to population). The modal split indicates the highest vehicle usage and lowest transit participation among the 12 CMAs, but does not stand out as an outlier from the rest. Looking at the figures in Table 4.1, Windsor's rankings stay approximately in the middle of the other CMAs for land area, population and employment. It can also be deduced that CMAs that have compact urban form characteristics for both population and employment (i.e. Hamilton and Windsor) also have medium/high population and land area size. However, CMAs that are compact with respect to population but more polycentric with respect to employment do not seem to have a relationship with population or land area size (i.e. Greater Sudbury, Kingston and Oshawa).

Interestingly, Kitchener is the only CMA that was characterized as polycentric based on both population and employment. Historically, this CMA consisted of two twin cities with two cores: 1) Kitchener and 2) Waterloo, along with a third city “Cambridge” to the southeast side of the CMA. The MDI map in Appendix A suggests the existence of three unique nodes. The sprawled CMAs based on population and employment (i.e. Peterborough and St. Catherines) do not seem to show any relationship between population or land area size, as Peterborough has the lowest population compared to St. Catherines which has the 4th highest population among the 12 CMAs. However, both CMAs have relatively low, almost equal MDI values and similar land areas. The two CMAs that are characterized as polycentric/sprawled, although opposite based on population and employment, are both low in land area and high in land use entropy (i.e. Barrie and Guelph).

The reader can refer to Appendix B for a complete set of population and employment density maps for the 12 CMAs. Appendix A, as noted earlier, also includes MDI and entropy maps that have been generated using ArcMap GIS to provide a visual guide for comparison with the characterization deduced in this section.

4.2 Commuting Patterns in Ontario

The theoretical average minimum, maximum and random commutes (based on the mean of 1000 commuting possibility simulations) were calculated at the CMA level to compare to the observed average commutes for the 12 CMAs. As shown in Table 4.3, excess commuting and commuting potential utilized were then calculated to explore the relationship between urban form and commuting efficiency. The results for the average commuting measures are presented in Figure 4.4. The results suggest a systematic and consistent pattern for all 12 CMAs in which $C_{min} < C_{obs} < C_{rnd} < C_{max}$. To evaluate if commuting distance is an important factor to travelers, the C_{obs} and C_{rnd} values are compared. Frequency distributions based on the 1000 simulated commuting possibilities used to calculate C_{rnd} are generated and can be seen in Appendix C. Further, the observed average commute is compared to the minimum random commute value as shown in Figure 4.5. The trend suggests that commuting distance is an important factor given that the C_{obs} value in all CMAs is well below the minimum average random commute. In other words, the observed average commute sits well far from the left tail of the frequency distribution given in Appendix C. Therefore, the observed commute does not belong to a commuting possibility where commuting distance is not a factor.

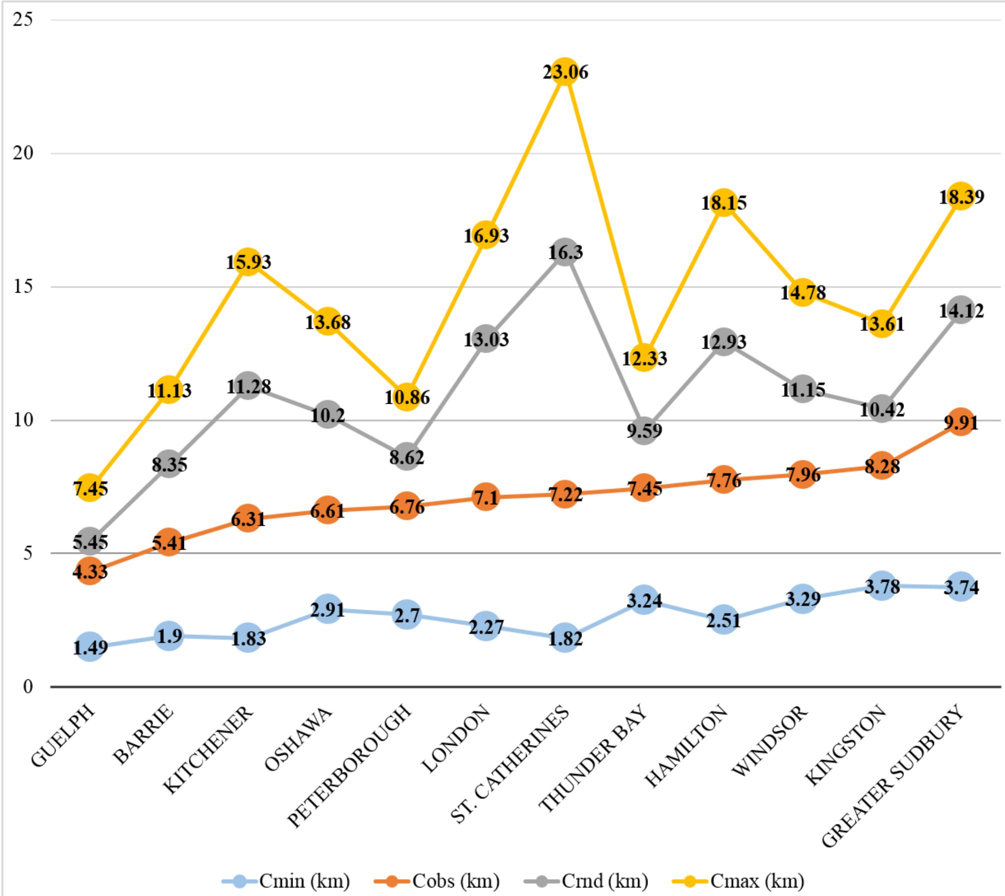


Figure 4.4 – Various Average Commuting Measures

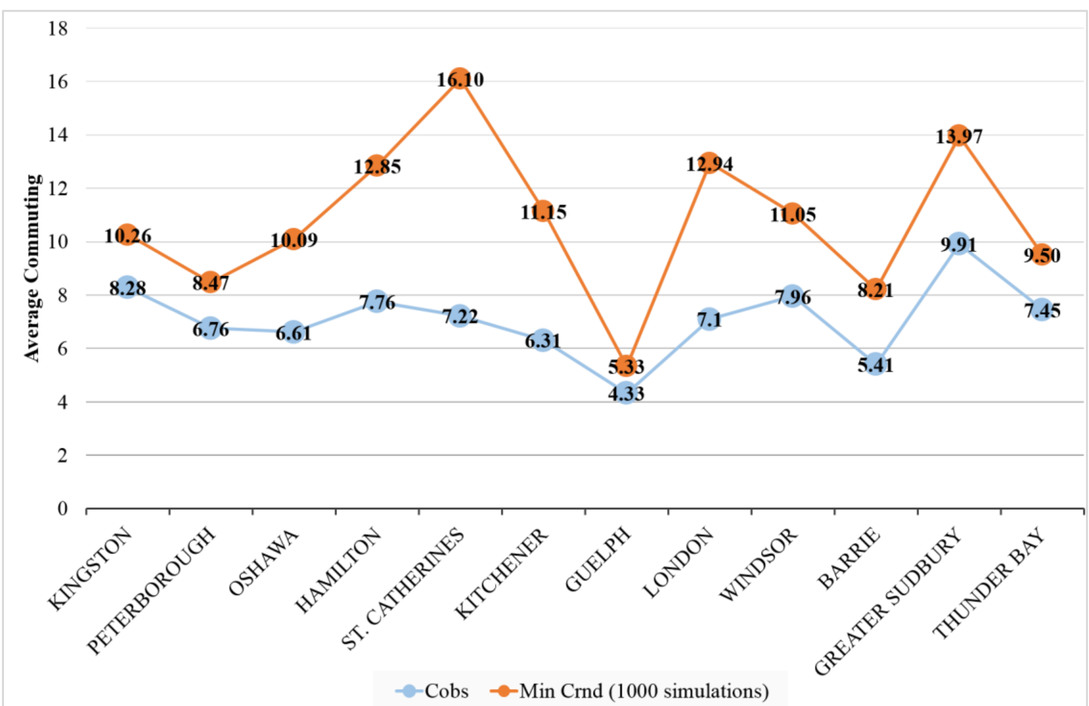


Figure 4.5 – C_{obs} versus Minimum C_{rnd} based on 1000 Simulations

Table 4.3 - Summary of Commuting Measures for 12 CMAs

CMA ID	CMA Name	C_{min} (km)	C_{obs} (km)	C_{rnd} (km)	C_{max} (km)	Excess Commuting (C_{ex})	Commuting Potential Utilised (C_u)
521	Kingston	3.78	8.28	10.42	13.61	54.3%	45.8%
529	Peterborough	2.70	6.76	8.62	10.86	60.1%	49.8%
532	Oshawa	2.91	6.61	10.20	13.68	56.0%	34.4%
537	Hamilton	2.51	7.76	12.93	18.15	67.6%	33.6%
539	St. Catherines	1.82	7.22	16.30	23.06	74.8%	25.4%
541	Kitchener	1.83	6.31	11.28	15.93	71.0%	31.8%
550	Guelph	1.49	4.33	5.45	7.45	65.6%	47.6%
555	London	2.27	7.10	13.03	16.93	68.0%	32.9%
559	Windsor	3.29	7.96	11.15	14.78	58.7%	40.7%
568	Barrie	1.90	5.41	8.35	11.13	64.8%	38.1%
580	G. Sudbury	3.74	9.91	14.12	18.39	62.2%	42.1%
595	Thunder Bay	3.24	7.45	9.59	12.33	56.5%	46.3%

Table 4.4 below provides a direct comparison between the value of excess commuting against urban form classification (with respect to population and employment) for each CMA. Further, Figure 4.6 below is created to analyze the potential relationship between transportation mode breakdown (see Table 3.3) against excess commuting and commuting potential utilized.

Table 4.4 - CMA Rankings by Excess Commuting

CMA ID	CMA Name	Rank by Excess Commuting (C_{ex})	Excess Commuting (C_{ex})	[1]Urban Form Class. Pop/Empl	[2]Trip Entropy
539	St. Catherines	1	74.8%	S / S	17,386,470
541	Kitchener	2	71.0%	P / P	18,007,740
555	London	3	68.0%	C / S	17,690,690
537	Hamilton	4	67.6%	C / C	27,912,020
550	Guelph	5	65.6%	P / S	2,065,000
568	Barrie	6	64.8%	S / P	2,974,715
580	G. Sudbury	7	62.2%	C / P	5,021,994
529	Peterborough	8	60.1%	S / S	1,975,074
559	Windsor	9	58.7%	C / C	8,361,829
595	Thunder Bay	10	56.5%	S / C	2,403,379
532	Oshawa	11	56.0%	C / P	7,045,335
521	Kingston	12	54.3%	C / P	3,783,421

1. Based on the *Moran's I* coefficient for population and employment per CMA C: Compact; P: Polycentric; S: Sprawled
2. Trip entropy is calculated according to equation 3.6 in Chapter 3

The Kingston CMA stands as the lowest among the 12 CMAs in terms of auto dependency and the highest in terms of its green mode contribution. According to Table 4.4, Kingston depicts the least excess commuting. The CMA exhibits a compact urban form in terms of its population distribution. The CMA also portrays a polycentric form in term of its job distribution. According to the results in Table 4.3, lower excess commuting gives rise to higher commuting potential utilized. This is reinforced by the negative correlation of -0.691 between the C_{ex} and C_u values shown in Table 4.3. The least efficient CMA in term of its commuting is St. Catherines with a 74.8% C_{ex} value. As expected, this lack of commuting efficiency is associated with a sprawled urban form in terms of both population and employment. Interestingly, the Peterborough CMA shares the same type of urban form with the St. Catherines CMA (i.e. polycentric form). Also, Peterborough has the same transit rider share with only 3% of commuters using buses to go to work. However, the CMA ranks eighth in terms of its excess commuting, as shown in Table 4.4. This raises the question as to why St. Catherines is not as efficient in terms of its commuting pattern. In trying to address this question, one should look at a number of factors. The Peterborough CMA is of a relatively similar size as St. Catherines in terms of land area. However, it stands as the smallest among the 12 CMAs with a population size of around 119,000 in the year 2011. By comparison, St. Catherines is about 3 times larger in terms of its working population size. Further, St. Catherines has a much larger trip entropy that is over 8.8 times larger than Peterborough. Such ratio suggests that spatial interaction relative to the size of workers is significantly lower in the Peterborough CMA compared to St. Catherines' CMA. Therefore, it is more likely that workers in Peterborough are more confined to their own centres when compared to travellers in St. Catherines.

The Kitchener CMA is associated with a high excess commute of 71% and it ranks 2nd in terms of its lack of commuting efficiency. The identified urban form for this CMA is polycentric for both population and employment. While polycentrism has been regarded as an efficient urban form (Maoh et al. 2010), it is only so if it has a strong transit system that connects the various centres. However, transit ridership in the Kitchener CMA is only 5%, suggesting a relatively poor and not well-connected system. As such, commuters end up driving longer distances. Both Windsor and Hamilton CMAs exhibit a compact urban form in terms of population and job densities. However, Windsor ranks 9th in terms of its commuting efficiency while Hamilton ranks 4th. Interestingly, Hamilton has a higher transit ridership compared to Windsor. Again, this begs the question as to why two CMAs that exhibit compact densities have different commuting efficiencies? Hamilton is about 1.4 times larger in terms of land area and has about 2.29 times more workers. However, Hamilton has a noticeably larger trip entropy compared to Windsor (3.34 times more). Therefore, despite that both CMAs are classified as compact densities, this qualitative measure cannot determine the level of commuting efficiency. In that respect, one should go back to the *Moran's I* coefficient for further examination. With respect to population, Hamilton's *Moran's I* is half of that for Windsor (0.137 versus 0.292). Therefore, Windsor is highly compact compared to Hamilton when it comes to its population density. In contrast, the employment *Moran's I* coefficient for Windsor and Hamilton is relatively similar with values equal to 0.127 and 0.152, respectively. Therefore, it is expected that workers in Hamilton have a higher level of spatial interaction compared to Windsor and will tend to travel longer compared to Windsorites. In general, CMAs with higher trip entropy are less efficient in terms of their commuting, as suggested by Figure 4.7.

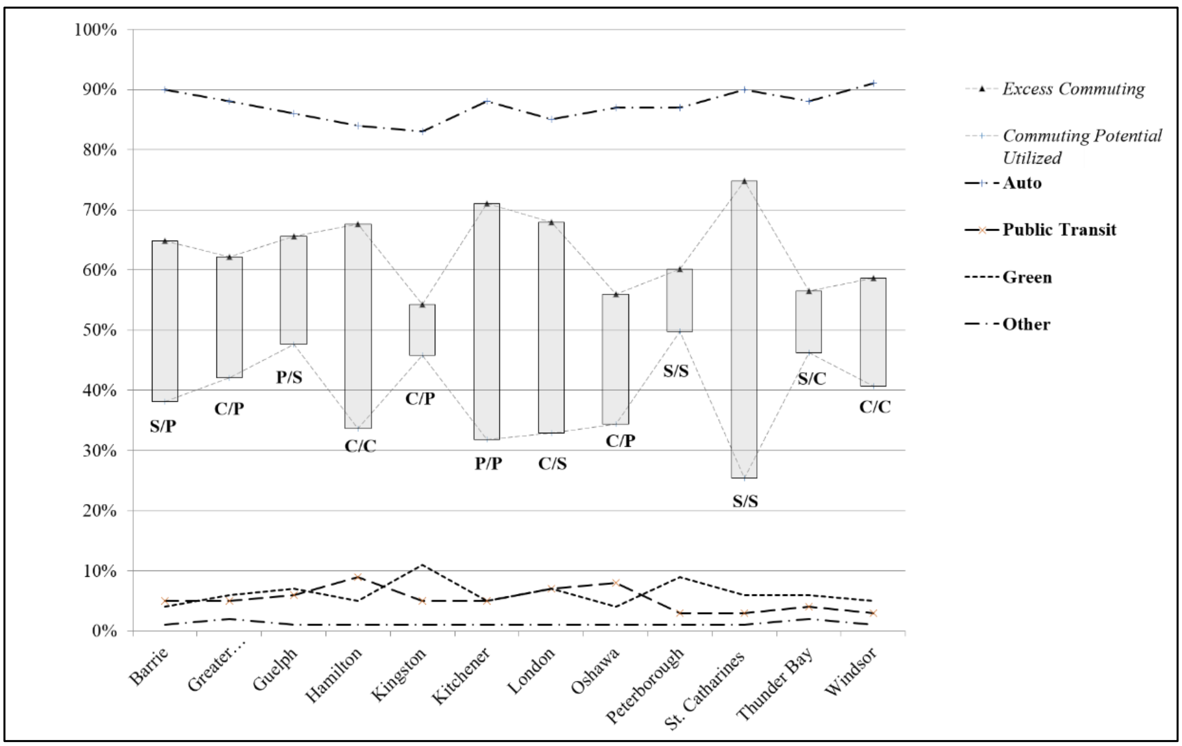


Figure 4.6 - Commuting Measures for 12 CMAs in Ontario

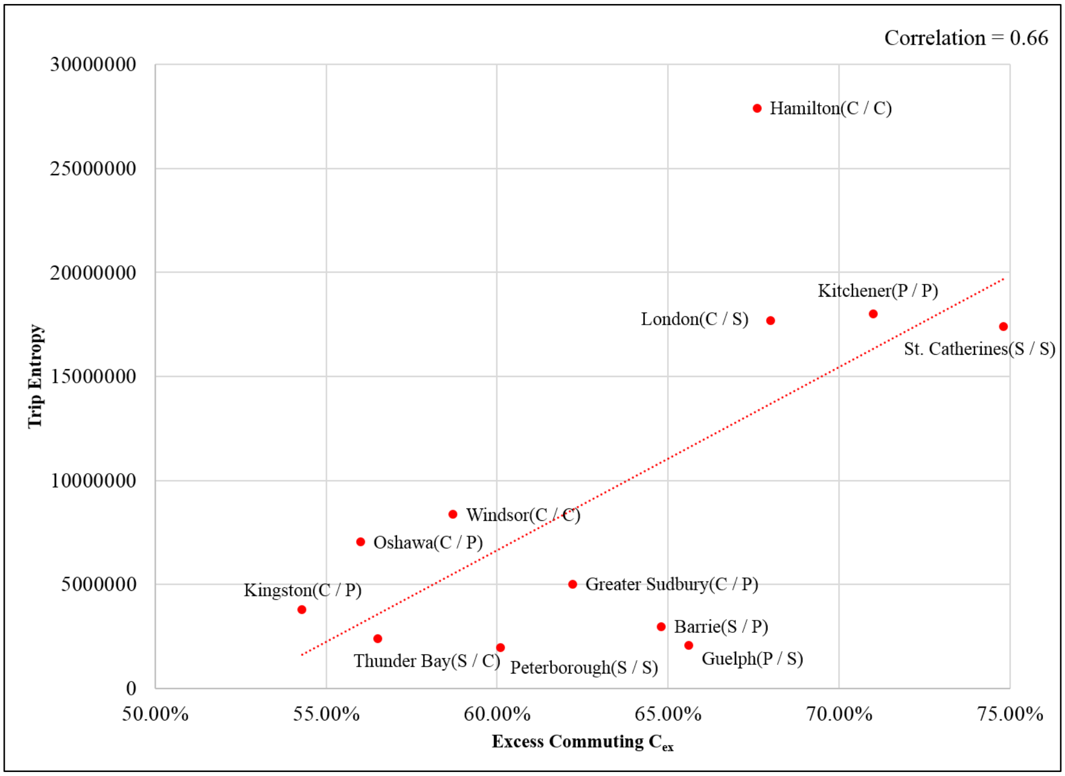


Figure 4.7 – Excess Commuting and Trip Entropy Relationship

4.3 Brotchie's Urban Triangles

Brotchie's urban triangles were generated for the 12 CMAs in the study area to provide a representation that can be utilized to compare urban form to the theoretical commuting measures. The jobs-housing dispersal and household dispersal indices were calculated using the formulas presented in Chapter 3. Table 4.5 presents the results for the job dispersal, household dispersal and jobs-housing dispersal index. Figure 4.8 presents the relative location of the observed commute with respect to the household dispersal index. Also, Brotchie's urban triangles for the 12 CMAs are illustrated in Figure 4.9. As can be seen in Figure 4.9, several CMAs (namely: Barrie, Kingston, London, Peterborough and Thunder Bay) have an observed average commuting distance that is above the household dispersal index calculated for each CMA. This indicates that these CMAs have in general less efficient commuting since their observed average commuting distance is above the line representing the commuting distance of a hypothetical monocentric urban form where jobs are located in the centre. Interestingly, both Windsor and Hamilton exhibit a compact urban form as discussed earlier on. Oshawa on the other hand, appears to have a balanced distribution of jobs and workers with a dispersal index of 1. CMAs with a dispersal index greater than 1 appear to either have polycentric (P) or sprawled (S) job distribution (e.g. St. Catherines, Kitchener and London).

Table 4.5 - Brotchie's Urban Triangle Calculation Results

CMA #	CMA Name	CBD Census Tract Number	Job Dispersal [km]	Household Dispersal (y) [km]	Jobs-Housing Dispersal Index (S)	Urban Form Class. Pop/Empl
1	Barrie	5680006	5.19	4.66	1.11	S / P
2	G. Sudbury	5800005	7.69	9.35	0.82	C / P
3	Guelph	5500006	3.76	3.61	1.04	P / S
4	Hamilton	5370037	8.96	7.53	1.19	C / C
5	Kingston	5210001	6.02	7.05	0.85	C / P
6	Kitchener	5410017	7.98	5.61	1.42	P / P
7	London	5550022	7.85	6.05	1.30	C / S
8	Oshawa	5320010	6.23	6.25	1.00	C / P
9	Peterborough	5290007	4.52	5.49	0.82	S / S
10	St. Catherines	5390005	12.40	8.29	1.50	S / S
11	Thunder Bay	5950014	5.82	6.10	0.95	S / C
12	Windsor	5590035	7.61	8.10	0.94	C / C

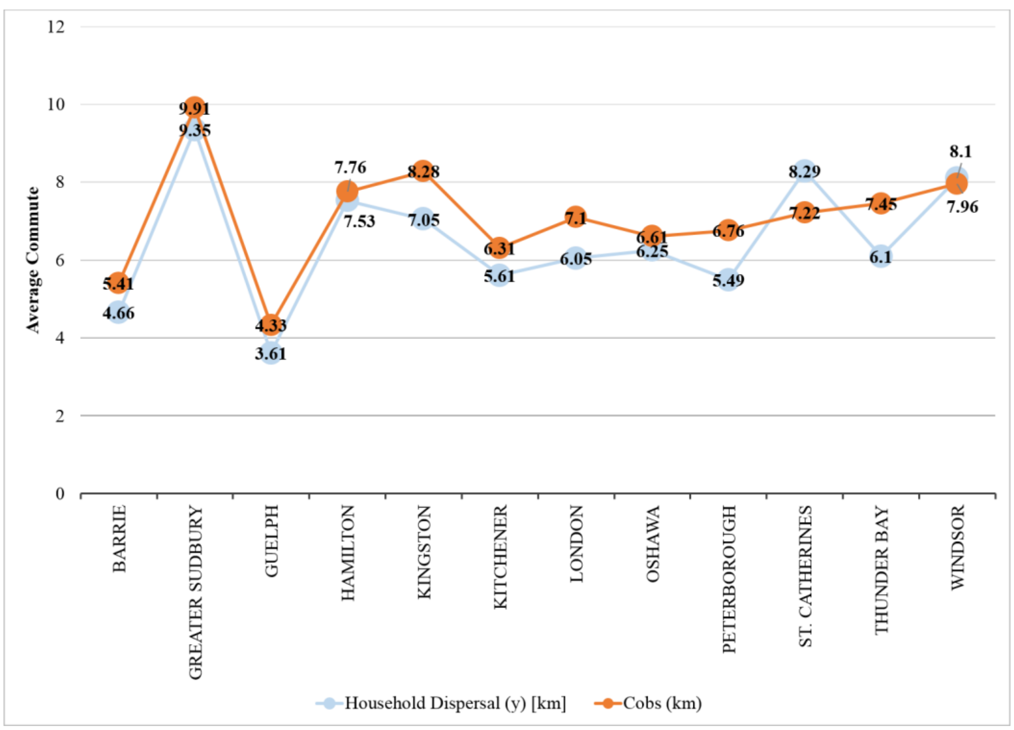


Figure 4.8 – Relative Location of C_{obs} with respect to Household Dispersal in Brotchie's Trainagles

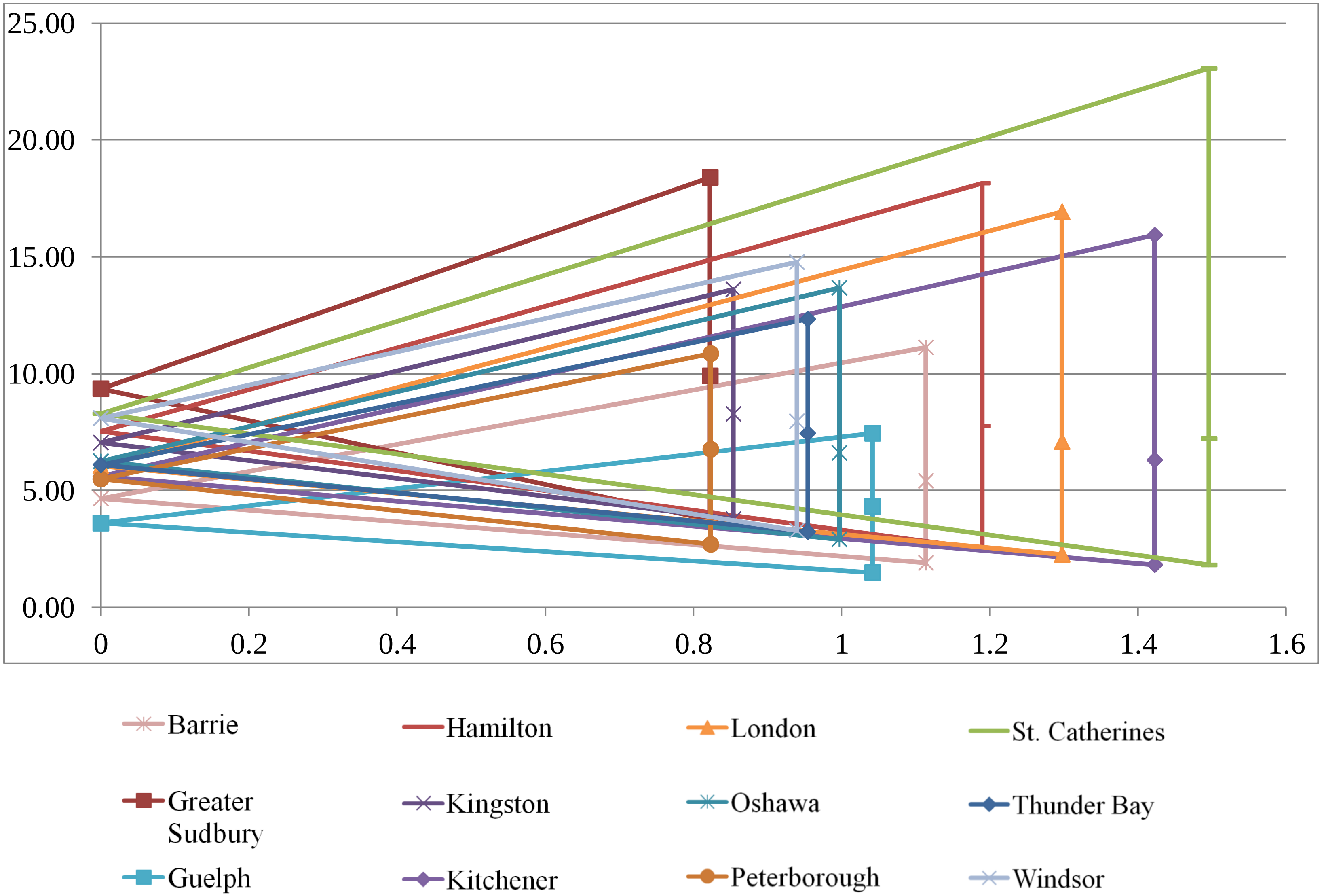


Figure 4.9 - Brotchie's Urban Triangles for 12 CMAs in Ontario

4.4 Excess Commuting by Occupation

The same theoretical commuting measures that were calculated for each CMA were also calculated for each of the 10 occupation types per CMA. Analyzing the data by the 10 occupations listed in Table 4.6 incorporates the constraint that workers be reassigned to jobs within their same occupation, which has not been addressed in previous studies. The results of the commuting variables are illustrated in Figure 4.10 with tabular results available in Appendix D. Each CMA number is labeled along the x-axis according to Table 4.5.

