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Empirical Analysis of Urban Sprawl in Canadian Census Metropolitan Areas using Satellite Imagery, 1986-2016

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Abstract

Many Canadian cities have experienced rapid sprawl over the last 30 years. This dissertation presents two studies that empirically examine the causes of urban sprawl, merging census socioeconomics data and satellite imageries of 11 major Census Metropolitan Areas (CMAs). The monocentric city model and the Tiebout model are the main traditional theories explaining urban boundary changes and residential mobility. The first study focuses on a cross-sectional comparison among the 11 CMAs in 2016. The second study zooms into the Toronto CMA and examine the longitudinal changes in its urban coverage at its fringes. The land cover/use changes are detected within the Toronto CMA from 1986 to 2016. In both studies, the role of price risk is inserted in understanding the timing of urban development. In doing so, both studies aim to contribute to the literature by broadening the traditional theories to include the role of risk as it influences urban development.

Keywords

Urban sprawl, Remote Sensing, monocentric city model, Canadian Metropolitan Areas

Summary for Lay Audience

Urban sprawl is one of the most important issues facing most cities around the world. Many Canadian cities have experienced rapid sprawl over the last 30 years. This dissertation presents two studies that empirically examine the causes of urban sprawl, merging census socioeconomics data and satellite imageries of 11 major Census Metropolitan Areas (CMAs) in 1986, 2006 and 2016. Two branches of traditional theories of urban sprawl, the monocentric city model and the Tiebout model, are used to explain urban boundary changes. The first empirical study focuses on a cross-sectional comparison among the 11 CMAs and attempts to study the role of price risk in influencing the extent of urban coverage expansion outside of the cities covered by the CMA boundaries. The second study focuses on the largest CMA in Canada, Toronto, and examine the longitudinal changes in its urban coverage at its fringes. The land cover/use changes are detected within the Toronto CMA for 1986-2006 and 2006-2016. The 1986, 2006 and 2016 satellite imageries are matched with residents' socioeconomic data from the corresponding census, forming a panel data set, based on Dissemination Areas, for the Toronto CMA. Similar to the first study, price risk is included as a variable to understand the timing of urban development. In doing so, both studies aim to contribute to the literature by broadening the traditional theories to include the role of risk in influencing urban development.

Co-Authorship Statement

I am responsible for nearly all data collection and experiments and conducted all statistical analyses and writing of the manuscript. Dr. Jinfei Wang and Dr. Diana Mok assisted with study design and improved the manuscript. In Chapter 3, Diana helped record sales data from the TREB. Matthew J. Roffey collected Landsat 5 satellite data of 1986 and 2005 and processed image classification.

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List of Abbreviations

CA — Census Agglomeration

CBD — Central Business District

CMA — Census Metropolitan Area

CPI — Consumer Price Index

CT — Census Tract

CV — Coefficient of Variance

DA — Dissemination Area

DB — Dissemination Block

DID — Difference-In-Difference

EA — Enumeration Area

ESA — European Space Agency

GB — Greenbelt Area

GIS — Geographic Information System

HPI — House Price Index

LTDB — Longitudinal Tract Database

MSI — Multi-spectral Instrument

NPV — Net Present Value

RS — Remote Sensing

SD — Standard Deviation

SI — Sprawl Index

TREB — Toronto Real Estate Board

UA — Urban Area

Chapter 1

1 Introduction

1.1 Research contents

Urban sprawl, a term often used to refer to leapfrog developments in the urban fringe, is commonly considered detrimental to activities of both the economy and the environment. Its negative impacts include, but are not limited to, higher levels of pollution, loss of agricultural land and green space, and increased commuting time (McGibany, 2004). Thus, sprawl has become a national debate for both the public and the government. Sprawl refers to the natural expansion of metropolitan areas as population grows (Brueckner & Fansler, 1983). Strong sentiment against sprawl has developed over the last decade in North American cities, particularly among Canadian cities—for example, among all 35 Census Metropolitan Areas (CMAs) in Canada, populations in central municipalities increased by 5.8%, compared to a 6.9% jump in the peripheral municipalities from 2011 to 2016 (Statistics Canada, 2017). Many scholars have attempted to introduce and address the issue of urban sprawl in Canada (Dupras, Alam, & Revéret, 2015; Filion, 2003; Sun, Forsythe, & Waters, 2007). In particular, Miron (2003) compares sprawl in Canada and America using local density and the variation in it. Miron’s result shows that local density tends to be higher on average in Canadian than American cities.

Some studies have provoked debates and provided thoughts on possible ways to control urban sprawl by establishing efficient policies (Song & Zenou, 2006; Yuan, Sawaya, Loeffelholz, & Bauer, 2005). However, few studies have actually looked at the process and extent of urban sprawl systematically. To achieve this, in the first place, it is important to provide an accurate assessment of the extent of urban boundary changes. The combination of Remote Sensing (RS) and Geographic Information System (GIS) techniques is expected to provide useful information for land cover/use classification and generate more precise maps of urban boundary expansions than any conventional statistical definitions can offer.

Some existing works have started applying remote-sensing methods to the analysis of urban sprawl—for example, Sutton (2003) used nighttime satellite imageries to measure the urban extent since they measure emitted radiation, which can divide land cover into developed and non-developed areas fairly accurately. Studies have shown that satellite data can be used to obtain land cover/use information, thereby revealing the process of urban sprawl (Feng, Du, Li, & Zhu, 2015; Jat, Garg, & Khare, 2008; Yuan et al., 2005). Yuan, Sawaya, Loeffelholz, and Bauer (2005) generated precise land cover/use maps, using the classification method with multi-temporal Landsat TM/ETM+ data, and analyzed patterns of land cover/use change in the Twin Cities Metropolitan Area. In recent years, the emergence of high-resolution satellite imagery has made acquiring observation data more convenient. These imageries provide opportunities for collecting the training and testing samples for land cover/use classification and assessment (Hu et al., 2013).

In particular, part of this thesis (Chapter 2) uses Sentinel-2 satellite imageries. Sentinel-2 is a monitoring mission from the EU Copernicus plan, and it consists of two identical satellites, Sentinel-2A and Sentinel-2B. The first satellite, Sentinel-2A, was launched in June 2015 and Sentinel-2B was launched on March 7, 2017. Each satellite carries a multi-spectral instrument (MSI) with 13 spectral bands. Since Sentinel-2 can provide relatively high-spatial resolution (10 m to 60 m) imagery, it is viewed as an important source for future applications in remote sensing. In the present study, Sentinel-2 data combined with conventional Landsat 5 satellite data (Chapter 3) are used to examine urban boundary expansion. The satellite imageries are matched with residents' socioeconomic data from the corresponding census, forming a data set based on Dissemination Areas (DAs) for the 11 most populous CMAs in Canada, namely Toronto, Montreal, Vancouver, Calgary, Ottawa–Gatineau, Edmonton, Quebec City, Winnipeg, Hamilton, Halifax, and Victoria.

Some scholars conjecture that urban sprawl can be examined in terms of eight different dimensions: density, continuity, concentration, clustering, centrality, nuclearity, mixed uses, and proximity (Galster et al., 2001).This dissertation focuses on one dimension only: nuclearity. This term refers to the extent to which an urban area is characterized by a mononuclear pattern of development. Focusing on this one dimension—nuclearity—

helps provide a first-step systematic and precise analysis of what causes urban sprawl in terms of urban boundary expansions away from the city core. Doing so also allows one to leverage on the long-standing, well-established urban economic theories about urban development. Essentially, the monocentric city model (Alonso, 1964; Muth, 1969; Mills, 1967) and the Tiebout model (Tiebout, 1956) have laid the groundwork and served as the theoretical framework for the analysis.

To be specific, indeed, many studies that have attempted to explain urban sprawl (Brueckner & Fansler, 1983; Burchfield, Overman, Puga, & Turner, 2006; McGrath, 2005; Oueslati, Alvanides, & Garrod, 2015) originate from two branches of theories: the monocentric city model and the Tiebout model. The monocentric city model assumes that a city's spatial size is determined by population, income, agricultural land rent, and commuting costs. According to Wheaton (1974), who has provided a thorough comparative analysis of the monocentric model, urban boundary expands with population and income, but contracts with increasing agricultural land rent and transportation costs. The Tiebout model, on the other hand, assumes residents may "vote by their feet" —that is residents move to locations with public services that meet their preferences. In its original formulation, the Tiebout model has several assumptions. First, residents are free to move across communities and have perfect information about local services. Second, there are enough communities that can meet residents' preferences. Third, the model assumes that there are no externalities or spillover of public goods across municipalities. This relationship between urban sprawl and public services has been examined and verified by a number of empirical studies (Carruthers & Ulfarsson, 2003; Dowding, John, & Biggs, 1994).

However, the existing theories have failed to adequately explain the causes of urban sprawl, by ignoring the role played by the developer in both the development decision (to develop or not to develop) and the timing decision (when to develop). In particular, developers often assess the risk and return of developing a piece of vacant land, fairly distant from the established city core, by calculating the expected discounted benefits of developing now versus the future. Here, risk refers to price risk, namely the total risk in price fluctuations of developments. While some of these risks are systematic, related to policy uncertainties, some others could be developer-specific, related to the developer's own financial risk. This empirical studies adopt a simple approach and focus on the total risk only—the sum of the systematic and unsystematic risk—as reflected in the price variance. Re-inserting this role into the existing theories helps researchers and policy makers in better understanding why certain growth policies might work and why some others are ineffective—this is one of the objectives and contributions of the two empirical studies.

The public data from Canadian census are not readily available for conducting long-term longitudinal studies—that is, it is not a straightforward task to determine and assess land use/cover changes over time. Allen and Taylor (2018) have developed an innovative set of bridging data that can be applied to Census Tracts (CT) over the years, using the combination of dasymetric areal interpolation and population weighting methods. Following Allen and Taylor's method, Chapter 3 focuses on smaller units, which are Dissemination Areas (DAs) and Enumeration Areas (EAs) and conduct boundary reconciliation and data reallocation for 1986, 2006, and 2016 (Chapter 3).

In sum, this dissertation presents two studies that empirically examine the causes of urban sprawl. The first paper focuses on 11 Canadian CMAs and tests the traditional theories of urban sprawl, the monocentric city model and the Tiebout model, using cross-sectional data in 2016. The second paper zooms into the largest CMA in Canada, Toronto, and examines the longitudinal changes in the urban coverage at the fringe. Land cover/use changes in the Toronto CMA for 1986-2006 and 2006-2016 are detected using remote-sensing techniques. Both papers are innovative in that they attempt to broaden the existing theories by inserting the role of price risk to the understanding of the timing of urban development. In particular, both papers seek to provide an empirical analysis of how price risk influences the extent and the timing of urban development from the developer's perspective.

1.2 Research objectives

The objectives of this thesis are as follows:

1. To refine previous studies by adopting a more precise delineation of urban coverage for statistical analysis of urban sprawl. Built-up areas extracted from land cover/use maps are used based on Sentinel-2 satellite imageries for the 11 CMAs in 2016 instead of using census data.

2. To detect changes in the land cover/use patterns for the Toronto CMA using a combination of Sentinel-2 and Landsat 5 satellite imageries from 1986, 2006, and 2016 at the DA (or EA) level.

3. To test the monocentric city model and the Tiebout model using the 11 most populous CMAs in Canada and particularly the Toronto CMA.

4. To fill in the research gap by inserting the role of price risk and, specifically, the availability of the real option, in affecting the speed of urban sprawl. The dissertation challenges the efficacy of contemporary urban growth policies: They focus mostly on the demand and supply side of growth, but have ignored important market factors such as price risks. Once price risks have been taken into account, developers do consider the timing of their development, thereby affecting both the extent and the speed of urban sprawl.

1.3 Study area and data

Chapter 2 examines the 11 most populous Canadian CMAs: Toronto, Montreal, Vancouver, Calgary, Ottawa—Gatineau, Edmonton, Quebec City, Winnipeg, Hamilton, Halifax, and Victoria (Figure 1.1). It focuses on these CMAs because of data availability: The study requires the use of price indices to construct the risk variable. Price indices are available for these CMAs only. According to Statistics Canada, a CMA is defined as an area that is formed by one or more adjacent municipalities located around a core (Statistics Canada, 2016). A CMA must have a total population of at least 100,000. The spatial vastness of a CMA implies that its boundary often encompasses the boundary of a city; the latter is defined politically by the city government.

In Chapter 3, the study narrows the scope to the largest CMA in Canada, Toronto. It is the most populous CMA in Canada and covers a total area of 7,124.15 km^2. The scope of the Toronto CMA includes the cities of Toronto, Mississauga, Brampton, Markham, and Vaughan. From the 2016 census, the total population of the Toronto CMA is 5,928,040, which increased by 6.18% from 2011. This increase in population came together with rapid urban coverage changes in the fringe outside of the city. It is indeed this land cover/use change at the edge of the city that urban sprawl is referred to in this study.

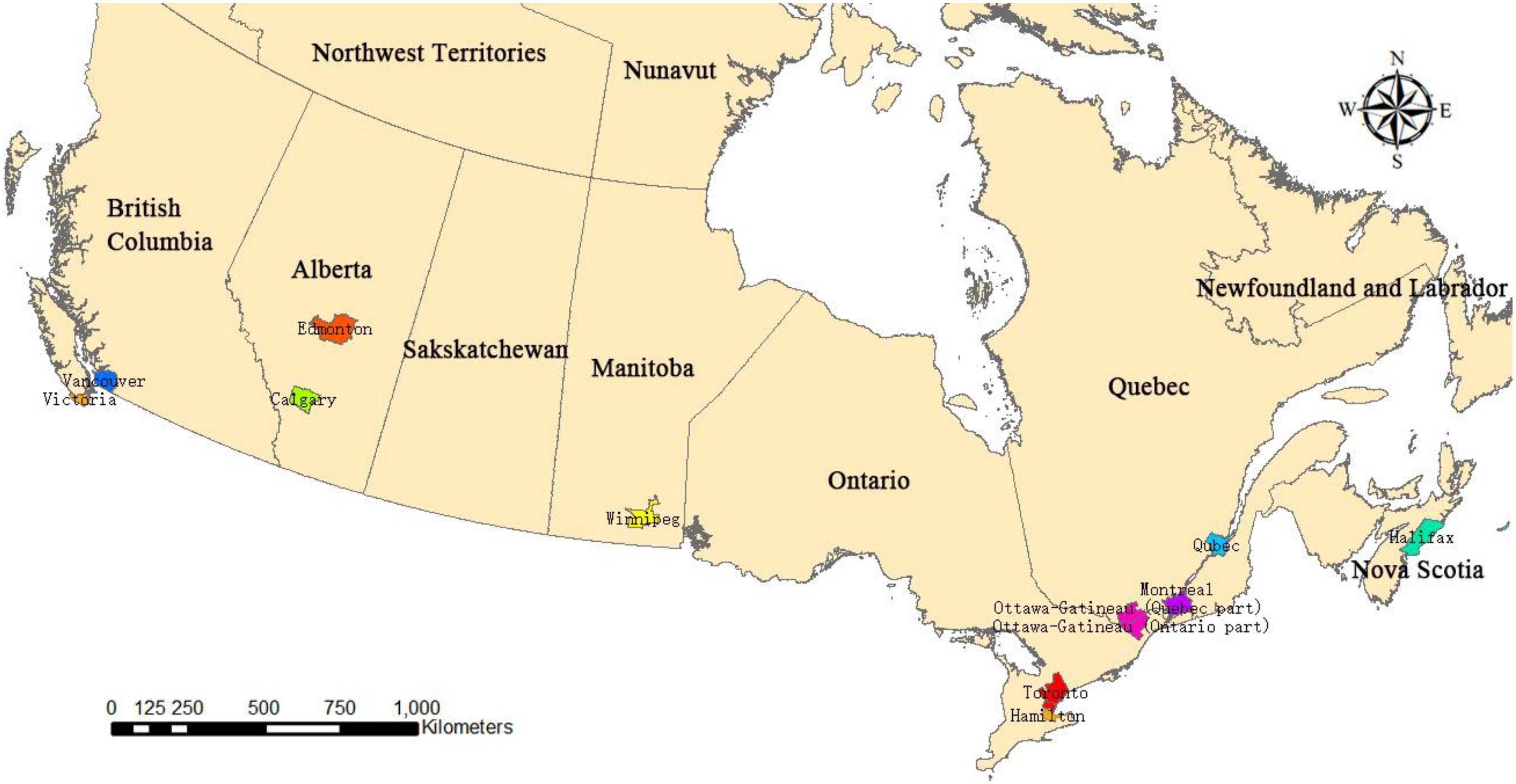

Figure 1. 1 Study area

Data used in this study can be generally categorized as two types: remote-sensing data and census data.

Landsat 5 was launched on March 1, 1984 and was a low Earth orbit satellite for collecting imagery, with the multi-spectral bands' resolution of up to 30 m. It is widely used to study climate change, agricultural practices, and the development of cities (Earth Observing System, 2012). Along with the technical progress, a new generation of high spatial-resolution satellite imagery makes it possible to widen the application of satellite imagery—for example, Sentinel-2 is a "Landsat-like" observatory from the Copernicus Programme of the European Space Agency (ESA). It achieves five-day repeat period with two twin satellites, S2A and S2B. S2A was launched on June 23, 2015, while S2B was launched on March 7, 2017. In the present study, only S2A data are used. Compared to the sensors of Landsat 5, those of Sentinel-2 have more spectral bands (i.e., 13 for Sentinel-2 sensors versus 7 for Landsat 5 sensors) and higher spatial resolution, which is up to 10 meters. The spatial resolution of main visible and near-infrared Sentinel-2A bands is 10 m, and that of red, near-infrared and two shortwave infrared bands is 20 m. The coastal/aerosol, water vapor, and cirrus bands have a spatial resolution of 60 m. Landsat 5 TM and ETM+ satellite imageries from 1986 and 2005 and Sentinel-2 data of 2016 were collected and used in this study. High-resolution imageries from Google Earth were also acquired as reference maps for selecting training samples and testing samples during image classification.

The CMA boundaries and census units' (e.g., EAs and DAs) boundaries were obtained from Statistics Canada. Census statistical data for residents' socioeconomic status in 1986, 2006, and 2016 from Statistics Canada are matched with remote-sensing data to test the monocentric city model. Residential property tax rates of municipalities are also used to examine the Tiebout model. In addition, the House Price Index (HPI) from the Teranet–National Bank and housing sales data from the Toronto Real Estate Board (TREB) are acquired to test the role of price risk.

1.4 Thesis organization

The research is presented in the integrated-article format. Chapters 2 and 3 are written independently, tailored for submissions to peer-reviewed journals.

The thesis is structured as follows. Chapter 1, Introduction, presents a brief overview of the dissertation. It reviews the theories and previous studies related to this research. It states the objectives and defines the study area as well as the data used in the dissertation.

Chapter 2 is the first of the two integrated papers. It presents a cross-sectional comparison among the 11 most populous CMAs in Canada in terms of their extent of urban sprawl. It examines the two traditional theories of urban sprawl: the monocentric city model and the Tiebout model. It also studies the role of price risk in affecting the extent of urban land cover/use changes in developable land outside of cities.

Chapter 3 is the second of the two integrated papers. It presents a longitudinal case study of the Toronto CMA. It employs the difference-in-difference model to study how price risk might have affected both the extent and the timing of urban land cover/use changes outside of the city in the Toronto CMA.

Chapter 4 provides a summary of the results, followed by a discussion of the contributions to the literature. It also presents the limitations of this research and suggestions for future research.

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2 Testing Theories of Urban Sprawl Using Sentinel-2 Imagery: A Cross-sectional Comparison among 11 Canadian Census Metropolitan Areas

2.1 Introduction

2.1.1 Background

Sprawl is among the most important issues facing contemporary cities. The issue has been placed on the national agenda, with the Canadian federal government calling for research on growth management policies to guide the "smart growth" of cities (Policy Horizons Canada, 2016). Strong sentiment against sprawl has developed over the last decade in North American cities. At the root of this sentiment are a number of problems associated with "unmanaged" urban growth (Alexander & Tomalty, 2002; Daniels, 2001; Filion, 2003). Cities encroach excessively on agricultural land, leading to a loss of open space and farmland. Urban expansion implies longer commutes, generating traffic congestion and air pollution. Low-density suburban developments increase residents' reliance on automobiles, potentially contributing to obesity due to a lack of physical exercise. Scattered developments cost more in terms of municipal services. A large number of studies have assessed the economic and environmental costs of sprawl and recommended policies to better manage urban growth; however, little has been done to document systematically the process and extent of sprawl. Knowing exactly the location and the extent of urban boundary changes are important, as they provide a basis for designing smart growth policies and for anticipating changes in financing and servicing the expansion. The objective of this study is to fill this research gap, using 11 Canadian Census Metropolitan Areas (CMAs) as comparative case studies, namely Toronto, Montreal, Vancouver, Calgary, Ottawa–Gatineau, Edmonton, Quebec City, Winnipeg, Hamilton, Halifax, and Victoria.

Definitions of urban sprawl vary. According to Brueckner and Fansler (1983), urban sprawl is characterized by vigorous spatial expansion of urban areas. Yuan et al. (2005) suggest that urban sprawl is an indication of economic activities. In the present study, urban sprawl is defined as increased urban land coverage in developable land in fringe areas outside of cities. Urban land coverage is measured as the amount of built-up land area in the fringe of the 11 CMAs. This definition excludes protected areas such as the greenbelt (see Appendix A). Note that the boundary of the greenbelt (mainly in Toronto and Ottawa) has remained stable over the last 30 years.

The present study differs from those in the past (Carruthers & Ulfarsson, 2003; Oueslati, Alvanides, & Garrod, 2015) in that it focuses on the urban extent in terms of urban land cover and land use. Census data have usually been used to form sprawl indices in past studies. The emergence of satellite imagery has provided a new method for monitoring land cover/use changes (Alberti, Weeks, & Coe, 2004). The combination of remote sensing and geographic information science (GIS) techniques can add details to the detection of land cover/use changes.

Traditional theories that explain urban sprawl stem mostly from two branches: the monocentric city model (Alonso, 1964; Muth, 1969; Mills, 1967) and the Tiebout model (Tiebout, 1956). The monocentric city model focuses on changes associated with the residents, such as changes in income and transportation costs. Based on the monocentric city model, existing empirical studies mostly find consistent evidence supporting the theory: increases in population and household incomes induce a higher demand for urban areas thereby causing urban boundaries to expand; urban boundaries shrink as the commuting costs and agricultural land rent increase (Brueckner & Fansler, 1983; Gao, Kii, Nonomura, & Nakamura, 2017; McGrath, 2005; Oueslati, Alvanides, & Garrod, 2015). It is arguable that one can hardly find, in reality, contemporary cities with only one employment center, thereby rendering the monocentric city model inapplicable. However, the monocentric city model is the starting point for understanding the crude, discrete location choices of in-versus-outside of the city, a simple application that allows the researcher to use the model to study urban sprawl.