Table 4.6 - 10 Occupation Types

Occupation #	Occupation Type	Short-Form Name
1	Management	Management
2	Business, finance and administration	Business
3	Natural and applied sciences	Science
4	Health	Health
5	Education, law and social community and government services	Education
6	Art, culture, recreation and sport	Art
7	Sales and services	Sales
8	Trades, transport and equipment operators	Trades
9	Natural resources, agriculture and related production occupations	Natural Resources
10	Manufacturing and utilities	Manufacturing

The results indicate that the majority of the occupations exhibit similar commuting patterns, except for natural resources and manufacturing where London spikes and does not adhere to the same pattern as the rest of the occupations. Guelph maintains the lowest commuting measures across all occupations, while it ranks 8th from the lowest for total CMA excess commuting presented in Section 4.2. St. Catherines tends to have the most extreme commuting measures for all occupations except natural resources.

The theoretical commuting measures were then used to calculate excess commuting for each of the 10 occupations in the 12 CMAs. The excess commuting results are illustrated in Figure 4.11 with tabular results available in Appendix E. Similar to Figure 4.10, each CMA number is labeled along the x-axis according to Table 4.5. The results indicate that management has the highest excess commuting for majority of the CMAs, possibly due to higher income and a greater ability or willingness to travel further for a management position. Education, law and social community and government services ("Education") and sales and services ("Sales) also display similar patterns of higher excess commuting than the rest of the occupations. This may be explained by educators and government services having less choice of which institution they are placed at or where the government facilities are located, and salespersons are usually required travel to solicit more sales and promote products through marketing. Manufacturing and utilities ("Manufacturing") appears to display the least amount of excess commuting, which prompts the suggestion that residences built near manufacturing areas tend to be geared towards the manufacturing workforce. Natural and applied sciences ("Science"), trades, transport and equipment operators ("Trades") and natural resources, agriculture and related production occupations ("Natural Resources") have approximately the same trend with average excess commuting for most CMAs. Business, finance and administration ("Business"), health and art, culture, recreation and sport ("Art") all have sporadic results across the CMAs and may reflect socioeconomic aspects of each CMA. Most CMAs follow a similar pattern for these 3 occupations; however, Oshawa (8) and Windsor (12) stand out as they do not adhere to the patterns of the rest. Oshawa and Windsor have low results for health, high for art and average for business.

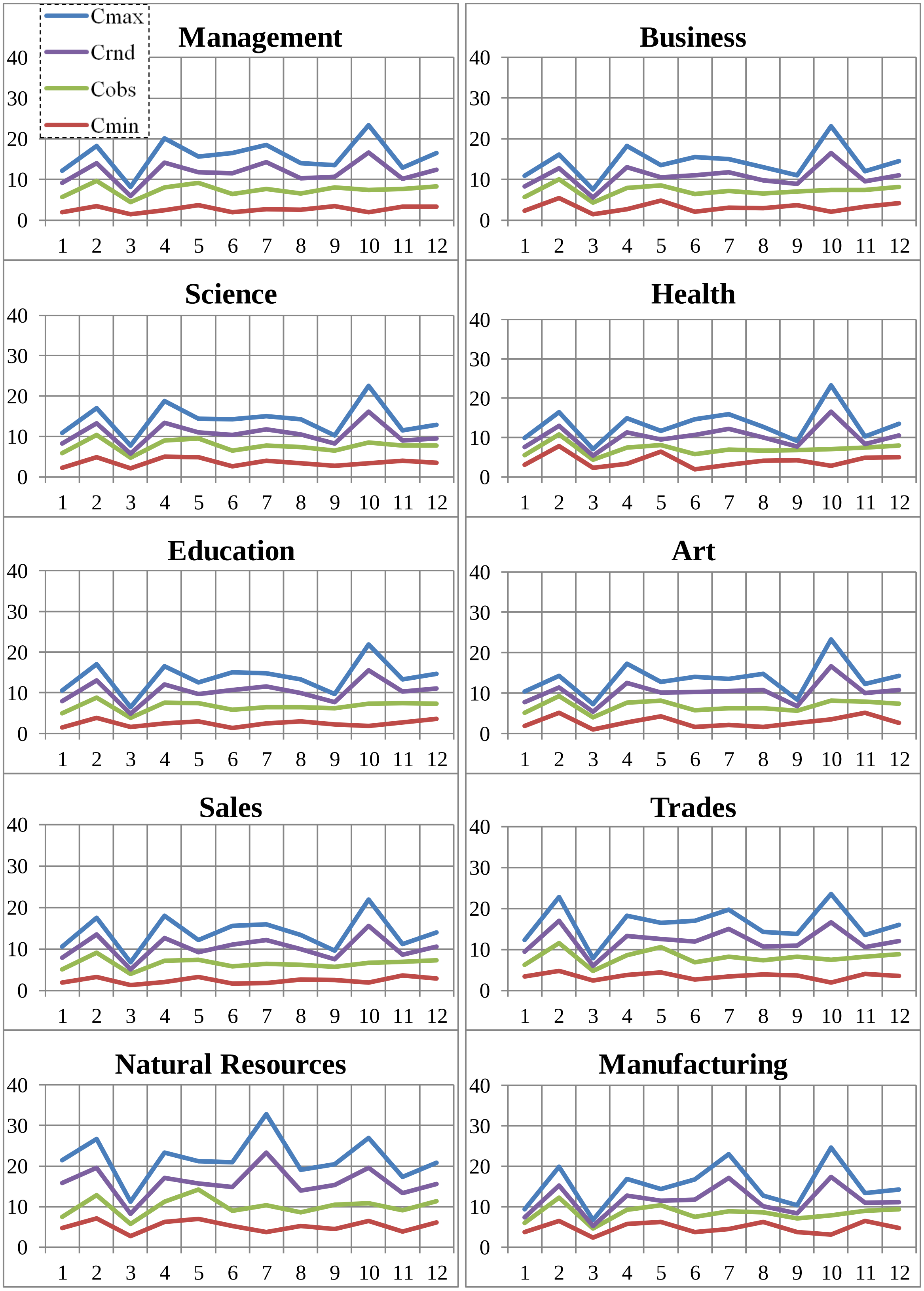


Figure 4.10 - Theoretical Commuting Measures Per CMA for 10 Occupation Types

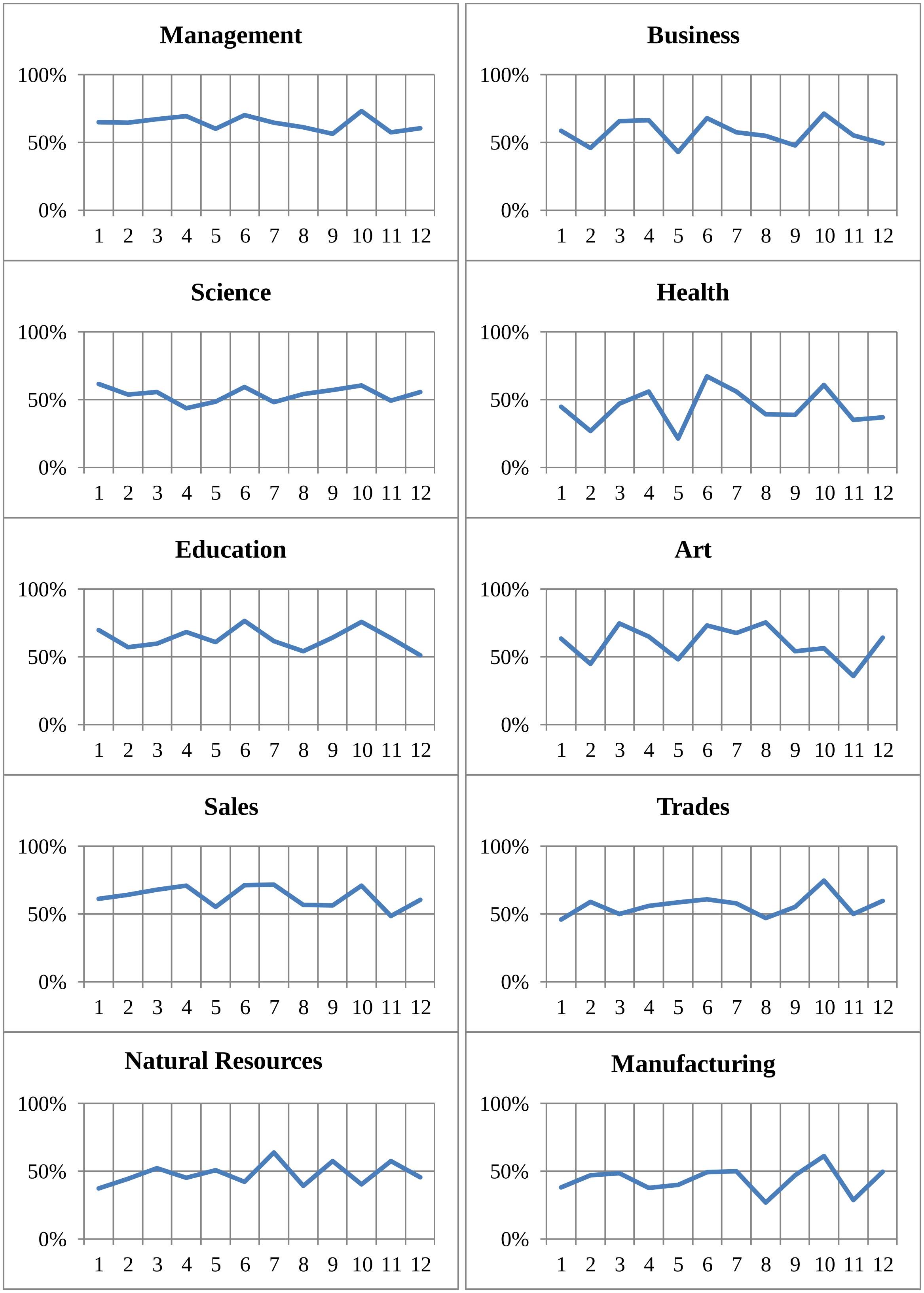


Figure 4.11 - Excess Commute (%) Per CMA for 10 Occupation Types

To look closely at each occupation, the results were organized by CMA to compare the excess commuting for each occupation to the overall CMA results in Section 4.2. The results of the excess commuting calculations per occupation for each CMA are illustrated in Figure 4.12 with tabular results available in Appendix E. Each occupation number is labeled along the x-axis according to Table 4.6. The results suggest the following for each occupation:

1) **Management:** excess commuting for this occupation is close to the CMA average for all types of urban form.
2) **Business, Finance and Administration:** majority of the CMAs experience excess commuting almost equal to their overall CMA average. The remaining CMAs demonstrate slightly lower excess commuting that the CMA average, 80% of which were found to be classified as compact under the review of urban form.
3) **Natural and Applied Science:** a mix of results, however all occupational excess commuting is below or approximately equal to the CMA-wide average.
4) **Health:** all CMAs except Kitchener experience less excess commuting than the CMA-wide averages.
5) **Education, Law, Social Community and Government Services:** a similar mix to occupation #3 (natural and applied science), however 5 of the 12 occupations experience higher excess commuting than the CMA-wide average.
6) **Art, Culture, Recreation and Sport:** very similar results to occupation #5, however Kingston has moved from being higher to lower and Windsor has moved from lower to higher commuting than the CMA-wide average.

7) **Sales and Services:** With the exception of Thunder Bay**,** the 11 other CMAs experienced approximately equal excess commuting to the CMA-wide averages. This is expected given the dominance of the service-based economy in Ontario.
8) **Trades, Transport and Equipment Operators:** majority of the CMAs experience less excess commuting than the CMA-wide averages for this occupation. Kingston stands out as the only CMA with a higher than the CMA-wide average.
9) **Natural Resources, Agriculture and Related Production Occupations:** similar to occupation #8, most CMAs experience less than the CMA-wide average; Kingston moves up to almost equal the CMA-wide average.
10) **Manufacturing and Utilities:** all of the CMA's experience lower (or much lower) excess commuting that the CMA-wide averages.

To combine the occupational excess commuting results with the total CMA excess commuting in Section 4.2 and urban form in Section 4.1, two summaries are provided (see Table 4.7 and Figure 4.13). Table 4.7 compares excess commuting for each occupation to the total CMA excess commuting by highlighting the number of CMAs that exhibit occupational excess commuting below, approximately equal to or higher than the entire CMA. The urban form classification results are also included, where "C" represents compact, "P" represents polycentric and "S" represents sprawled. It is evident that most of the occupational excess commuting results are lower than the CMA total excess commuting, and compact urban form dominates these CMAs. Education has the highest contribution of occupational excess commuting above the CMA total, and sprawled urban form dominates those CMAs. Management (#1) has approximately equal excess commuting by occupation and by CMA total for all CMAs. Sales and services (#7) was almost equal for all CMAs except Thunder Bay which was lower (polycentric). Health (#4) is mostly lower except for Kitchener which is approximately equal (polycentric). Results for trades (#8) are generally lower, with three CMAs approximately equal and Kingston which is slightly greater (compact). Natural and applied science (#3) and manufacturing (#10) are the only two occupations that are identified as having much lower excess commuting than the CMA totals (Hamilton and London; Barrie, Hamilton, Oshawa and Thunder Bay, respectively).

Figure 4.13 is provided to visualize the distribution of the urban land form classifications among the excess commuting results. It is easy to identify that management, health and sales provide consistent excess commuting results that are approximately equal to or lower than the CMA total results, while visualizing the general urban form breakdown for that number of CMAs. A summary of the results that identifies all the CMAs in this discussion are provided in Appendix F.

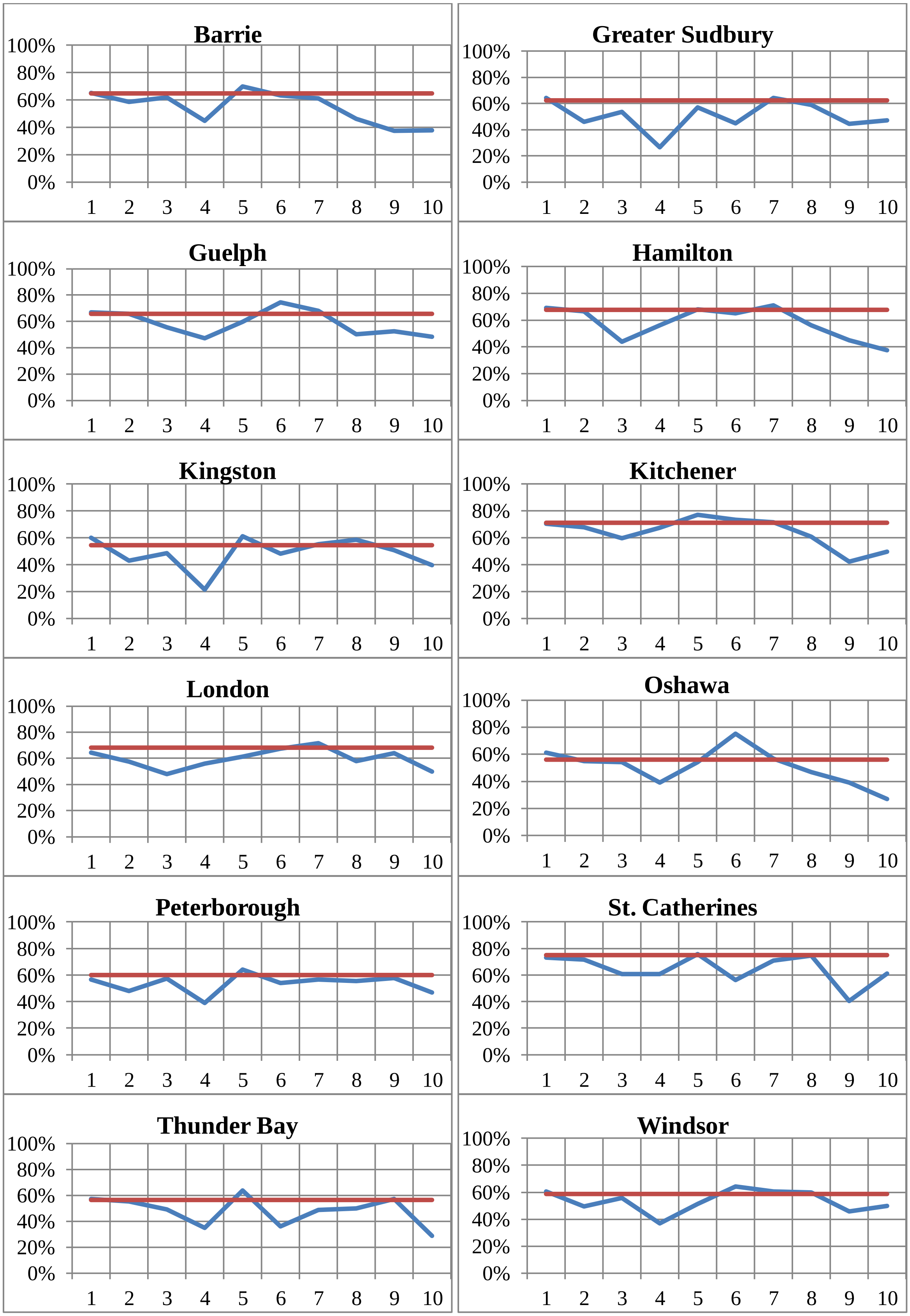


Figure 4.12 - Excess Commuting for 10 Occupation Types vs. CMA-Wide

Table 4.7 - Summary of Occupational/CMA Total Excess Commuting with Urban Form

			Relation of Occupational vs. Total CMA Excess Commuting											
Occupation			Much Lower			Lower			Approx. Equal			Higher		
		Urban Form Type	C	P	S	C	P	S	C	P	S	C	P	S
1	Management	Majority Result	0			0			*Majority*			0		
		Type of Urban Form							All Form					
		Total CMAs							(All 12)					
		CMA per Urban Form							2	2	3			
2	Business, finance and administration	Majority Result	0						*Majority*			0		
		Type of Urban Form				Mostly Compact			Mix					
		Total CMAs				(5 total)			(7 total)					
		CMA per Urban Form				4	0	1	2	2	3			
3	Natural and applied sciences	Majority Result				*Majority*						0		
		Type of Urban Form	All Compact			Mix			Compact/Sprawl					
		Total CMAs	(2 total)			(6 total)			(4 total)					
		CMA per Urban Form	2	0	0	2	2	2	2	0	2			
4	Health	Majority Result	0			*Majority*						0		
		Type of Urban Form				Mostly Compact			All Polycentric					
		Total CMAs				(11 total)			(1 total)					
		CMA per Urban Form				6	1	4	0	1	0			
5	Education, law and social community and government services	Majority Result	0			*Majority*						*Majority*		
		Type of Urban Form				Mostly Compact			All Compact			Mostly Sprawl		
		Total CMAs				(5 total)			(2 total)			(5 total)		
		CMA per Urban Form				3	1	1	2	0	0	1	1	3

Table 4.7 - Summary of Occupational/CMA total Excess Commuting with Urban Form (cont.)

			Relation of Occupational vs. Total CMA Excess Commuting											
Occupation			Much Lower			Lower			Approx. Equal			Higher		
			C	P	S	C	P	S	C	P	S	C	P	S
6	Art, culture, recreation and sport	Majority Result	0			***Majority***								
		Type of Urban Form				Sprawl/Compact			Mix			Compact/ Polycentric		
		Total CMAs				(5 total)			(4 total)			(3 total)		
		CMA per Urban Form				2	0	3	2	1	1	2	1	0
7	Sales and services	Majority Result	0						***Majority***			0		
		Type of Urban Form				All Polycentric			Mostly Compact					
		Total CMAs				(1 total)			(11 total)					
		CMA per Urban Form				0	0	1	6	2	3			
8	Trades, transport and equipment operators	Majority Result	0			***Majority***								
		Type of Urban Form				Mix			Mostly Compact			All Compact		
		Total CMAs				(8 total)			(3 total)			(1 total)		
		CMA per Urban Form				3	2	3	2	0	1	1	0	0
9	Natural resources, agriculture and related production occupations	Majority Result	0			***Majority***						0		
		Type of Urban Form				Mostly Compact			Mostly Polycentric					
		Total CMAs				(9 total)			(3 total)					
		CMA per Urban Form				5	2	2	1	0	2			
10	Manufacturing and utilities	Majority Result				***Majority***			0			0		
		Type of Urban Form	Compact/Polycentric			Compact/Mix								
		Total CMAs	(4 total)			(8 total)								
		CMA per Urban Form	2	0	2	4	2	2						

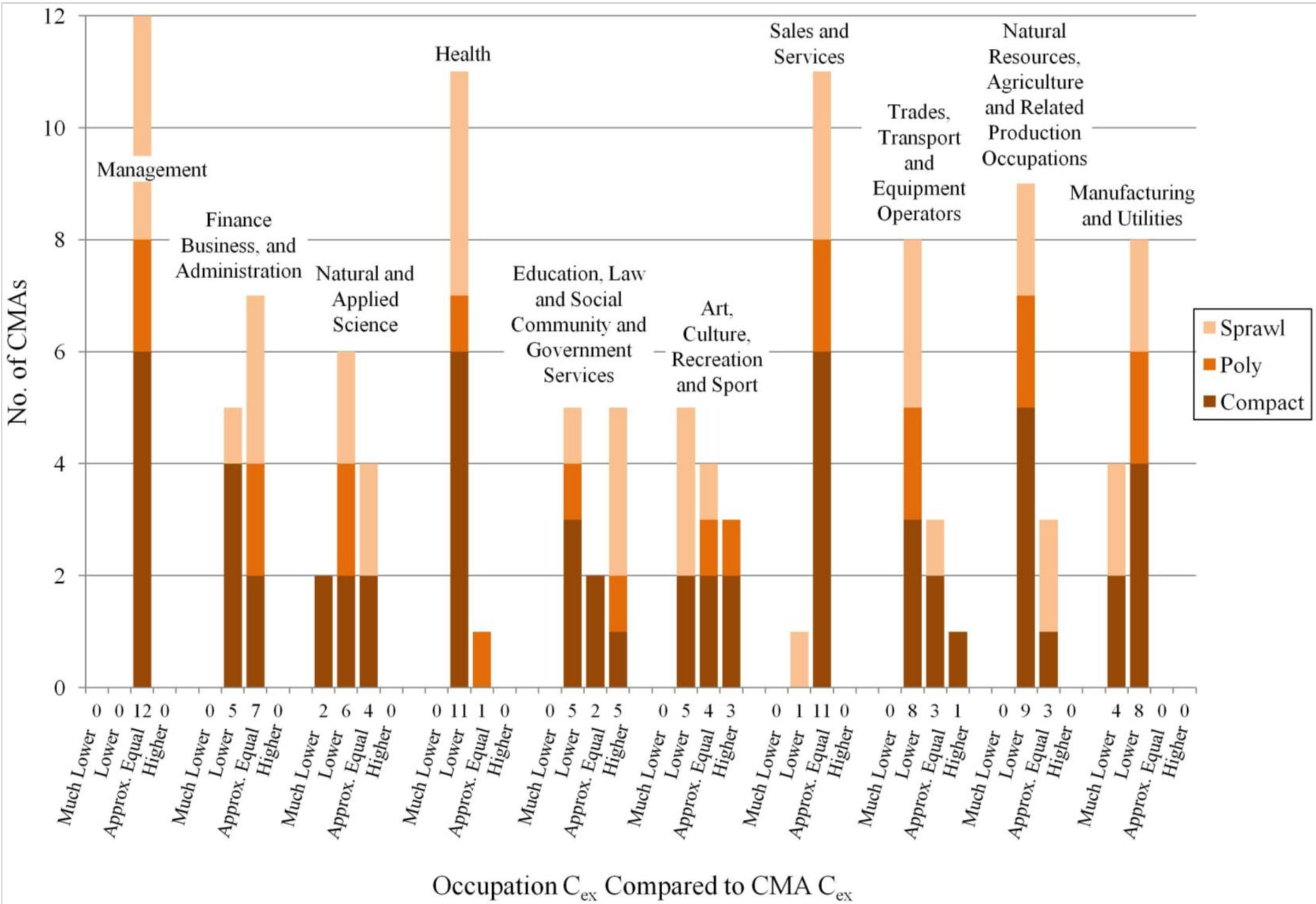


Figure 4.13 - Summary of Occupation Excess Commuting Results Compared to CMA Results

CHAPTER 5: CONCLUSIONS

5.1 Introduction

Many developed countries have been experiencing continuous changes over the past century with respect to land use planning, transportation modes and the level of spatial interaction. It is important to monitor these changes and the resulting effects they have on the environment with continuously evolving research to guarantee prompt actions that will ensure sustainability of our communities. These efforts are as effective as the current data and methods provide. Applying quantitative analysis using proven methods of calculating key variables allows us to present results and discuss suggestions for future implementation and research. It is important to be mindful of our land development patterns and commuting choices, as it relates to the sustainability of the community as a whole and generally has a direct impact on our lives, whether we realize it or not.