The Tiebout model, on the other hand, focuses on people searching for public goods and services; residents move to locations that meet their preferences by “voting with their feet”. Empirical studies have been carried out on this relationship between urban development and public services (Carruthers & Ulfarsson, 2003; Dowding, John, & Biggs, 1994).

What is missing in the literature is the role of price risk, which refers to uncertain future prices of housing. Focusing on price risk requires the researcher to adopt the developer's perspective when studying the timing of urban development. Price risk has at least two opposing forces on the timing decision—in terms of the developer's risk aversion and of the availability of the real option. The former favors more instantaneous developments at the present time; the latter creates incentives for developers to delay. Reinserting the role of price risk in understanding urban sprawl helps policy makers in formulating more informed and timely growth policies in light of market conditions.

Note that, here, price risk refers to the total risk observed in transacted prices. Ideally, one would like to separate the total risk into systematic, market risk versus non-systematic, developer-specific risk. The former might be related to general market uncertainties such as interest rate and policy uncertainties. The latter could refer to the financing and business risk confronted by individual developers. However, one cannot find specific variables to help separate the two types of risk; therefore, this study focuses on the two types combined, as reflected in the variance and the coefficient of variation of transacted prices.

Using cross-sectional datasets for the 11 CMAs in 2016, this study empirically tests the causes of urban sprawl using the monocentric city and Tiebout models, along with the role of price risk. Sentinel-2 satellite imagery from 2016 obtained by the EU Copernicus Programme is used to help measure the urban extent. The imagery is matched with the 2016 census data. The present study focuses on the 11 most populous CMAs: Toronto, Montreal, Vancouver, Calgary, Ottawa–Gatineau, Edmonton, Quebec City, Winnipeg, Hamilton, Halifax, and Victoria. Note that a CMA is an economic region defined by Statistics Canada. A city, on the other hand, usually lies within the CMA based on political boundaries. Two price risk variables are constructed to measure the total risk: standard deviation (SD) and the coefficient of variation (CV) of the House Price Indices (HPI). The results provide evidence supporting the availability of real options to developers. They show that risk has a negative impact on the extent of urban development in the fringe: developers tend to delay development due to the presence of the real option.

2.1.2 Previous studies and theories

The monocentric city model focuses on the result of a competitive bidding process of location choice. The model assumes perfect mobility among homogeneous residents, who live on a featureless plain and compete for proximity to a central workplace. At the equilibrium, those residents who move away from the central business district (CBD) save housing rent, but at the same time incur higher commuting costs—that is, higher commuting costs are completely offset by lower housing rents within the monocentric city model.

Wheaton (1974) has provided a thorough set of comparative static analysis for the monocentric city model:

$$\frac{\partial \overline{x}}{\partial n} > 0,\ \frac{\partial \overline{x}}{\partial t} < 0,\ \frac{\partial \overline{x}}{\partial y} > 0,\ \frac{\partial \overline{x}}{\partial r_a} < 0 \qquad (2.1)$$

where $\overline{x}$ is the distance to the CBD; n is the total urban population; t is the one-way commuting cost per mile; y is annual income, and r_a is the agricultural land rent in areas outside of a fixed city boundary. Wheaton's analysis shows that the urban boundary $\overline{x}$ expands with population and income, but contracts with rising agricultural land rent and commuting costs.

Numerous studies have attempted to empirically test the monocentric city model—for example, Brueckner and Fansler (1983) apply the Box-Cox model to 40 cities in the U.S. Their results show that urban size indeed increases with population and income, but decreases with agricultural land rent. The authors use auto usage and public transit as proxies for commuting costs, neither variable was significantly related to urban size. Similarly, McGrath (2005) uses a more comprehensive data set of 33 cities in the U.S from 1950 to 1990 and conducts a cross-sectional study. Unlike Brueckner and Fansler, McGrath finds that transportation costs have a negative impact on urban scale and concludes that the monocentric city model is empirically robust. Young, Tanguay, and Lachapelle (2016) conduct a study on 10 CMAs between 1996 and 2011. Their results show that gasoline fees have more significant effects on urban sprawl than off-street parking fees. The authors agree that higher transportation costs can restrain the extent of sprawl. The present study follows Brueckner and Fansler and uses cross-sectional data to examine the role of the monocentric city model and the Tiebout model in explaining urban sprawl in the 11 Canadian CMAs.

Unlike the monocentric city model, The Tiebout model focuses on the supply of public goods and services and residents' choices of public goods in terms of their preferences—that is, residents tend to move to locations that offer public goods that meet their preferences and "vote by their feet" (Tiebout, 1956). Carruthers and Ulfarsson (2003) use various prices of municipal services as proxies for the Tiebout model and show that the relative strength of the property tax base can lead to the sprawling of a metropolitan area. The present study follows but modifies Carruthers and Ulfarsson, by using property tax rates to study the extent to which pricy municipal public goods might be positively related to more urban development in sprawling areas.

Both the monocentric city and Tiebout models ignore the developer's view of development on the fringe, especially in light of price risk. Consider a developer who confronts uncertain future price (return) of the development. The developer needs to decide when to develop—either now or the future—in light of discounted benefits with the presence of price (return) risk. Price risk exerts three impacts on the timing decision. First, if the developer is risk-averse, price risk creates an incentive for the developer to build now as opposed to confronting the risk in the future.

Second, mathematically, the convexity of the discount function creates an incentive for the developer to defer development—Jensen's inequality (Jensen, 1906). Jensen's inequality implies that the discounted price at the expected return is less than the expected price (benefit) discounted separately for different states of uncertain return.

Third, the presence of the real option lessens the downside price risk and increases the net present value (NPV) from delaying development. Put differently, if the developer owns the land, he or she has an additional option to delay developing the land and earn the agricultural land rent if the price drops in the future, thereby obviating the need to take a loss. The NPV with real option is, therefore, greater than that without. This higher NPV creates an incentive for the developer to delay.

In sum, the present study uses 11 CMAs in Canada to test the theories of the monocentric city model and the Tiebout model. It contributes to the literature by inserting the role of the developer in light of price risk, that is, how price risk could delay or speed up urban sprawl.

2.2 Data and variables

2.2.1 Study Area

This study focuses on the 11 most populous CMAs in Canada: Toronto, Montreal, Vancouver, Calgary, Ottawa–Gatineau, Edmonton, Quebec City, Winnipeg, Hamilton, Halifax, and Victoria. Statistics Canada defines a CMA as an area consisting of at least one municipality located around a core city, which also includes a population of at least 100,000 (Statistics Canada, 2016). Given the vastness of its spatial scale, a CMA is usually greater in area than a city, with the latter defined mostly politically by the city government.

The unit of analysis in this study is the dissemination area (DA). A DA is a small geographic area which contains 400 to 700 people. It is the smallest standard geographic unit for Statistics Canada to partition the national map and disseminate census information.

2.2.2 Data

Data are drawn from six different sources. First, Sentinel-2 satellite imageries of summer 2016 (Appendix C) are used for generating the land cover/use data for the 11 CMAs. The imageries are clear with no or low cloud cover. All the spectral bands are included in the classification and for further analysis. Compared to previous satellite imageries such as

Landsat, Sentinel-2 has more spectral bands and higher spatial resolution (see details in Table 2.1). It can provide more useful and accurate information for land cover/use classification. Data acquisition dates are shown in Table 2.2.

Table 2. 1 Details of the Sentinel-2 spectral bands

Band name		S2A		S2B		Spatial resolu-tion (m)
		Central wavelength (nm)	Bandwidth (nm)	Central wavelength (nm)	Bandwidth (nm)	
1	Costal aerosol	442.7	21	442.2	21	60
2	Blue	492.4	66	492.1	66	10
3	Green	559.8	36	559.0	36	10
4	Red	664.6	31	664.9	31	10
5	Vegetation red edge	704.1	15	703.8	16	20
6	Vegetation red edge	740.5	15	739.1	15	20
7	Vegetation red edge	782.8	20	779.7	20	20
8	NIR	832.8	106	832.9	106	10
8A	Narrow NIR	864.7	21	864.0	22	20
9	Water vapour	945.1	20	943.2	21	60
10	SWIR – Cirrus	1373.5	31	1376.9	30	60
11	SWIR	1613.7	91	1610.4	94	20
12	SWIR	2202.4	175	2185.7	185	20

Source: European Space Agency

Table 2. 2 Sentinel-2 data acquisition dates (year=2016)

CMA name	Date
Toronto	September 24
Montreal	July 20
Vancouver	August 29
Calgary	August 30
Ottawa–Gatineau	June 23
Edmonton	May 2
Quebec City	September 5
Winnipeg	September 8
Hamilton	September 24
Halifax	June 18/August 31
Victoria	August 29

Training samples and testing samples are used to process classification and estimate classification accuracy, separately. Google Earth imageries for corresponding dates in 2016 are used as reference maps to choose these samples randomly for each class.

Second, the study uses Statistics Canada's boundary and census data that are publicly available. The pixels from the classified Sentinel imageries are aggregated to match the boundaries of the 2016 DA of the corresponding CMA. The boundary data for DAs and CMAs are drawn from Statistics Canada's cartographic boundary files. The aggregated socioeconomic characteristics of DA residents are obtained from the 2016 census profile series. As shown in Table 2.3, census data for the DAs include total population, median income, number of dwellings, median value of dwellings, and median monthly rent. All dollar values are measured in the 2016 Canadian dollar.

Table 2. 3 Census data definition

Name	Description
DAUID	The unique identifier for each DA
Population	Total population in the DA
Dwelling	No. of private dwellings occupied by usual residents in the DA
Med_income	Median total income ($) in the DA
Med_dwelling	Median value of dwellings ($) in the DA
Med_rent	Median monthly rent ($) in the DA

Source: 2016 Canadian census profile series for Dissemination Areas

Third, municipal property tax rates are assembled. Ideally, municipal services or expenses data are needed to serve as proxies for the Tiebout model, but such data are not publicly or readily available. Instead, municipal services are summarized by the price—the mill rate—of the core city of each CMA. Municipal governments levy taxes on each property to fund public infrastructures and services. Residential property tax rates data (the Mill rate) are collected for the 11 CMAs from local government websites or related services (see Table 2.4), which is used to calculate property tax payable per $1,000 of property's assessed value. The Mill rate, which is the approximation for the Tiebout model, measures the within-CMA incentive for residents to move from a location (city) with pricy public goods to a less expensive location.

Table 2. 4 Mill rate for the 11 Census Metropolitan Areas in 2016

CMA Name	Property tax rate
Hamilton	0.0137
Halifax	0.0121
Winnipeg	0.0118
Ottawa	0.0105
Montreal	0.0099
Quebec City	0.009
Edmonton	0.008
Toronto	0.0069
Victoria	0.0068
Calgary	0.0062
Vancouver	0.0032

Source: Municipal websites and services

Notes: Some CMAs comprise more than one municipalities/cities—for example, the Toronto CMA has at least nine major cities: the city of Toronto, Oakville, Mississauga, Ajax, Pickering, Whitby, Richmond Hill, Markham, Vaughan, and some other smaller municipalities. The present study uses the mill rate from only the largest, *core* city in the CMA, such as the city of Toronto, as a proxy for the centrifugal force that drives residents away from the pricy locations to more outer areas of a CMA. For this reason, the study does not model the intra-CMA residential mobility and tends to underestimate the Tiebout forces that might have led to the previously sprawled areas.
The regression model, which is a cross-section analysis, compares the extent to which the within-CMA Tiebout effects might vary across the 11 CMAs.

Fourth, price risk data is computed from the house price index. Ideally, price risks should be measured at the parcel level from the perspective of the landowner and should be forward-looking rather than being retrospective price movements aggregated at an areal level. Given the time and resource constraints, this dataset is not readily available. Instead, the total price risk is measured at the CMA level and is used as a proxy for the risk confronted by all developers in each CMA. Price data are obtained from the Taranet–National Bank. Taranet–National Bank House Price Indices (HPI) for the 11 CMAs are collected from Teranet and National Bank of Canada (https://housepriceindex.ca). The HPIs are monthly indices based on repeat sales, which are not quality-adjusted. The time period in this study is January 2006 to December 2016. By far, this is the best and the most available index for calculating price risk.

Figure 2.1 shows the HPI of the 11 CMAs (June 2005=100) and Table 2.5 summarizes the indices. Almost all CMAs demonstrated steady price growth between 2006 and 2016.

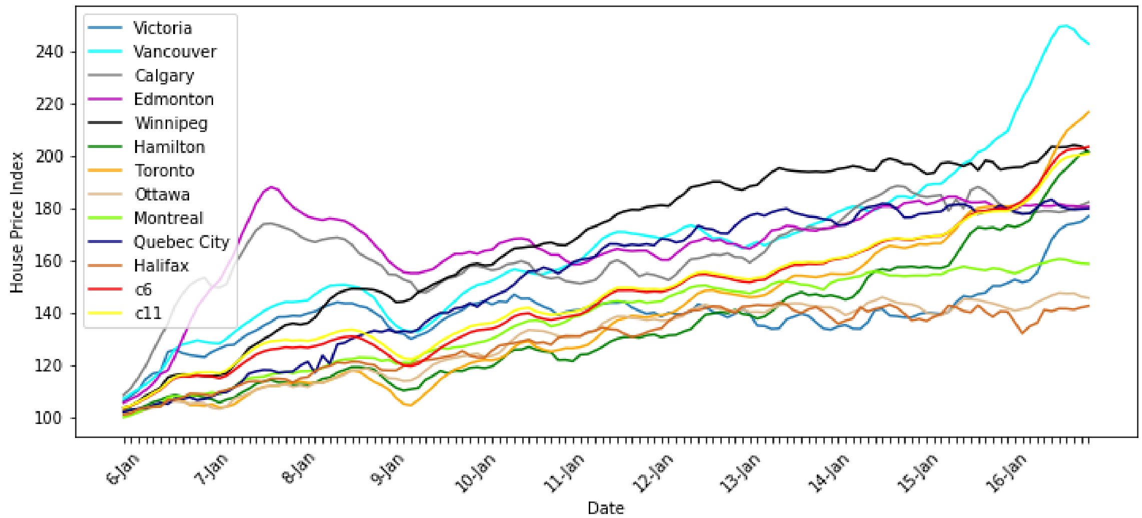


Figure 2. 1 House Price Indices of the 11 Canadian Census Metropolitan Areas from January 2006 to December 2016

Notes: c6 refers to Victoria, Vancouver, Winnipeg, Montreal, Quebec City, and Halifax; and c11 refers to the above six CMAs plus Calgary, Edmonton, Hamilton, Toronto, and Ottawa.

The summary statistics presented in Table 2.5 show that the average HPI of the 11 CMAs is 147.1, with a standard deviation of 23.0. Vancouver, Winnipeg, and Toronto experienced the greatest volatility in their price indices—for example, Vancouver had a max of 150.6 in July 2008 and dropped by 11.9% to 132.7 in May 2009. Likewise, Winnipeg experienced large price fluctuations with a standard deviation of 29.6. Calgary and Edmonton had a similar trend between January 2007 and January 2009, which first increased and peaked in September 2007 with an HPI of 174.0 and 187.9, respectively, and then decreased back to the initial level.

Table 2. 5 Summary statistics of House Price Indices

CMA Name	Min.	Mean	Max.	Std. Dev.	CV[a]
Victoria	106.09	139.51	176.78	11.28	0.081
Vancouver	107.16	164.89	249.53	31.13	0.189
Calgary	108.45	163.40	188.35	15.74	0.096
Edmonton	105.57	166.18	187.91	17.19	0.103
Winnipeg	103.67	167.25	204.03	29.59	0.177
Hamilton	102.89	134.52	201.47	24.43	0.182
Toronto	102.21	138.48	216.53	28.94	0.209
Ottawa	101.15	129.31	147.49	14.62	0.113
Montreal	99.96	136.86	160.47	17.73	0.130
Quebec City	102.06	152.88	183.19	26.82	0.175
Halifax	100.98	128.93	143.90	12.33	0.096
6 cities	103.51	146.03	203.32	24.09	0.165
11 cities	103.65	147.06	200.69	23.02	0.157

Source: Teranet–National Bank House Price Index (n=132)

Notes: [a] $\text{CV}=\frac{\text{Std. Dev.}}{\text{Mean}}$

Fifth, the urban boundaries for each CMA in 2006 are also drawn from Statistics Canada. To focus on urban sprawl, this study is limited only to developable land outside of the city in each CMA. Statistics Canada defines an urban area (UA) as a community with at least 1,000 people and a population density of at least 400 persons per square kilometer. This definition has remained unchanged since 2006.

Sixth, greenbelt areas are obtained from the Ministry of Municipal Affairs and Housing. Urban developments in the Toronto CMA and the Ottawa CMA are bounded by a greenbelt to control and contain boundary expansion. In this study, areas covered by the greenbelt are excluded.

2.2.3 Variables

The dependent variable is the built-up area in the DAs, which are within the CMA but lie outside of the city and which do not encroach on any greenbelt restricted areas. These DAs are, henceforth, referred to as the developable DAs. Four land cover/use types are reclassified as built-up area: residential, industrial, transportation, and golf. Table 2.6 shows a summary of the dependent variable for the 11 CMAs.

Table 2. 6 Summary statistics of the dependent variable (built-up area in the Dissemination Area) for each Census Metropolitan Area

CMA name	Number of Observations	Mean (km^2)	Std. Dev (km^2)
Toronto	113	0.44	0.40
Montreal	159	2.06	1.91
Vancouver	60	0.91	1.75
Calgary	74	2.08	1.79
Ottawa–Gatineau	198	1.41	1.15
Edmonton	158	2.75	2.79
Quebec City	77	1.22	1.22
Winnipeg	78	1.97	2.39
Hamilton	70	0.49	2.28
Halifax	86	1.89	2.87
Victoria	31	0.59	0.39

A total of 1,104 DAs are observed in the 11 CMAs. Variable definitions and summary statistics for the independent variables are shown in Table 2.7.

Table 2. 7 Statistical summaries of the independent variables

Mnemonics	Description	Level[a]	Mean	Std. Dev.	Data source
n	Number of the total population measured in 100,000	DA	842.4	875.1	Census
y	Median household income in 100,000 Canadian Dollars	DA	41058.7	11963	Census
t	Distance (km) from the DA to CBD	DA	31.4	14.3	GIS
r	Agricultural land value per square foot 70 km away from CBD for the CMA	CMA	8.4	15.7	REALTOR®
Mill	Residential property tax rate (%) for the CMA	CMA	0.9	0.3	Municipal websites
SD	Standard deviation of House price index for the CMA	CMA	20.1	6.4	Teranet–National Bank House Price Index™
CV	Coefficient of variation of House price index for the CMA	CMA	0.1	0.04	Teranet–National Bank House Price Index™
D_i (i=1,…,5)[b]	Provincial dummies	CMA	–	–	Province

Notes: [a] Total number of DA is 1,104; Total number of CMA is 11.
[b] Alberta is taken as the reference. The identifier *i* represents Ontario, British Columbia, Manitoba, Quebec, and Nova Scotia, respectively.

Price risk is the key variable in the empirical model. Two variables are used to measure price risk, based on the price index for the 11 CMAs. They both measure the total risk. The first is the standard deviation (SD). Since SD does not account for the magnitude of the arithmetic mean, a second risk variable is used, the coefficient of variation (CV), which is calculated as the SD divided by the mean of the CMA's price index in the time period.

To model the monocentric city model, four variables are used: population, income, agricultural land value, and distance to the Central Business District (CBD). The agriculture land rent is proxied by agricultural land value per square foot 70 km away from CBD for each CMA. This value is obtained from the current Multiple Listing Services. The agricultural land rent is an approximation, and 70 km is a crude measurement to find a realistic piece of agricultural land. Following the monocentric city model, it is assumed that agricultural land rent is flat everywhere outside of the city. Note that the study previously attempted to use corn prices as a proxy for measuring agricultural land rent, but the results were not satisfactory; therefore, MLS land rent is employed instead.

Commuting cost is proxied by the distance between the geometric center (the centroid) of each DA and the CBD. Since most job opportunities centralize in the CBD, residents can live close to the center to reduce commute time, thereby lowering the costs for commuting. To model the polycentric aspects of the CMAs, the study attempted to include distance variables to other secondary employment centers; however, these additional distance variables were mostly insignificant, while, at the same time, created multicollinearity into the regression model. For this reason, this study excludes them from the estimation.

The cities' mill rates are used to model for the Tiebout effect. It is expressed as dollar amount of property tax payable per $1,000 of assessed property value.

2.3 Methods and Empirical Strategy

2.3.1 Data Pre-processing

The main pre-processing methods of remote-sensing data include geometric correction, image registration, image fusion, layer stacking, and seamless mosaic. All these methods were processed in ENVI version 5.3. All shapefiles were clipped by the corresponding CMA boundaries using ArcGIS version 10.4.1. All imageries were in the Universal

Transverse Mercator (UTM) coordinate system and the World Geodetic System (WGS-1984).

The Smoothing Filter-based Intensity Modulation (SFIM) technique (Liu, 2000) is used to enhance the spatial details without altering the spectral properties. SFIM is an image fusion method to fuse lower spatial-resolution multispectral bands with higher-resolution bands. A ratio between a higher resolution image and its low-pass mean filtered image was used to modulate a lower spatial-resolution multispectral image without changing its spectral properties. The SFIM is defined as

$$\mathrm{DN}(\lambda)_{\mathrm{fus}} = \frac{\mathrm{DN}(\lambda)_{\mathrm{low}}\,\mathrm{DN}(\gamma)_{\mathrm{high}}}{\mathrm{DN}(\gamma)_{\mathrm{mean}}} \tag{2.2}$$

where $\mathrm{DN}(\lambda)_{fus}$, $\mathrm{DN}(\lambda)_{low}$, $\mathrm{DN}(\gamma)_{high}$, $\mathrm{DN}(\gamma)_{mean}$ are DN values of fused higher spatial resolution image, original low spatial resolution image, original high spatial resolution panchromatic image, low spatial resolution panchromatic image (after applying the low-pass filtering in the original panchromatic image), correspondingly. Since Sentinel-2 satellite imagery does not include panchromatic bands, relatively higher-resolution red bands were used during the image fusion process. Compared to the original imagery, fusion imagery provides more spatial details. After image fusion, all generated bands were processed using the layer stacking method to obtain layers for classification. Finally, the seamless mosaic workflow in ENVI 5.3 was used to combine adjacent imageries with color balance. The mosaicked image was then clipped by the boundary of the corresponding CMA.