The objectives of this research were to examine the relationship between urban form and excess commuting by analyzing population, employment and commuting data for 12 different Census Metropolitan Areas (CMA) in Ontario, Canada and to conduct a comparative analysis between the urban form and excess commuting results to provide better insights that could help inform the current planning process. In terms of key academic contribution, what makes this thesis unique is the application of occupational constraints on the analysis of excess commuting, which has yet to be incorporated into previous research. This thesis is comprised of two main components: analysis of urban land form and calculation of "excess" commuting.

To fulfill the objectives set in this thesis, 12 of the 19 CMAs comprising the province of Ontario were selected for analysis. These 12 CMAs had population sizes in the range of 100,000 to 1 million. Each of the selected CMAs were broken down into smaller zones called census tracts, or traffic analysis zones (TAZ). Population, employment and commuting data were collected from Statistics Canada for each TAZ. The most recent data available at the beginning of this study was collected in 2011. Therefore, the conducted analysis was performed for the year 2011. The results of the 2011 National Household Survey, which was part of the 2011 Canadian Census, indicated that auto was the dominant mode choice (87%) for commuters age 15 and over (driver or passenger of car, truck or van) in the selected CMAs. This is a high percentage suggesting that auto is the most dominant mode of travel to go to work.

Following the work of Tsai (2005), the *Moran's I* statistic, applied to population and employment at the TAZ level, was used to classify the urban form of the CMAs into one of the following three types: monocentric, polycentric or dispersed sprawl. Further, land use measures including the mixed density index (MDI) and entropy index (EI) were also calculated for each CMA at the TAZ level and then averaged for the entire CMA. The key measures considered to quantify the nature of commuting in each CMA were the theoretical minimum, maximum and random average commutes, as well as the observed average commute. Excess commuting was then calculated as the difference between the theoretical minimum and average observed commute, expressed as a percent of the observed average commute. The various measures were also compared to gain better insights about the nature of commuting. The iterative proportional fitting (IPF) method was employed to create commuting trip matrices by occupation type for 10 occupations in the studied CMAs. Similar measures of average commuting were then calculated at the occupation level.

5.2 Policy Implications

The analysis of urban form provided an analytical evaluation of the 12 CMAs and classified each in one of the following three categories: monocentric, polycentric and sprawled patterns. The results not only provide useful insight for transportation planners with respect to the current urban forms in the year 2011, but also offer directions for analyzing these patterns over time when future data (e.g. 2016 Canadian Census) becomes available.

The conducted urban form analysis indicated that cities vary in terms of their compactness, sprawl or polycentrism. Such variation is very important to note since it can affect how planners think about specific urban forms. That is, our analysis suggested that while two cities might share the same urban form classification, they do not necessarily have the same level of commuting efficiency. For example, the analysis identified both Windsor and Hamilton to have a compact urban form. However, Windsor was found to be more efficient in terms of its commuting patterns compared to Hamilton. A closer look at the *Moran's I* revealed that Windsor is highly compact in terms of its population compared to Hamilton. The same could be said about CMAs that were found to possess a sprawled urban form. In the latter case, the size of the CMA and the amount of spatial interaction activities, measured by trip entropy, are key determining factors with respect to commuting efficiency. Other interesting findings from the analysis pertained to the Kitchener CMA. The latter was found to enjoy a polycentric urban form. However, its commuting efficiency was ranked among the worst. The obtained measures regarding the type of urban form and commuting efficiency for a place like Kitchener is very insightful. Given the nature of urban form, a place like Kitchener could benefit from a reliable transit system that connects its major cores and facilitates the movement of workers to reduce auto dependency.

As a key finding in the conducted analysis, commuting efficiency by type of occupation could help transportation planners devise better land use policies. The analysis found that certain occupations have higher excess commuting than the CMA-wide measure. Therefore, the analysis provides a basis for dissecting the elements of commuting based on occupation to phase out those occupational types that generate the least amount of commuting efficiency. It was found that workers in occupation class #5 (i.e. education, law and social community and government services) had the least efficient commute. These workers pertain to 5 of the 12 CMAs, three of which were identified to have sprawled urban form. Therefore, planners could utilize the findings from the performed analysis to channel land use development that will attract that occupational class, or they could focus on building transit systems that connect these workers to their places of work.

Finally, the results of the urban form classification and excess commuting per CMA as a whole were presented in the framework of Brotchie's urban triangles, which provided a useful representation to equate similar CMA's by urban form to compare their commuting behaviour. The household dispersal and job-housing balance are reported along with the theoretical average minimum and maximum commutes. The observed average commute due to the nature of urban form from these triangles could shed light about how urban form affects commuting efficiency. Planners could compare the observed average commute to household dispersal values to evaluate if the current urban form is associated with an efficient commuting pattern. Also, comparing the different triangles could help planners identify what types of urban form could give rise to more commuting efficiency.

5.3 Direction for Future Research

The analysis conducted in this thesis identified limitations in the raw data. More specifically, there were some cases with missing records or inconsistent values due to the rounding and masking of information. These issues are attributed to the data disclosure protocols set by Statistics Canada for confidentiality purposes. Researchers conducting analysis with the datasets used in this thesis should be aware of these limitations. The thesis provided ways to account for some of these limitations to ensure consistency in the analysis performed. Another limitation in the conducted analysis had to do with the shape of the zones forming the study area and its relation on the obtained *Moran's I* values. As noted earlier, the use of *Moran's I* to classify urban form was inspired by the work of Tsai (2005). However, the work by Tsai (2005) was based on uniform zone sizes (i.e. grid cells) that comprised the study area. When applied to the zoning system forming our CMAs, some of the obtained results were surprising. However, we believe that *Moran's I* is capturing the global effect in the data and represents how density (in terms of population and employment) manifests itself over space. Therefore, *Moran's I* is a measure of density and not size.

Based on the above, this thesis leaves room for future research. Testing the impact of zoning size on the type of urban form is an important exercise to assess if various zoning delineations will lead to different conclusions with respect to the type of urban form. Other areas of future research may include comparing urban land development and commuting efficiency changes for a particular city over time. This would account for demographic and economic fluctuations. For example, Windsor may experience higher population and employment rates as well as more commuting during a time when employment is rapidly increasing; however, development and commuting rates may decrease significantly during a slow market period. Additionally, another area is to perform similar analysis across Canada to include a larger sample of CMAs, where areas of similar size could be compared against each other. Also, similar analysis for the three largest CMAs in Canada (i.e. Toronto, Montreal and Vancouver) could be performed to enrich the analysis conducted in this thesis. Finally, the analysis in this thesis assumed that each CMA is a closed system in which workers live and work within the CMA. Future research could also consider the impact of having workers commuting to jobs outside the CMA or vice versa.

REFERENCES

Statistics Canada general data from www.statcan.ca, or census or dissemination area data from Statistics Canada: accessible through the http://dc1.chass.utoronto.ca/census/ website.

Behan, K; Maoh, H; Kanaroglou, P 2008, 'Smart growth strategies, transportation and urban sprawl: simulated futures for Hamilton, Ontario'.

Bertaud, A 2002, 'Clearing the air in Atlanta: transit and smart growth or conventional economics?', Journal of Urban Economics, vol. 54, issue 3, p. 379-400.

Camagni, R; Gibelli, M C; Rigamonti, P 2002, 'Urban mobility and urban form: the social and environmental costs of different patterns of urban expansion', Ecological Economics, 40, p. 199-216.

Cervero, R; Kockelman, K. 1997, 'Travel demand and the 3ds: Density, diversity, and design', Transportation Research Part D: Transport and Environment, vol. 2, no.3: p. 199-219.

Charron, M 2007, 'From excess commuting to commuting possibilities: more extension to the concept of excess commuting', Environment and Planning, vol. 39, p. 1238-1254.

Chowdhury, T; Scott, D; Kanaroglou, P 2013, ‘Urban form and commuting efficiency: a comparative analysis across time and space’, Urban Studies, vol. 50, no.1, p. 191-207.

Chu, Y. L 2002, 'Automobile ownership analysis using ordered probit models', Transportation Research Record, 1805, p. 60-67.

Ewing, R 1997, 'Is Los Angeles-style sprawl desirable?', Journal of the American Planning Association, 63 (1), p. 107-126.

Handy, S 2005, 'Smart growth and the transportation-land use connection: what does the research tell us?', International Regional Science Review, vol. 28(2), p. 146-167.

Giuliano, G; Small, K. A 1993, 'Is the journey to work explained by urban structure?', Urban Studies 30(9), p. 1485-1500.

Hess, G; Daley, S; Derrison, B; McGuinn, R; Morin, V; Shelton, W; Lubkin, S; Potter, K; Savage, R; Snow, C; Wrege, B 2001, ‘Just what is sprawl, anyway?’ Carolina Planning, vol. 26, no. 2, p. 11–26.

Horner, M 2002, 'Extensions to the concept of excess commuting', Environment and Planning, vol. 34, p. 543-566.

Horner, M; Murray, A 2002, 'Excess Commuting and the Modifiable Areal Unit Problem', Urban Studies, vol. 39, p. 131-139.

Kanaroglou, P; Higgins, C; Chowdhury, T 2015, 'Excess commuting: a critical review and comparative analysis of concepts, indices, and policy implications', Journal of Transport Geography, vol. 44, p. 13-23.

Ma, K; Banister, D 2007, 'Urban spatial change and excess commuting', Environment and Planning, vol. 39, p. 630-646.

Maoh, H; Kanaroglou, P; Koronios, M 2010, ‘Exploring the land development process and its impact on urban form in Hamilton, Ontario’, The Canadian Geographer, vol. 54, no. 1, p. 68-86.

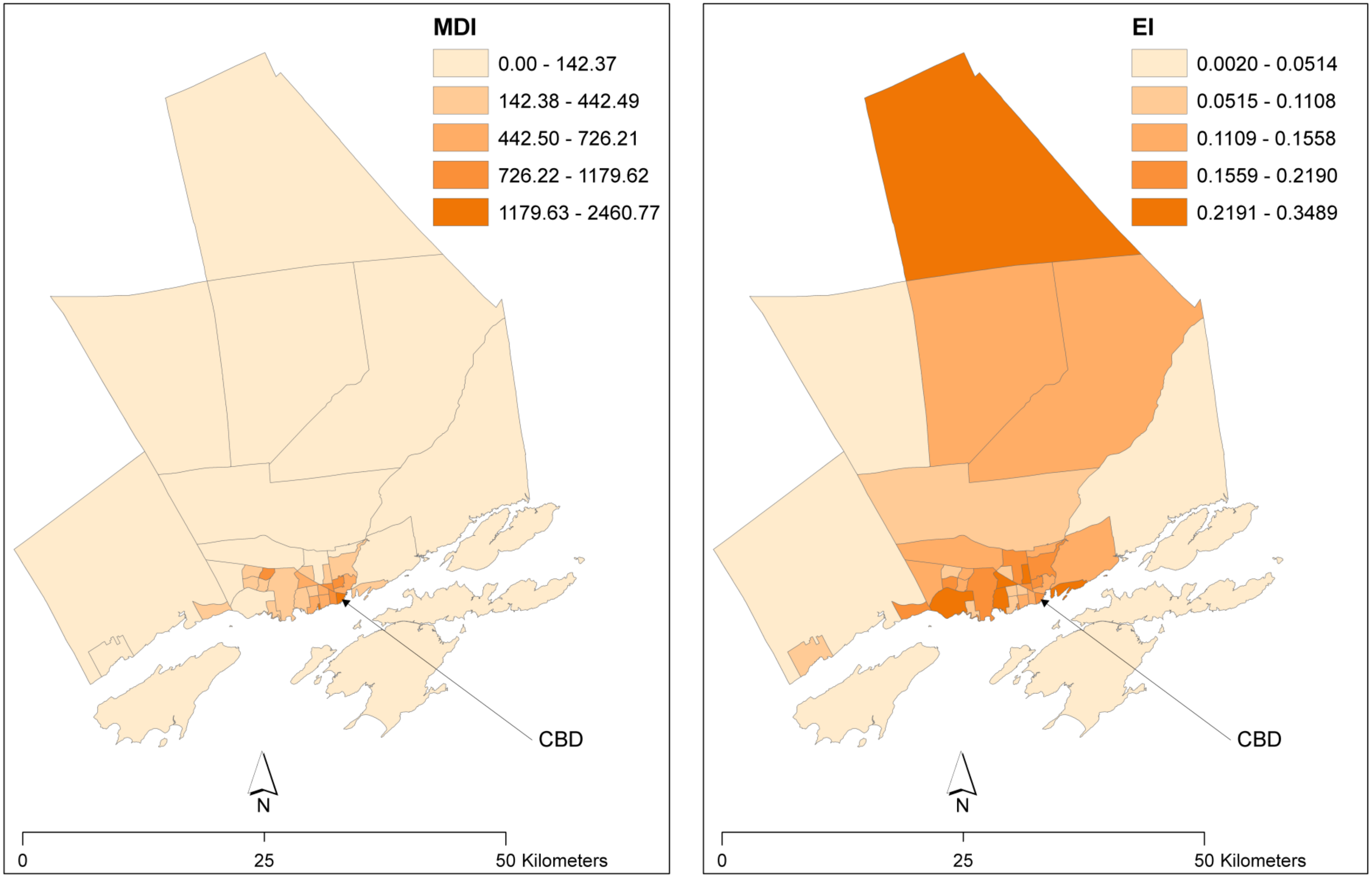
Ortuzar, J; Willumsen, L 2011, ‘Modeling transport’, 4th Edition. John Wiley & Sons.

Rouwendal, J; Nijkamp, P 2004, 'Living in Two Works: A Review of Home-to-Work Decisions', Growth and Change, vol. 35, no. 3 (Summer 2004), p. 287-303

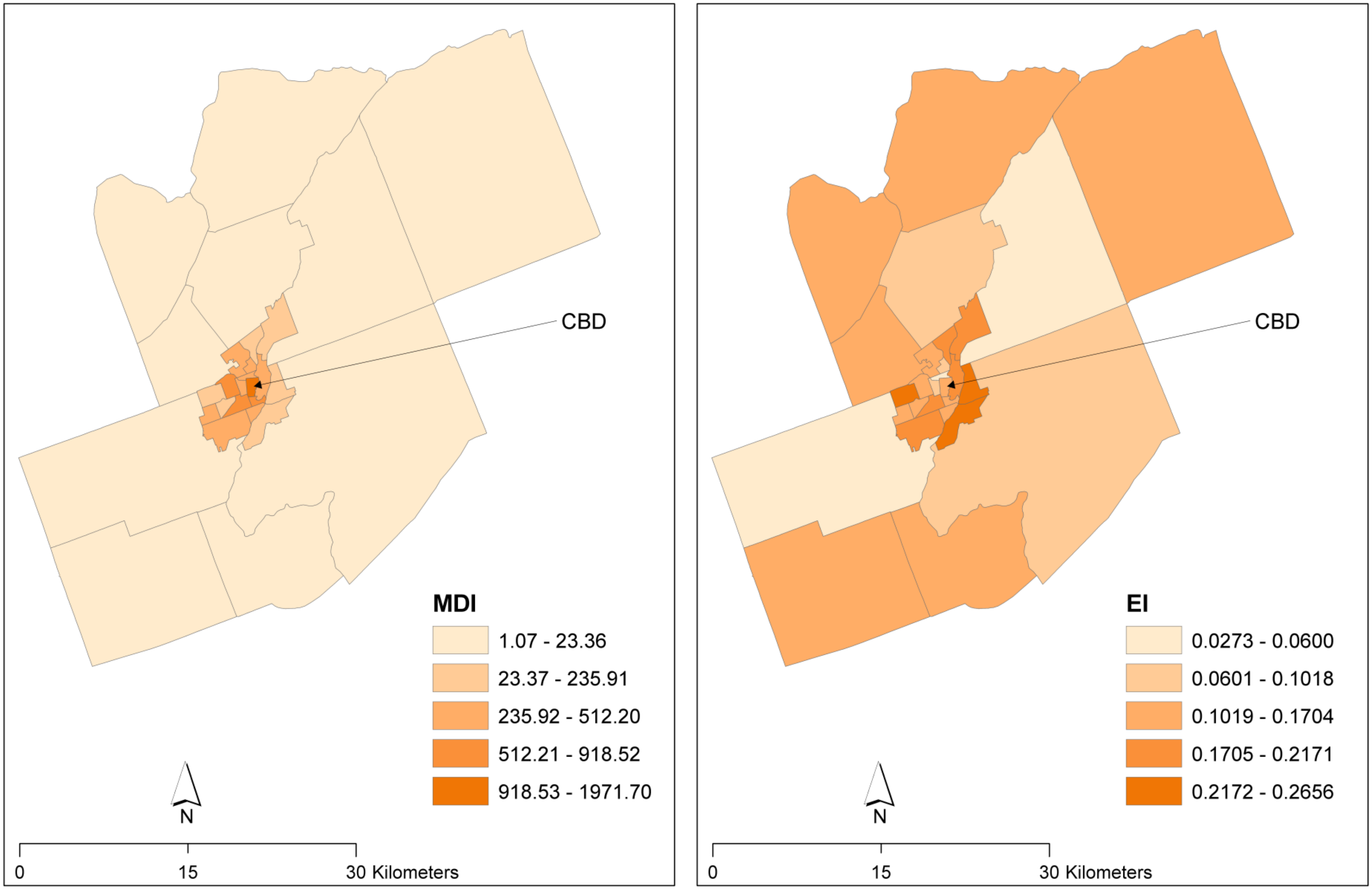
Tsai, Y 2005, 'Quantifying Urban Form: Compactness versus 'Sprawl', Urban Studies, vol. 42, no. 1, p. 141-161.

Wegener, M 1995, ‘Current and Future Land Use Models’, In proceedings of Land Use Model Conference, Texas Transportation Institute, Dallas, February 19-21, 1995.

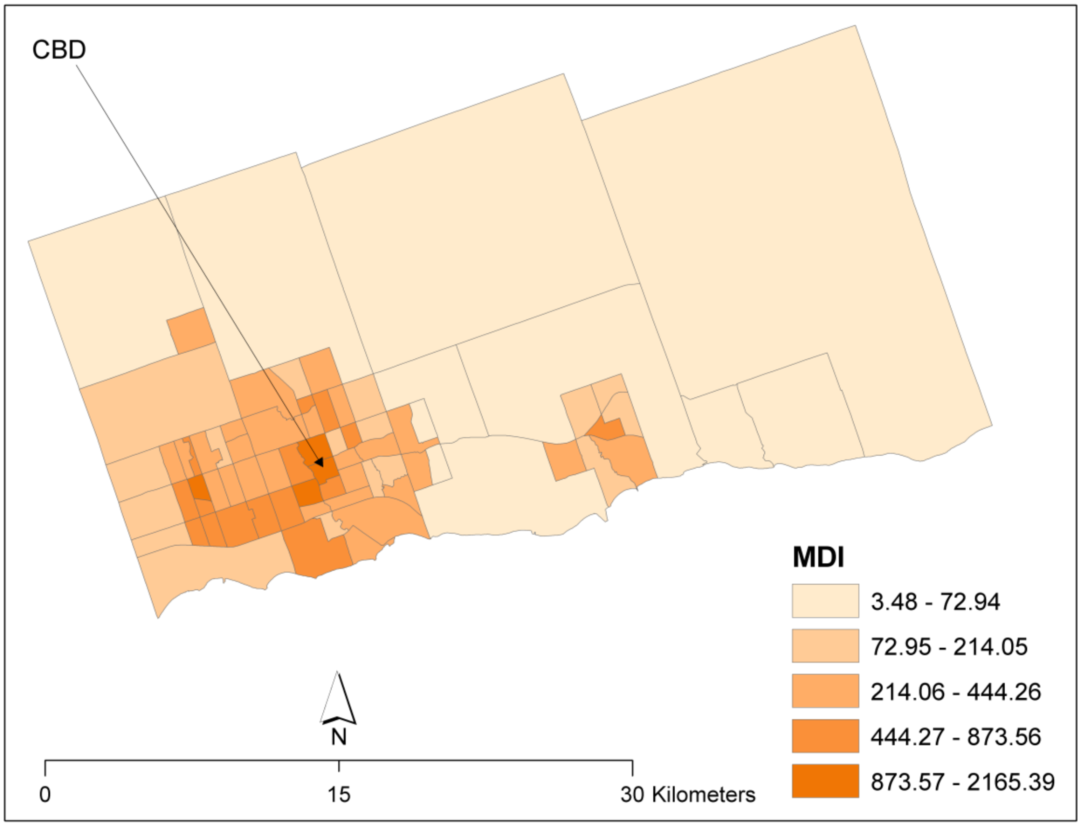
APPENDIX A: MDI and Land Use Entropy Maps for the 12 CMAs

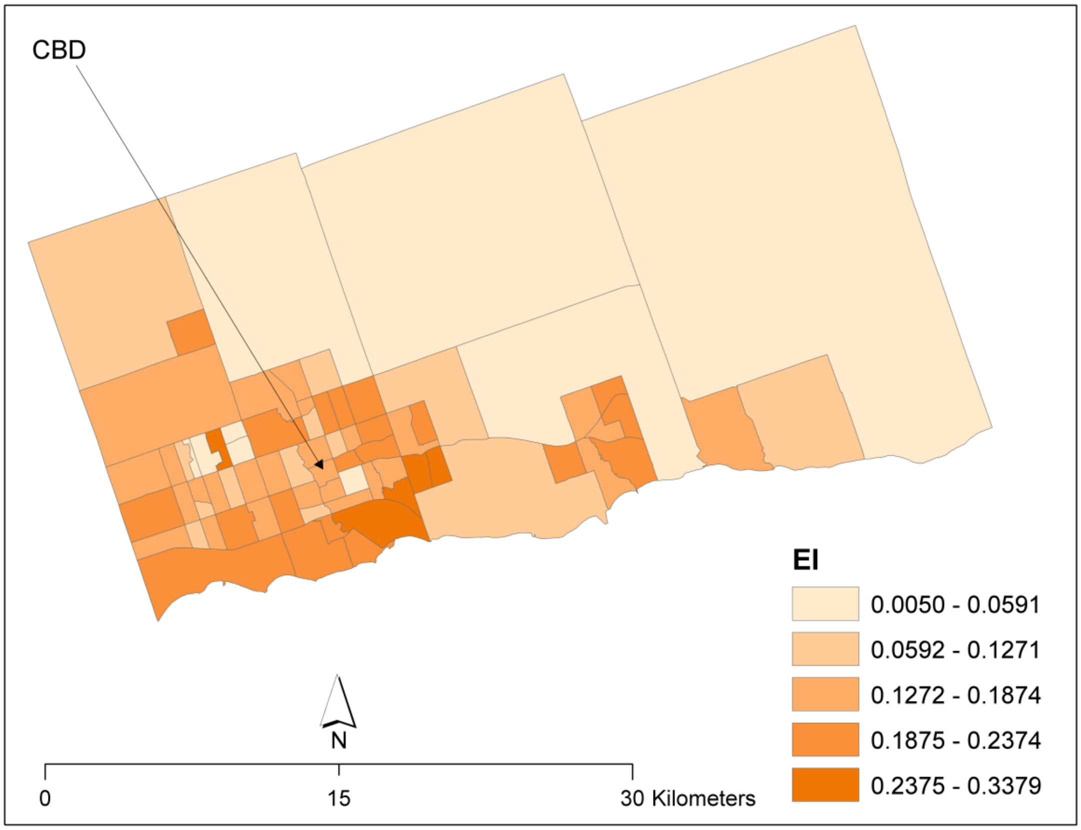


Kingston CMA

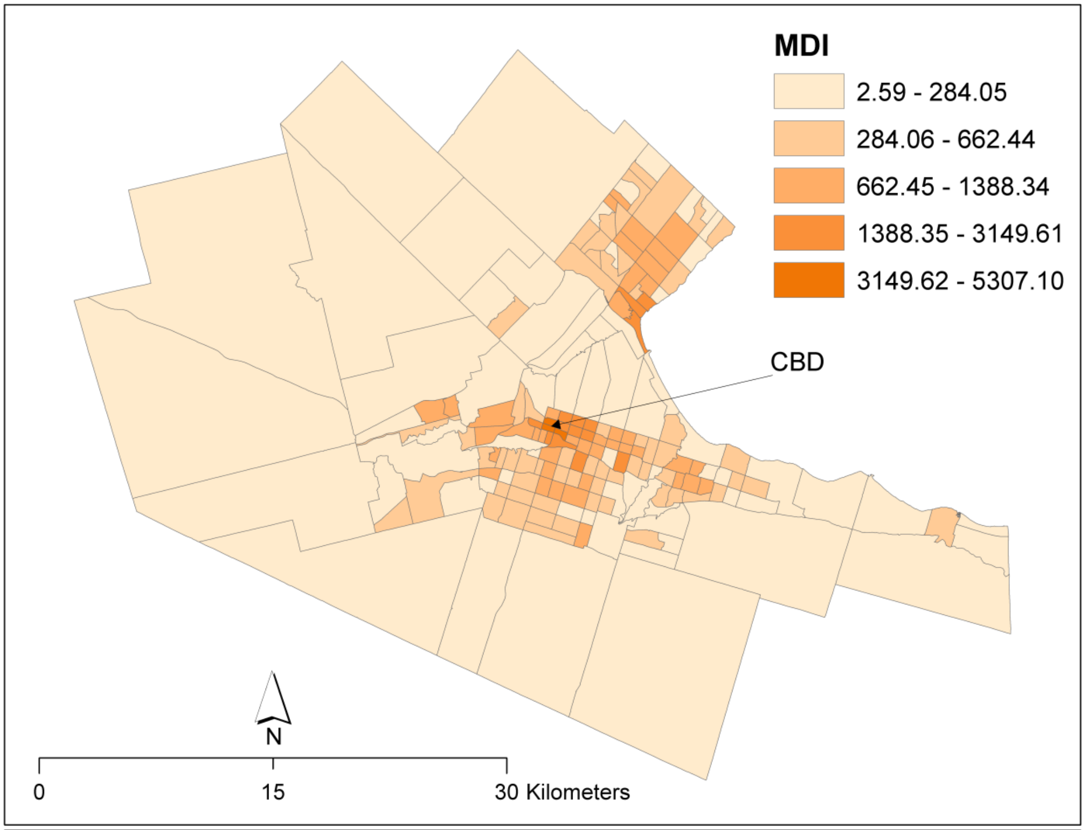


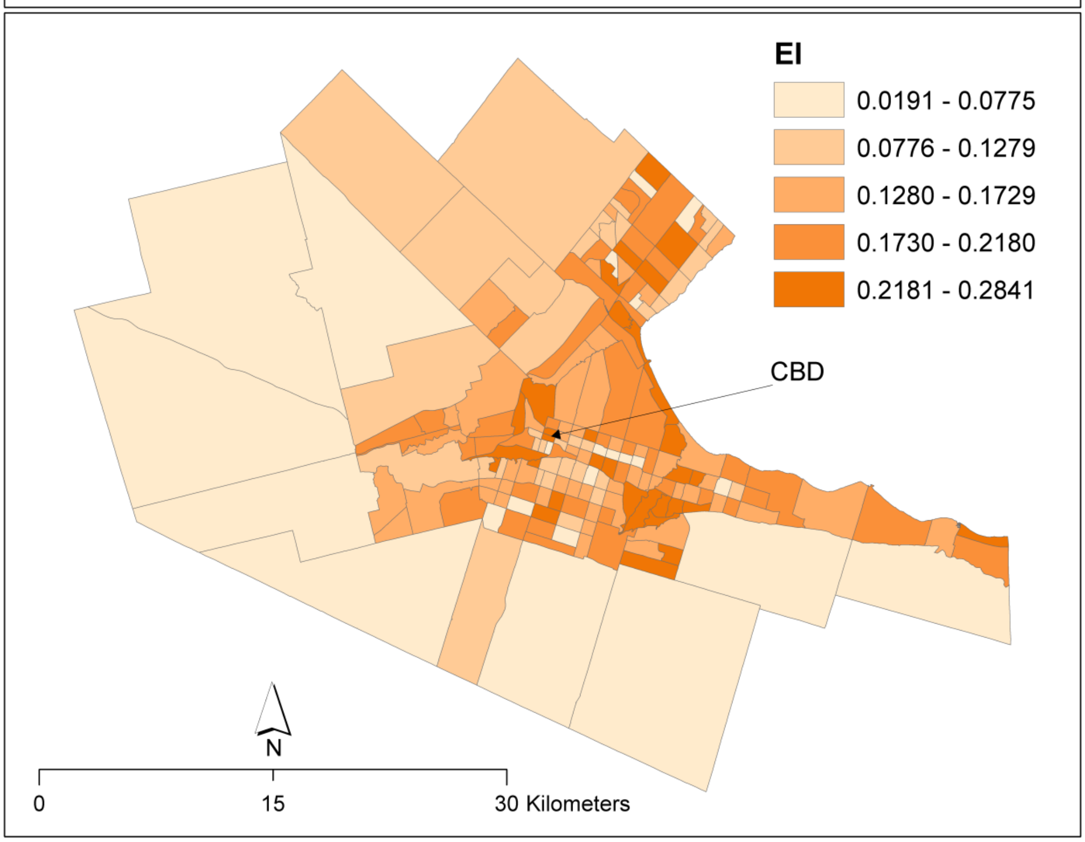
Peterborough CMA


CBD
MDI
3.48 - 72.94
72.95 - 214.05
214.06 - 444.26
444.27 - 873.56
873.57 - 2165.39
N
0
15
30 Kilometers

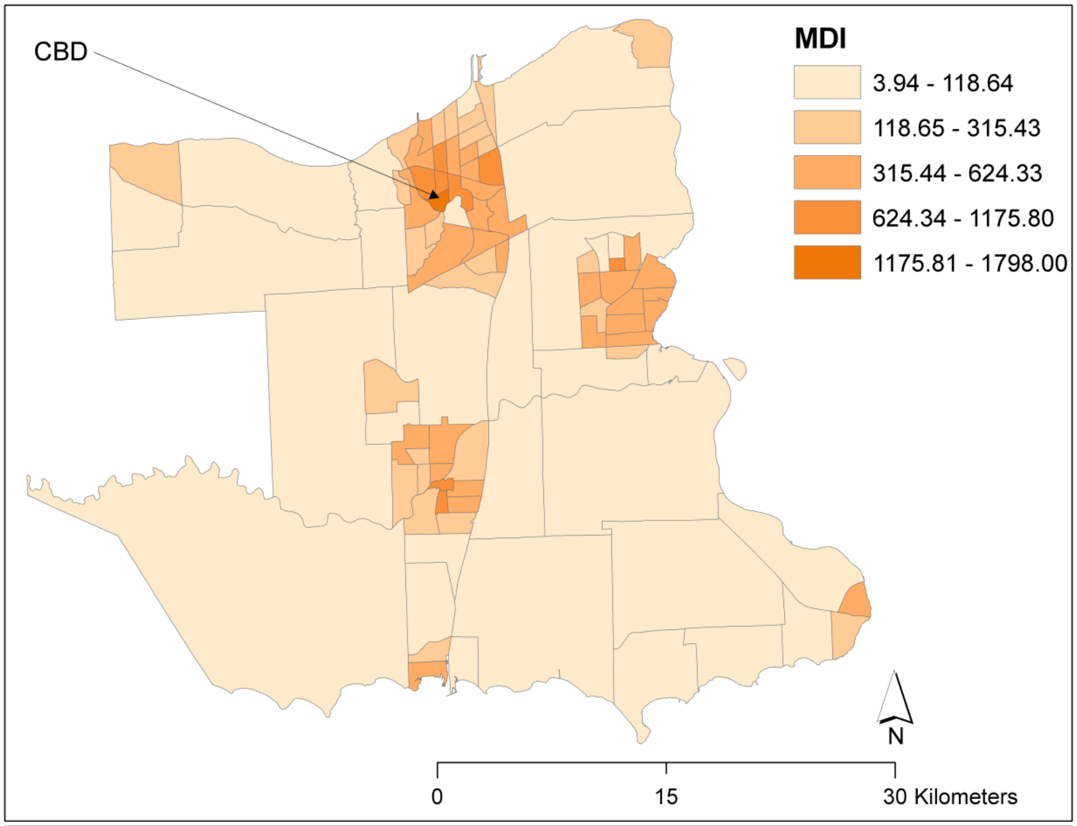

CBD
EI
0.0050 - 0.0591
0.0592 - 0.1271
0.1272 - 0.1874
0.1875 - 0.2374
0.2375 - 0.3379
N
0
15
30 Kilometers

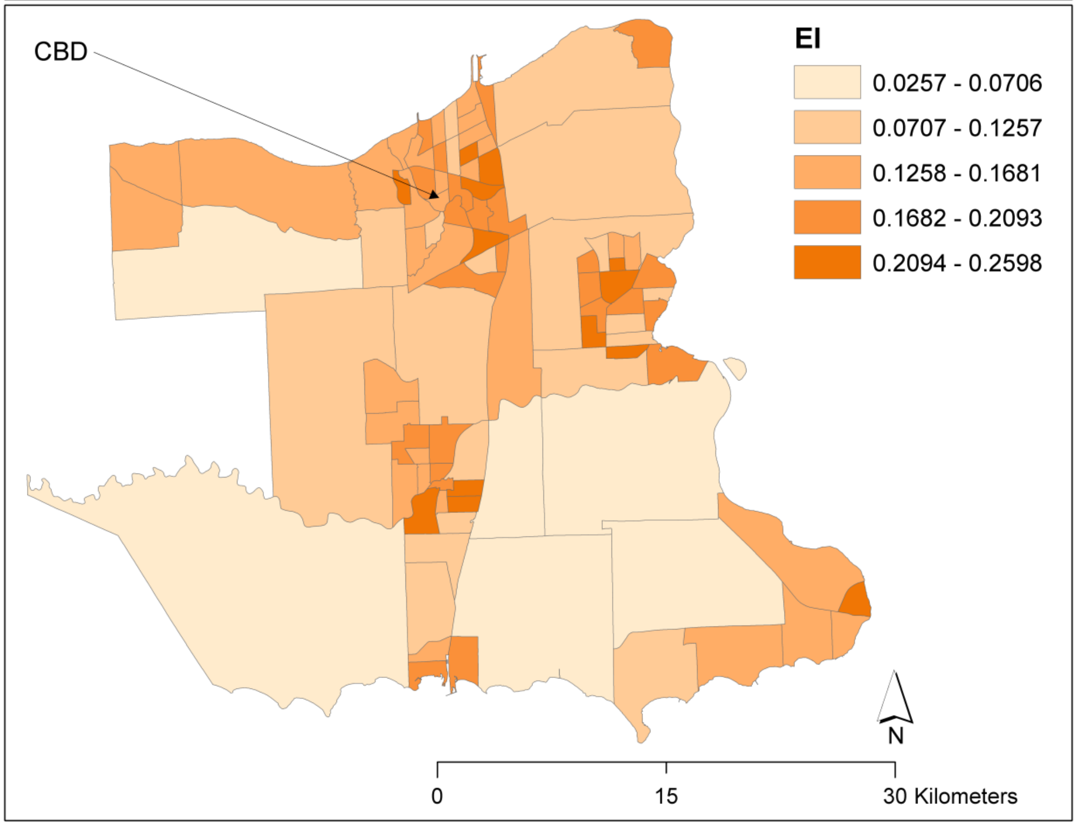
Oshawa CMA



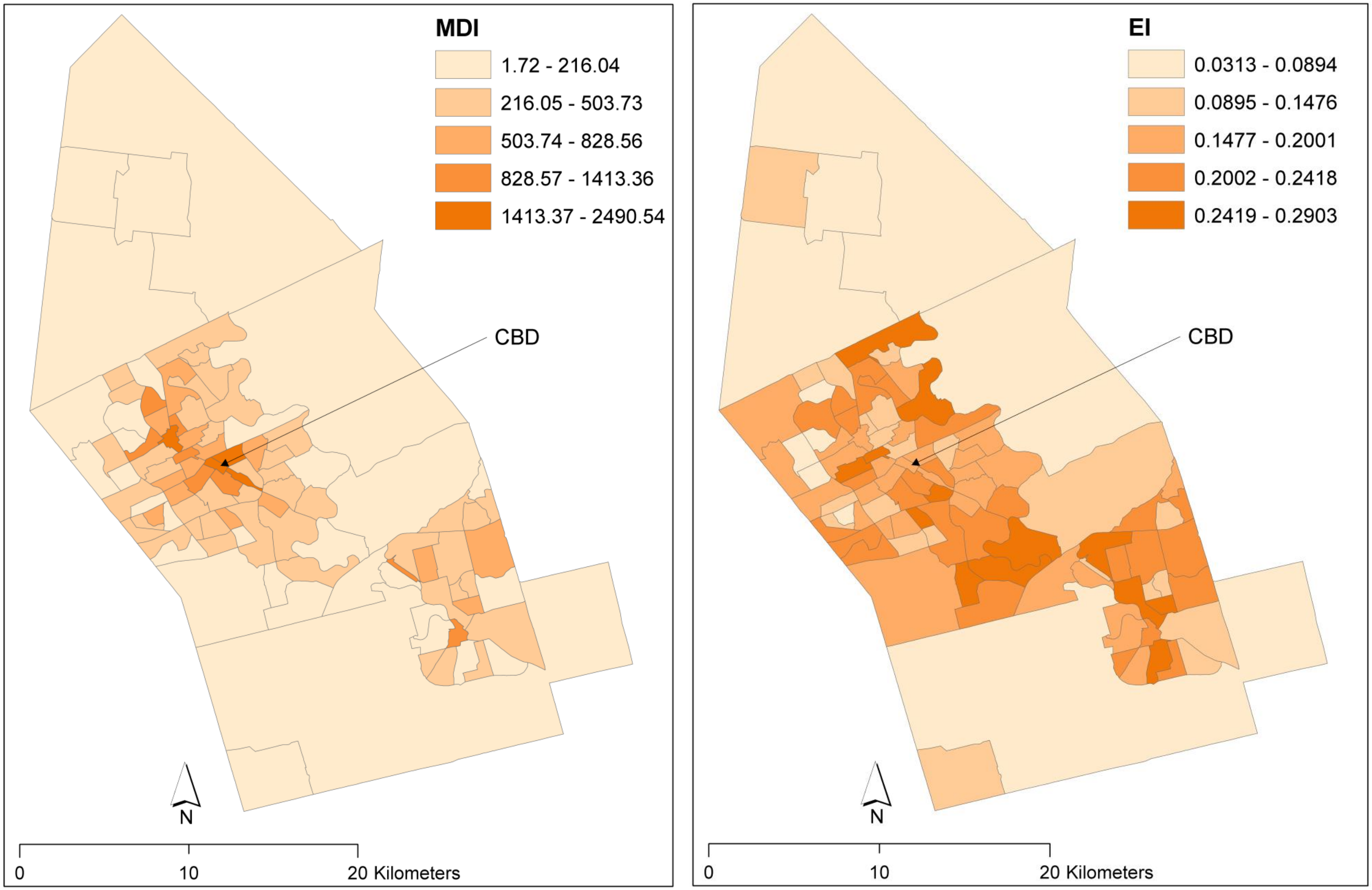


Hamilton CMA





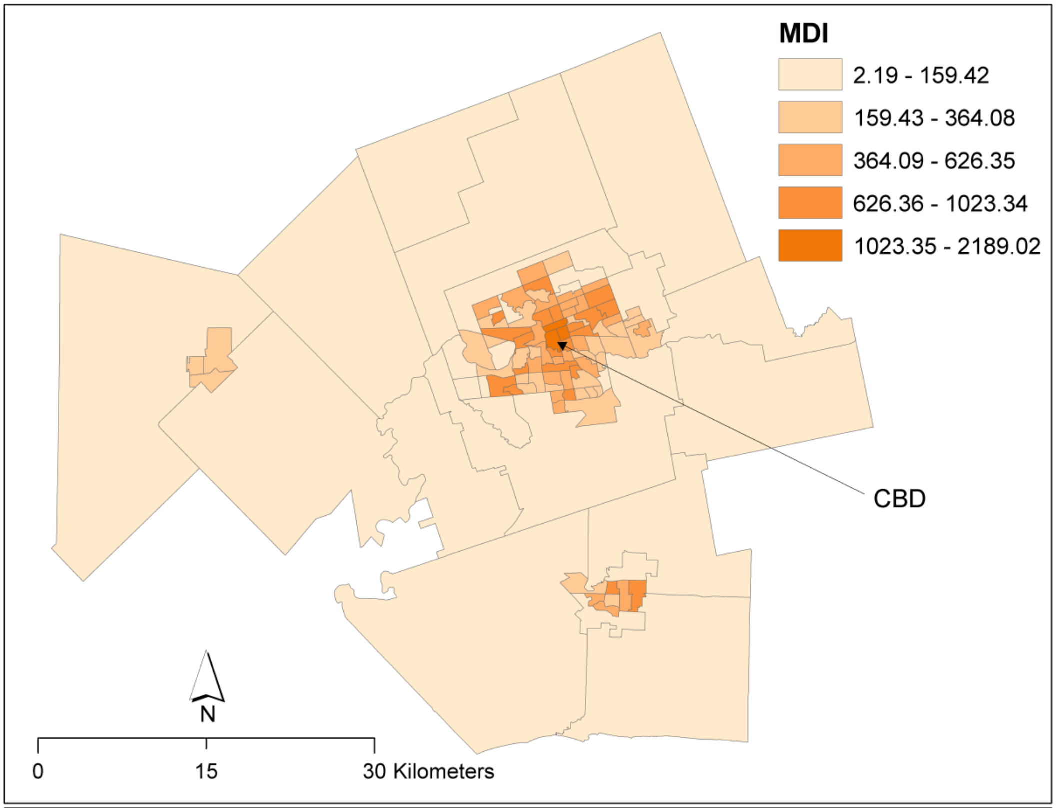
St. Catherines CMA

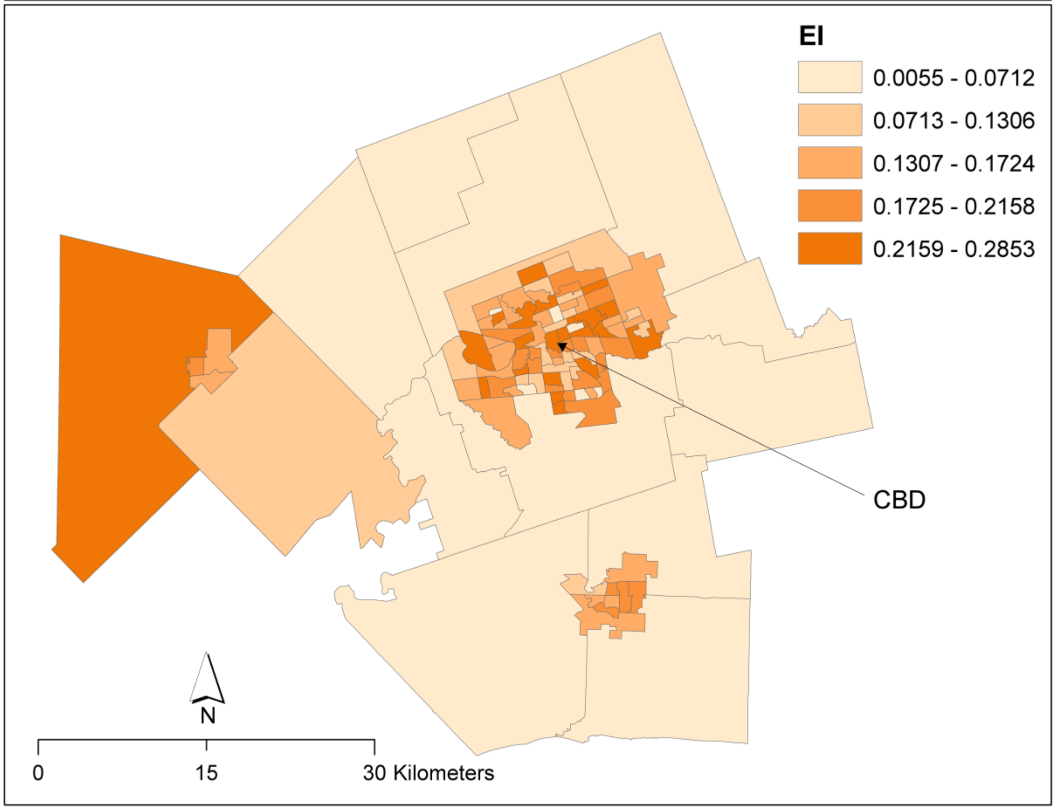


Kitchener CMA

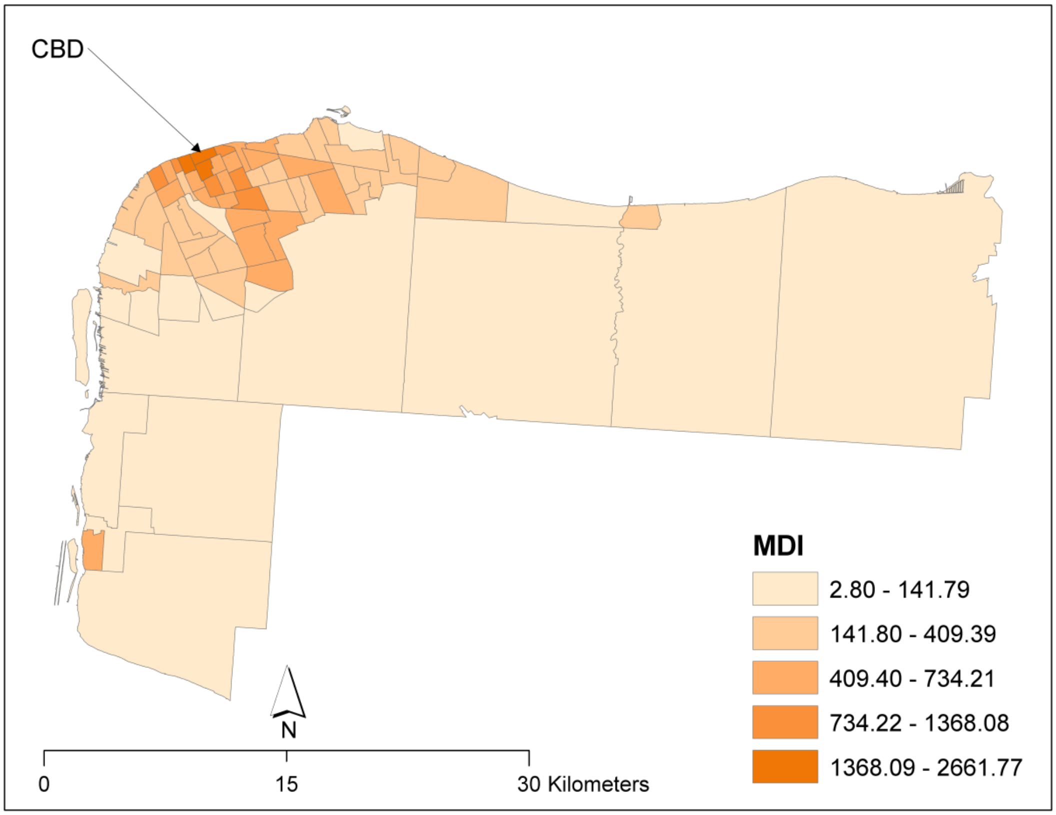

MDI
8.27 - 115.80
115.81 - 256.02
256.03 - 429.83
429.84 - 711.61
711.62 - 1719.52
CBD
N
0
10
20 Kilometers
EI
0.0295 - 0.0905
0.0906 - 0.1606
0.1607 - 0.1897
0.1898 - 0.2190
0.2191 - 0.2751
CBD
N
0
10
20 Kilometers

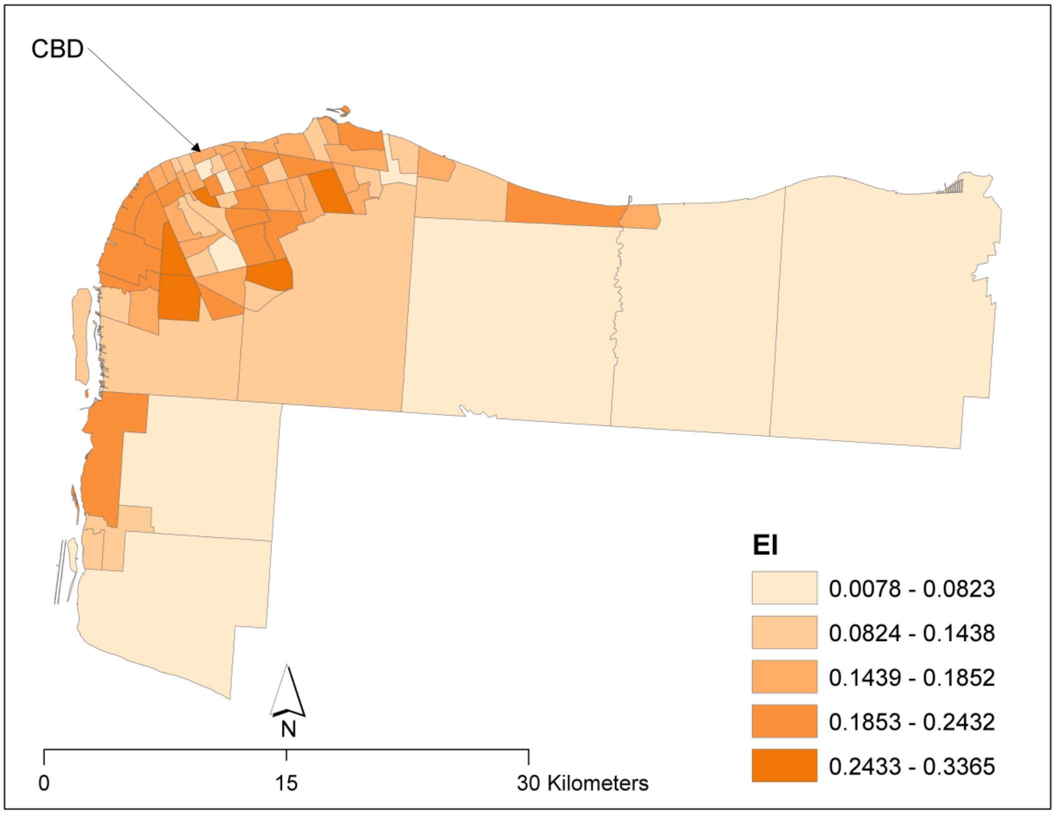
Guelph CMA


MDI
2.19 - 159.42
159.43 - 364.08
364.09 - 626.35
626.36 - 1023.34
1023.35 - 2189.02
CBD
N
0
15
30 Kilometers