2.3.2 Image Classification

After pre-processing, the supervised maximum likelihood classification (MLC) method was used to obtain the land cover/use maps. Land cover/use types were classified into ten classes (Table 2.8), which were based on the land cover/use classification system developed by Anderson et al. (1976). The classes include agriculture, grass, golf, gravel, industrial, residential, transportation, tree, water, and wetland.

Table 2. 8 Land cover/use classification scheme

Land cover/use class	Description
Agriculture	Cropland, pasture, and other agricultural lands
Grass	Lawn fields
Golf	Golf courses fields
Gravel	Strip mines, quarries, and gravel pits
Industrial	Industrial and commercial complexes
Residential	High-density and low-density residential land
Transportation	Highways, railways, airports, seaports, communications, and utility areas
Tree	Deciduous, evergreen, and mixed forest land
Water	Steams, canals, reservoirs, lakes, bays, and estuaries
Wetland	Forested and non-forested wetland

In this study, the Maximum Likelihood Classifier (MLC) method was used to process classification because it performs well when studying land cover/use change (Otukei & Blaschke, 2010). The way MLC works is that it supposes the pixels in each class are normally distributed; each pixel is assigned to the class with the greatest maximum likelihood value (Scott & Symons, 1971).

2.3.2.1 Classification Accuracy Assessment

The accuracy assessment was then conducted to evaluate the performance of classification by estimating the percentage of the testing samples that match the classification results. Congalton and Green (2008) noted that, to be cost-effective, one needs a minimum of 50 testing samples for each class. The Google Earth imagery from 2016 was chosen as imagery sources to randomly select testing samples. Each class was assigned over 100 random samples to get precise results. As a result, the confusion matrices including the Kappa coefficient, overall accuracy, producer’s accuracy, and user’s accuracy were generated. The Kappa coefficient is a statistic that denotes the agreement between the classification and the reference data after correcting any chance agreement (Cohen, 1960). Overall accuracy represents the probability that the reference data are classified correctly.

2.3.2.2 Post-classification Processing

The built-up area in each DA was defined in two ways. The first way was the measured amount of land area that is built-up in the DA. The second way treated built-up area as a dichotomous variable: it was a one if built-up area is the single largest land-cover/use class in the DA and a zero otherwise. In the latter case, zonal statistics method was applied to identify the predominant land cover/use type in each DA. This step ensured the unit of observation from satellite imagery matches with census unit. In the regression model, the dependent variable is the actual measurement of the built-up area.

2.3.3 Empirical Strategy

Figure 2.2 shows the conceptual diagram relating theories, data, and methods. Using the MLC classification and zonal statistics, all land cover/use types in the DA are identified. The land cover/use data are then matched with the census socioeconomic variables, which are aggregated data at the DA level. A list of datasets with all attributes is imported to R for estimating the regression model, based on the Ordinary Least Squares (OLS) method.

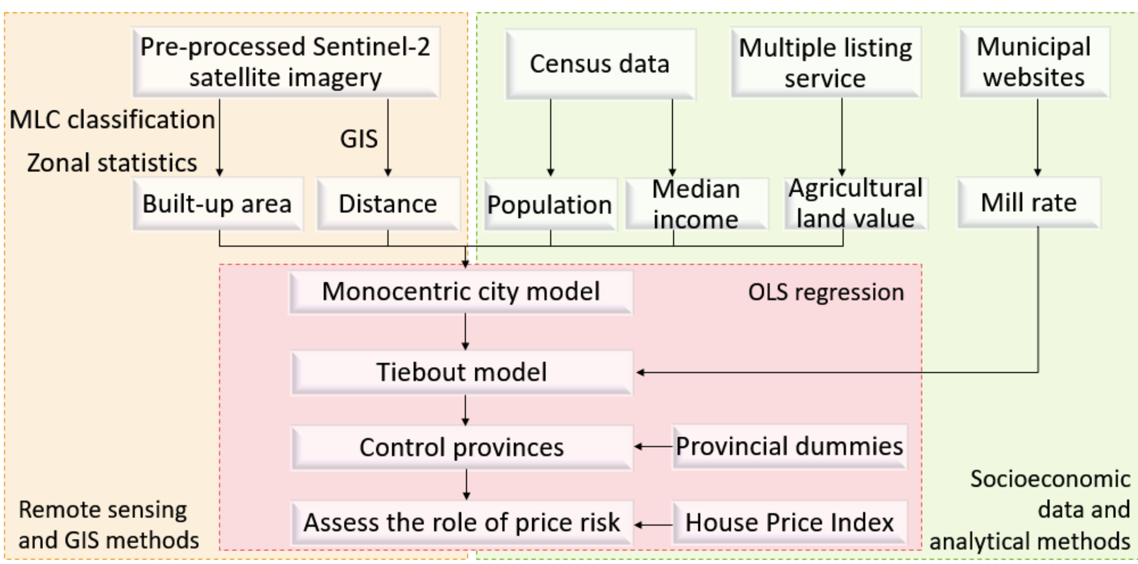


Figure 2. 2 Conceptual diagram of the empirical model

The estimating regression equation between the dependent variable and independent variables is given as follows:

$$p_{ij} = \alpha_0 + \alpha_1 n_{ij} + \alpha_2 y_{ij} + \alpha_3 t_{ij} + \alpha_4 r_i + \alpha_5 Mill_i + \sum_{k=1}^{5} \beta_k d_{i,j,k} + \alpha_6 SD_i + \alpha_7 CV_i + \varepsilon_{ij} \quad (2.3)$$

where *i* and *j* represent provinces and CMAs, respectively; *p* (the dependent variable)is the amount of built-up land area in 2016; *n* represents population; *y* is median income; *t* is the proxy for commuting costs; *r* stands for agricultural land value; *Mill* refers to the mill rate; d stands for regional dummies (British Colombia, Manitoba, Quebec, Nova Scotia, and Ontario; Alberta is the referenced region); *SD* and *CV* are the standard deviation and the coefficient of variation of the House Price Index, correspondingly, and ε_{ij} is the error term. The errors are assumed to independent and identically distributed as normal.

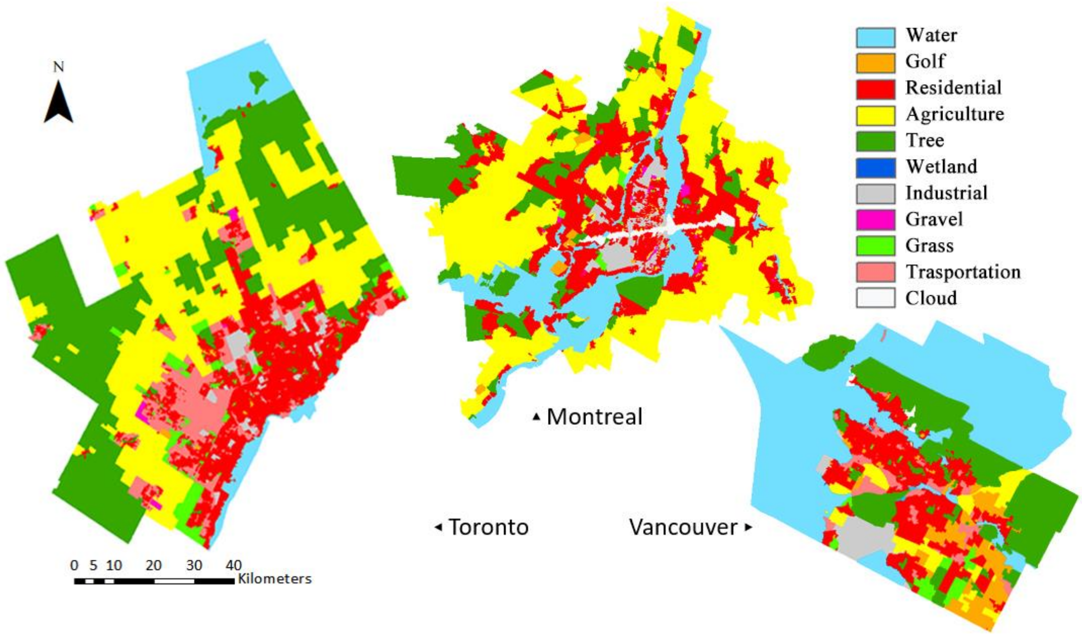
One might argue that urban developments might exhibit the "spillover effect" in that new developments tend to cluster around developed land to be cost effective in serving land. In this case, the OLS model fails to capture the spillover effect; instead, one should estimate a spatial regression model either in the form of spatial lag, spatial error, or a combination of both. However, estimating a spatial model is beyond the scope of the present study; the next phase of the research beyond the dissertation would include testing and estimating spatial models.

One might also argue that the amount of built-in areas (the dependent variable) probably captures a similar effect to the number of potential property transactions in the area; the latter would influence price risk directly. If this is indeed the case, the estimating model here would suffer from an endogeneity issue. The argument here is that the endogeneity issue, if exists, would be minimal because the price risk variable is not calculated based on transacted prices in the fringe area *per se*. Instead, price risk is computed at the CMA level, representing the overall risk for the entire CMA market. The fact that the volume of transactions at the fringe is small relative to that of the CMA, the impact of the dependent variable on price risk would be insignificant. Nonetheless, the endogeneity issue will be addressed, using the instrumental variable approach, in the next phase of the research beyond the dissertation.

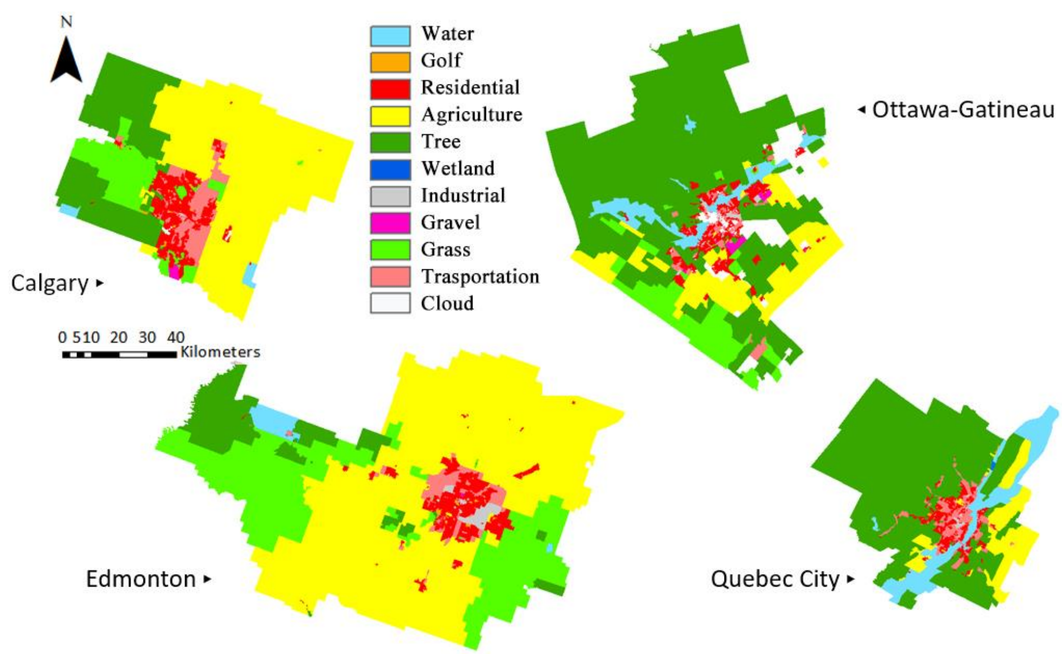
2.4 Results and Discussion

2.4.1 Land Cover/Use Estimates

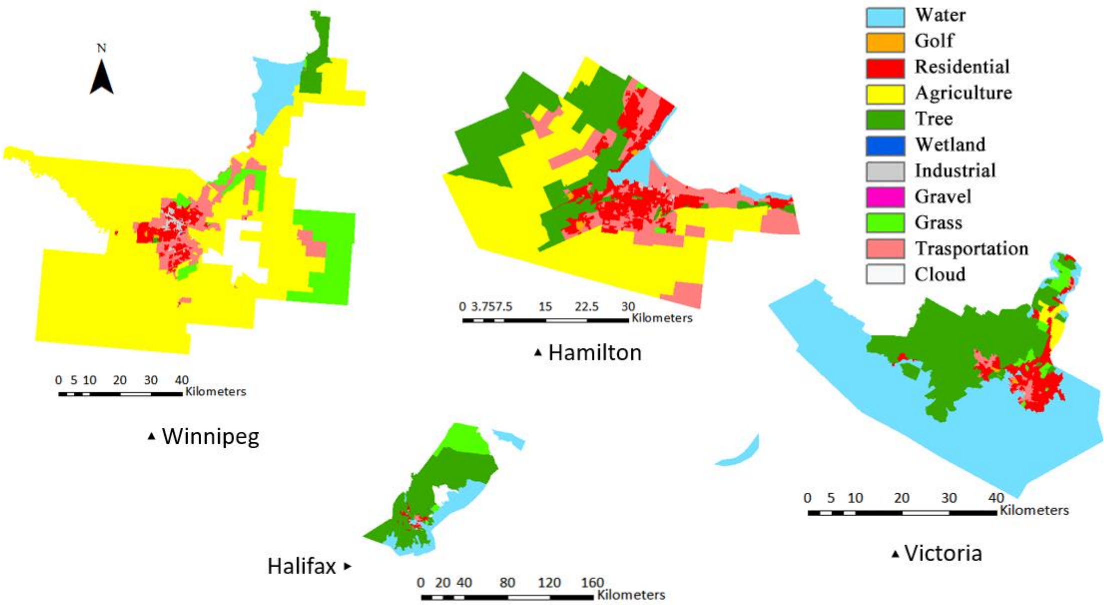
The land cover/use maps of 11 CMAs are generated using the zonal statistics method. As an example, Figure 2.3 shows the result for all the 11 CMAs.



(a) Toronto, Montreal, and Vancouver CMAs



(b) Edmonton, Ottawa-Gatineau, and Quebec City CMAs



(c) Winnipeg, Halifax, Hamilton, and Victoria CMAs

Figure 2. 3 (a) (b) (c) Land cover/use patterns for the 11 Census Metropolitan Areas using zonal statistics

As shown in Table 2.9, the overall classification accuracy for the 11 CMAs ranges between 82.3 and 94.7%. The Montreal CMA shows the lowest accuracy, 82.3%, with a Kappa coefficient of 0.80, and the highest accuracy is the Edmonton CMA (94.7%), with a Kappa coefficient of 0.94.

Table 2. 9 Accuracy assessment

CMA name	Overall accuracy	Kappa coefficient
Toronto	86.54%	0.85
Montreal	82.30%	0.80
Vancouver	88.93%	0.88
Calgary	90.62%	0.90
Ottawa-Gatineau	88.39%	0.87
Edmonton	94.68%	0.94
Quebec City	88.00%	0.87
Winnipeg	90.50%	0.89
Hamilton	84.29%	0.82
Halifax	91.77%	0.91
Victoria	93.57%	0.93

2.4.2 Statistical Analysis

The OLS regression results of the five models are presented in Table 2.10. The dependent variable is the measurement of built-up land area in the DA.

Model 1 focuses on the traditional monocentric city model. Its independent variables include population, income, agricultural land rent, and commuting costs. As expected, the coefficients of median income and agricultural land value show significant positive and negative impacts, respectively.

Model 2 expands the monocentric city model to include the Tiebout model; in model 3, the regional dummies are also further included to control for any unobserved influences at the provincial level. Models 4 and 5 include two different measurements of price risks, SD and CV. As expected, the coefficients of population, income, commuting costs, mill rate, and price risk are highly significant, as indicated by the small p-values (<0.1).

The main results show that risk is significant in affecting the amount of land developed at the fringe of a city. In models 4 and 5, both risk variables are positive and significant. Consider the impact of price risk on urban land coverage outside of the cities. On average, a 1% point increase in the CV of the house price index is associated with close to 10 square kilometers less built-up areas in the fringe. It conforms with the theory that price risk slows down urban development—that is, risks might create an incentive for developers to delay development due to the presence of the real option, an option that hedges the risk of a price decline for the developer.

The OLS estimates show that the coefficients of population, income, mill rate, and risks are all significant with signs consistent with expectations. However, the coefficients of the agricultural land rent and income are not significant. Although the coefficient of proxy for commuting costs present a significant result, the positive coefficient is against the initial expectation. All five models show reasonable values of the adjusted R-squares, ranging from 0.16 (Model 1) to 0.27 (Model 5).

Table 2. 10 OLS estimation results (n=1,104)

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-0.513*	-0.637	-1.937***	-0.381	-0.282
	(1.90)	(1.61)	(4.52)	(0.67)	(0.51)
n	0.076	0.099	1.489**	1.607***	1.658***
	(0.12)	(0.16)	(2.42)	(2.63)	(2.72)
y	15.463***	15.453***	11.835**	8.892*	8.197*
	(3.18)	(3.18)	(2.47)	(1.85)	(1.70)
r	-2.477***	-2.389***	-0.03	1.076	0.983
	(7.12)	(5.93)	(0.05)	(1.63)	(1.54)
t	5.339***	5.381***	5.873***	5.710***	5.737***
	(13.45)	(13.16)	(14.60)	(14.23)	(14.35)
Mill	–	0.112	2.540***	1.857***	1.818***
		(0.43)	(6.77)	(4.55)	(4.50)
D_1	–	–	-2.131***	-1.876***	-1.573***
			(10.90)	(9.20)	(6.88)
D_2	–	–	-1.179***	-0.871***	-0.669***
			(6.41)	(4.40)	(3.13)
D_3	–	–	-0.749**	-1.122***	-1.023***
			(2.09)	(3.06)	(2.84)
D_4	–	–	-1.405***	-0.450	-0.406
			(5.11)	(1.25)	(1.16)
D_5	–	–	-1.395***	-1.332***	-1.129***
			(5.04)	(4.84)	(4.03)
SD	–	–	–	-0.052***	–
				(4.09)	
CV	–	–	–	–	-9.192***
					(4.59)
Adjust R^2	0.163	0.162	0.251	0.262	0.265

Notes: The dependent variable is built-up area in square kilometer in the DA. The absolute values of the *t*-statistics are presented in parentheses.

***, **, * represent the coefficient is significant at the 1%, 5%, 10% level, correspondingly, with two-tailed tested.

The variations in the independent variables explain about 16% (Model 1) of the variation in the dependent variable. In particular, the risk variable increases the explanatory power of the model by about 10%, to a relatively higher R-square of 26.5% (Model 5).

2.5 Conclusions

This study mixes remote-sensing and GIS with empirical techniques to test the causes of urban sprawl in light of price risk. It demonstrates that Sentinel-2 satellite imagery can provide useful information for land cover/use classification. From the classification results, built-up areas can be explored for studying urban sprawl with high accuracy. The combination of remote sensing measures and census data adds details to the analysis of urban sprawl since the two types of information cannot substitute for each other.

The results show that the relationships between urban coverage and population, and between urban coverage and the mill rate are consistent with the traditional theories in the urban fringe area of the 11 CMAs in which urban sprawl can potentially happen. The analysis shows that urban sprawl is positively related to population, income, and the mill rate. In the case of the Tiebout model, the positive coefficient of mill rate is logical: higher prices for similar public goods might push residents to move to areas that offer a similar bundle but at a lower price.

More importantly, this study contributes to the literature on urban sprawl in that it takes into account of price risk. The results suggest that risk does matter in urban boundary expansion. In particular, urban sprawl is negatively related to price risk. This empirical result is consistent with the financial theory of real option: a greater price volatility creates an incentive for the developer to delay the decision to build due to the presence of real options. At any point in time, the developer can always delay and earn the agricultural land rent if prices drop thereby enabling the developer to hedge the risk of a price drop.

One needs to be mindful that some of the estimation results here are inaccurate due to simplifications—for example, the results from testing the monocentric model are not as robust as in some previous studies in the literature. One possible reason is that the proxy variable for commuting costs may not be appropriate in this study. The limited statistical data do not allow one to explore in more details on some variables. Also, the monocentric city model may not represent all patterns of urban sprawl because of the inherent complication of urban activities. Nevertheless, this simplified model has its merits for studying urban sprawl in terms of socioeconomic activities.

One shortcoming of the present study is that it is a cross-sectional comparison among the CMAs. To appropriately study developer's timing decisions for urban development, one needs to examine the pattern of sprawl over time, longitudinally, in order to examine the causes of urban sprawl. To achieve this, the ideal situation is to use both Sentinel-2 imageries from 2006 and 2016 to obtain the land use/cover maps and then process change detection to make a comparison between 2006 and 2016. However, data for Sentinel-2 before 2015 is unavailable. The second-best solution is to collect other satellite imagery, such as Landsat imagery from 2006, to conduct a panel study—this is the goal of the second empirical study that follows. In the next Chapter, results for the Toronto CMA are verified using the second-best solution based on low-resolution imagery.

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3 Analysis of Urban Sprawl in the Toronto Census Metropolitan Area Using Panel Data from 1986 to 2016

3.1 Introduction

3.1.1 Background

Rapid boundary expansions outside of cities—often referred to as urban sprawl—are thought to pose serious problems for many cities. The Toronto Census Metropolitan Area (CMA), for example, has experienced rapid developments outside of the city in the past 30 years. Some pundits criticize sprawl as causes of some economic and environmental issues, including higher levels of pollution, loss of agricultural lands and wetlands, and increased commuting cost and time (McGibany, 2004). A number of studies have contributed to these debates and attempted to recommend policies for controlling and/or containing the size and speed of urban sprawl (Song & Zenou, 2006; Yuan, Sawaya, Loeffelholz, & Bauer, 2005).

To understand the determinants of urban sprawl, one must first clarify the definition and measurement of urban sprawl. Many scholars have attempted to define the concept of sprawl (Bhatta, 2010; Brueckner, 2000; Burchell, Downs, McCann, & Mukherji, 2005; Carruthers & Ulfarsson, 2003; Karakayaci, 2016). For example, Galster et al. (2001) give explicit definitions of sprawl, which include: (1) a specific example; (2) an aesthetic judgement, which is usually described as “ugly”; (3) the cause of an externality; (4) the consequence or effect of some independent variable; (5) one or more existing patterns of development, and (6) a process of development as an urban area expands. These six interpretations described by Galster et al. are, even collectively, not precise enough in their understanding of sprawl. Although the definitions of sprawl vary among scholars, the general consensus is that urban sprawl is a multidimensional phenomenon (Oueslati, Alvanides, & Garrod, 2015), which is reflected in the unplanned and uneven pattern of urban development and which is driven by a myriad of factors. Following this idea, Galster (2001) then further characterizes sprawl slightly differently according to eight dimensions, namely, density, continuity, concentration, clustering, centrality, nuclearity, mixed uses, and proximity. Of these dimensions, here, the present study focuses mainly on nuclearity. Nuclearity describes the extent to which an urban area is characterized by a mononuclear pattern of development. Focusing on nuclearity alone provides the theoretical convenience to readily employ the existing theory, the monocentric city model (Alonso, 1964; Muth, 1969; Mills, 1967) , as the workhorse of this study.