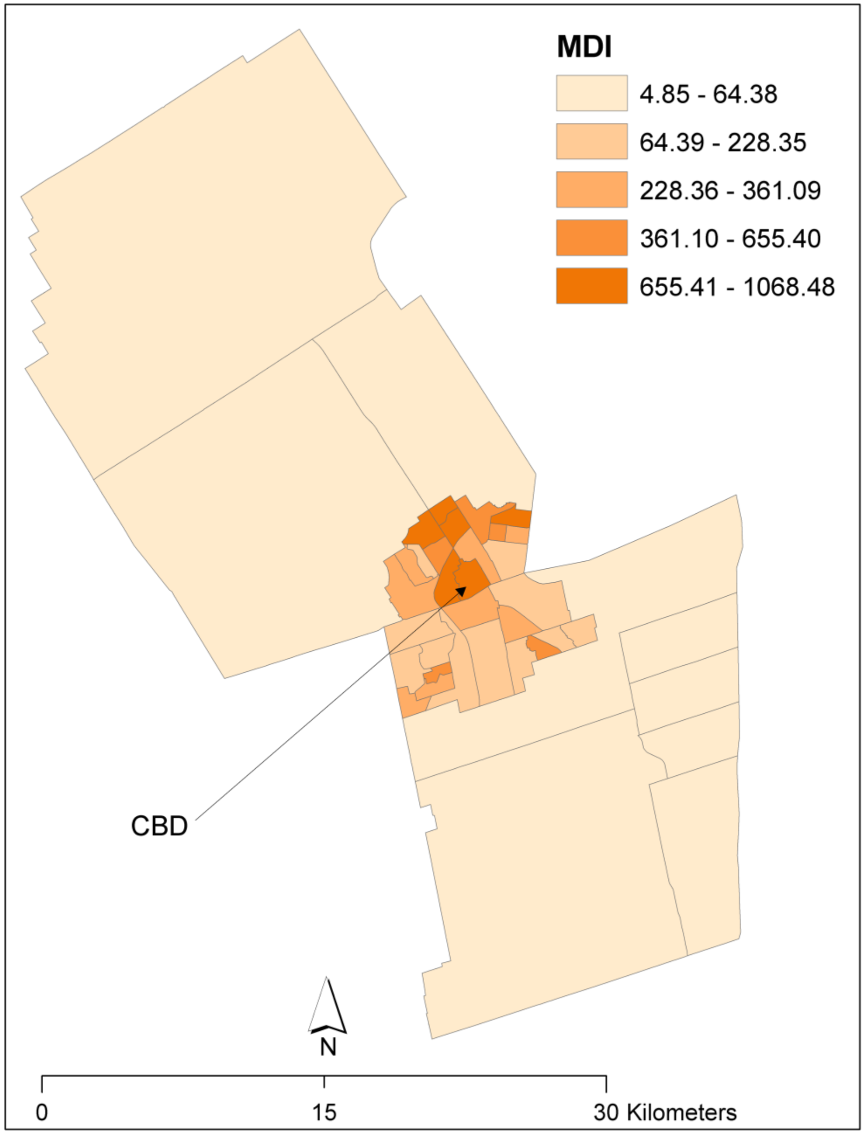

EI
0.0055 - 0.0712
0.0713 - 0.1306
0.1307 - 0.1724
0.1725 - 0.2158
0.2159 - 0.2853
CBD
N
0
15
30 Kilometers

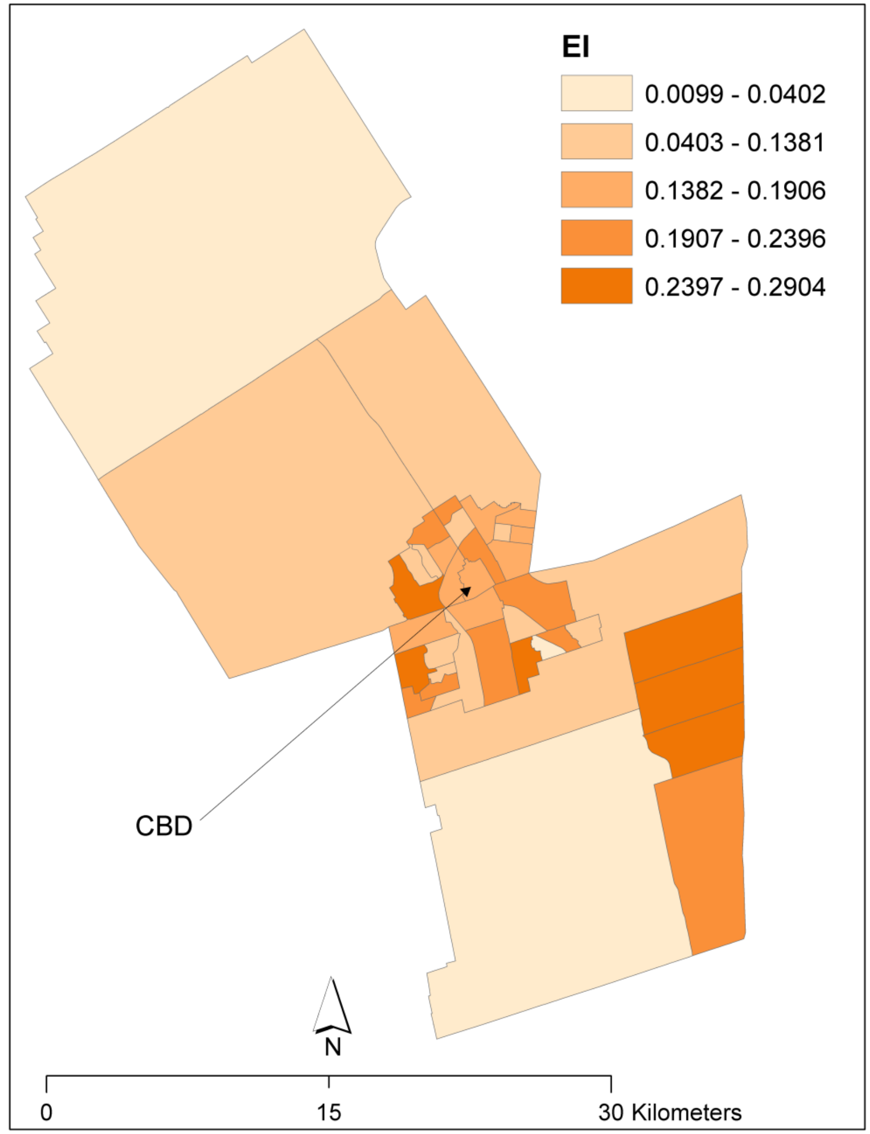
London CMA


CBD
MDI
2.80 - 141.79
141.80 - 409.39
409.40 - 734.21
734.22 - 1368.08
1368.09 - 2661.77
N
0
15
30 Kilometers

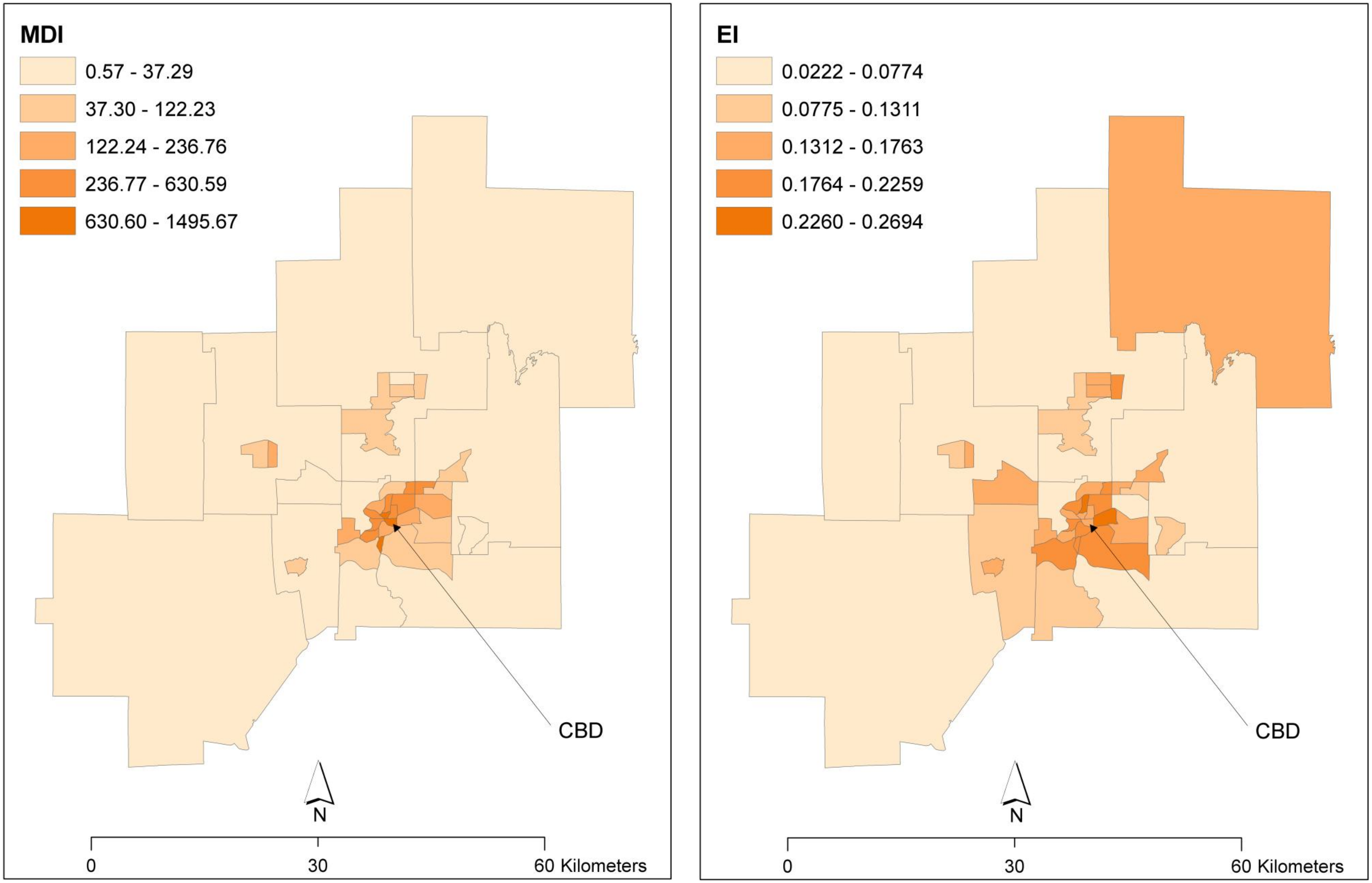

CBD
EI
0.0078 - 0.0823
0.0824 - 0.1438
0.1439 - 0.1852
0.1853 - 0.2432
0.2433 - 0.3365
N
0
15
30 Kilometers

Windsor CMA

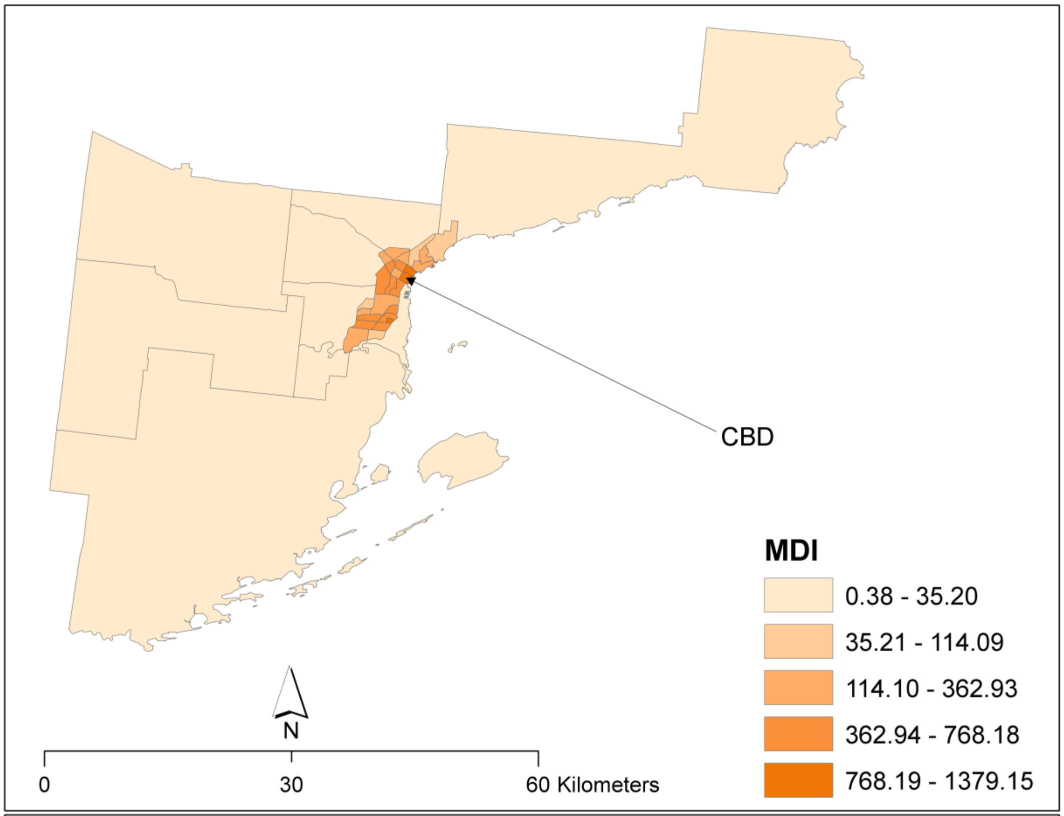

MDI
4.85 - 64.38
64.39 - 228.35
228.36 - 361.09
361.10 - 655.40
655.41 - 1068.48
CBD
N
0
15
30 Kilometers

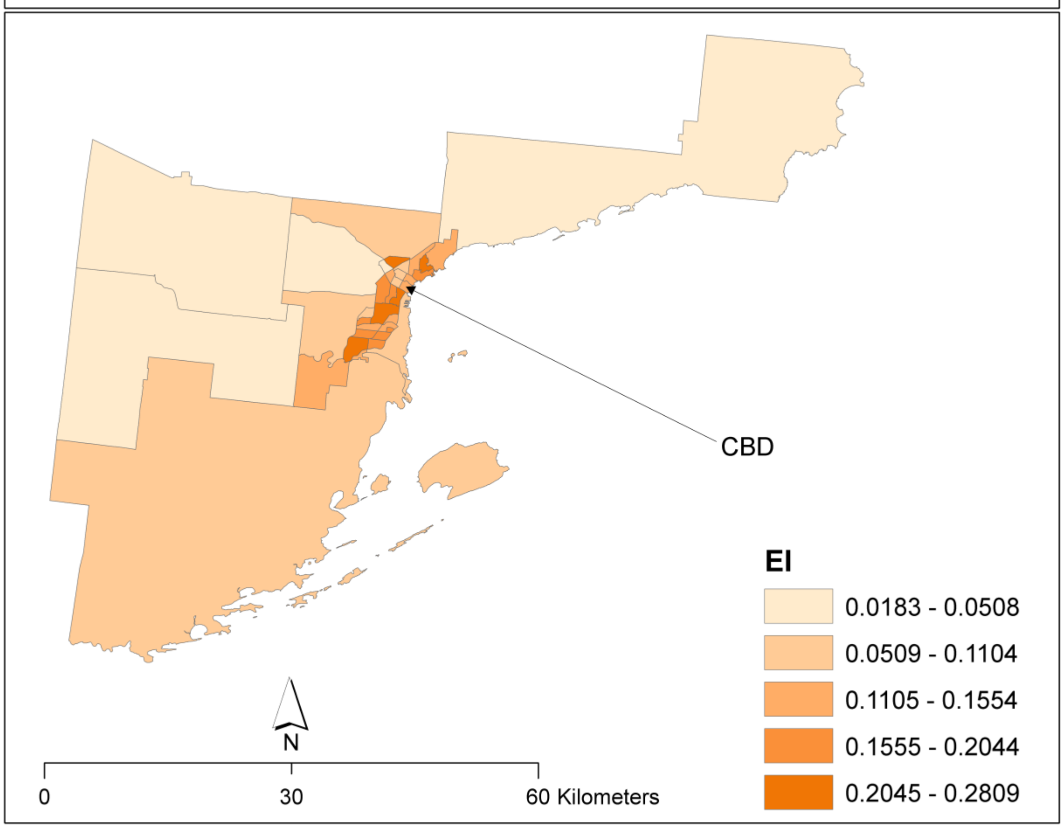

EI
0.0099 - 0.0402
0.0403 - 0.1381
0.1382 - 0.1906
0.1907 - 0.2396
0.2397 - 0.2904
CBD
N
0
15
30 Kilometers

Barrie CMA



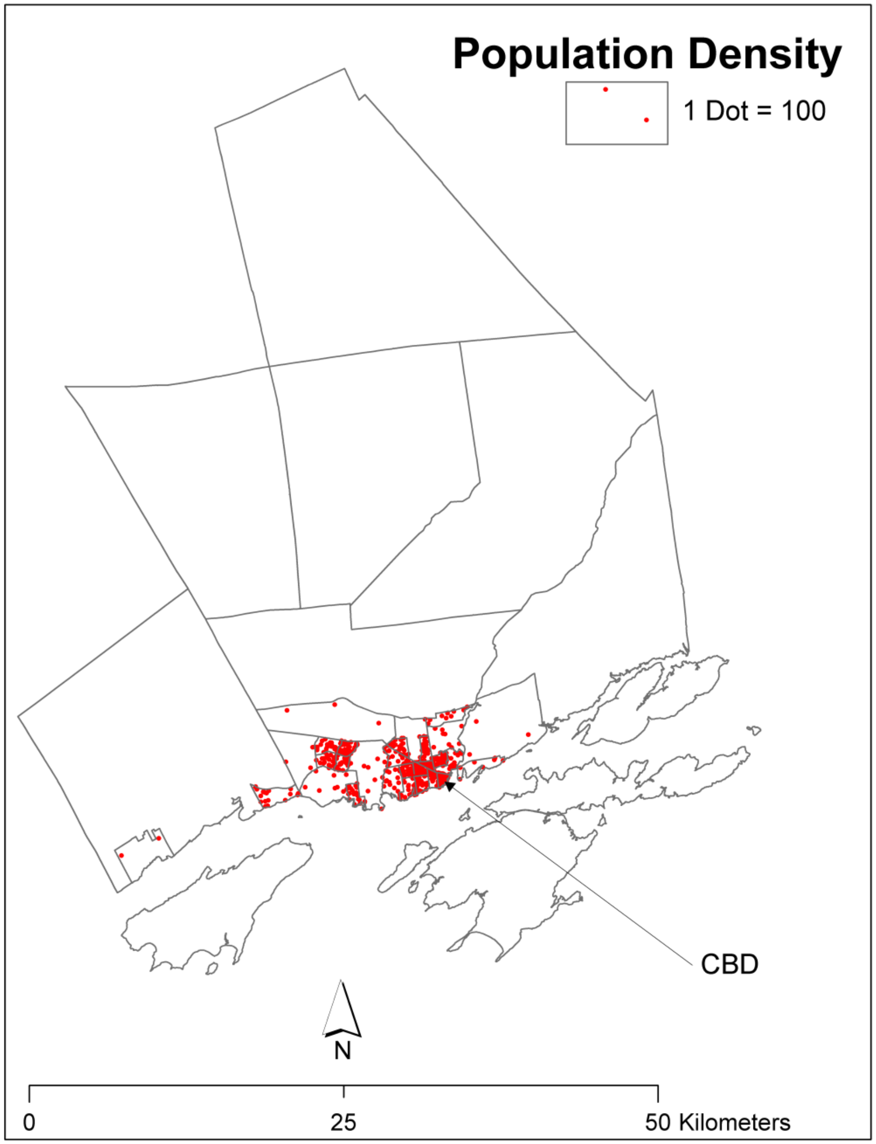
Greater Sudbury CMA

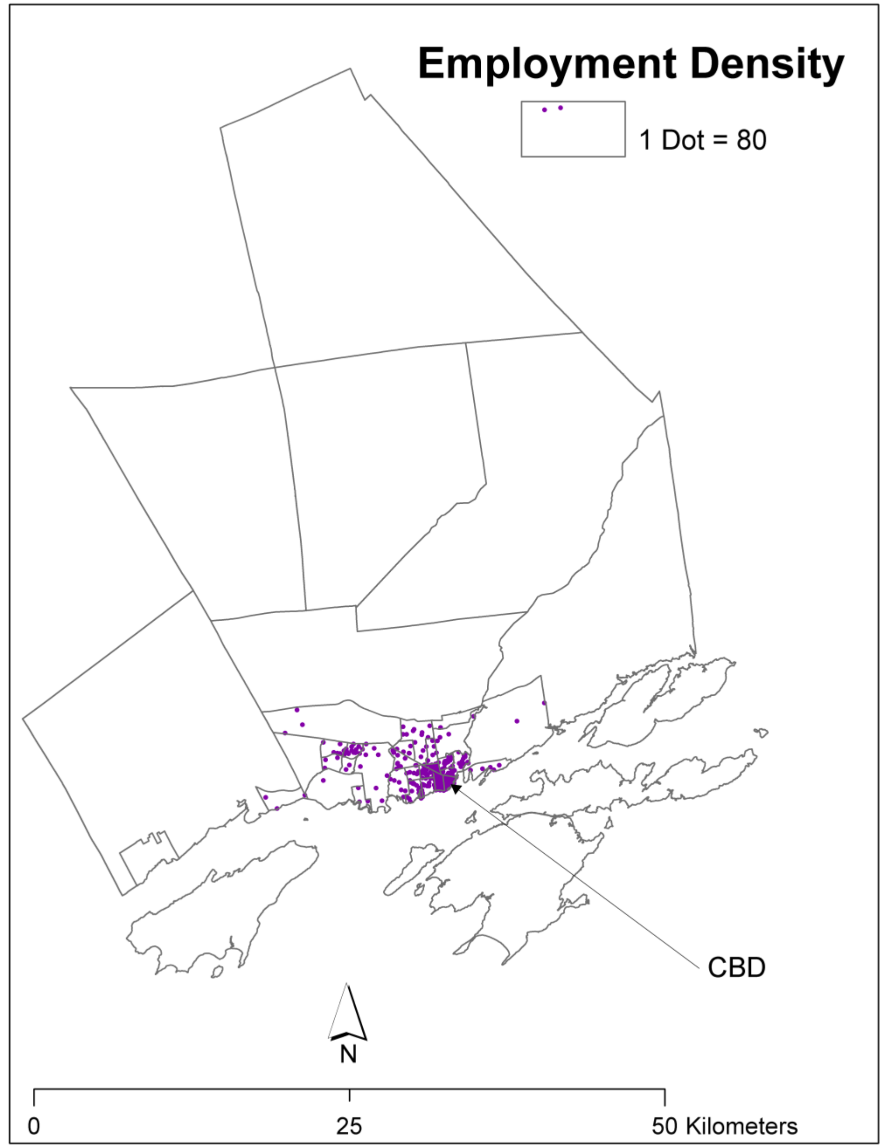




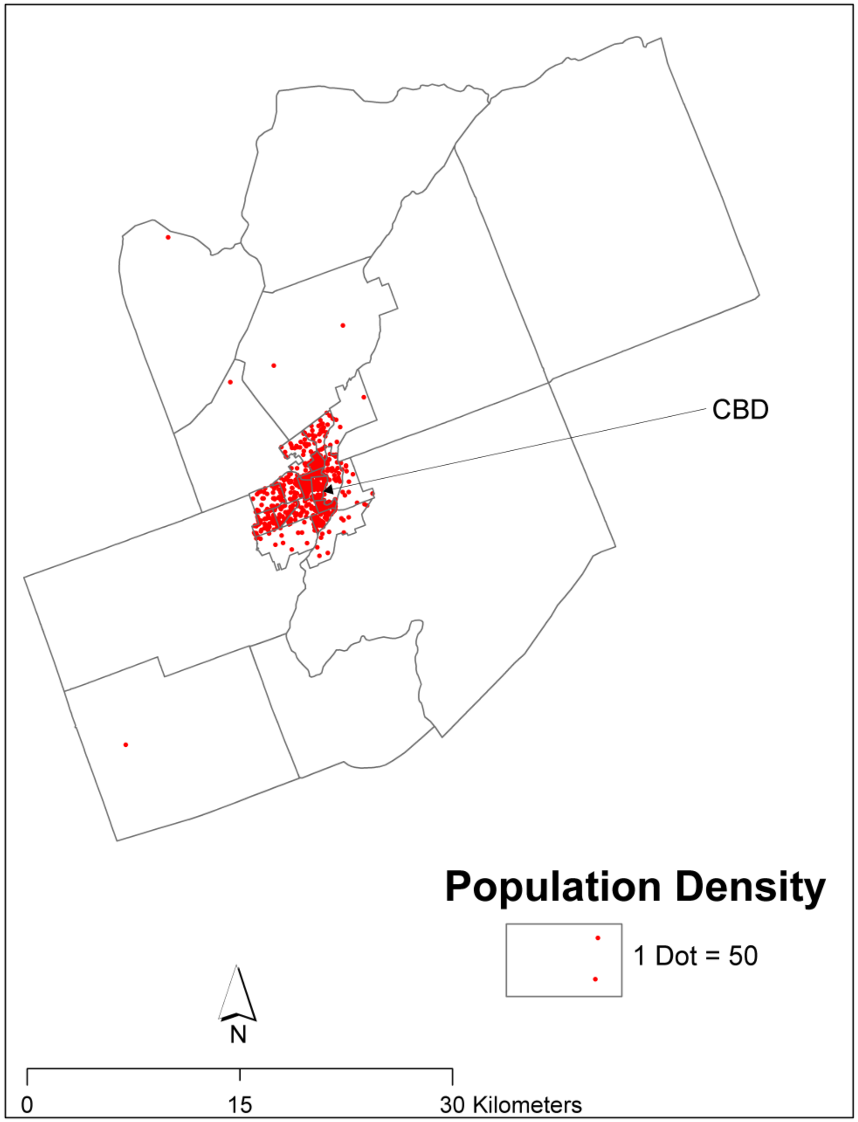
Thunder Bay CMA

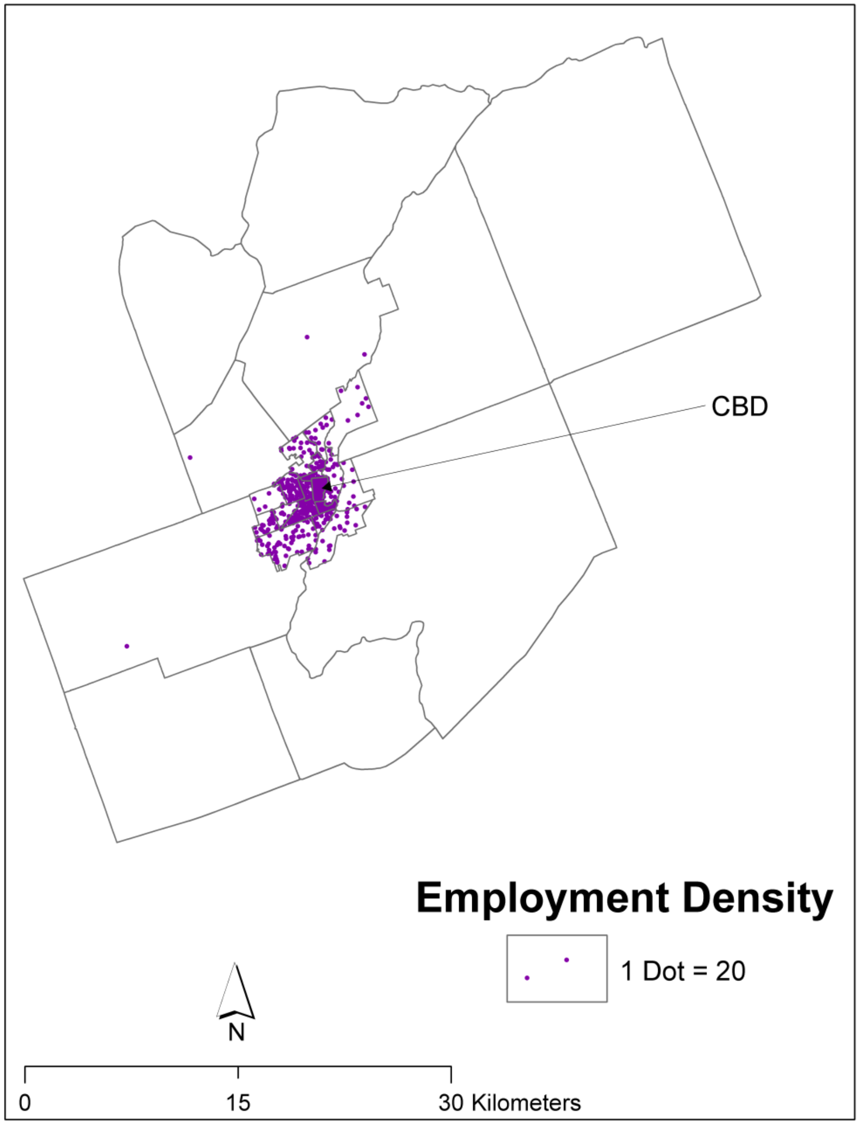
APPENDIX B: Population and Employment Density Maps for the 12 CMAs