In this paper, up-to-date remotely sensed data are used to help monitor dynamic changes in urban coverage (Alberti, Weeks, & Coe, 2004). As a common strategy for studying sprawl, McGibany (2004) indicates that sprawl refers to spatial expansion in urban areas. Using this definition, the largest CMA in Canada, Toronto, is taken as a case study to empirical test urban sprawl.

Few studies have considered the role of price risk in urban sprawl. Price risk refers to uncertain future prices from the developer's perspective. Two opposing forces of price risk on timing decision are main concerns in the present study: the developer's risk aversion and the availability of real options. Examining the role of price risk in understanding urban sprawl can help policy makers with formulating more informed and timely growth policies in light of market conditions such as price risk.

This study examines the socioeconomic and market determinants on urban sprawl in the Toronto Census Metropolitan Area (CMA), using panel datasets for the years 1986, 2006 and 2016. A comprehensive analysis of panel datasets was generated to match with socioeconomic data and then test the usefulness of the monocentric city model in explaining urban boundary changes in the Toronto CMA. The results here show that urban coverage is positively related to population and income, but is negatively associated with price risk.

This study follows but refines previous studies by adopting a more precise delineation of urban coverage. Landsat 5 and Sentinel-2 imageries were collected; these imageries are used as inputs for detecting land cover/use changes. The change detection serves as a foundation for reflecting urban sprawl. There are no other similar studies of urban sprawl in Canada have been conducted with a focus on Dissemination Areas (DA) or Enumeration Areas (EA). The study contributes to the literature on urban sprawl by focusing on one dimension: urbanized area land use/cover changes at the DA/EA level.

Finally, the study aims to test the role of real option, vis a vis price risk, in affecting the speed of urban coverage expansion.

3.1.2 Previous studies and theories

The starting point for exploring the determinants of urban sprawl is to focus on the monocentric city model (Alonso, 1964; Muth, 1969; Mills, 1967). The model assumes perfect mobility among homogeneous residents, who live on a featureless plain and compete for proximity to a central workplace. At the equilibrium, those residents who move away from the central business district (CBD) spend less on housing rent, but incur higher transportation costs. Put differently, higher transportation costs are completely offset by lower housing rents within the monocentric city model. The model identifies population, income, agricultural land rent, and commuting costs as the factors that drive urban sprawl.

Wheaton's (1974) comparative statistics analysis for the monocentric city model thoroughly spells out the relationship between urban size and the exogenous variables of the model:

$$\frac{\partial \bar{x}}{\partial n} > 0, \ \frac{\partial \bar{x}}{\partial t} < 0, \ \frac{\partial \bar{x}}{\partial y} > 0, \ \frac{\partial \bar{x}}{\partial r_a} < 0 \qquad (3.1)$$

where $\bar{x}$ is the distance to the CBD; n is the total urban population; t is the one-way commuting cost per mile; y is annual income, and r_a is agricultural land rent in areas outside of a fixed city boundary. Wheaton's analysis shows that urban boundary $\bar{x}$ expands with population and income, but contracts with rising agricultural land rent and commuting costs.

To empirically test these results, Brueckner and Fansler (1983) applied the Box-Cox model to 40 cities in the U.S. The result confirmed that urban size is an increasing function of population and income, and a decreasing function of agricultural rent. Brueckner and Fansler used auto usage and public transit as proxies for commuting cost, but they found that neither variable was significantly related to urban size. McGrath (2005) used a more comprehensive data set of 33 cities in the U.S from 1950 to 1990 to conduct a cross-sectional study. Unlike Brueckner and Fansler, McGrath found that transportation costs had a negative impact on the urban scale and confirmed that the monocentric city model was empirically robust.

When studying urban sprawl, the definition of sprawl is an important start point. The measures of urban sprawl differ between areas of research. Several studies employ census data to construct measures of sprawl—for example, Glaeser and Kahn (2001) use decentralization as a sprawling measure of the American city. Similarly in the US, Lopez and Hynes (2003) design a Sprawl Index (SI) based on the density and concentration dimensions of sprawl. Besides, expansion in urban spatial extent is one of the common measures of sprawl (McGibany, 2004).

Previous studies ignore the developer's perspective and decision that give rise to sprawl. How does price risk affect the timing of land conversion and development? Answering this question involves the understanding of real options. Consider a developer deciding whether the land is to be developed now or in the future in light of price (return) uncertainty. Price risk may have three impacts on the timing decision of development. First, if the developer is risk-averse, he/she might choose to develop now as opposed to confronting the risk in the future. Second, Jensen's inequality (Jensen, 1906) indicates that the convexity of the discount function creates a mathematical incentive for the developer to defer the development. It implies that the discounted price at the expected return is less than the expected price discounted separately for different states of uncertain return. Third, consider the downside risk (the risk of a price decline), the presence of the real option lessens the downside price risk and increases the net present value (NPV) from delaying the development. Put differently, if the developer is a landowner, he/she has an additional option to leave the land undeveloped and earn the agricultural land rent, thereby obviating the need to take a loss if price declines. The NPV with real options is greater than that without. This higher NPV creates an incentive for the developer to delay developing the land.

Another common issue in existing studies is the mismatch in the units of data over time. Specifically, census boundaries of Canada are revised each census year due to changing populations and delineation methods, which lead to inconsistencies. For this reason, it is needed to interpolate data from a census geographic unit (source layer) to another unit (target layer)—that is, the target layer provides the same geographical boundaries, which makes it possible to examine the same variables evaluated for a constant areal unit. A number of studies are conducted to figure out the ways to deal with these inconsistencies (Allen & Taylor, 2018; Logan, Xu, & Stults, 2014; Martin, Dorling, & Mitchell, 2002; Schroeder, 2017; Tatian, 2002). In the US, the Longitudinal Tract Database (LTDB) created by Logan, Xu, and Stults (2014) is one of the key projects which allocate 1970-2010 US census data to 2010 tracts using areal interpolation method with ancillary population data. In Canada, Allen and Taylor (2018) apply similar techniques of LTDB and conduct a dataset to bridge Canadian Census Tracts data to another boundary, which is convenient for longitudinal neighbourhood-scale studies.

For the interpolation methods, there are three common approaches. One approach is simple areal weighting. Goodchild and Lam (1980) first summarize the areal interpolation method and apply it to London, Ontario. The weight of spatial data between the source layer and the target layer can be calculated by dividing the area of the overlapping region of the source layer and the target layer by the total area of the source layer. The shortcoming of this method is that it assumes a uniform distribution of all the objects across the source area, which is not usually applicable when analyzing factors related to population (Allen & Taylor, 2018). The simple areal weighting method can be improved by the second method, which is called the dasymetric techniques. This method considers unpopulated areas such as water and land area within a greenbelt and assigns data to the rest before processing the areal weighting. A third method is by population weighting. It works similarly to areal weighting, but requires the availability of population counts for smaller units.

This study follows Allen and Taylor’s strategy and uses a combination of all these three interpolation methods to reallocate the census data of 2006 and 2016, based on DAs, to match those of 1986, based on EAs. The dasymetric areal interpolation method is first used to identify the water layer and built-up area; then, the weights between the DA and EA units are computed using population counts at the Dissemination Block (DB) level.

DB is the smallest geographic area for disseminating population and dwelling counts (Statistics Canada, 2016).

Since there is no direct way to observe agricultural land rent, many studies use proxies to estimate it (Chakir & Lungarska, 2017). The most common proxies include agricultural land value, yield, land quality, and farmer's revenue (Mann et al., 2010; Plantinga, 1996; Wu & Segerson, 1995). Among these, agricultural land value is usually used in the literature on urban sprawl (Brueckner & Fansler, 1983; McGrath, 2005; Song & Zenou, 2006). Since both agricultural land rent and value data for DA/EA units are not available, area of agricultural land is used from the land cover/use map generated from remote sensing imagery as a proxy for agricultural land rent.

The difference-in-difference (DID) model is widely used to analyze the effects of a policy or some other shocks (i.e., treatment) in econometrics. The DID model uses a panel set of untreated (control) group to explore what would have occurred in the absence of the intervention. There are many existing studies based on the DID method. Eissa and Liebman (1996) examine the impact of the Tax Reform Act of 1986 in the US. Their result shows that the reform increased the labor force participation of single women with children. Card and Krueger (1993) use survey data on wages and employment and find that the increase in New Jersey's 1992 minimum wage did not decrease employment.

In general, a natural experiment includes a treatment, an outcome, and a control group. When evaluating the impact of the "treatment" on the "outcome", the control group is viewed as a reference. The sprawl happened in the Toronto CMA can be regarded as a "quasi-experiment" because it lacks the element of random assignment to control group. In the process of sprawl, areas with greater housing price risk (above the average) will be considered as the "treatment" group; those experience with less risk (below the average) are considered as the "control" group. To explore the role of price risk in urban sprawl, it is needed to compare the growth of built-up areas before and after the "treatment". A panel set of EA data can be used to measure the differences between the control and treatment group over time. Consider the model

$$Y_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 A_{it} + \beta_3 \; T_{it} A_{it} + \varepsilon_{it} \tag{3.2}$$

where Y_{it} is the dependent variable (the outcome) for unit *i* and *t*; *i* and *t* are identifiers for units in the control and treatment groups, respectively; *A* is a dummy variable for group membership; *T* is a dummy variable for time period; $T{\cdot}A$ equals to the cross-product of *T* and *A*, and ε is the error term.

The DID model can be implemented according to Table 3.1. The term $\Delta\Delta Y$ will measure the treatment effect; any unobserved factors other than the treatment will disappear after employing the DID model. Thus, the coefficient of the interaction term will be the main concern, which indicates the difference in changes over time. One can expect more accurate estimates of the net impact of the treatment on outcome. All the assumptions of the Ordinary Least Squares (OLS) model apply to the DID model, but the DID model requires parallel trend assumption.

Table 3. 1 The implement of the DID model.

	Before	After	Difference
Treatment group	$\beta_0 + \beta_1$	$\beta_0 + \beta_1 + \beta_2 + \beta_3$	$\Delta Y_t = \beta_2 + \beta_3$
Control group	β_0	$\beta_0 + \beta_2$	$\Delta Y_c = \beta_2$
Difference			$\Delta\Delta Y = \beta_3$

Hsiao (2007) indicates the advantages of using panel data. Compared to single cross-sectional and time series data, panel data include inter-individual differences and intra-individual dynamics, thus will offer a better explanation for the complexity of human behavior in investigating economic issues.

In short, the present study examines the role of price risk in affecting urban land coverage. It presents a panel comparison of the Toronto CMA 1986-2016 using the DID model, while controlling for variables from the monocentric city model.

3.2 Data and variables

3.2.1 Study area

The study area is the Toronto Census Metropolitan Area (CMA) (43°44 N 79°22′W) in southeastern Canada (Figure 3.1). Statistics Canada (2016) defines a CMA as an area consisting of at least one neighboring municipality situated around a core. It must have a total population of at least 100,000, of which 50,000 or more live in the core. Among all CMAs in Canada, the Toronto CMA is the most populous one, with a population of 5,928,040 in 2016. Given its vastness in spatial scale, a CMA is usually greater in scale than a city; the geographic boundary of the latter is often defined politically by the government.

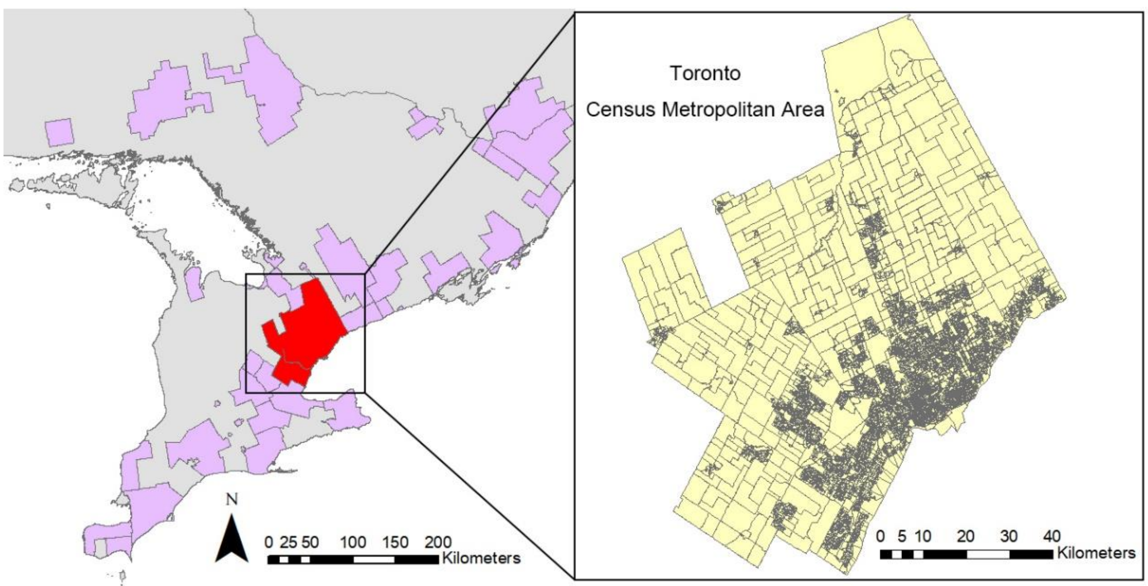


Figure 3. 1 Study area

According to tacit knowledge, the Toronto city areas that already exist before 1986 were extracted. The boundary was defined by four roads for each direction: Meadowvale Road in the east, Steeles Avenue in the north, Waterfront in the south, and Kipling Avenue in the west. Areas out of the main city were expected as potential sprawling areas over the time period.

3.2.2 Data

In the present study, three types of data from six sources are used. They can be categorized as remotely sensed data, socioeconomic data from census, and Geographic Information System (GIS) data.

First, the three available cloud-free scenes of the Toronto CMA used in this study are acquired for the years with no strictly equal intervals, 1986, 2005, and 2016. The imageries are used as inputs for the land cover/use classification. Landsat 5 TM and ETM+ satellite data of 1986 and 2005, and Sentinel-2 data of 2016 are obtained for this study. For the Landsat 5 TM imagery data, the 1986 imagery is acquired on June 3, while in 2005, the imagery is taken on August 26. The Sentinel-2 imagery is acquired on September 24, 2016. Although the census year is 2006, there is no clear imagery of the study area in the summer of 2006. From the imagery of 2005, clouds show an over-average availability. Thus, the 2005 imagery is taken to match with the 2006 census data. Table 3.2 shows the characteristics of the sensors between Landsat 5 and Sentinel-2. Compared to Landsat 5, Sentinel-2 has more spectral bands and higher spatial resolution, which is up to 10 meters, and it has a shorter revisit period. Hence, Sentinel-2 imageries are expected to provide more useful information for land cover/use classification. Figure 3.2 shows a false-color Sentinel-2 satellite imagery of the Toronto CMA using the near-infrared, red and green spectral bands mapped to RGB. False-color imagery is a visual interpretation of vegetation and classification. Vegetation appears bright red in the image because it has a high reflectance in the near-infrared. Water appears green since it has high absorption of red.

Table 3. 2 Comparison of the characteristics of the sensors between satellites Landsat 5 and Sentinel-2

	Landsat 5	Sentinel-2
Multi-spectral resolution	30 m	10, 20, and 60 m
Revisit periods (days)	16	5
Field of view (km)	180	300
Number of bands	7	13
Spectral Range (μm)	0.45-2.35	0.44-2.19
Launch date	1984	2013 (Sentinel-2A) 2014 (Sentinel-2B)

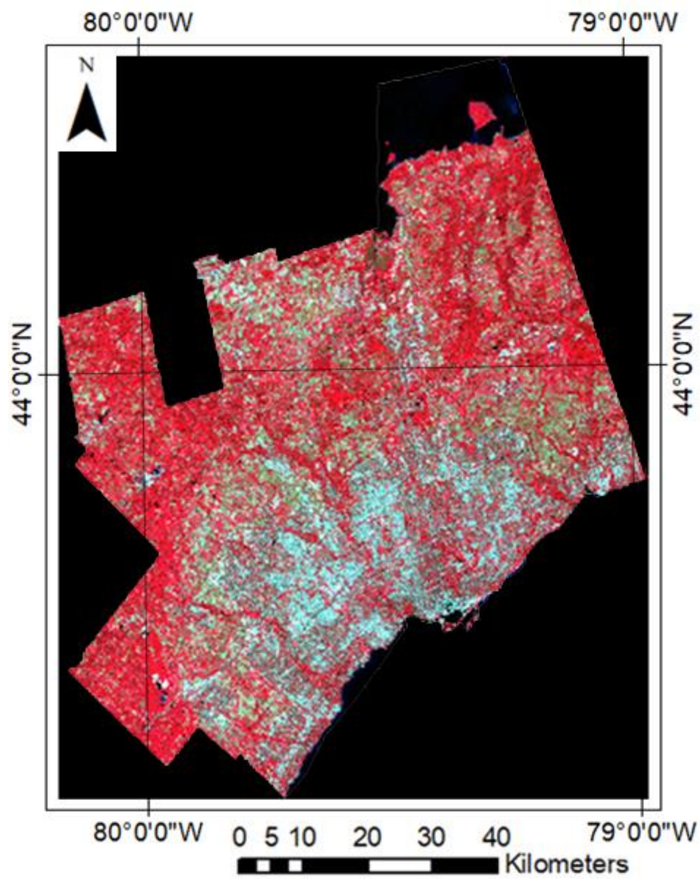


Figure 3. 2 False-color Sentinel-2 satellite imagery of the Toronto Census Metropolitan Area on September 24, 2016

Second, Google Earth imageries are used. Training samples and testing samples are used to process classification and estimate classification accuracy. Google Earth imageries for corresponding dates are used as reference maps to choose these samples for each class randomly and get ground truth data.

Third, census data are acquired from Statistic Canada to obtain variables that describe residents' socioeconomic status, which are key variables for empirically testing the theories. Table 3.3 shows the definition of the original census data used in this study.

Table 3. 3 Census data definition

Mnemonics	Description
DAUID	Unique identifier
Population	Total population
Dwelling	No. of private dwellings occupied by usual residents
Owner	No. of owners
Renter	No. of renters
One_person	No. of single person households
Med_income	Median total income ($)
Ave_income	Average total income ($)
Med_dwelling	Median value of dwellings ($)
Ave_dwelling	Average value of dwellings ($)
Transit_auto	No. of employed labor force aged 15 years and over (including drivers and passengers) use the car, truck, or van for commuting
Transit_public	No. of employed labor force aged 15 years and over who use public transit for commuting

Source: Canadian census profile series for Dissemination Areas in 2006 and 2016 and Enumeration Areas in 1986
Notes: Transit data of 1986 are not available.

All values of income and dwellings acquired from Statistics Canada are nominal values (i.e., denominated in the corresponding year's dollar without correcting for inflation). Thus, the average all-items Consumer Price Index (CPI) is acquired. All nominal values are then adjusted to 2016 Canadian dollar.

Fourth, geographic units are acquired from Statistics Canada. Figure 3.3 is a diagram of part of geographic hierarchy for census dissemination which shows the geographic units of this study.

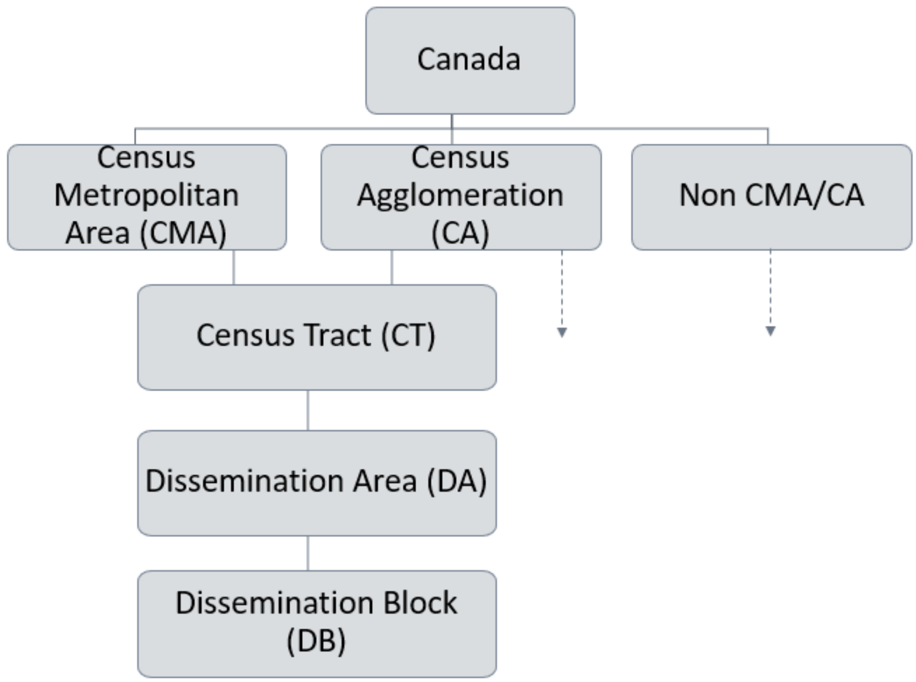


Figure 3. 3 Geographic hierarchy for census dissemination

Notes: In 2001, the DA replaced the Enumeration Area (EA) as a basic unit for dissemination.

Three units in the boxes are used in this study: CMA, DA, and Dissemination Block (DB). A DA is the smallest statistical unit composed of at least one adjacent DB and is used for Statistics Canada to disseminate census information (Statistics Canada, 2016). It is uniform in terms of population size, which consists of 400 to 700 people. The entire map of Canada is divided into DAs. The boundary of DA updates every five years based on population. In 2001, DA replaced Enumeration Area (EA), which has a similar but shifted boundaries. Thus, the EA boundary for 1986 is acquired as well as the DA boundaries for 2006 and 2016. DB is a basic geographic area defined on all sided by road networks and/or boundaries and is used to disseminate population and dwelling counts (Statistics Canada, 2016). In the present study, the DB data are used to reallocate 2006 and 2016 socioeconomic data to match with 1986 EA boundaries.

These spatial units (i.e., CMA, DA, and EA) for 1986, 2006, and 2016 are acquired from Statistics Canada. Population counts from census data and land cover/use shapefiles, which includes water areas for the respective years, are also used as ancillary data.

Fifth, another important dataset used in this study is the outer boundary of the Greenbelt Area (GB) defined by Ontario Regulation 59/05 obtained from the Ontario Ministry of Municipal Affairs and Housing. The original dataset includes four designations: Niagara Escarpment Plan, Oak Ridges Moraine Conservation Plan, Protected Countryside, and Urban River Valley. The Greenbelt areas that cover the Toronto CMA are extracted and then discarded during the exploration of urban sprawl.

Sixth, to define the reference-treatment groups in the DID regression analysis, housing sales data are also acquired from the Toronto Real Estate Board (TREB). Since the oldest data that can be accessed after 1986 are data of 1996, sales data which include the average transaction prices of all-home types are collected among the TREB zones in the Toronto CMA between 1996 and 2016.

3.2.3 Variables

In the present study, built-up area in km^2 is used as the dependent variable to measure the increase in the spatial extent of sprawl.

A set of socioeconomic variables is included as independent variables. Table 3.4 provides the descriptions and sources of these independent variables, while Table 3.5 presents the statistical summary. The income variable refers to the average annual income per person in the EA. Medians are discarded because medians cannot be assigned to EA units accurately when doing data interpolation between EA and DA—that is, the distribution of observations is not clear. The values of income between 1986 and 2016 are converted to 2016 Canadian dollars.

Table 3. 4 Descriptions and sources of the independent variables

Mnemonics	Description	Data source
Population	Number of the total population measured in 100,000	Census
Income	Median household income in 100,000 Canadian Dollars of 2016	
Proxy_car	No. of employed labor force use autos for commuting in 10,000	
Proxy_public	No. of employed labor force use public transit for commuting 10,000	
Distance	Distance from the geometric center of EA to CBD in 100 kilometers	RS and GIS
Proxy_ agriculture	Agricultural land area in 10 square kilometers	
SD_price	Standard deviation of all-type housing transaction prices for each TREB region	Toronto Real Estate Board
CV_price	Coefficient of variation of all-type housing transaction prices for each TREB region	

Notes: TREB data of 1986 are not available.

Table 3. 5 Summary statistics of socioeconomic variables among Enumeration Areas (n=6,726)

	1986		2006		2016	
	Average	S.D.	Average	S.D.	Average	S.D.
Population	319	431	1135	1793	1272	2914
Income	32679	42116	39534	22236	40709	25772
Proxy_car	133	196	443	748	461	1125
Proxy_public	6	16	82	127	104	216
Proxy_agriculture	0.57	0.27	0.73	0.13	0.79	0.10

Source: Statistics Canada and Toronto Real Estate Board

However, due to the unavailability of transportation costs data for the Toronto CMA, three variables are identified as proxies for commuting costs, based on the previous empirical studies. They are the distance from the geometric center (centroid) of EA to Central business district (CBD); the number of people who go to their workplace by car, and the number of people who use the public transit to work. Since there are no commuting data available in 1986, data imputation is conducted using 1996 commuting data to fill this gap.

3.3 Methods

3.3.1 Data pre-processing

Figure 3.4 is a flowchart of the main methods used in this study. The main stages are image pre-processing, mapping of urban coverage, and formation of variables. Details of the methods in each stage are given below.

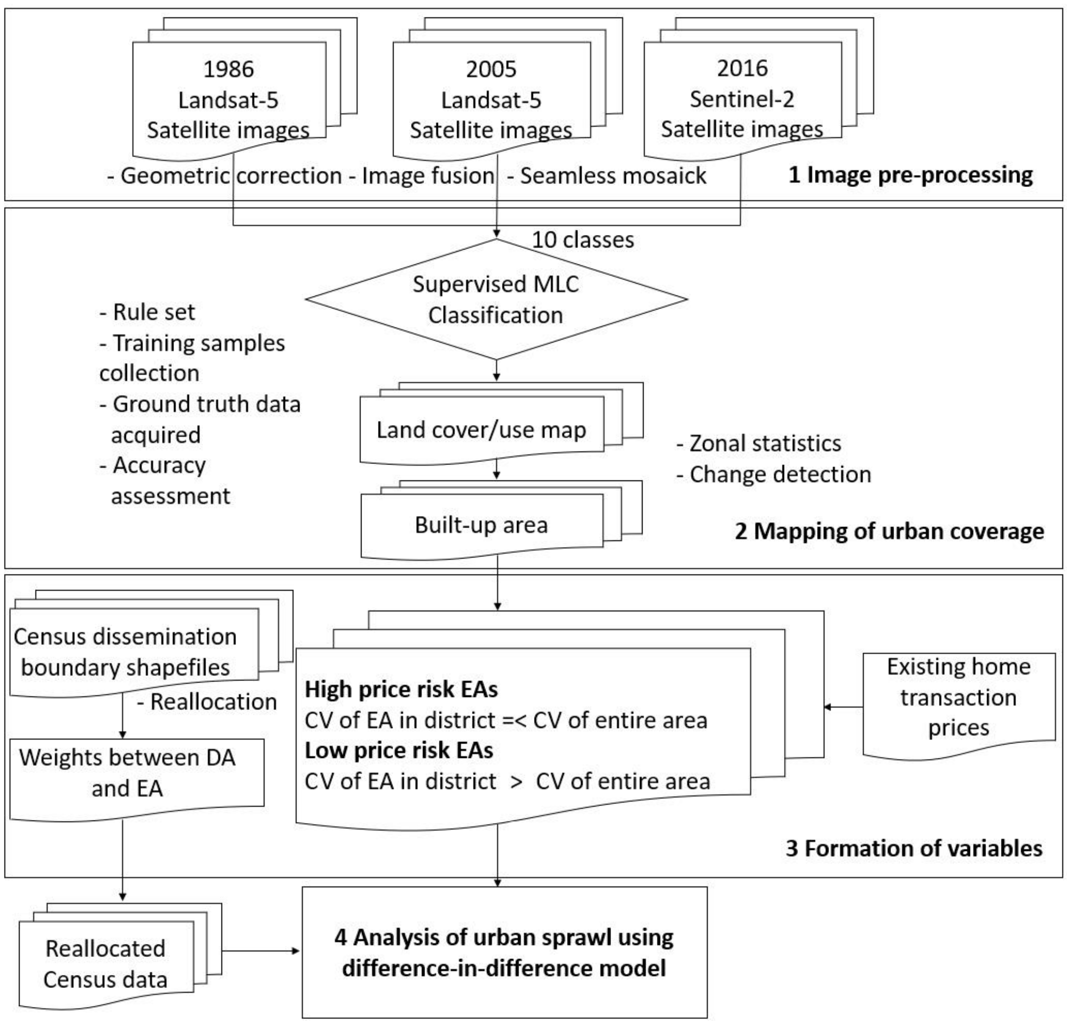


Figure 3. 4 Flowchart of methods used in this study

Pre-processing of the remote sensing imageries included geometric correction, image registration, image fusion, layer stacking, and seamless mosaic. Several imageries were mosaicked to cover the whole study area using the seamless mosaic method, and then got the subset image based on the boundary of the Toronto CMA. The Smoothing Filter-based Intensity Modulation (SFIM) technique (Liu, 2000) was used to enhance the spatial details without altering the spectral properties of the Sentinel-2 imageries.

Furthermore, the imageries were projected to Universal Transverse Mercator (UTM) coordinate system and World Geodetic System (WGS-1984).

3.3.2 Image classification and accuracy assessment

First, various band combinations were checked to visually display differences in pixel values for all bands and created training samples for classification. The combination of NIR/R/G was useful for vegetation, while the combination of SWIR2/SWIR1/NIR was useful for exploring bare soil. All spectral bands were used to process the supervised maximum likelihood classification (MLC). Ten classes were developed in total; they are: agriculture, grass, golf, gravel, industrial, residential, transportation, tree, water, and wetland.

Training samples were selected to represent the differences in each land cover/use category. Then 1,000 random samples were generated for each imagery as testing samples and assigned classes to each sample, based on the satellite imagery and higher resolution imagery in Google Earth. Once all points were assigned to their classes, accuracy report which includes confusion matrices, producer's, and user's accuracies was generated. In the confusion matrices, the Kappa coefficient is a statistic which denotes the agreement between the classification and the reference data after correcting any chance agreement (Cohen, 1960). Overall accuracy represents the total percentage of the reference data that are classified correctly. Producer’s accuracy is the map accuracy from the producer’s (i.e., map maker) perspective, which refer to the percentage of the ground truth that is correctly classified by the classification model, while user’s accuracy is the map accuracy from the user’s point of view, which indicated the percentage of the model that will be actually present on the ground.

3.3.3 Post-classification processing

The zonal statistics method was used to identify the predominant land cover/use class in the EA for further analysis. Residential, industrial, golf, and transportation lands were extracted from the land cover/use map as built-up area. If the single largest land-cover/use class in the EA was built-up, the EA was then classified to built-up EA. To form corresponding socioeconomic variables, census data of different census dissemination boundaries were reallocated and then were matched with the variables of EAs.

For the treatment and control groups in the DID method, the whole built-up area was divided into two classes: high price-risk EAs (above average) and low price-risk EAs (below average), based on the average transacted prices of resale homes acquired from the Toronto Real Estate Board. The EA in the region with the coefficient of variation (CV) of housing prices over and above the overall sample mean CV was assigned to treatment group: they are the high-risk EAs (treatment). Those EAs whose CV of housing prices fall below the overall sample mean CV was assigned to the control group (control).

3.3.4 Change detection

Change detection was processed to detect the urban expansion pattern between 1986 and 2016. Comparisons were carried out over three periods: 1986-2006, 2006-2016, and 1986-2016.

Each land cover/use class has a unique identifier, which the values are between 1 and 10. All values of 10 classes of 1986 were multiplied by 100 and add the adjusted values of 1986 (e.g., if the identifier of grass is 9, now 900) to the values of 2016 (e.g., the identifier of residential area is 4). The result will be 904, which show the changes in grass area to residential area. As a result, the detailed “from-to” maps and relevant statistics for the three periods were generated. To study patterns of urban sprawl, the classes of the changes were merged into seven categories: unchanged built-up, unchanged non-builtup, agriculture to built-up, tree to built-up, gravel to built-up, grass to built-up, and built-up to non-builtup.

3.3.5 Data interpolation

The starting point of the data interpolation method is to determine the conversion process. More specifically, there were three ways to complete the allocation. Ideally, the 1986 EA census data could be distributed to each grid and integrate them to match with the 2006 and 2016 DA units. Since this method would take too much time to execute the program, this plan was abandoned. Second, the 1986 EA census data could be assigned to match with the 2006 and 2016 DA units with the ancillary DB data. The third option, which is used in this study, is to allocate the 2006 and 2016 DA census data to match with the 1986 EA units with the help of the DB units. The reason that this study reallocated census data from DA to EA was to reduce statistical errors. The process of interpolation would introduce errors, but it is difficult to estimate the differences between estimates and real values. To account for this option, it is needed to realize the types of changes between DA and EA. The changes can be categorized as splits, consolidations, and complex changes (Logan et al., 2014).

Figure 3.5 shows these changes in census boundaries used in this study in 1986, 2006, and 2016. It is noted that the changes have occurred in census units contain more split and many-to-many than consolidations from 1986 to 2016. Hence, when conducting data interpolation from DA to EA, the process will include more data aggregations. Though this study does not include testing for the errors, it is expected that the process of aggregation might result in a less potential error as there are more real values rather than estimates.

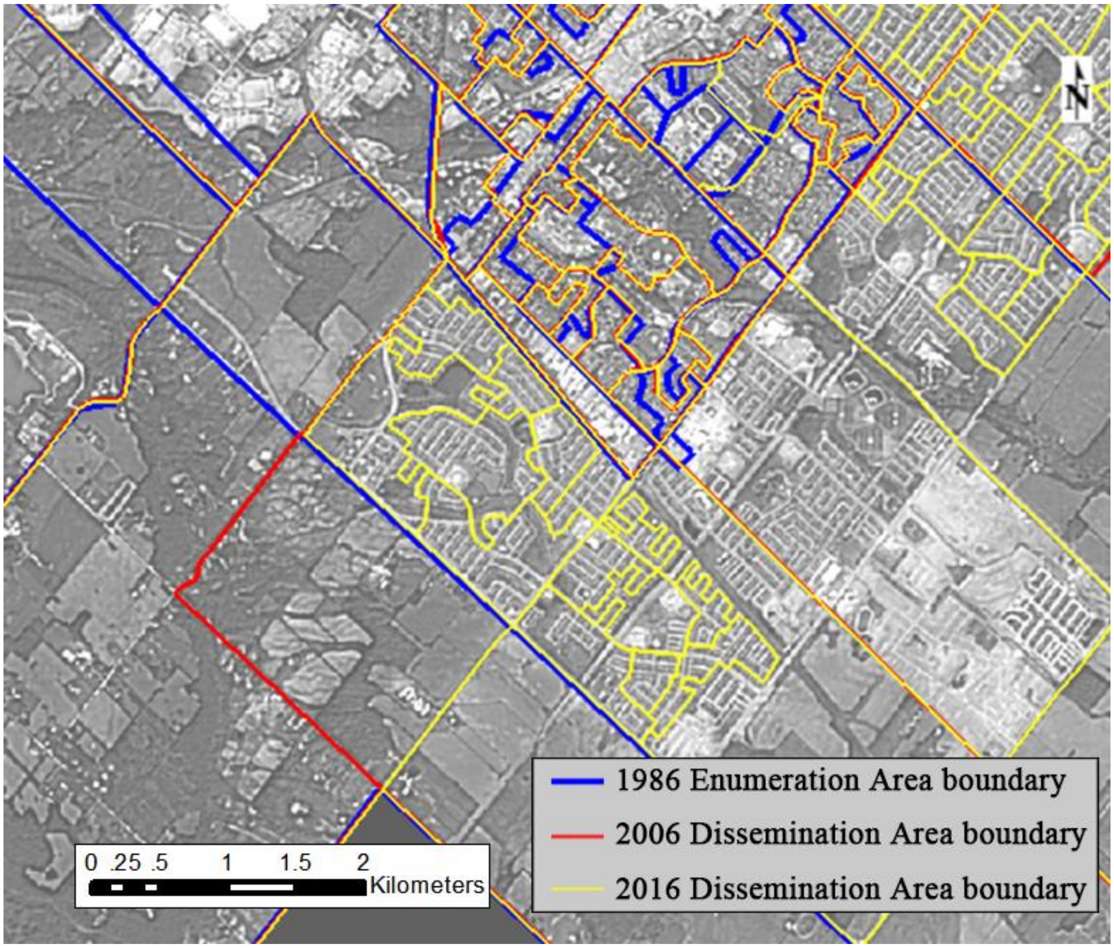


Figure 3. 5 Census units' boundary changes in the Toronto Census Metropolitan Area 1986, 2006, and 2016

The whole processes of interpolation for census data in a year are as follows. First, for the procedure of dasymetric method, water bodies extracted from land cover/use maps and the greenbelt areas from DBs were removed—that is, the smallest available census units that can be acquired. Next, the ratios of the DB population to the pertaining DA population were calculated. Third, the clipped DB was intersected with the target layer, EA. Similarly, the ratios of the intersection areas to the total DB areas were then computed. Next, the weights were calculated by multiplying the above two ratios and removing some slightest parts that meet three conditions: (1) the weights were less than 0.05; (2) the numbers of source DA were greater than 1; (3) the numbers of target EA were greater than 1. The value of 0.05 was decided by minimized error after tests (Allen

& Taylor, 2018). Then reweighing was processed to make sure the sum of weights of DBs from one source DA equals to 1—that is, distributing the differences among the remaining weights. In the last step, the final weights, $w_{s,t}$, were created by grouping the DBs based on target EA units and summing the adjusted weights of each DB. Each pair of DA and EA was assigned a unique identifier.

For count variables (e.g., population) and continuous variables (e.g., average income), there are different ways to calculate the corresponding variables for each EA unit:

$$V_{t,c} = \sum_s w_{s,t} V_s \tag{3.3}$$

$$V_{t,nc} = \frac{\sum_s w_{s,t} V_s r_s}{\sum_s w_{s,t} V_s} \tag{3.4}$$

where V_s is the variable from the source layer; $V_{t,c}$ is the count variable in the target layer; $V_{t,nc}$ is the continuous variable in the target layer; r_s indicates the attribute of the variable of the source layer. For example, if V_s is average income per person, then r_s will be the size of the population.

3.3.6 Statistical analysis using the difference-in-difference model

In the last step, the difference-in-difference (DID) analysis was conducted. There are three time periods in the present study: 1986-2006, 2006-2016, and 1986-2016. For each pair of time periods, a DID model is employed that compares the amount of urbanized areas in the initial ("before") and the subsequent ("after") period. Thus, the observations can be divided into four groups. They are the treatment group before ($time_{it}$=0, $treatment_{it}$=1), the treatment group after ($time_{it}$=1, $treatment_{it}$=1), the control group before ($time_{it}$=0, $treatment_{it}$=0), and the control group after ($time_{it}$=1, $treatment_{it}$=0). The following equation was estimated:

$$\begin{aligned} Y_{it} = {} & \alpha_0 + \alpha_1 time_{it} + \alpha_2 treatment_{it} + \alpha_3 time_{it} \cdot treatment_{it} + \\ & \sum_{j=1}^{N} \alpha_j \times control_{jt} + \varepsilon_{it} \end{aligned} \tag{3.5}$$

where *i* represents EA; *t* represents time; *time* is a dummy variable for the period; *treatment* is a dummy variable for the groups which indicate the levels of price risk;

control includes variables of population, income, a proxy for agricultural land rent, and a proxy for commuting costs; ε is the error term. The coefficient of the interaction term, α_3, indicates the net impact of the price risk in urban sprawl.

Control group included EAs that have lower price risks and therefore have smaller changes in the built-up area over the time period. Conversely, treatment group contained EAs that have higher price risks and therefore are more likely to develop faster.

Coefficient of Variance (CV) of housing sales prices was brought in to indicate the housing price risk. The CV is defined as the ratio of the standard deviation to the mean:

$$CV = \frac{\sigma}{\mu} \tag{3.6}$$

For example, if the CV of EA *i* is greater than the grand mean CV defined over the study area, EA *i* belongs to the treatment group, then the dummy variable *treatment* will receive a value of 1; 0 otherwise. The time variable *t* equals to a 0 if it is the base year and a 1 if it is the later year.

3.4 Results and discussion

3.4.1 Accuracy assessment

The confusion matrices used to assess classification accuracy for 1986, 2005, and 2016 are summarized in Table 3.6. The overall accuracies were 79%, 77.6%, and 86.5%, respectively, with a Kappa coefficient of 0.735, 0.731, and 0.849. The accuracies of several classes were consistently high, such as water, agriculture, and tree, ranging from 77.1 to 100. However, user’s and producer’s accuracies of transportation are relatively low.

Table 3. 6 Summary of classification accuracies for 1986, 2005, and 2016

Land cover/use class	1986		2005		2016	
	Producer's (%)	User's (%)	Producer's (%)	User's (%)	Producer's (%)	User's (%)
Water	94.6	100	99.1	100	93.3	98.2
Residential	67.9	69.6	72.4	85.7	91.5	78.3
Industrial	56.5	83.0	59.7	80.0	61.3	82.6
Gravel	62.8	77.1	72.7	80.0	94.4	70.8
Tree	77.1	80.8	74.6	84.2	96.5	98.8
Agriculture	87.4	88.1	87.1	85.2	93.0	93.8
Grass	64.3	70.6	57.6	62.3	80.0	92.3
Golf	85.0	53.1	90.9	52.6	93.2	88.7
Wetland	83.9	66.7	56.0	29.2	85.2	100
Transportation	45.2	25.3	51.2	34.4	67.8	64.5

3.4.2 Change detection analysis

Figure 3.6 shows urban boundary, or urban coverage changes over the time periods. On average, being reallocated to EAs, every EA received 14% growth in built-up area from 1986 to 2016. The results show that sprawl has increased over the time period in the Toronto CMA.