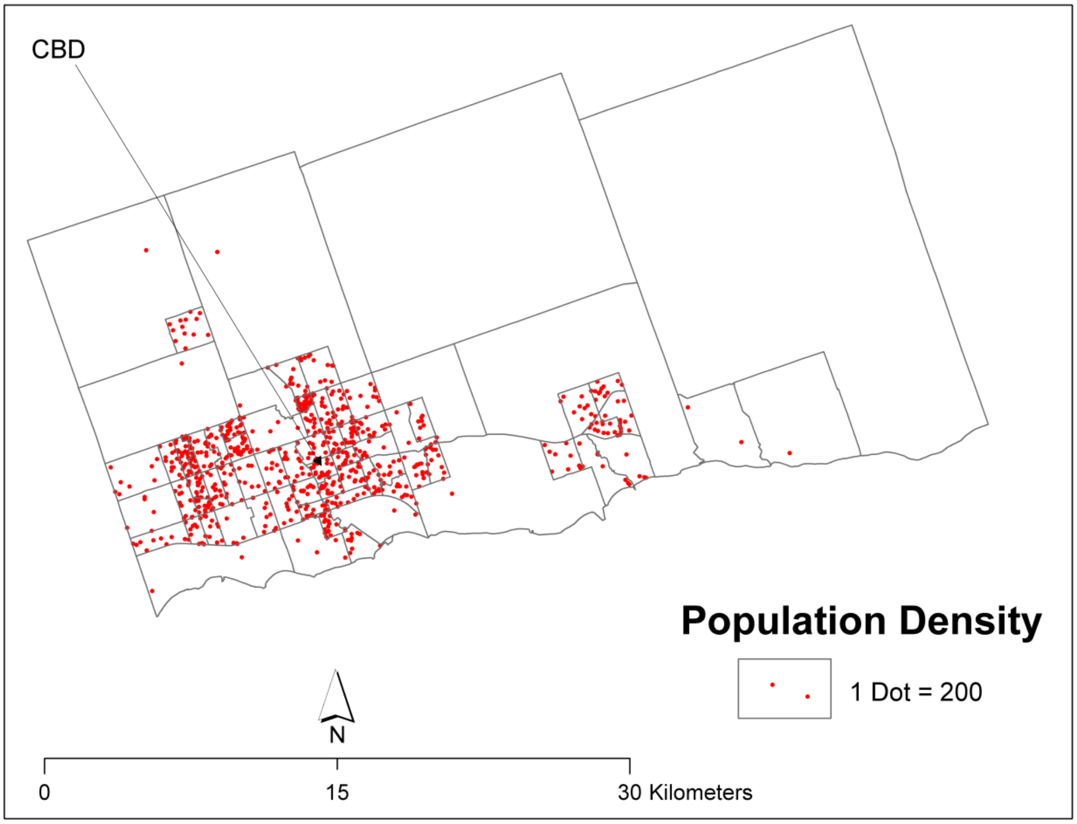


Kingston CMA



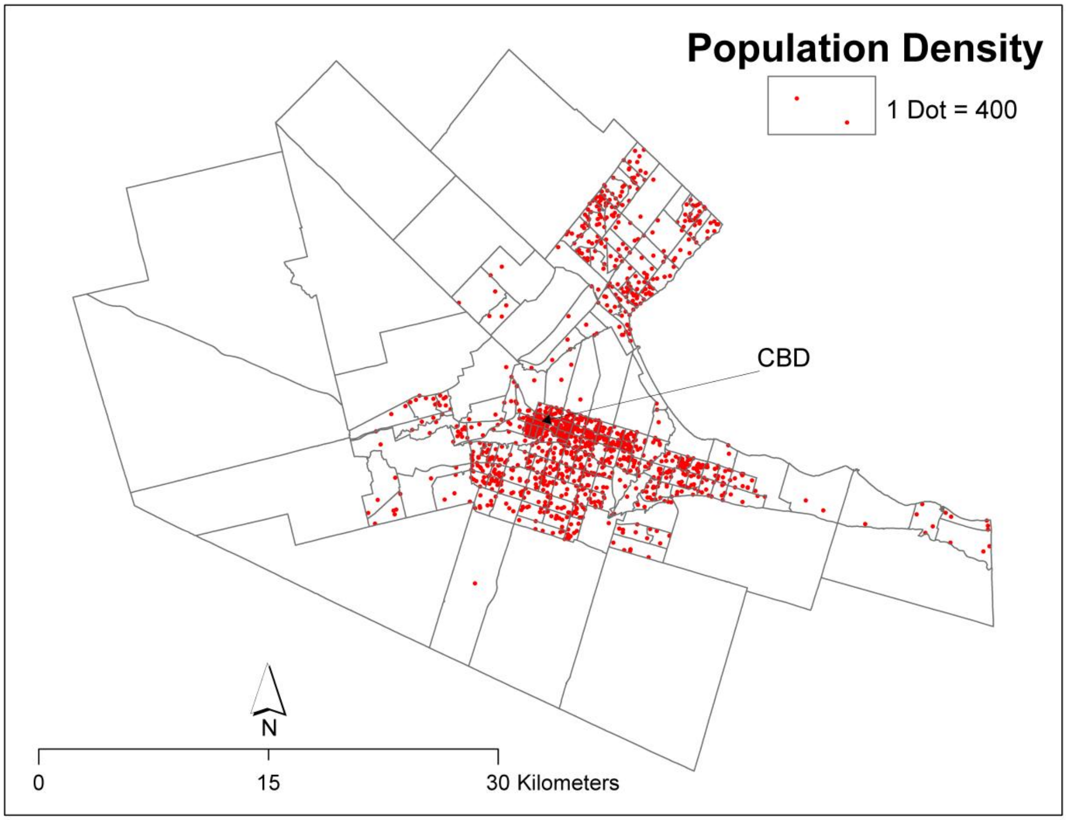


Peterborough CMA

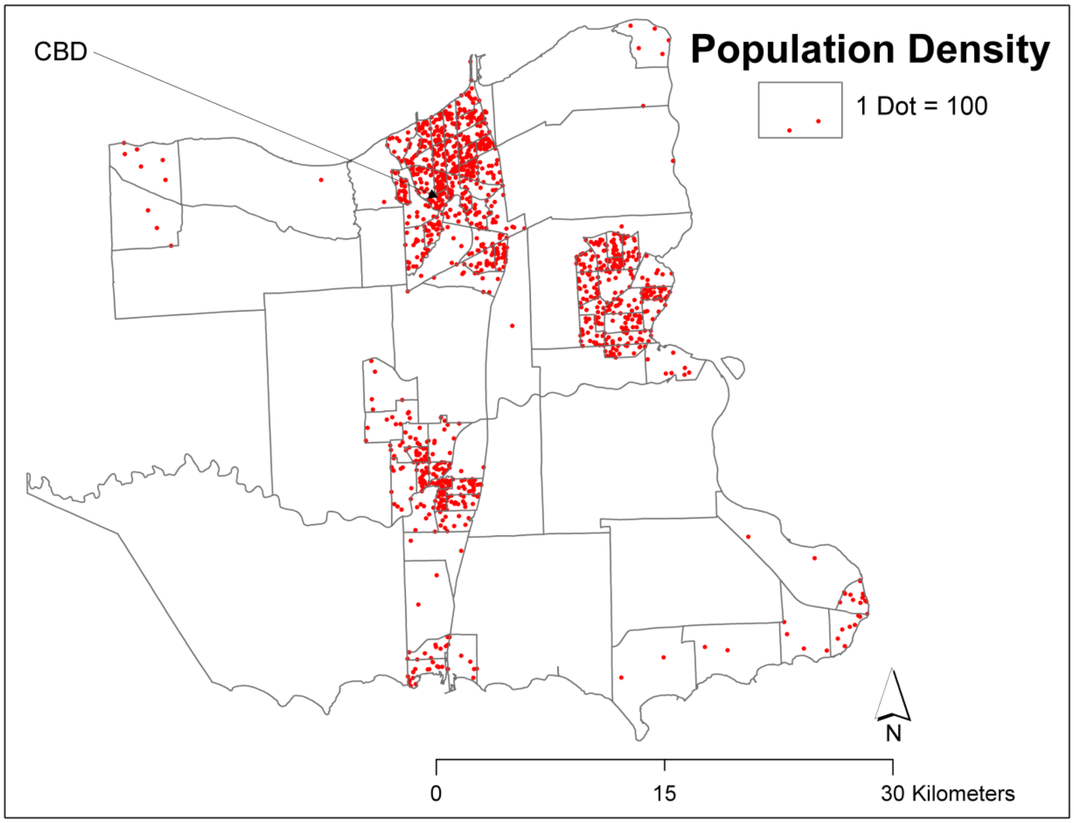

CBD
Population Density
1 Dot = 200
N
0
15
30 Kilometers

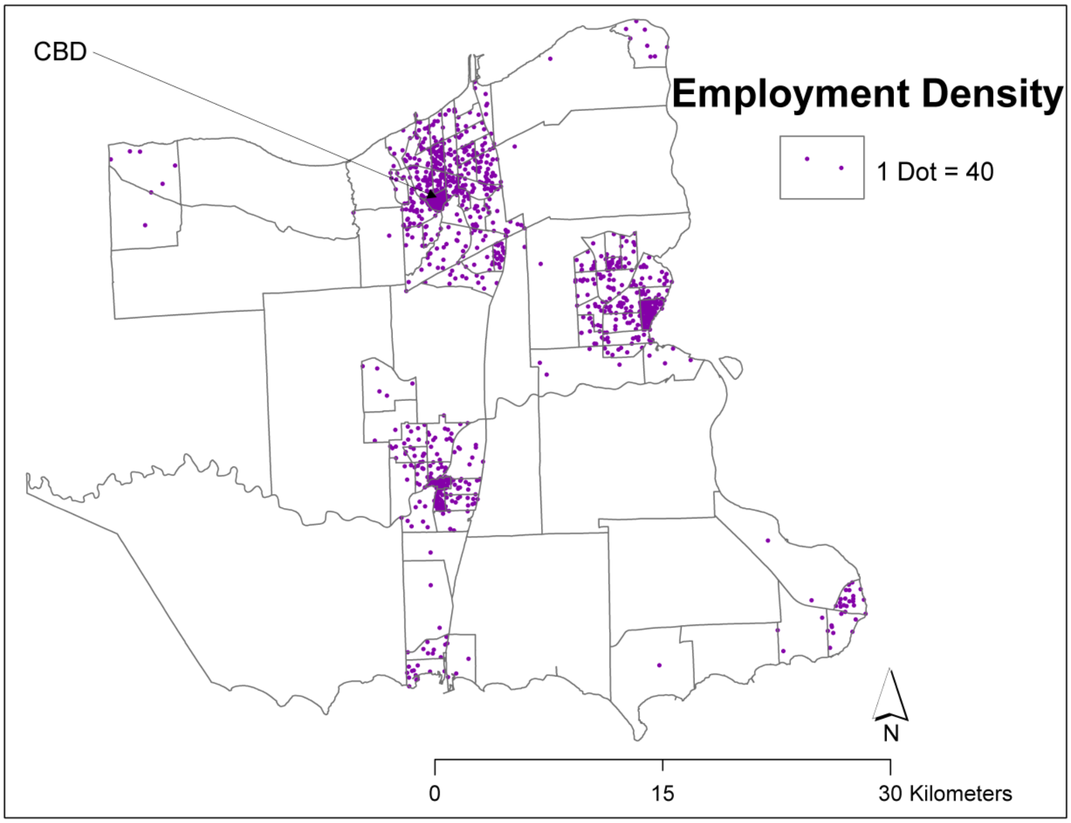

CBD
Employment Density
1 Dot = 40
N
0
15
30 Kilometers

Oshawa CMA

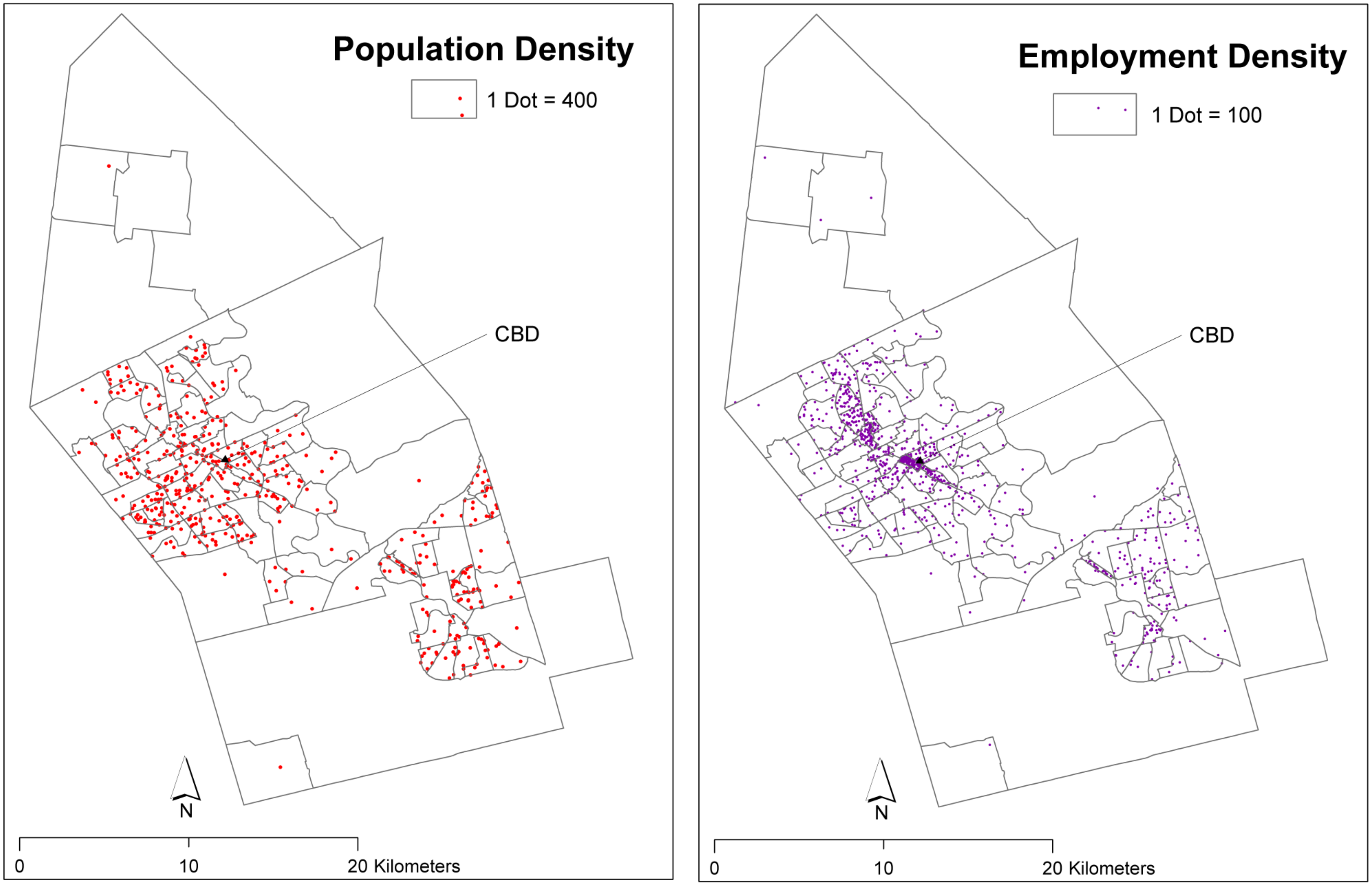


Hamilton CMA

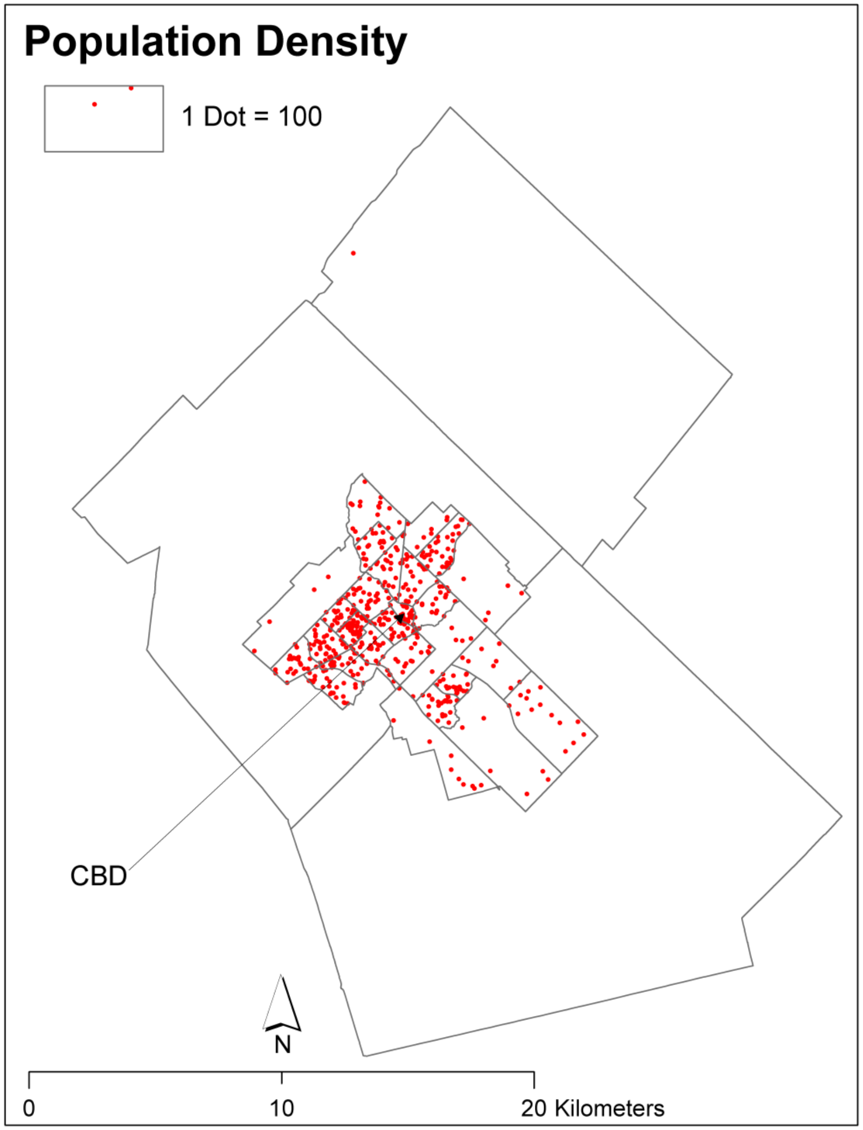


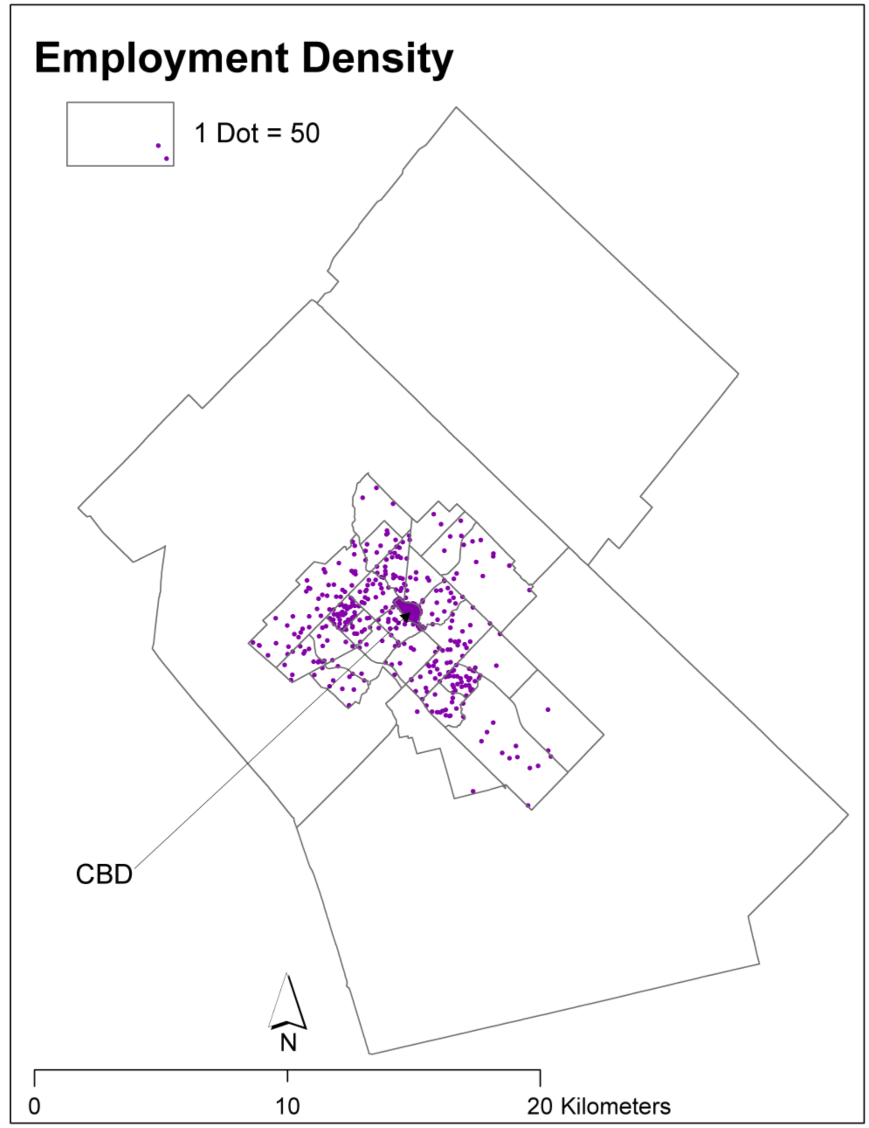


St. Catherines CMA

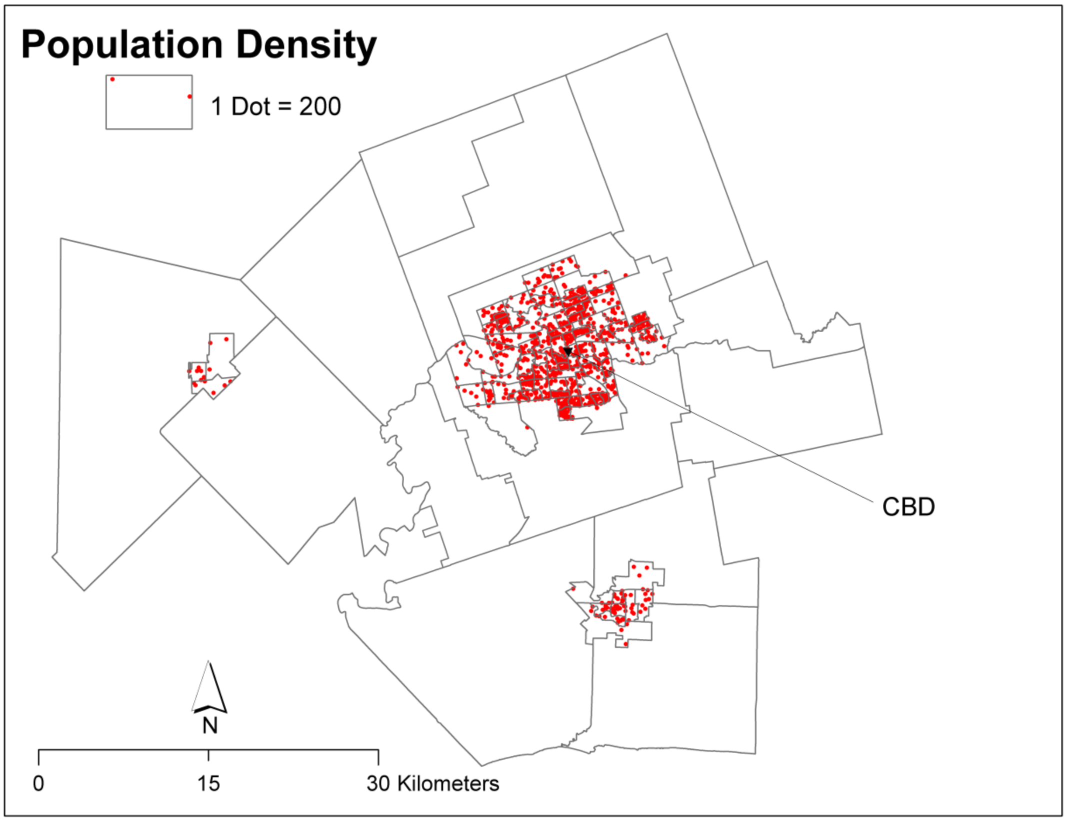


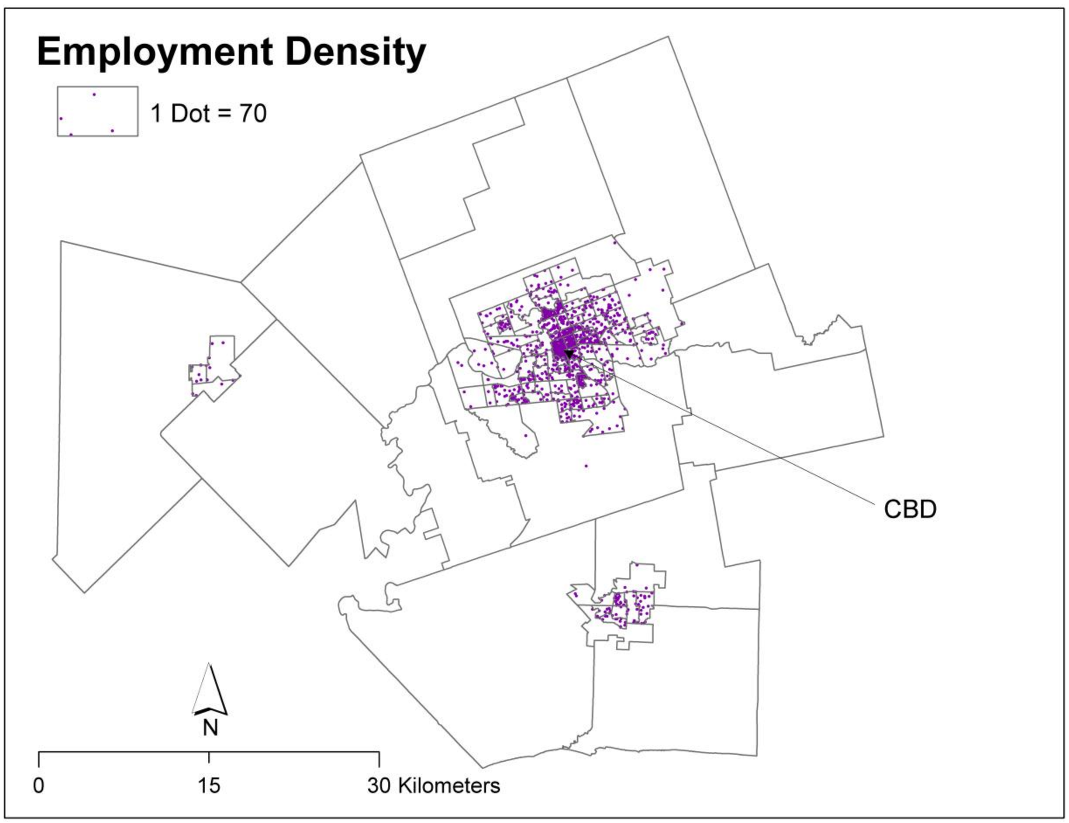
Kitchener CMA


Population Density
1 Dot = 100
CBD
N
0
10
20 Kilometers

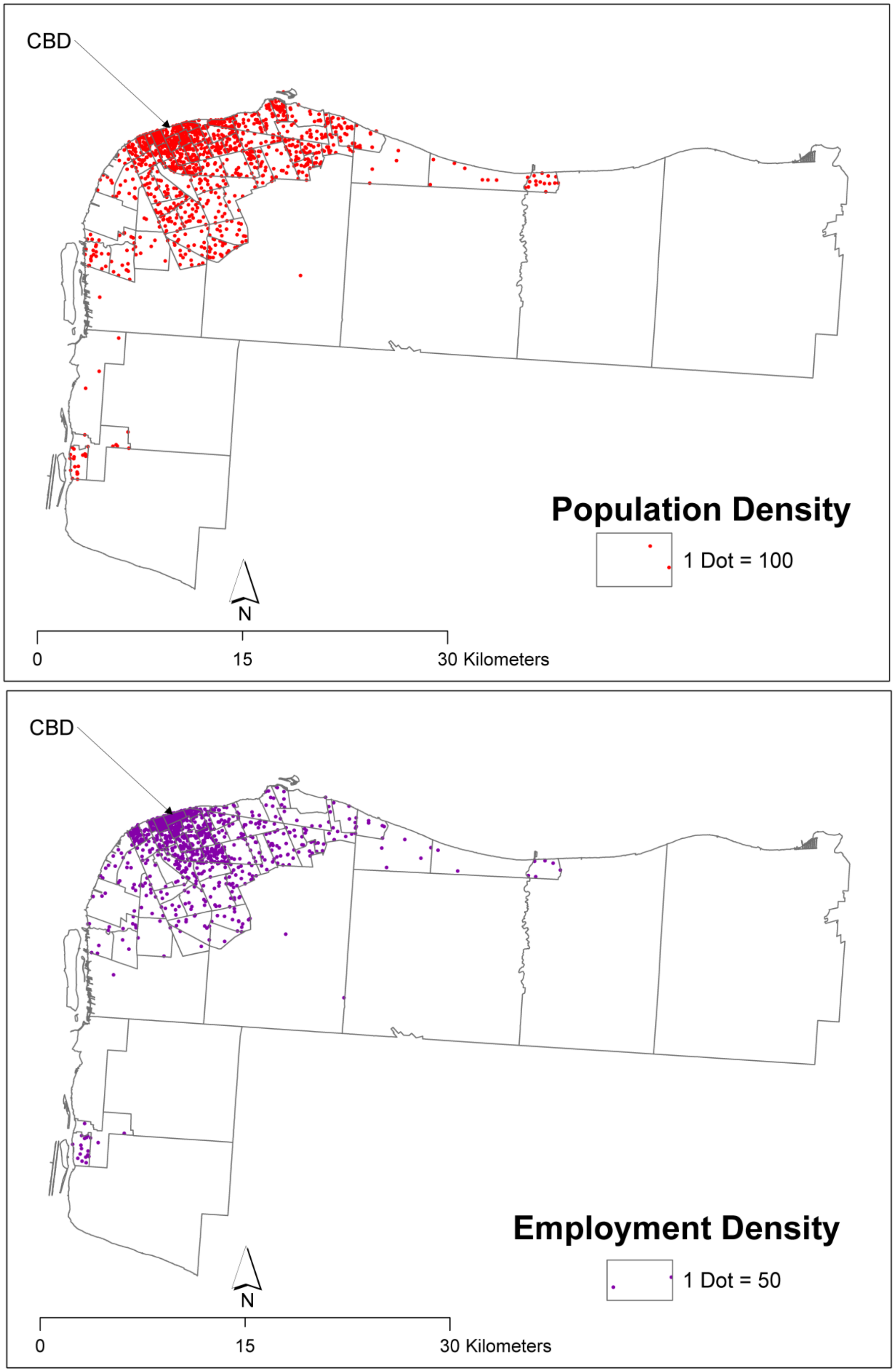

Employment Density
1 Dot = 50
CBD
N
0
10
20 Kilometers

Guelph CMA


Population Density
1 Dot = 200
CBD
N
0
15
30 Kilometers