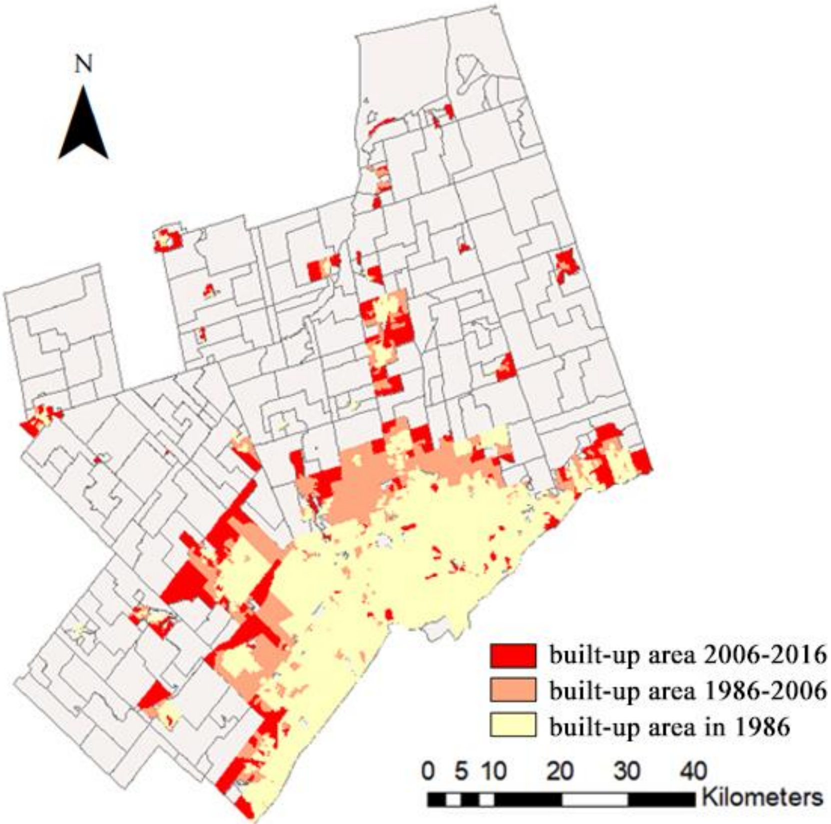
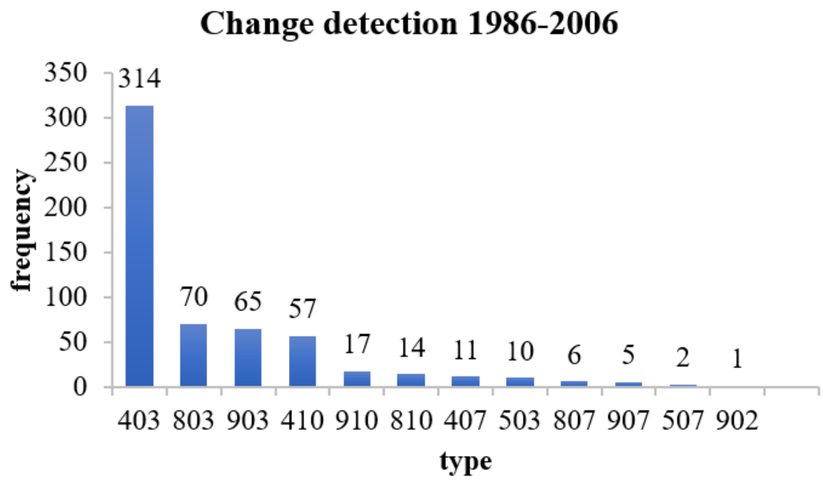
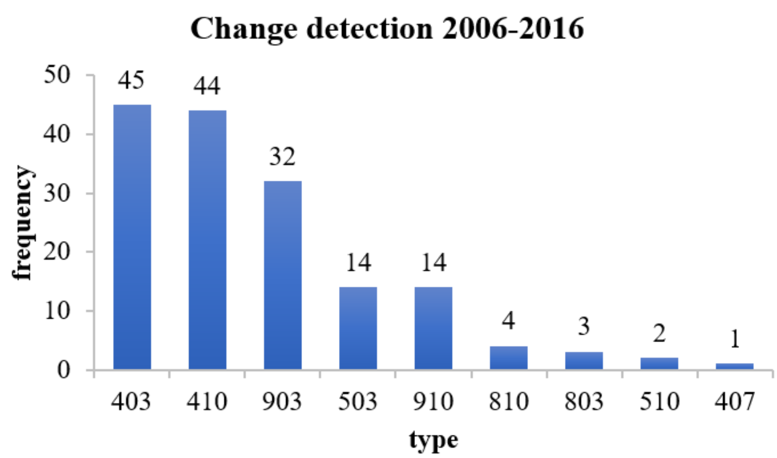


Figure 3. 6 Urban area within the Toronto CMA from 1986 to 2016

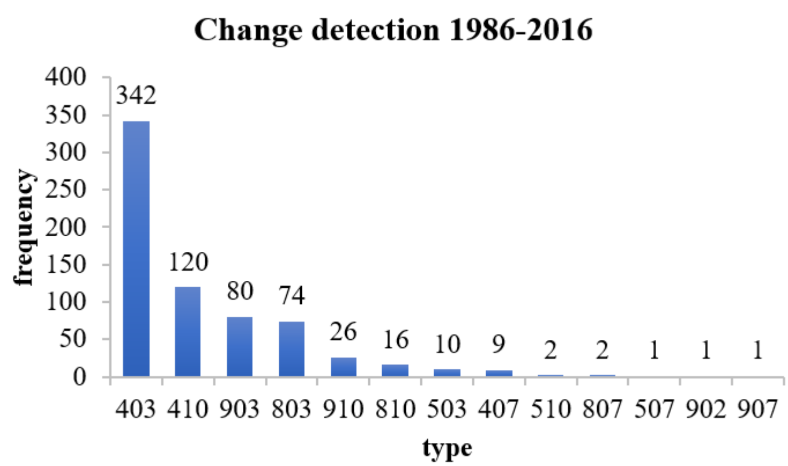
Figure 3.7 and Table 3.7 show the frequency of different land cover/use area in 1986 that finally converted to the built-up area in 2016. The highest frequency of occurrence is the shift from agriculture area to golf area, which accounts for more than 50% of the conversion, followed by residential area to industrial area, as well as grass area to golf area. Figure 3.8 illustrates these changes merged into seven categories: unchanged built-up, unchanged non-builtup, agriculture to built-up, tree to built-up, gravel to built-up, grass to built-up, and built-up to non-builtup.



(a)



(b)

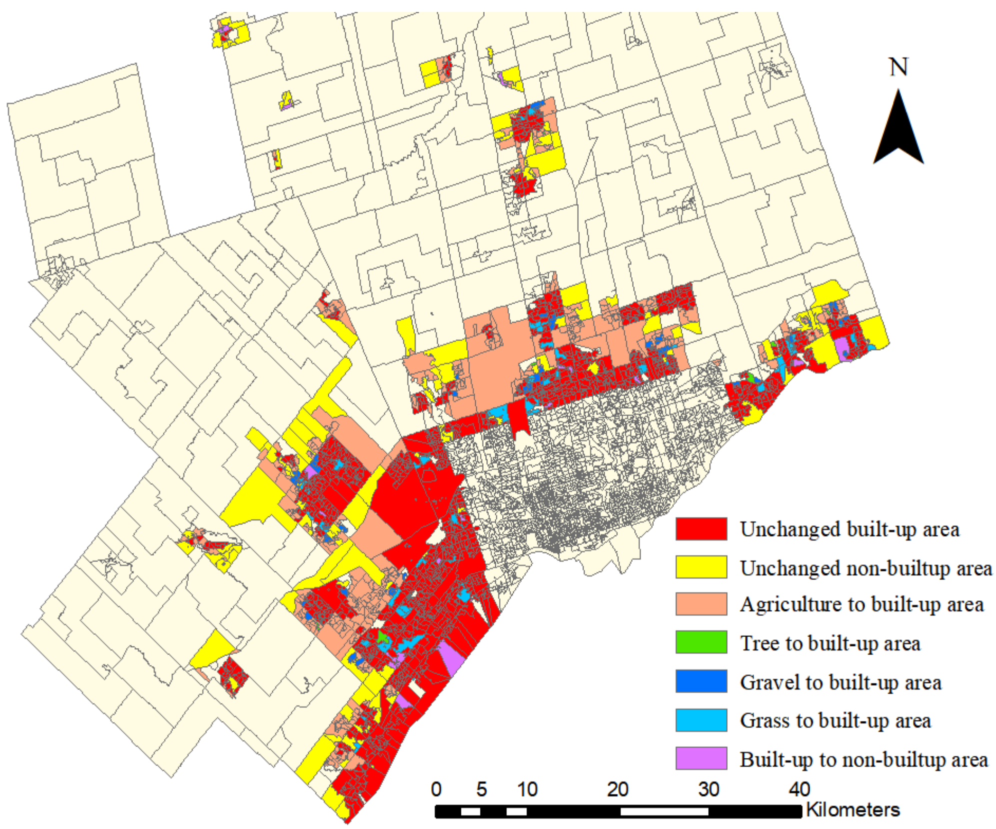


(c)

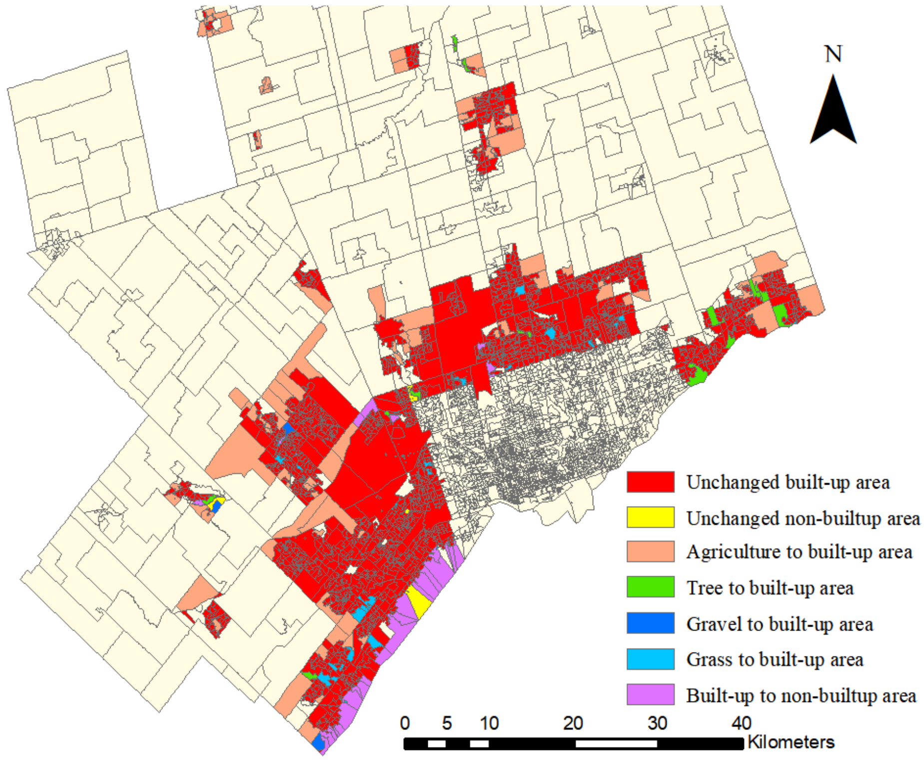
Figure 3. 7 Change detection results (a) 1986-2006; (b) 2006-2016, and (c)1986-2016

Table 3. 7 Description of the change detection result

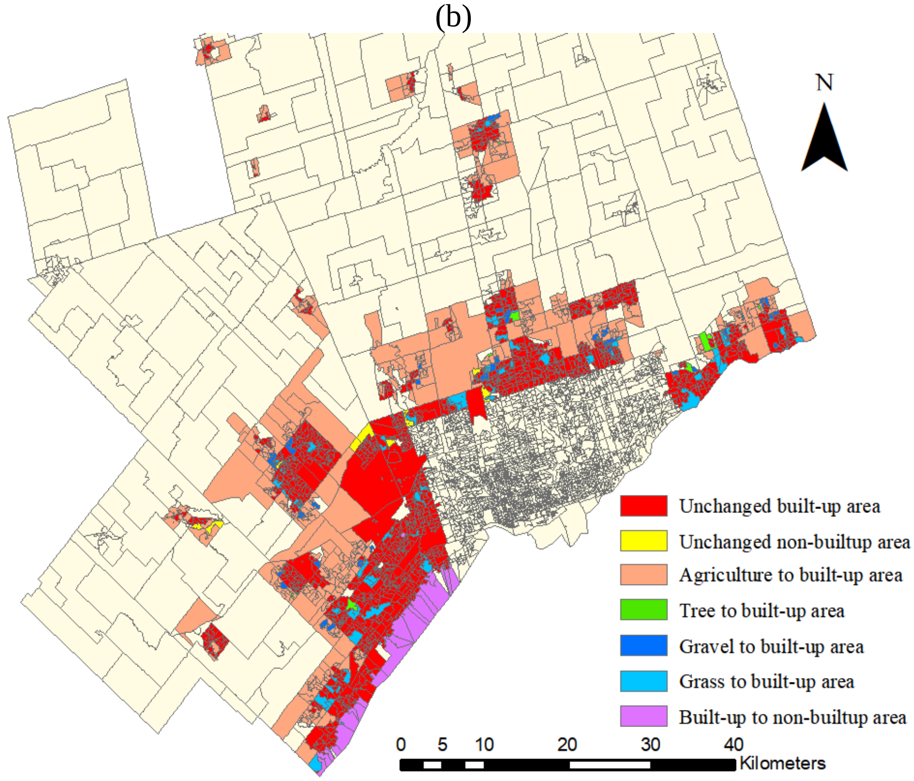
Mnemonics	Transition type	Mnemonics	Transition type
403	Agriculture to residential	807	Gravel to industrial
407	Agriculture to industrial	810	Gravel to transportation
410	Agriculture to transportation	902	Grass to golf
503	Tree to residential	903	Grass to residential
507	Tree to industrial	907	Grass to industrial
510	Tree to transportation	910	Grass to transportation
803	Gravel to residential		



(a)



(b)



(c)

Figure 3. 8 Change detection of the predominant class in the Enumeration Area (a) 1986-2006; (b) 2006-2016, and (c)1986-2016

3.4.3 Statistical analysis

Table 3.8 and 3.9 show the results of the DID models, with the dependent variable defined as the amount of built-up land area. In each model, the effects of price risk and the control variables (population, average income, agriculture land area, and either proxy for commuting costs) were estimated. In models 1, 2, and 3, the distance variable was used as the proxy for commuting costs. In 1986-2006 and 2006-2016 (models 1 and 2), the distance variable is significant at 5% level, with signs consistent with the theory.

Table 3. 8 DID estimation results using distance as the proxy for commuting costs (n=6,726)

	1986-2006 Model 1	2006-2016 Model 2	1986-2016 Model 3
Intercept	0.195^{***} (3.79)	0.051 (0.83)	0.145^{***} (2.89)
Time	0.036 (1.09)	0.074^{**} (2.06)	-0.036 (1.12)
Treatment	0.096^{**} (2.21)	0.054 (0.28)	0.097^{**} (2.25)
Time_ treatment	-0.116^{**} (1.97)	-0.091 (1.35)	-0.111^{*} (1.92)
Population	1.889^{***} (17.31)	2.240^{***} (30.63)	2.872^{***} (45.43)
Income	-0.300 (0.74)	2.11^{***} (3.26)	-1.004^{***} (2.67)
Proxy_ agriculture	3.013^{***} (19.79)	6.932^{***} (17.01)	2.324^{***} (14.61)
Distance	-0.328^{**} (2.04)	-0.363^{*} (1.93)	-0.116 (0.73)
Adjust R^2	0.184	0.350	0.359

Notes: The dependent variable is Builtup, which is the area of built-up region in square kilometer in the DA. The absolute values of the *t*-statistics are presented in parentheses. ***, **, * represent the coefficient is significant at the 1%, 5%, 10% level, correspondingly, with two-tailed tested.

For models 2 and 3, the variation in the independent variables explains above 35% of the variation in the data.

In models 1 and 3, the net impacts of the treatment are reflected in the coefficients of the interaction term, which is the coefficient of *Time_treatment*. The coefficients are all negatively significant at the 10% level, which indicate that the higher price risk will create an incentive for the developer to delay developments when the downside risk is high.

Table 3. 9 DID estimation results using numbers of people commute by car/public transit as proxies for commuting costs (n=6,726)

	1986-2006		2006-2016		1986-2016	
	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Intercept	0.103***	0.103***	-0.038	-0.04	0.112***	0.113***
	(4.07)	(4.07)	(1.02)	(1.17)	(4.51)	(4.559)
Time	0.035	0.038	0.062*	0.069*	-0.028	-0.036
	(1.05)	(1.14)	(1.71)	(1.90)	(0.86)	(1.12)
Treatment	0.122***	0.123***	0.059	0.065	0.111***	0.106***
	(2.93)	(2.95)	(1.21)	(1.33)	(2.72)	(2.60)
Time_ treatment	-0.118**	-0.111*	-0.085	-0.088	-0.103*	-0.112*
	(2.00)	(1.85)	(1.27)	(1.31)	(1.78)	(1.92)
Population	2.154***	1.975***	3.742***	1.889***	1.839***	2.855***
	(3.65)	(9.61)	(7.94)	(10.86)	(4.10)	(16.11)
Income	-0.305	-0.364	1.974***	1.996***	-1.097***	-1.003***
	(0.75)	(0.87)	(3.09)	(3.12)	(2.91)	(2.61)
Proxy_ agriculture	2.996***	2.983***	7.289***	7.092***	2.306***	2.318***
	(19.64)	(19.56)	(17.11)	(16.97)	(14.52)	(14.59)
Proxy_car	-0.641	–	-3.94***	–	2.703**	–
	(0.45)		(3.22)		(2.33)	
Proxy_ public	–	-1.341	–	4.945**	–	0.234
		(0.48)		(2.22)		(0.10)
Adjust R^2	0.183	0.183	0.351	0.350	0.360	0.360

Notes: The dependent variable is Builtup, which is the area of built-up region in square kilometer in the DA. The absolute values of the *t*-statistics are presented in parentheses. ***, **, * represent the coefficient is significant at the 1%, 5%, 10% level, correspondingly, with two-tailed tested.

In Table 3.9, the results show that during the two periods of 1986-2006 and 1986-2016, which are shown in models 4, 5, 8, and 9, urban area increases with population and agricultural land area, with significant coefficients. However, the proxies for transit do not perform well. Similarly, the coefficients of interaction terms are all negatively significant at the 1% level.

In models 8 and 9, despite the relatively high values of R^2 (about 0.35), the coefficients of the time dummy variable, population, income, agricultural land area, and two proxy variables for transit are significant. However, the signs of the coefficients of the proxies for transit disaccord with expectations.

In models 6 and 7, the time dummy variable, population, income, agricultural land area, and the proxy of transit are significant, however, the interaction term is not significant enough.

3.5 Conclusions

This study empirically examines the causes of urban sprawl using Landsat 5 and Sentinel-2 satellite images of the Toronto CMA between 1986 and 2016. The change detection technique was applied to the images of the Toronto CMA; the results showed that urban area increased by 14% over the study period. It is worth noting that urban sprawl mainly happened on the edges of the city of Toronto. One can speculate that these land-use transitions might be due to the conventional explanation of "highest and best use". These transitions could be modelled through a multinomial-logit model, but which is the not the focus of the present study. The land cover/use maps were matched with residents' socioeconomic data from the corresponding census, forming a panel data set of the DAs of the Toronto CMA. The study used the panel data set to test and confirm that the monocentric city model is sufficient to explain the causes of sprawl to some extent. However, it should be noted that the selection of proxies for variables will affect the accuracy of the models. An alternative theory based on price risk was also tested. Though the results of testing the theories are not as robust as in previous studies, the study contributes to the literature by broadening it to include the role of risk. When looking at risk alone, that is more aligned with the theory of the real options. Thus, developers tend to delay developments due to the presence of the real options.

The procedure provided in this study can help generate land cover/use maps with remote sensing techniques. When reallocating census data in different years, minimizing error was conducted by using the combination of areal, dasymetric, and population-based interpolation methods.

Although the variables explain a large part of the variation of the sprawling area, their explanatory power for modeling commuting costs is relatively low. Using the monocentric city model to control for the possible correlation between explanatory variables and urban boundary expansion, the analysis shows that the conclusions of the traditional monocentric city model are valid for the Toronto CMA to some extent.

One of the advantages of using the DID model is that it supposes interventions are not random but systematic. Also, it can capture differences across groups that are constant over time. Similarly, it can capture differences over time that can be applied to all groups. The DID estimate β_3, which is the coefficient of the interaction term, indicates that high price risk speeds up urban sprawl. The results suggest that policy makers may be able to control the growth of urban sprawl by stabilizing housing prices. To investigate the endogeneity, it is needed to test for spatial error and spatial dependence in a future study.

As possible developments in the future, further studies could look for more precise measures of commuting costs. Also, for the process of data interpolation, there might be a need to assess the impact of errors in the estimation results.

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4 Conclusions

4.1 Summary and conclusions

Urban development in Canada has been characterized by low-density construction on the fringes of cities, which is known as urban sprawl. As this urban sprawl continues in Canadian cities, it is believed that it is timely that this research focuses on studying the determinants of urban sprawl. In Chapter 2, the study examines the causes of urban sprawl, using a combination of census socioeconomics data and Sentinel-2 satellite imageries of the 11 most populous CMAs in 2016. The results show that urban coverage increases with population and property tax rates. In Chapter 3, the study focuses on the Toronto CMA and reinserts the role of price risk in understanding the timing of urban development in 1986-2006, 2006-2016, and 1986-2016. In both Chapters, the results point to the fact that price risk delay the speed of urban sprawl.

Overall, the research presented in this thesis provides the following responses to the objectives in the Introduction:

1. The high spatial-resolution Sentinel-2 satellite imagery can provide useful information for land cover/use classification. The imagery makes it possible to extract built-up areas for studying urban sprawl with relatively high accuracy. The combination of remote sensing measures and census data also adds details to the analysis of urban sprawl.

2. Sentinel-2 and Landsat 5 imageries together provide an accurate assessment of the extent of urban boundary changes over a period from 1986 to 2016.

3. The conclusions of the traditional monocentric city model are valid for the 11 CMAs and the Toronto CMA to some extent. The theories of the Tiebout model are verified in the 11 CMAs, which indicate that higher prices for similar public goods might push residents to move to areas that offer a similar bundle but at a lower price. Note that the monocentric and Tiebout models are not competing models: The validity of one would not necessarily eliminate that of the other. Instead, the two models represent concurrent forces at work, which might at the same shape people's preferences and mobility, thereby affecting the extent of urban sprawl at the same time.

4. High price risk creates an incentive for the developer to delay the development—that is, with the presence of the real option, a lower downside risk (with the option to delay and reap the agricultural land rent) drives more urban development to a later time. When looking at urban development, these are market forces that are beyond the control of urban policies. Developers might delay development despite the fact that there are no policies. However, developers might actually speed up development, even in light of urban policies. There might be policies related to control development, but then urban sprawl is heavily influenced by market forces that are beyond the control of policy makers. The revelation is: Do not tinker with urban development with more growth policies. Developers follow their own timing, by observing market forces such as price risk—how would policy makers be able to increase or reduce price risks? Just because policy makers have been tinkering the market with the wrong tools, by ignoring risk, most policies are therefore ineffective. Let the market takes care of itself.

4.2 Contributions

The study shows the advantages of high spatial-resolution data—Sentinel-2 imagery—in land cover/use classification. By looking at urban boundary expansion using high spatial-resolution remote-sensing data, Sentinel-2 series imagery is verified to be applied to identify and generate land cover/use patterns with relatively higher accuracy. A combination of satellite imagery and socioeconomic data also allows readily testing the existing theories related to urban sprawl.

Another contribution of this research is reinserting the role of real options. The results of this study can be used by policy makers to formulate more informed and timely growth policies based on market conditions.

4.3 Limitations

There are some limitations to this study that include the insufficient proxies for commuting costs. Ideally, commuting costs data are needed to test the monocentric city model, but there are no such data at the DA/EA level. Three proxies, the distance to the

CBD, number of people who use public transit to go to work, and number of people who go to their workplace by car, were included in this study, but none of them perform well.

Also, it might be difficult to look at the changes in census data over time for a specific area due to the changing census boundaries. These changes are slight, but will become larger as time passes. Although a fairly systematic interpolation method was used to solve this problem, there might still be errors in the estimation results.

4.4 Possible future research

Future research is discussed in two directions.

First, the model can be refined by using more precise measures of independent variables, especially for commuting costs. This also has the advantage of reducing the uses of inaccurate proxies.

A second way would be testing for spatial error and spatial dependence in light of endogeneity. The next step of this study is to explicitly test if urban development in a subject spatial unit can be affected by the amount of development in its neighboring units. Or, one might also wonder if the error in the model could violate the homoscedastic assumption.

Finally, one might suspect that, while price risk (X) affects the extent and speed of urban sprawl (Y), the volume of developments and therefore the property transactions in the sprawling area (Y) could also affect price risk (X)—that is, the risk variable could be endogenous. Testing and correcting for this endogeneity issue will be the next phase of the study, which is beyond the scope of the dissertation.

Appendices

Appendix A Peripheral municipalities of Census Metropolitan Areas

According to Statistics Canada, the majority of the mega municipalities are central municipalities of a census metropolitan area (CMA). The name of a central municipality is defined as the name of the corresponding CMA or census agglomeration (CA). All other municipalities within a CMA or CA, except the central municipality, namely peripheral municipalities. For example, the largest municipality in Canada by population, Toronto (2,731,571 in 2016), is the central municipality of the Toronto CMA. Other municipalities located within the Toronto CMA are peripheral municipalities, such as Mississauga and Brampton. A few of the large municipalities in Canada are peripheral municipalities included in a CMA: Mississauga, Brampton, Markham, Vaughan (Toronto CMA); Surrey and Burnaby (Vancouver CMA); Laval and Longueuil (Montreal CMA). Distinguishing central and peripheral municipalities is useful to assess some specific phenomena such as urban sprawl.

Previous findings confirm urban sprawl is occurring or continuing in many Canadian CMAs. For several decades, peripheral municipalities have been growing faster than central municipalities in Canada. From 2011 to 2016, population growth was higher among peripheral municipalities (+6.9%) of CMAs, compared with central municipalities (+5.8%).

Appendix B Greenbelt area

The importance of greenbelt is also noted in restraining urban sprawl. According to Furberg et al. (Furberg et al., 2012), the Oak Ridges Moraine (ORM), which is an important geological region for the Greater Toronto Area (GTA), comes threat from urban sprawl in recent years. If there are no actions, urban sprawl is likely to play a vital role in the environment and resource of similar areas. In 2005, the issue of the Ontario Places to Grow Plan set a permanent greenbelt area of green space and shows one attempt to solve urban sprawl (Ministry of Municipal Affairs and Housing, 2005). It was in effect from July 1, 2017 to May 15, 2019. The act enables:

(1) designation of any geographic region of the province as a growth area with a specific focus.

(2) development of a growth plan in consultation with local officials, stakeholders, public groups, and members of the public and Indigenous communities for a particular region.

(3) decisions about growth to be made in ways that increases and promotes greater housing and transportation options, investments in regional public service facilities in downtown areas, and maximizes infrastructure investments in communities, while balancing regional needs for farmland and natural areas.

Figure B.1 shows the greenbelt designation in the Greater Toronto Area.

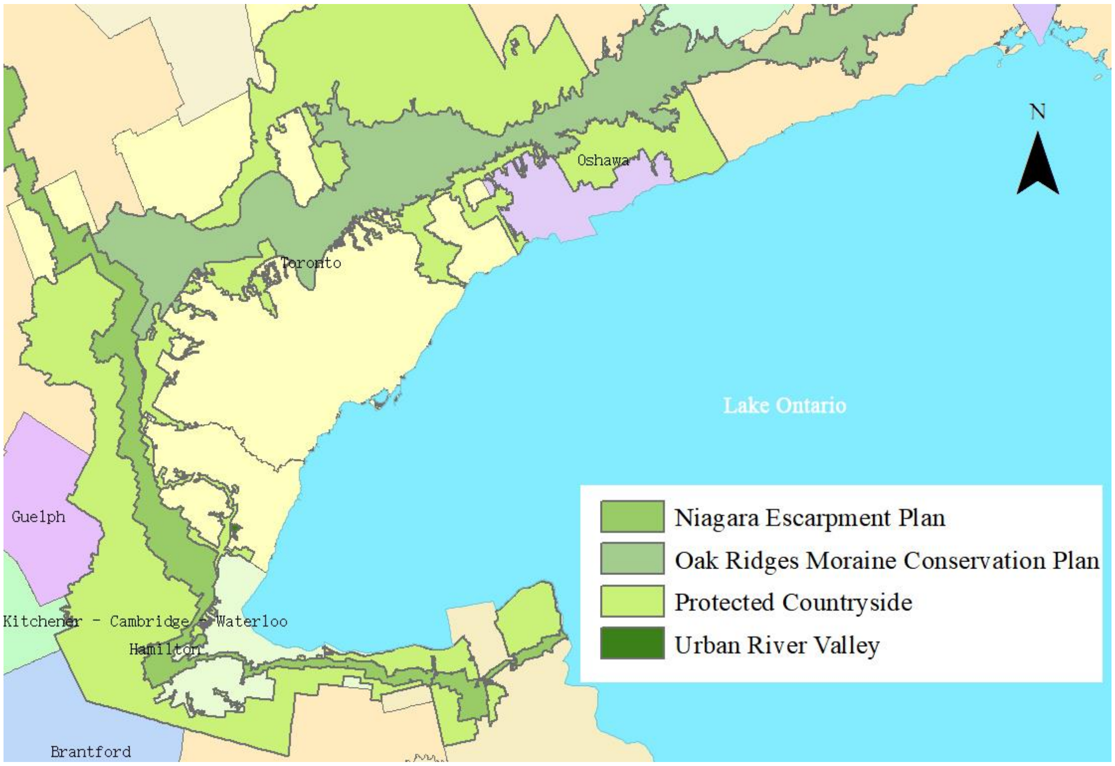

Figure B. 1 Greenbelt Designation for the Greater Toronto Area

References:

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Appendix C Sentinel-2 imageries for the 11 Census Metropolitan Areas