Employment Density
1 Dot = 70
CBD
N
0
15
30 Kilometers

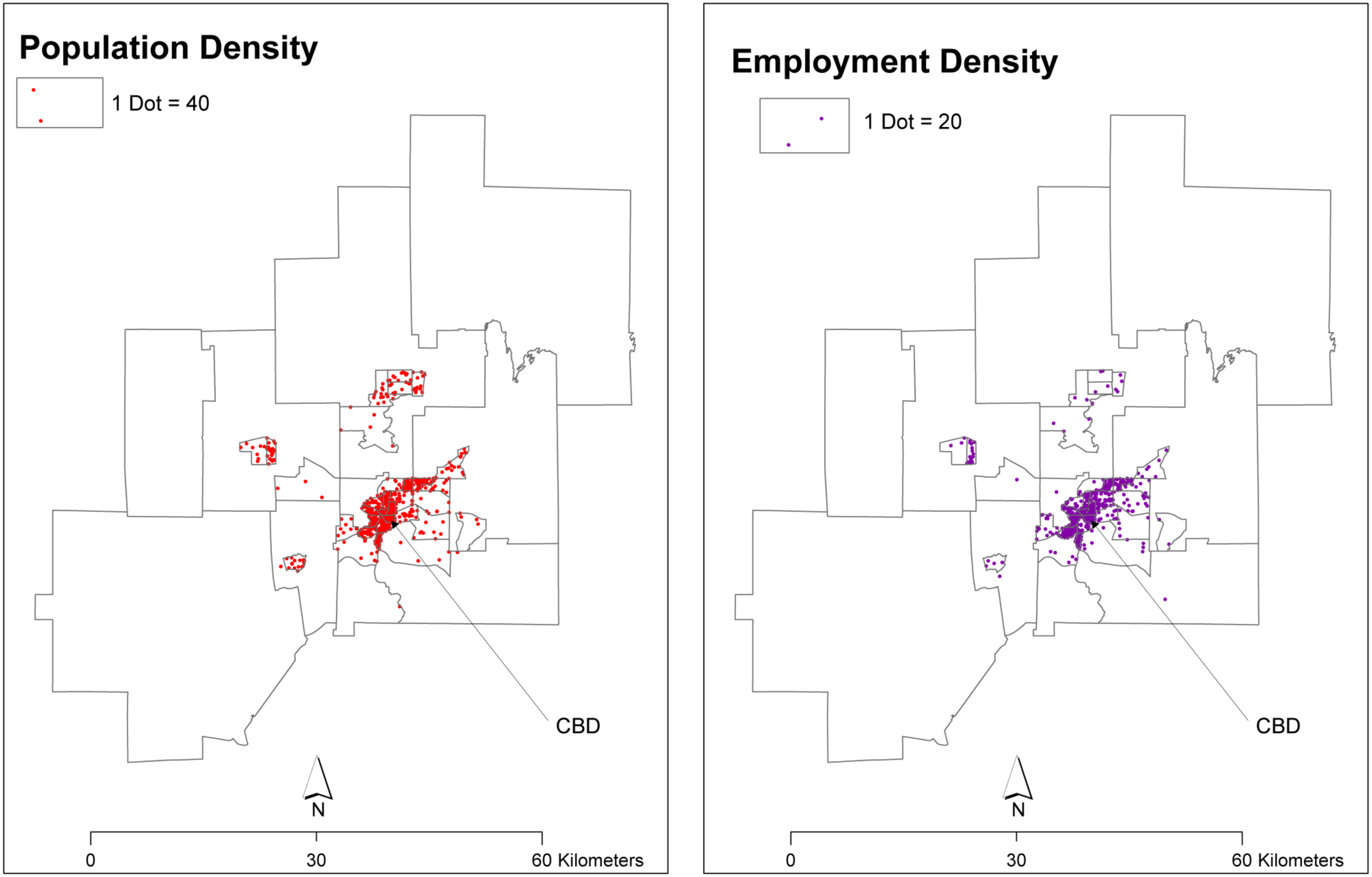
London CMA


CBD
Population Density
1 Dot = 100
N
0
15
30 Kilometers
CBD
Employment Density
1 Dot = 50
N
0
15
30 Kilometers

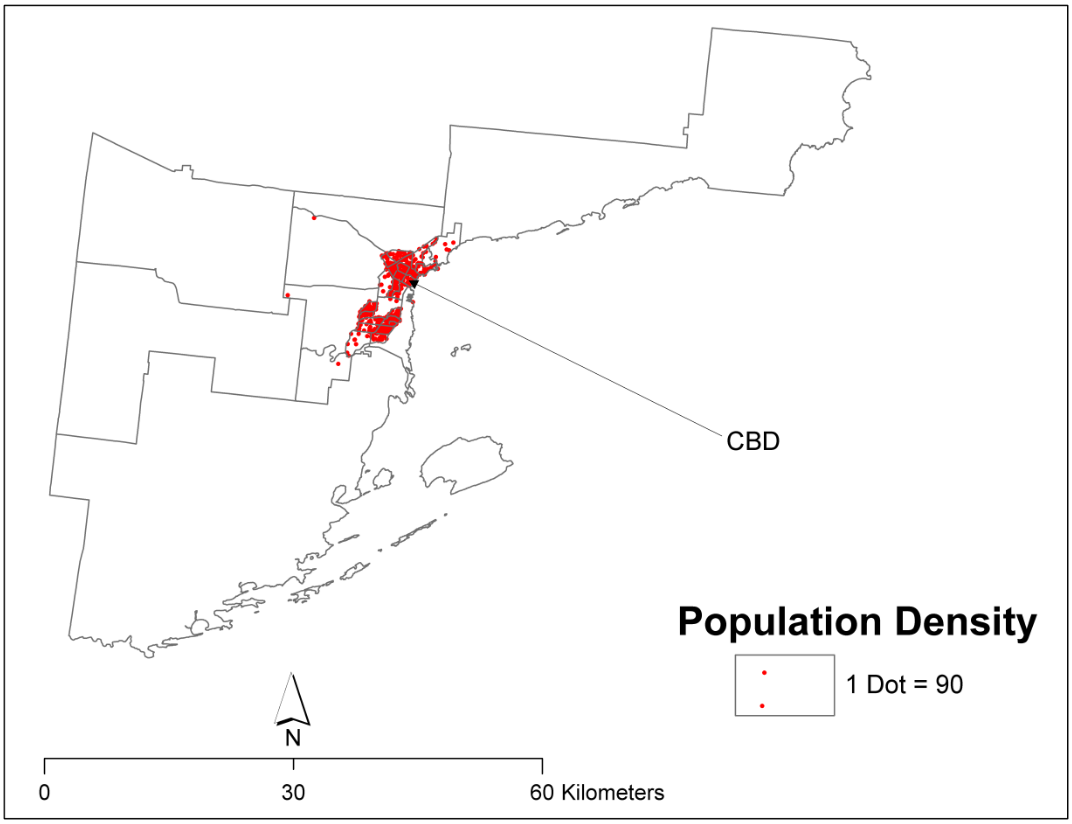
Windsor CMA

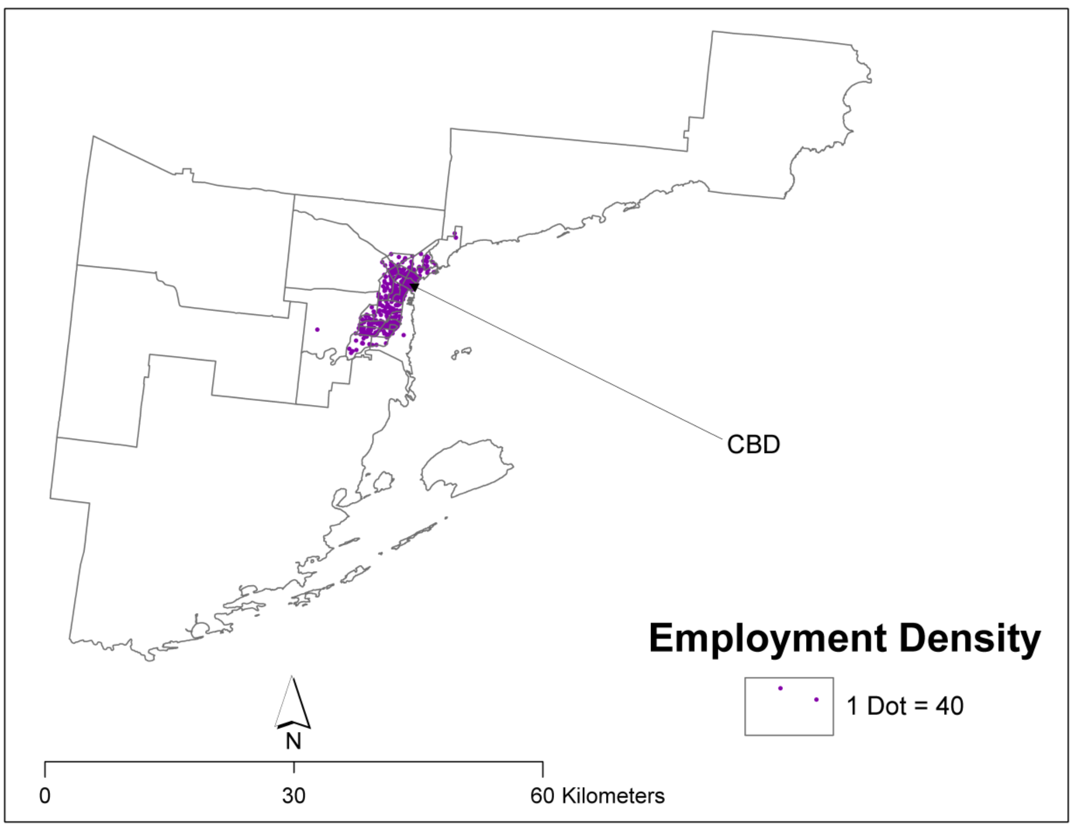

Population Density
1 Dot = 90
CBD
N
0
15
30 Kilometers
Employment Density
1 Dot = 50
CBD
N
0
15
30 Kilometers

Barrie CMA



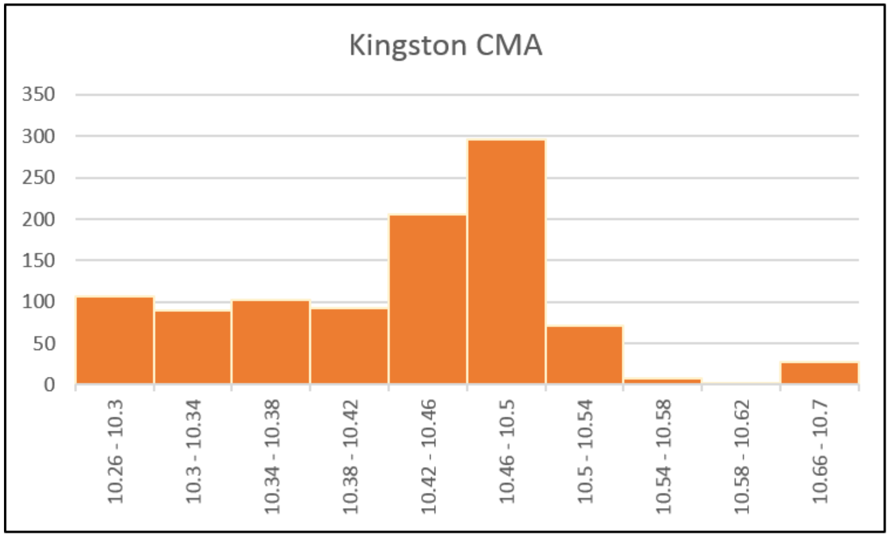
Greater Sudbury CMA

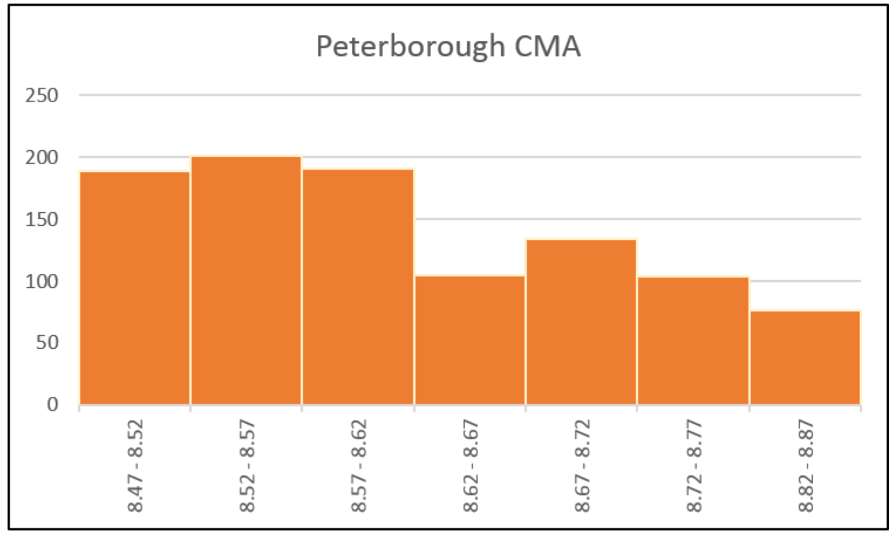


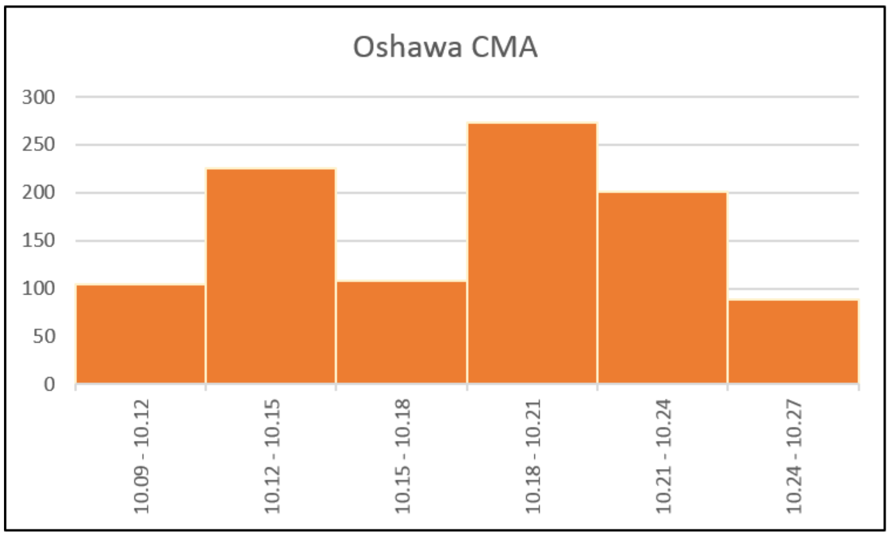


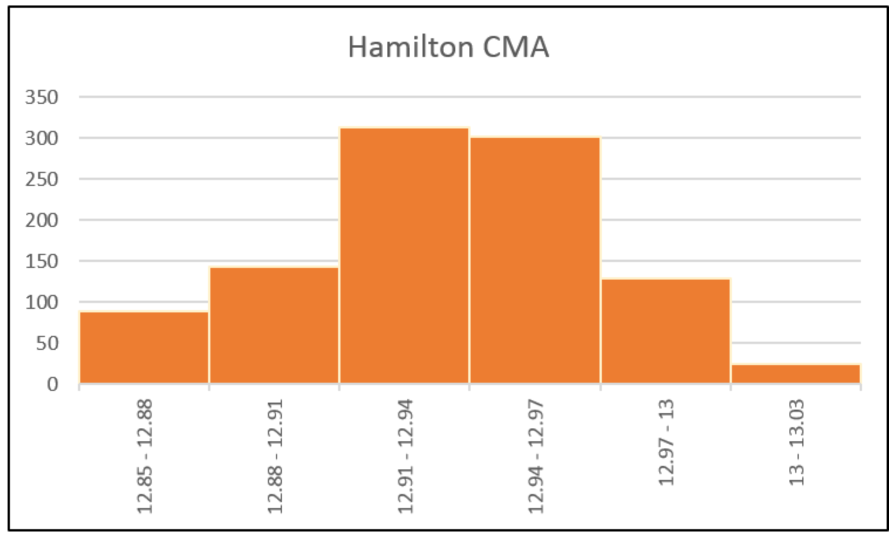
Thunder Bay CMA

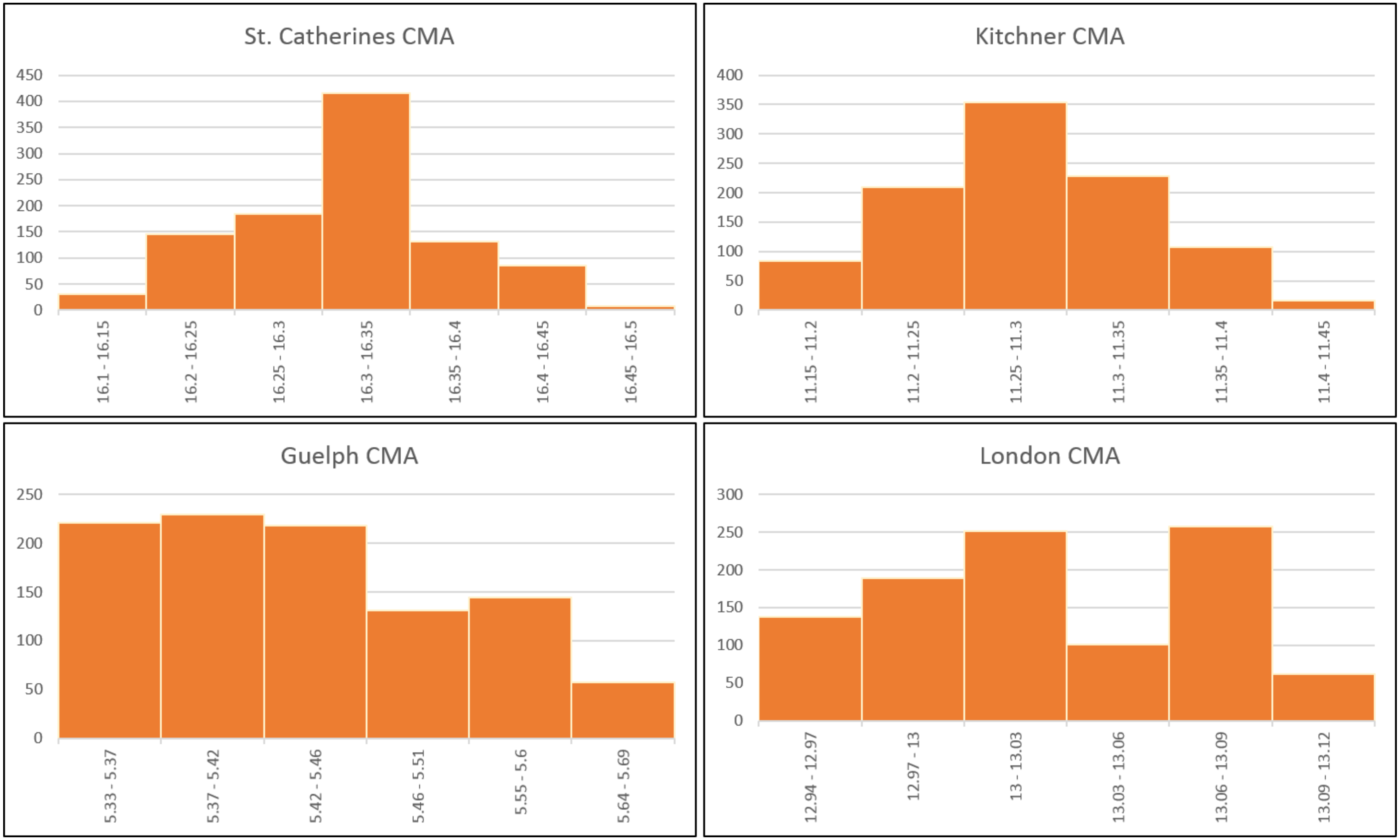
APPENDIX C: Frequency Distributions based on the 1000 Simulated Commuting Possibilities Used to Calculate C_{rnd}

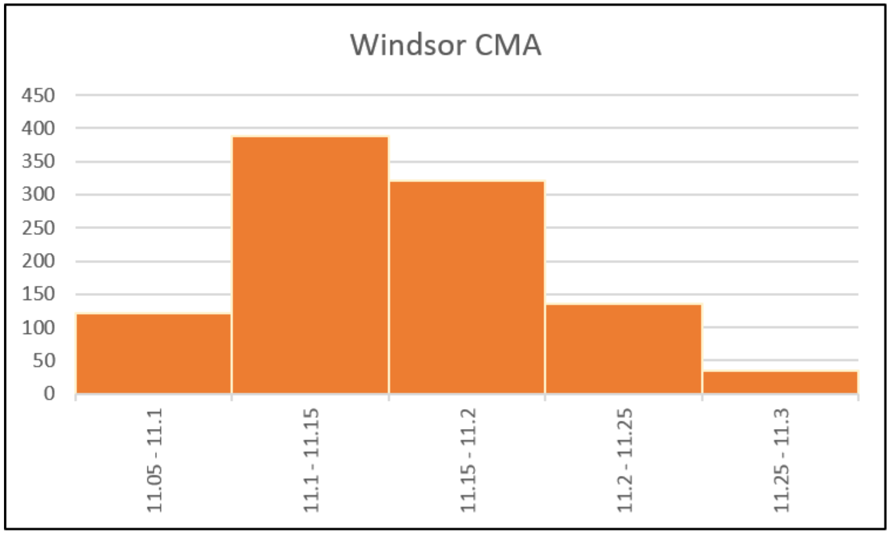

Kingston CMA
350
300
250
200
150
100
50
0
10.26 - 10.3
10.3 - 10.34
10.34 - 10.38
10.38 - 10.42
10.42 - 10.46
10.46 - 10.5
10.5 - 10.54
10.54 - 10.58
10.58 - 10.62
10.66 - 10.7

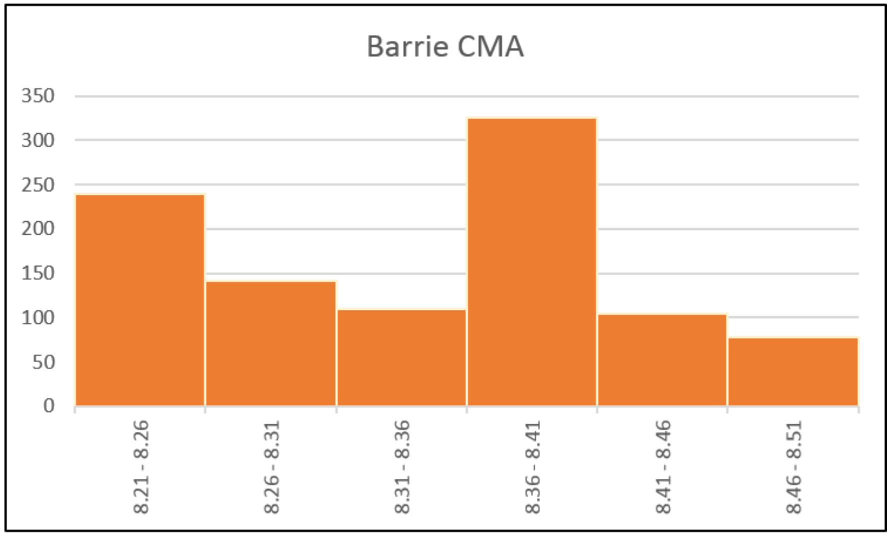

Peterborough CMA
250
200
150
100
50
0
8.47 - 8.52
8.52 - 8.57
8.57 - 8.62
8.62 - 8.67
8.67 - 8.72
8.72 - 8.77
8.82 - 8.87

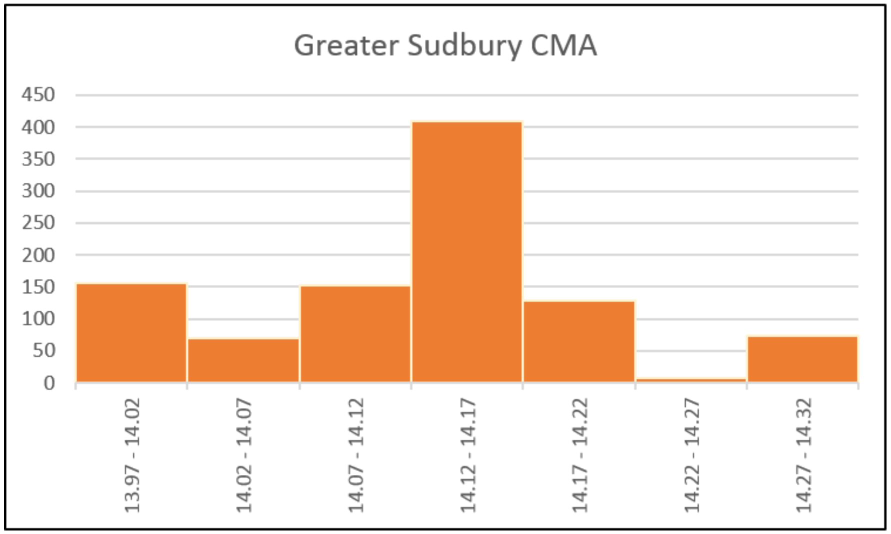

Oshawa CMA
300
250
200
150
100
50
0
10.09 - 10.12
10.12 - 10.15
10.15 - 10.18
10.18 - 10.21
10.21 - 10.24
10.24 - 10.27

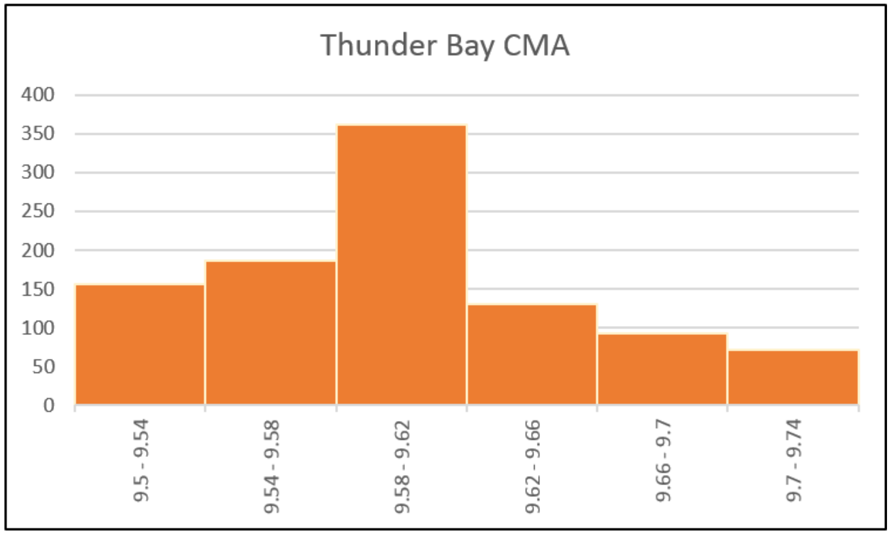

Hamilton CMA
350
300
250
200
150
100
50
0
12.85 - 12.88
12.88 - 12.91
12.91 - 12.94
12.94 - 12.97
12.97 - 13
13 - 13.03


St. Catherines CMA
450
400
350
300
250
200
150
100
50
0
16.1 - 16.15
16.2 - 16.25
16.25 - 16.3
16.3 - 16.35
16.35 - 16.4
16.4 - 16.45
16.45 - 16.5
Kitchner CMA
400
350
300
250
200
150
100
50
0
11.15 - 11.2
11.2 - 11.25
11.25 - 11.3
11.3 - 11.35
11.35 - 11.4
11.4 - 11.45
Guelph CMA
250
200
150
100
50
0
5.33 - 5.37
5.37 - 5.42
5.42 - 5.46
5.46 - 5.51
5.55 - 5.6
5.64 - 5.69
London CMA
300
250
200
150
100
50
0
12.94 - 12.97
12.97 - 13
13 - 13.03
13.03 - 13.06
13.06 - 13.09
13.09 - 13.12


Windsor CMA
450
400
350
300
250
200
150
100
50
0
11.05 - 11.1
11.1 - 11.15
11.15 - 11.2
11.2 - 11.25
11.25 - 11.3


Barrie CMA
350
300
250
200
150
100
50
0
8.21 - 8.26
8.26 - 8.31
8.31 - 8.36
8.36 - 8.41
8.41 - 8.46
8.46 - 8.51


Greater Sudbury CMA
450
400
350
300
250
200
150
100
50
0
13.97 - 14.02
14.02 - 14.07
14.07 - 14.12
14.12 - 14.17
14.17 - 14.22
14.22 - 14.27
14.27 - 14.32


Thunder Bay CMA
400
350
300
250
200
150
100
50
0
9.5 - 9.54
9.54 - 9.58
9.58 - 9.62
9.62 - 9.66
9.66 - 9.7
9.7 - 9.74

APPENDIX D: Summary of Commuting Measures and Excess Commuting for 10 Occupation Types in the 12 CMAs

Occupation #1 - Management

CMA ID	CMA Name	C_{min} (km)	C_{obs} (km)	C_{rnd} (km)	C_{max} (km)	Excess Commuting (C_{ex})	Commuting Potential Utilised (C_u)
568	Barrie	1.99	5.69	9.12	12.14	65%	36%
580	G. Sudbury	3.42	9.64	14.06	18.31	64%	42%
550	Guelph	1.48	4.49	5.97	8.15	67%	45%
537	Hamilton	2.48	8.08	14.13	20.16	69%	32%
521	Kingston	3.67	9.15	11.79	15.68	60%	46%
541	Kitchener	1.93	6.46	11.59	16.53	70%	31%
555	London	2.72	7.65	14.28	18.52	64%	31%
532	Oshawa	2.54	6.55	10.29	14.01	61%	35%
529	Peterborough	3.49	8.01	10.72	13.49	56%	45%
539	St. Catherines	2.00	7.47	16.66	23.41	73%	26%
595	Thunder Bay	3.28	7.69	10.19	12.93	57%	46%
559	Windsor	3.31	8.36	12.36	16.51	60%	38%

Occupation #2 - Business, Finance and Administration

CMA ID	CMA Name	C_{max} (km)	C_{min} (km)	C_{obs} (km)	C_{rnd} (km)	Excess Commuting (C_{ex})	Commuting Potential Utilised (C_u)
568	Barrie	10.92	2.35	5.66	8.26	58%	39%
580	G. Sudbury	16.17	5.42	10.02	12.83	46%	43%
550	Guelph	7.53	1.49	4.35	5.57	66%	47%
537	Hamilton	18.25	2.65	7.90	13.01	66%	34%
521	Kingston	13.51	4.87	8.50	10.50	43%	42%
541	Kitchener	15.47	2.06	6.38	11.04	68%	32%
555	London	14.97	3.03	7.15	11.79	58%	34%
532	Oshawa	13.07	2.94	6.50	9.82	55%	35%
529	Peterborough	11.06	3.69	7.09	8.94	48%	46%
539	St. Catherines	23.12	2.12	7.43	16.51	71%	25%
595	Thunder Bay	12.04	3.34	7.42	9.51	55%	47%
559	Windsor	14.52	4.16	8.21	11.07	49%	39%

Occupation #3 - Natural and Applied Sciences and Related Occupations

CMA ID	CMA Name	C_{max} (km)	C_{min} (km)	C_{obs} (km)	C_{rnd} (km)	Excess Commuting (C_{ex})	Commuting Potential Utilised (C_u)
568	Barrie	10.85	2.24	5.86	8.19	62%	42%
580	G. Sudbury	17.01	4.80	10.39	13.22	54%	46%
550	Guelph	7.67	2.08	4.70	5.67	56%	47%
537	Hamilton	18.74	5.03	8.95	13.33	44%	29%
521	Kingston	14.34	4.88	9.44	11.05	48%	48%
541	Kitchener	14.23	2.65	6.53	10.31	59%	33%
555	London	14.95	4.01	7.72	11.81	48%	34%
532	Oshawa	14.28	3.37	7.34	10.49	54%	36%
529	Peterborough	10.28	2.76	6.46	8.22	57%	49%
539	St. Catherines	22.47	3.33	8.46	16.10	61%	27%
595	Thunder Bay	11.53	3.94	7.73	8.99	49%	50%
559	Windsor	12.88	3.45	7.77	9.54	56%	46%

Occupation #4 - Health

CMA ID	CMA Name	C_{max} (km)	C_{min} (km)	C_{obs} (km)	C_{rnd} (km)	Excess Commuting (C_{ex})	Commuting Potential Utilised (C_u)
568	Barrie	9.92	3.05	5.50	7.60	45%	36%
580	G. Sudbury	16.45	7.86	10.73	12.99	27%	33%
550	Guelph	7.05	2.32	4.39	5.33	47%	44%
537	Hamilton	14.96	3.28	7.45	11.29	56%	36%
521	Kingston	11.63	6.34	8.06	9.50	21%	32%
541	Kitchener	14.65	1.89	5.75	10.65	67%	30%
555	London	15.96	3.06	6.94	12.25	56%	30%
532	Oshawa	12.73	4.09	6.70	9.96	39%	30%
529	Peterborough	9.13	4.19	6.86	7.66	39%	54%
539	St. Catherines	23.25	2.79	7.09	16.54	61%	21%
595	Thunder Bay	10.23	4.87	7.48	8.38	35%	49%
559	Windsor	13.52	5.04	7.99	10.54	37%	35%

Occupation #5 - Education, Law and Social, Community and Government Services

CMA ID	CMA Name	C_{max} (km)	C_{min} (km)	C_{obs} (km)	C_{rnd} (km)	Excess Commuting (C_{ex})	Commuting Potential Utilised (C_u)
568	Barrie	10.55	1.49	4.93	7.88	70%	38%
580	G. Sudbury	16.97	3.77	8.81	13.01	57%	38%
550	Guelph	6.40	1.52	3.79	4.81	60%	47%
537	Hamilton	16.50	2.39	7.55	12.02	68%	37%
521	Kingston	12.53	2.90	7.45	9.69	61%	47%
541	Kitchener	14.96	1.36	5.84	10.71	77%	33%
555	London	14.74	2.49	6.45	11.51	61%	32%
532	Oshawa	13.31	2.93	6.40	9.89	54%	33%
529	Peterborough	9.62	2.19	6.14	7.63	64%	53%
539	St. Catherines	21.80	1.77	7.30	15.48	76%	28%
595	Thunder Bay	13.24	2.72	7.48	10.23	64%	45%
559	Windsor	14.70	3.58	7.35	11.07	51%	34%

Occupation #6 - Art, Culture, Recreation and Sport

CMA ID	CMA Name	C_{max} (km)	C_{min} (km)	C_{obs} (km)	C_{rnd} (km)	Excess Commuting (C_{ex})	Commuting Potential Utilised (C_u)
568	Barrie	10.37	1.85	5.04	7.77	63%	37%
580	G. Sudbury	14.28	5.09	9.21	11.36	45%	45%
550	Guelph	7.23	1.00	3.95	5.36	75%	47%
537	Hamilton	17.24	2.66	7.61	12.46	65%	34%
521	Kingston	12.72	4.19	8.10	10.10	48%	46%
541	Kitchener	14.06	1.54	5.73	10.29	73%	34%
555	London	13.56	2.05	6.28	10.50	67%	37%
532	Oshawa	14.80	1.56	6.29	10.77	75%	36%
529	Peterborough	8.39	2.58	5.60	6.71	54%	52%
539	St. Catherines	23.28	3.52	8.06	16.61	56%	23%
595	Thunder Bay	12.29	5.08	7.91	10.00	36%	39%
559	Windsor	14.30	2.65	7.37	10.78	64%	41%

Occupation #7 - Sales and Service

CMA ID	CMA Name	C_{max} (km)	C_{min} (km)	C_{obs} (km)	C_{rnd} (km)	Excess Commuting (C_{ex})	Commuting Potential Utilised (C_u)
568	Barrie	10.61	1.97	5.09	7.96	61%	36%
580	G. Sudbury	17.56	3.23	9.07	13.53	64%	41%
550	Guelph	6.86	1.27	3.97	5.04	68%	48%
537	Hamilton	18.05	2.06	7.13	12.70	71%	32%
521	Kingston	12.22	3.31	7.38	9.25	55%	46%
541	Kitchener	15.60	1.68	5.86	11.05	71%	30%
555	London	15.91	1.81	6.40	12.15	72%	33%
532	Oshawa	13.36	2.67	6.17	9.94	57%	33%
529	Peterborough	9.59	2.50	5.74	7.57	56%	46%
539	St. Catherines	21.98	1.94	6.65	15.54	71%	24%
595	Thunder Bay	11.16	3.57	6.95	8.69	49%	44%
559	Windsor	14.02	2.86	7.23	10.60	61%	39%

Occupation #8 - Trades, Transport, Equipment Operators and Related Occupations

CMA ID	CMA Name	C_{max} (km)	C_{min} (km)	C_{obs} (km)	C_{rnd} (km)	Excess Commuting (C_{ex})	Commuting Potential Utilised (C_u)
568	Barrie	12.27	3.38	6.26	9.52	46%	32%
580	G. Sudbury	22.85	4.73	11.58	17.08	59%	38%
550	Guelph	7.88	2.41	4.82	5.97	50%	44%
537	Hamilton	18.24	3.76	8.57	13.30	56%	33%
521	Kingston	16.49	4.38	10.55	12.52	58%	51%
541	Kitchener	17.01	2.71	6.90	11.95	61%	29%
555	London	19.71	3.48	8.24	15.00	58%	29%
532	Oshawa	14.34	3.93	7.39	10.73	47%	33%
529	Peterborough	13.85	3.70	8.28	11.01	55%	45%
539	St. Catherines	23.58	1.90	7.53	16.61	75%	26%
595	Thunder Bay	13.50	4.10	8.21	10.65	50%	44%
559	Windsor	16.01	3.59	8.90	12.09	60%	43%

Occupation #9 - Natural Resources, Agriculture and Related Production Occupations

CMA ID	CMA Name	C_{max} (km)	C_{min} (km)	C_{obs} (km)	C_{rnd} (km)	Excess Commuting (C_{ex})	Commuting Potential Utilised (C_u)
568	Barrie	21.50	4.69	7.49	15.82	37%	17%
580	G. Sudbury	26.68	7.11	12.79	19.56	44%	29%
550	Guelph	11.17	2.73	5.72	8.16	52%	35%
537	Hamilton	23.29	6.17	11.23	17.04	45%	30%
521	Kingston	21.21	6.99	14.21	15.70	51%	51%
541	Kitchener	20.93	5.17	8.93	14.79	42%	24%
555	London	32.76	3.72	10.30	23.30	64%	23%
532	Oshawa	19.11	5.20	8.54	13.90	39%	24%
529	Peterborough	20.41	4.45	10.50	15.26	58%	38%
539	St. Catherines	26.99	6.47	10.86	19.55	40%	21%
595	Thunder Bay	17.32	3.89	9.13	13.30	57%	39%
559	Windsor	20.83	6.14	11.28	15.61	46%	35%

Occupation #10 - Manufacturing and Utilities

CMA ID	CMA Name	C_{max} (km)	C_{min} (km)	C_{obs} (km)	C_{rnd} (km)	Excess Commuting (C_{ex})	Commuting Potential Utilised (C_u)
568	Barrie	9.33	3.70	5.95	7.35	38%	40%
580	G. Sudbury	19.91	6.50	12.28	15.20	47%	43%
550	Guelph	6.75	2.37	4.59	5.19	48%	51%
537	Hamilton	16.81	5.77	9.23	12.77	38%	31%
521	Kingston	14.42	6.26	10.39	11.51	40%	51%
541	Kitchener	16.73	3.78	7.46	11.71	49%	28%
555	London	23.01	4.41	8.79	17.12	50%	24%
532	Oshawa	12.76	6.25	8.55	10.09	27%	35%
529	Peterborough	10.41	3.78	7.12	8.35	47%	50%
539	St. Catherines	24.61	3.04	7.84	17.35	61%	22%
595	Thunder Bay	13.41	6.43	9.00	11.04	29%	37%
559	Windsor	14.29	4.69	9.31	11.07	50%	48%

APPENDIX E: Summary of Excess Commuting Results for the 10 Occupation Types

Compared to CMA-Wide Excess Commuting for the 12 CMAs

CMA #	CMA Name	Excess Commute										
		CMA Wide	**Occ. #1**	**Occ. #2**	**Occ. #3**	**Occ. #4**	**Occ. #5**	**Occ. #6**	**Occ. #7**	**Occ. #8**	**Occ. #9**	**Occ. #10**
1	Barrie	65%	65%	58%	62%	45%	70%	63%	61%	46%	37%	38%
2	G. Sudbury	62%	64%	46%	54%	27%	57%	45%	64%	59%	44%	47%
3	Guelph	66%	67%	66%	56%	47%	60%	75%	68%	50%	52%	48%
4	Hamilton	68%	69%	66%	44%	56%	68%	65%	71%	56%	45%	38%
5	Kingston	54%	60%	43%	48%	21%	61%	48%	55%	58%	51%	40%
6	Kitchener	71%	70%	68%	59%	67%	77%	73%	71%	61%	42%	49%
7	London	68%	64%	58%	48%	56%	61%	67%	72%	58%	64%	50%
8	Oshawa	56%	61%	55%	54%	39%	54%	75%	57%	47%	39%	27%
9	Peterborough	60%	56%	48%	57%	39%	64%	54%	56%	55%	58%	47%
10	St. Catherines	75%	73%	71%	61%	61%	76%	56%	71%	75%	40%	61%
11	Thunder Bay	57%	57%	55%	49%	35%	64%	36%	49%	50%	57%	29%
12	Windsor	59%	60%	49%	56%	37%	51%	64%	61%	60%	46%	50%

Occupation Numbers:

#1 Management
#2 Business
#3 Science
#4 Health
#5 Education
#6 Art
#7 Sales
#8 Trades
#9 Natural Resources
#10 Manufacturing

APPENDIX F: Summary of Occupation Excess Commuting Results Compared to CMA Results

1 - Management												
Much Lower:												
Lower:												
Almost Equal:	Greater Sudbury	Hamilton	Kingston	London	Oshawa	Windsor	Guelph	Kitchener	St. Catherines	Thunder Bay	Peterborough	Barrie
Higher:												
2 - Business, Finance and Administration												
Much Lower:												
Lower:	Greater Sudbury	Kingston	London	Windsor	Peterborogh							
Almost Equal:	Hamilton	Oshawa	Guelph	Kitchener	St. Catherines	Thunder Bay	Barrie					
Higher:												
3 - Natural and Applied Sciences												
Much Lower:	Hamilton	London										
Lower:	Greater Sudbury	Kingston	Guelph	Kitchener	St. Catherines	Thunder Bay						
Almost Equal:	Windsor	Oshawa	Peterborough	Barrie								
Higher:												

Urban Form:

Compact	Polycentric	Sprawl

4 - Health												
Much Lower:												
Lower:	Greater Sudbury	Windsor	Hamilton	Kingston	London	Oshawa	Guelph	Peterborough	St. Catherines	Thunder Bay	Barrie	
Almost Equal:	Kitchener											
Higher:												

5 - Education, Law, Social Community and Government Services												
Much Lower:												
Lower:	Greater Sudbury	London	Windsor	Guelph	St. Catherines							
Almost Equal:	Hamilton	Oshawa										
Higher:	Kingston	Kitchener	Peterborough	Thunder Bay	Barrie							

6 - Art, Culture, Recreation and Sport												
Much Lower:												
Lower:	Greater Sudbury	Kingston	Peterborough	St. Catherines	Thunder Bay							
Almost Equal:	London	Hamilton	Kitchener	Barrie								
Higher:	Oshawa	Windsor	Guelph									

7 - Sales and Services												
Much Lower:												
Lower:	Thunder Bay											
Almost Equal:	Greater Sudbury	Windsor	Hamilton	Kingston	London	Oshawa	Kitchener	Guelph	Peterborough	St. Catherines	Barrie	
Higher:												
8 - Trades, Transport and Equipment Operators												
Much Lower:												
Lower:	Hamilton	London	Oshawa	Guelph	Kitchener	Peterborough	Thunder Bay	Barrie				
Almost Equal:	Greater Sudbury	Windsor	St. Catherines									
Higher:	Kingston											
9 - Natural Resources, Agriculture and Related Production Occupations												
Much Lower:												
Lower:	Greater Sudbury	Windsor	Hamilton	London	Oshawa	Guelph	Kitchener	St. Catherines	Barrie			
Almost Equal:	Kingston	Peterborough	Thunder Bay									
Higher:												
10 - Manufacturing and Utilities												
Much Lower:	Hamilton	Oshawa	Thunder Bay	Barrie								
Lower:	Greater Sudbury	Kingston	London	Windsor	Kitchener	Guelph	St. Catherines	Peterborough				
Almost Equal:												
Higher:												

VITA AUCTORIS

NAME:	Laura J. Ash
PLACE OF BIRTH:	Windsor, Ontario, Canada
EDUCATION:	Assumption College Catholic Secondary School, Windsor, ON. 2005
	University of Windsor, B.A.Sc. Honours Civil Engineering Co-op, Minor: Mathematics, Windsor, ON. 2009
	University of Windsor, M.A.Sc. Civil Engineering, Windsor, ON. 2017
MEMBERSHIP:	Professional Engineers of Ontario, P.Eng.