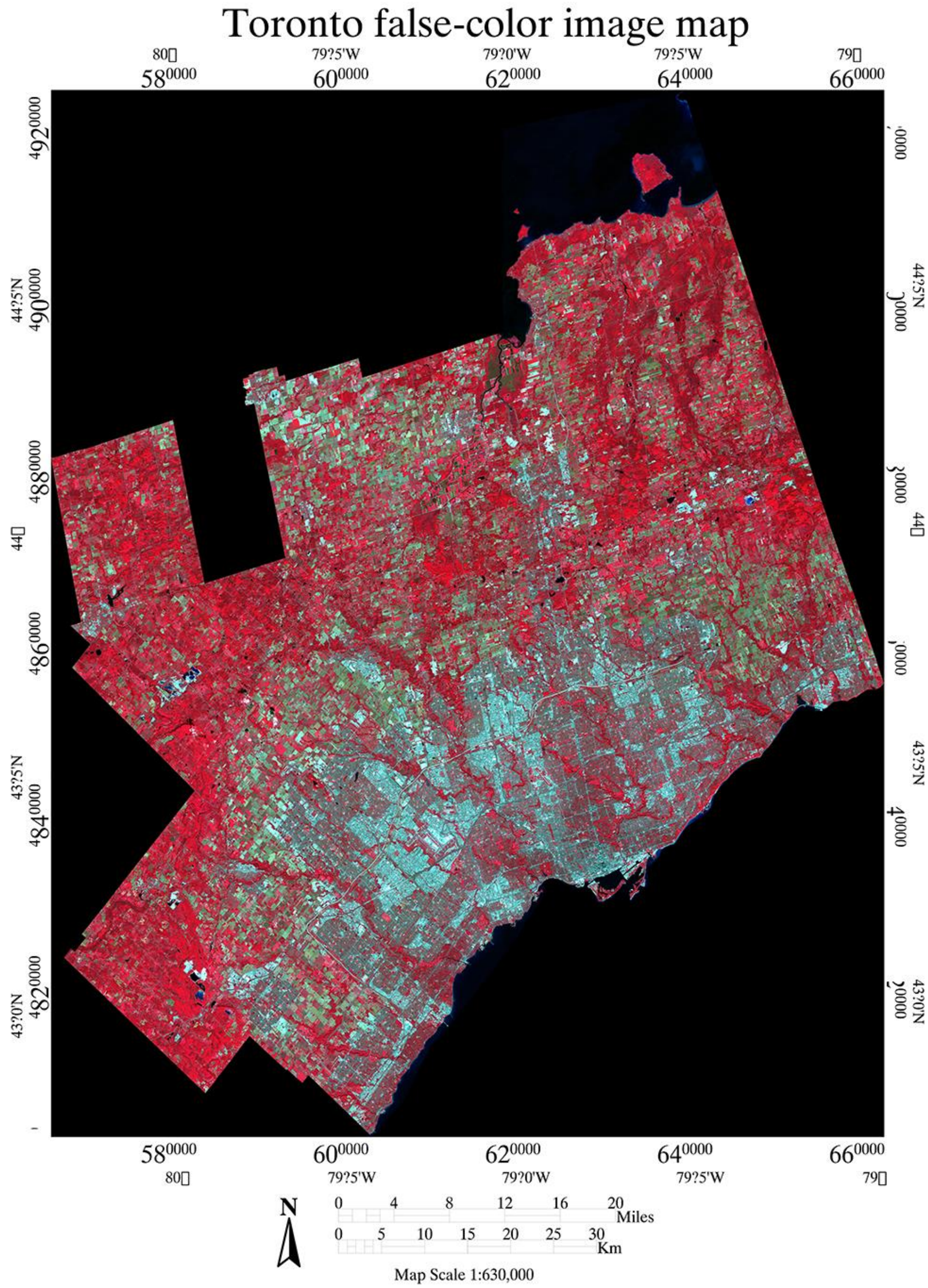

Figure C. 1 Toronto CMA false-color image map

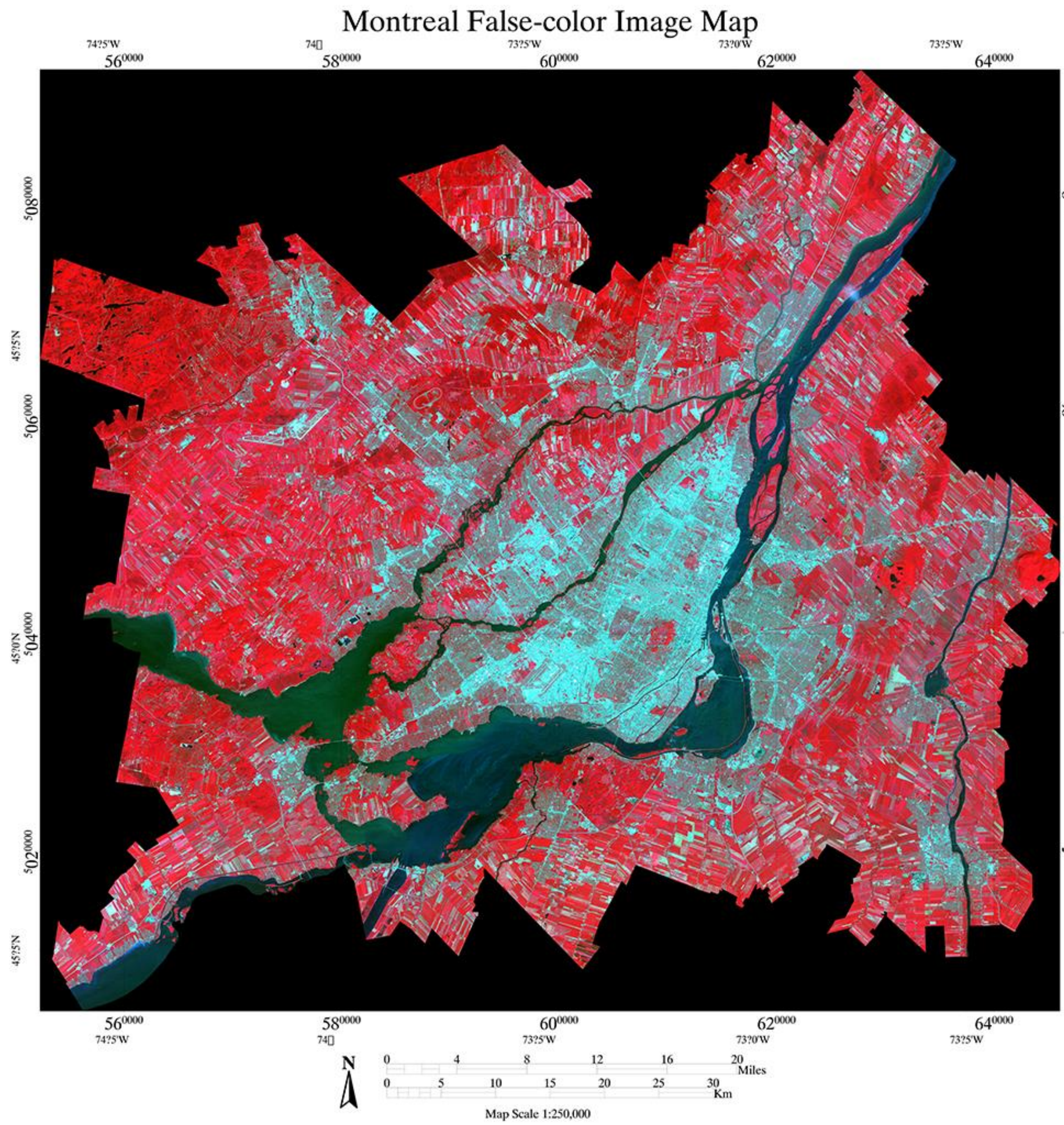

Figure C. 2 Montreal CMA false-color image map

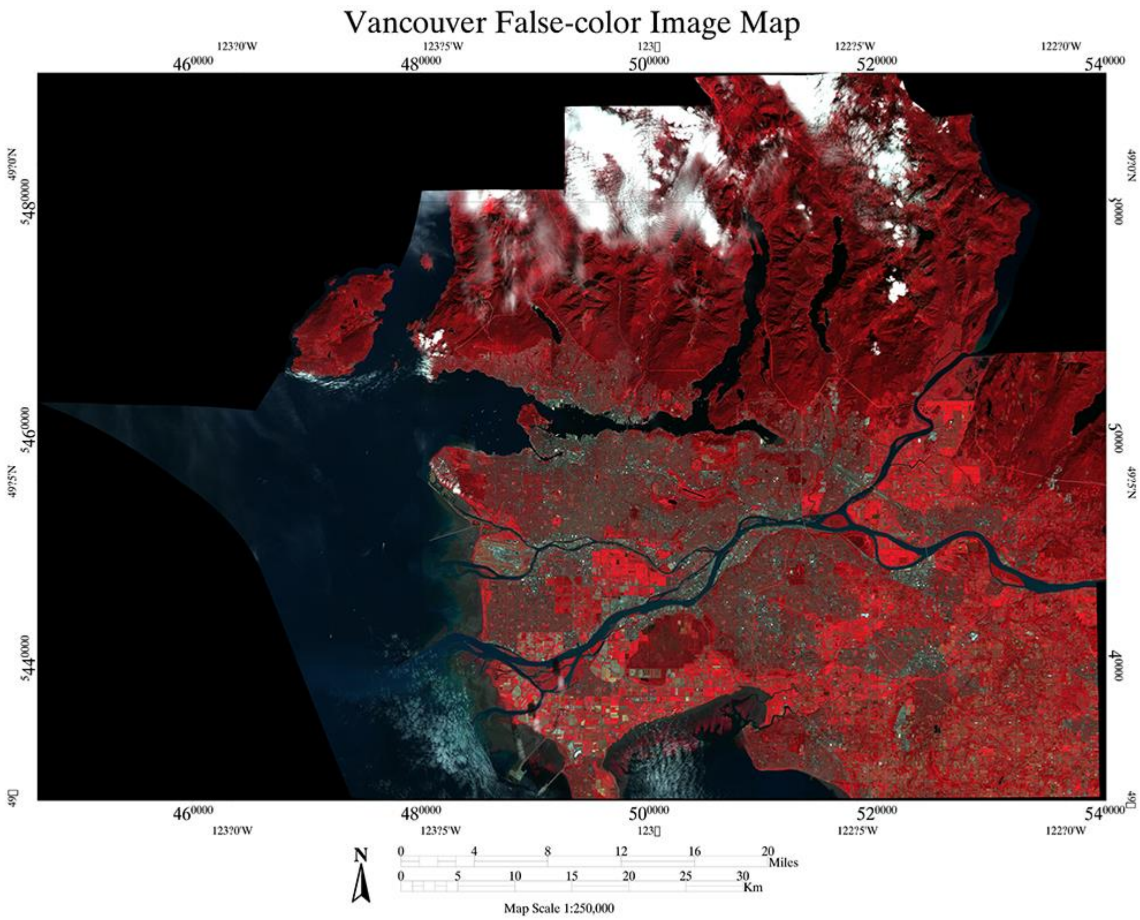

Figure C. 3 Vancouver CMA false-color image map

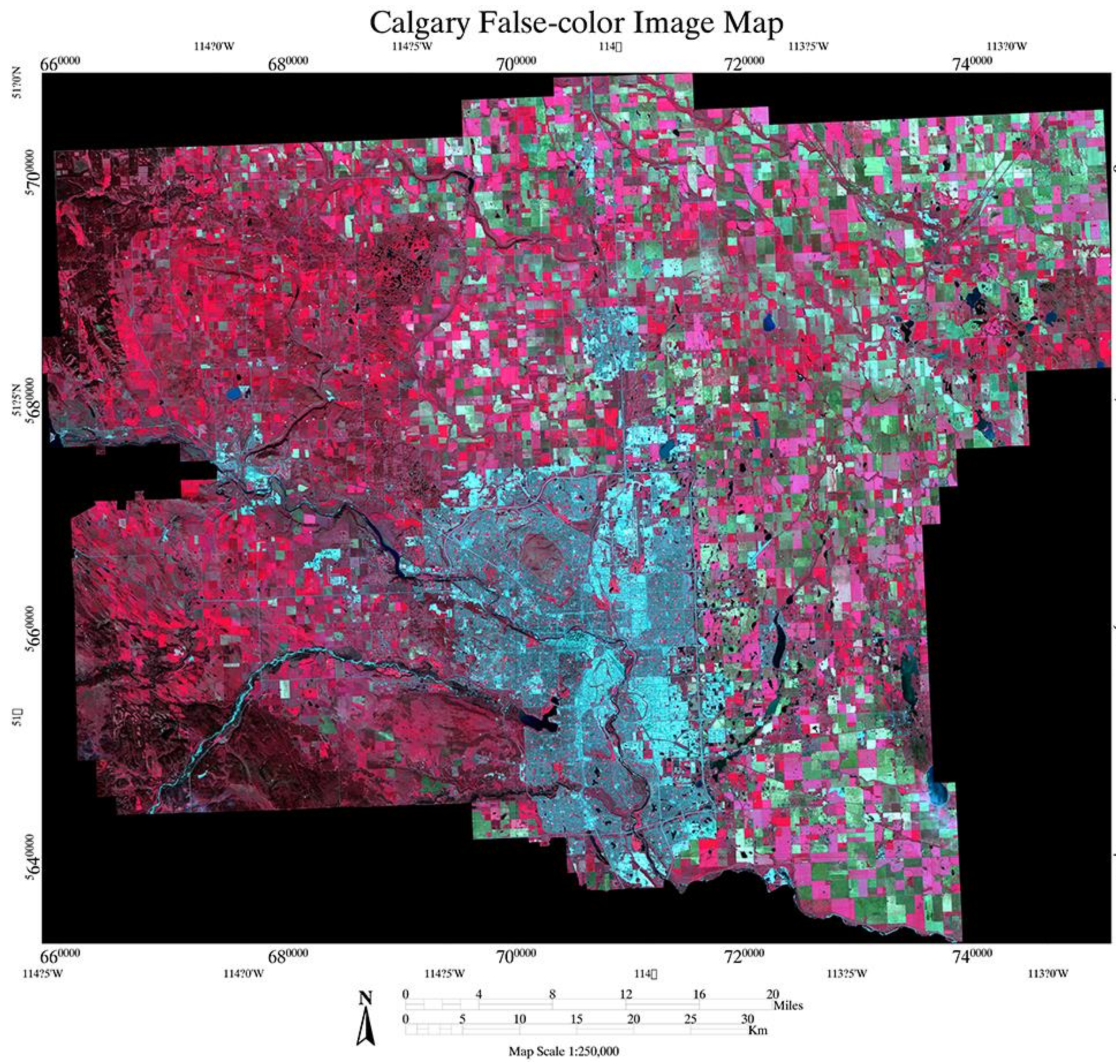

Figure C. 4 Calgary CMA false-color image map

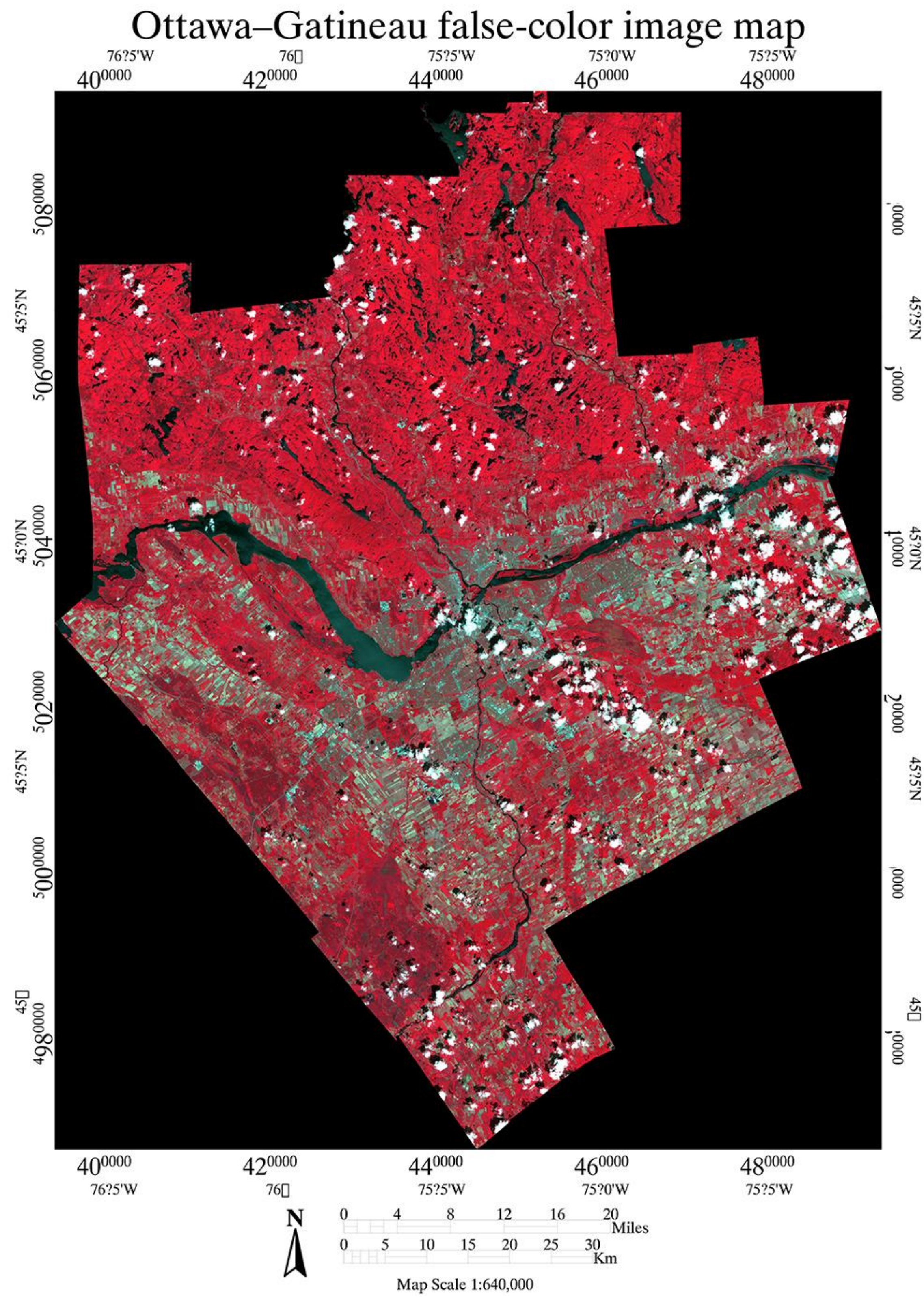

Figure C. 5 Ottawa-Gatineau CMA false-color image map

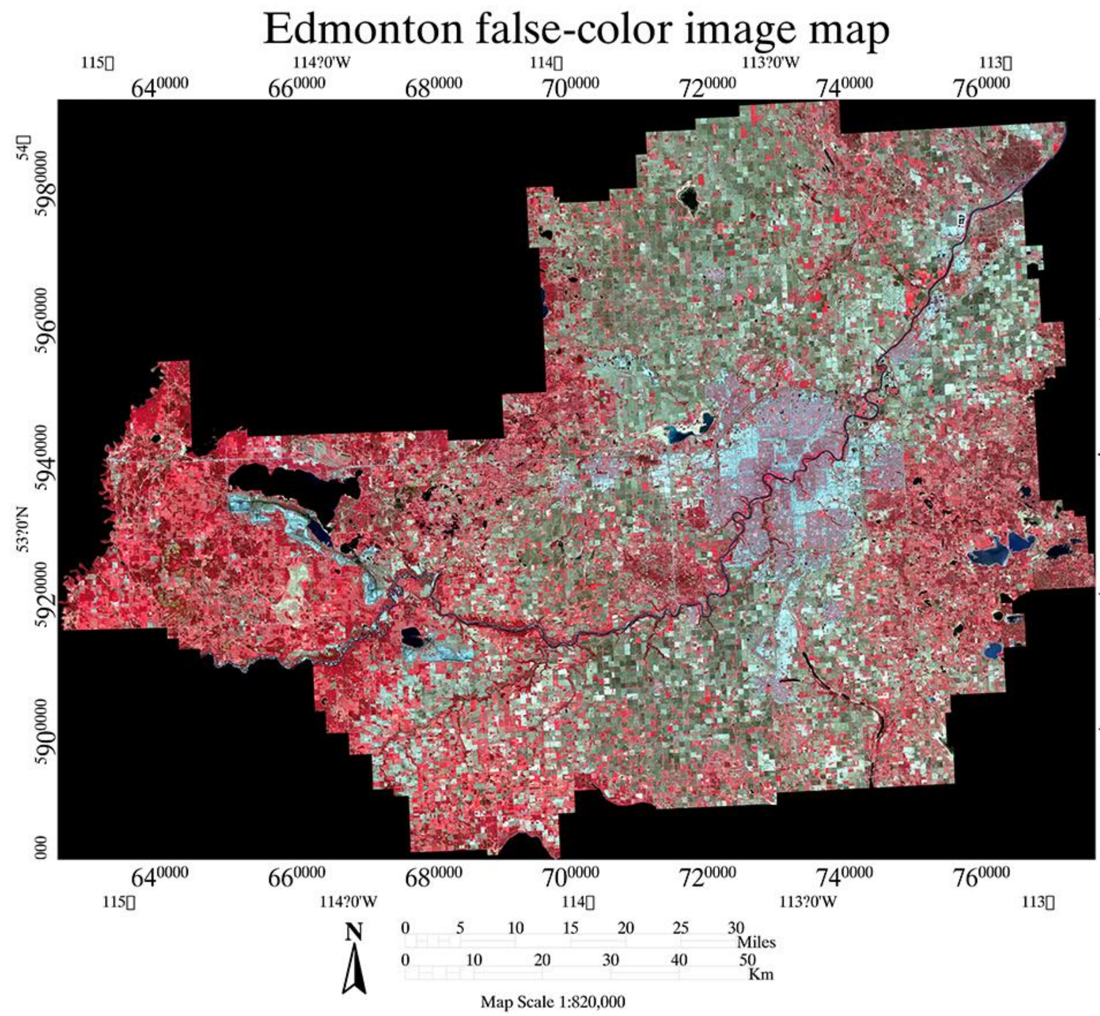

Figure C. 6 Edmonton CMA false-color image map

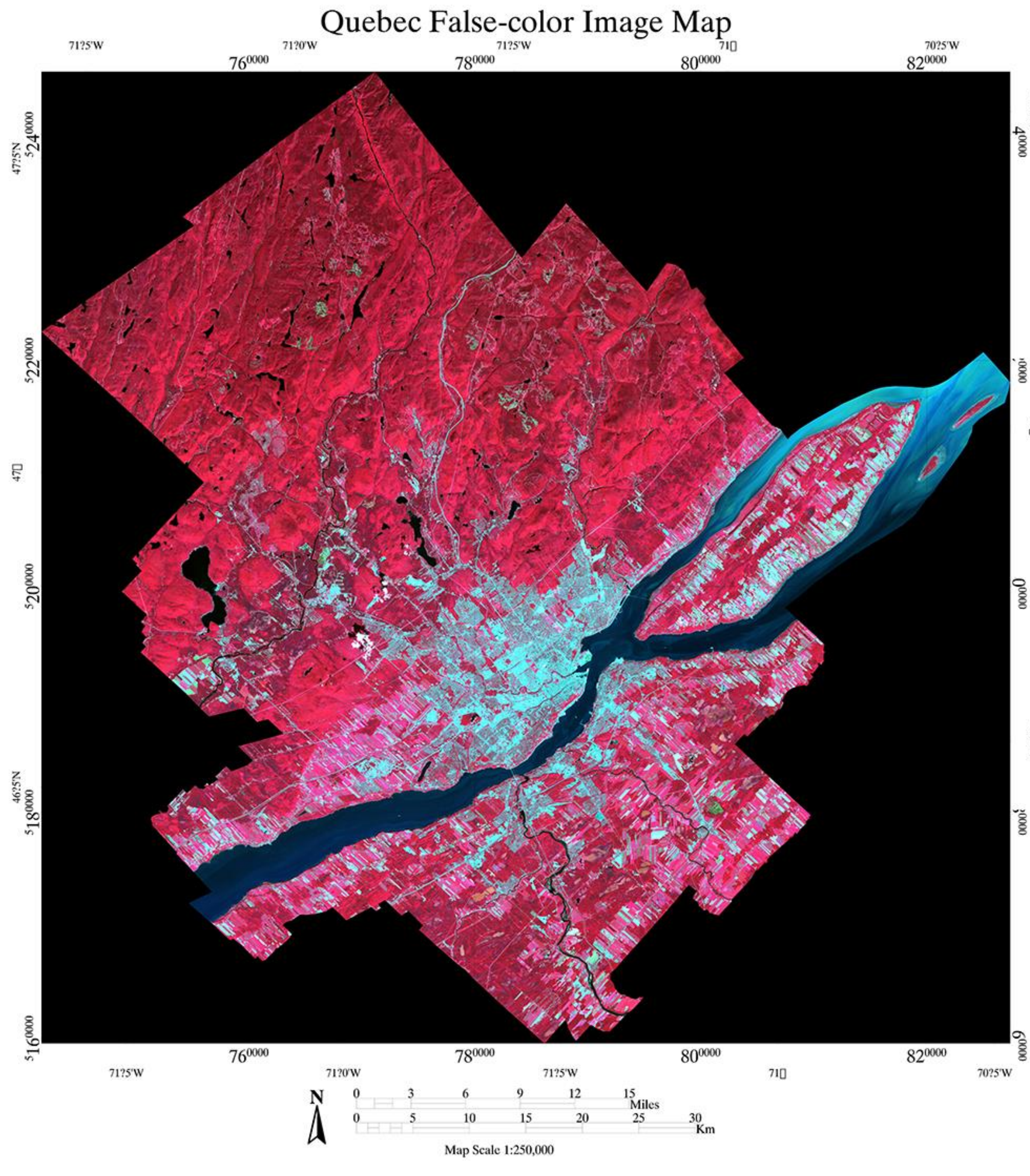

Figure C. 7 Quebec CMA false-color image map

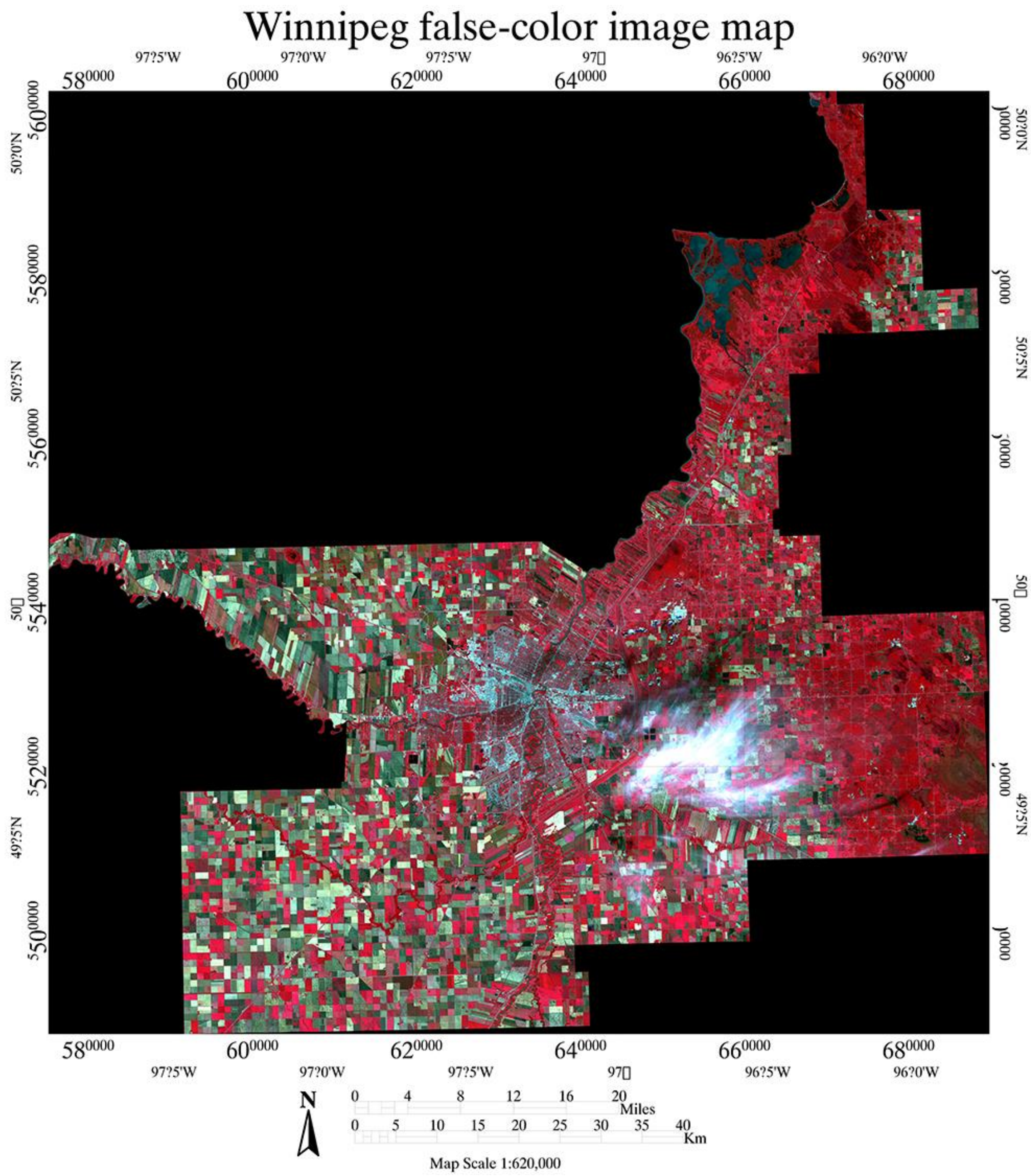

Figure C. 8 Winnipeg CMA false-color image map

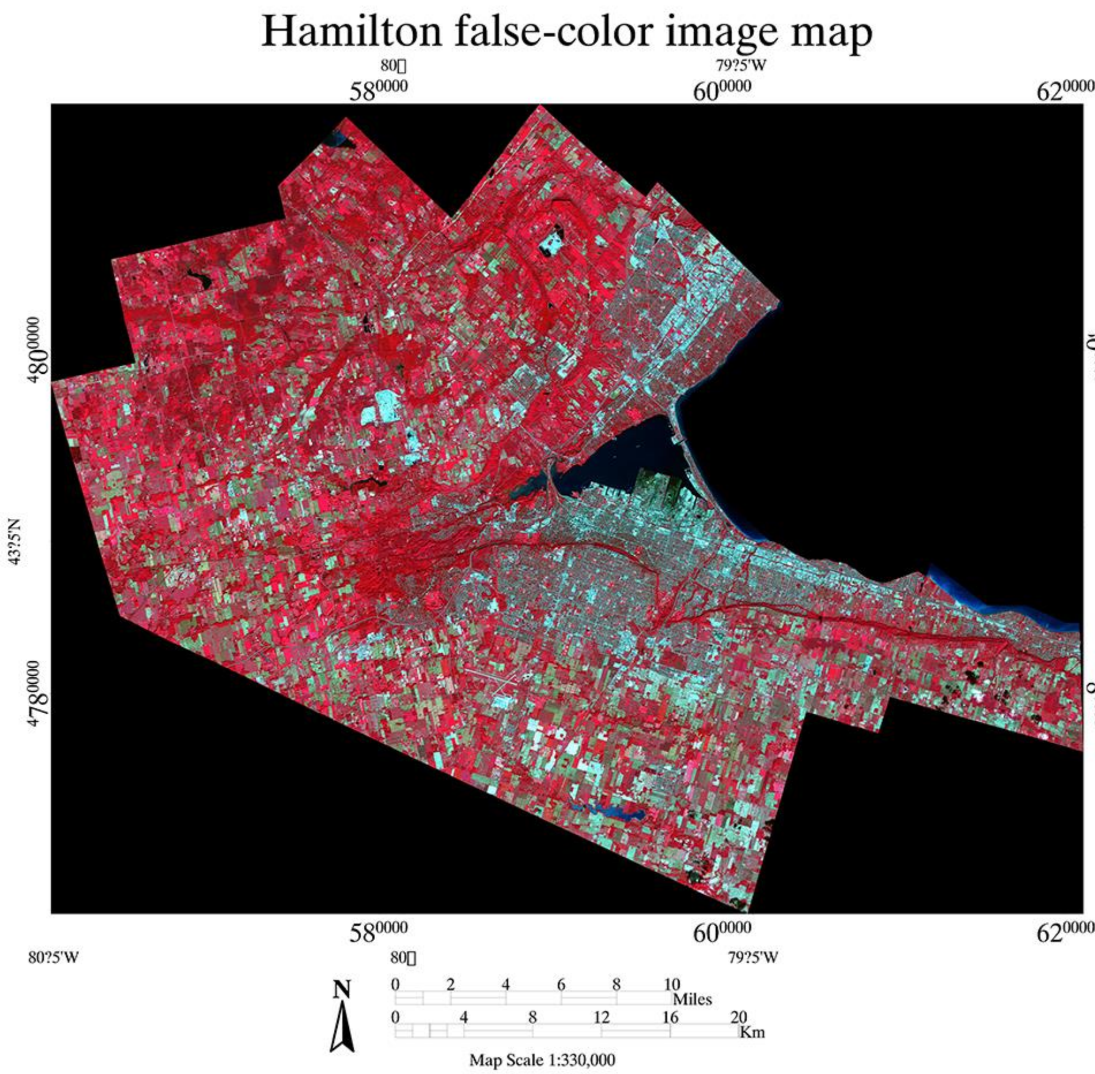

Figure C. 9 Hamilton CMA false-color image map

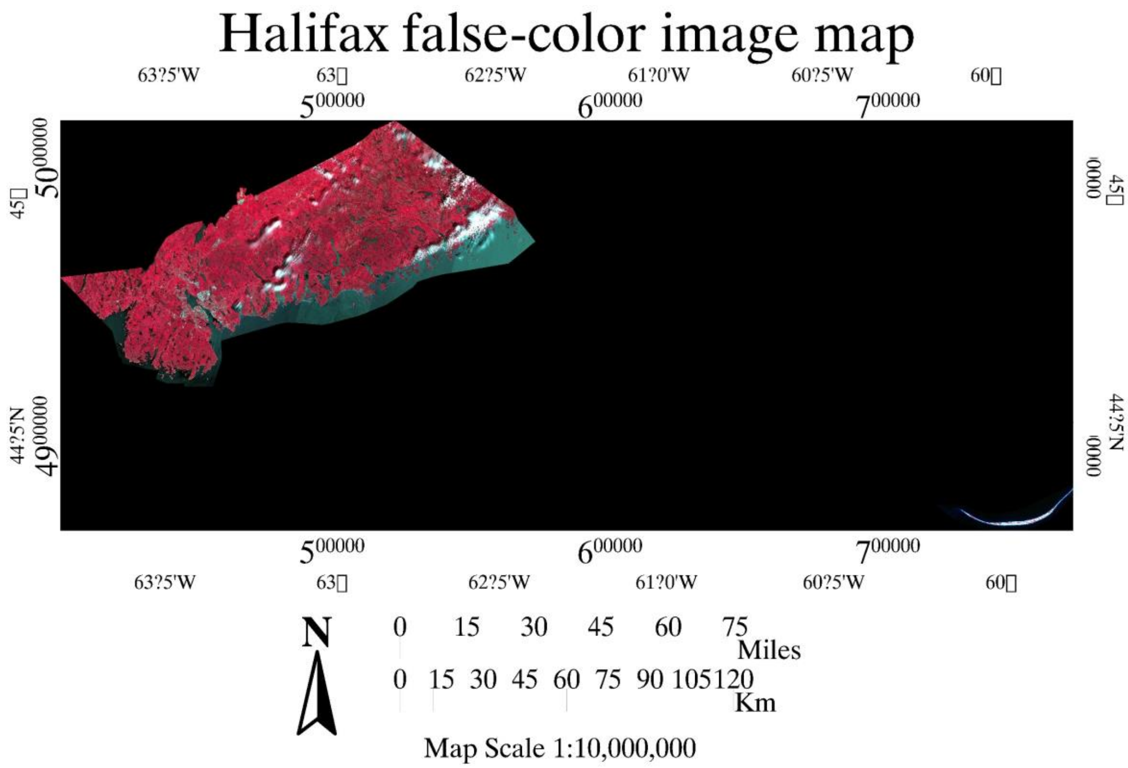

Figure C. 10 Halifax CMA false-color image map

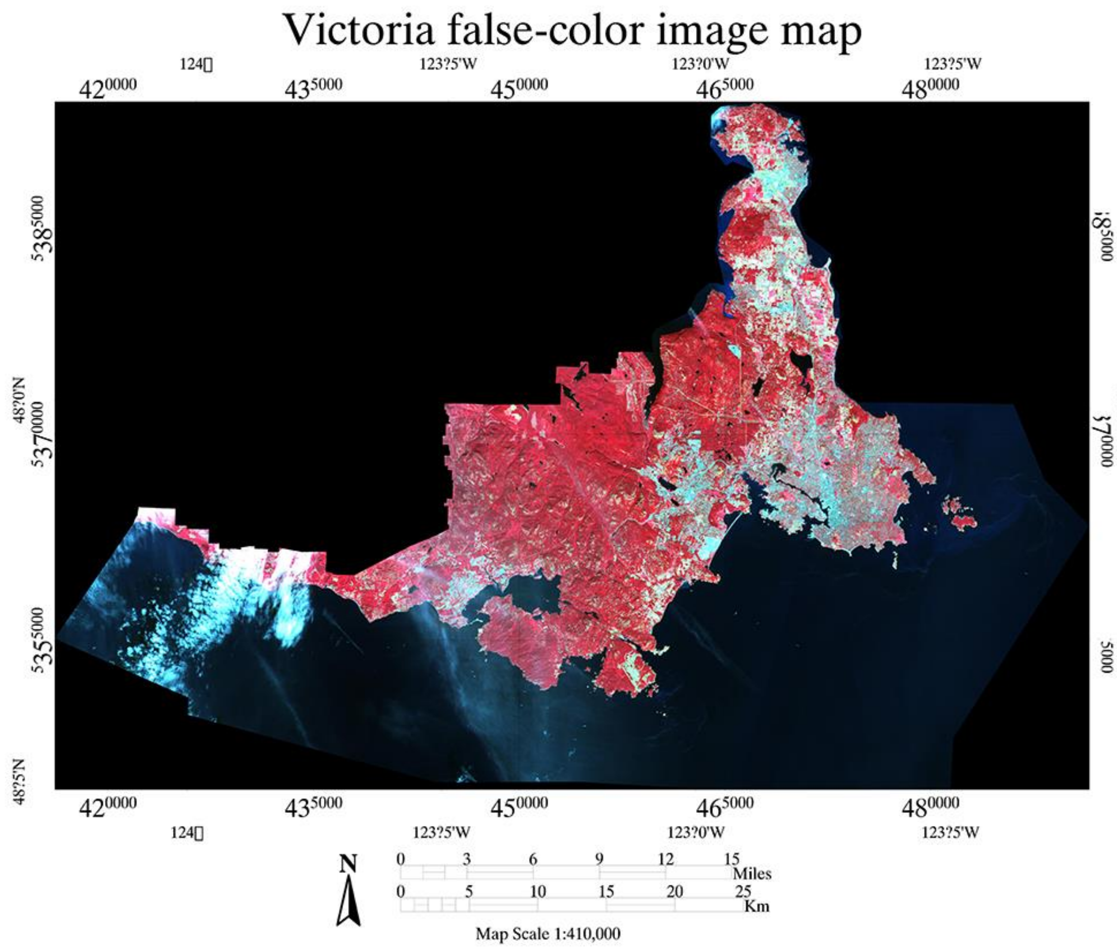

Figure C. 11 Victoria CMA false-color image map

Appendix D Data Interpolation Python Code

The script is used to process data interpolation from 2006 and 2016 Dissemination Areas to 1986 Enumeration Areas.

Interpolation:

```
import pandas as pd
import numpy as np
df = pd.read_csv("E:/Toronto_classification/0518/2006re1.csv")

df1 = df[df.duplicated('DAUID',keep=False)==True]
#Find duplicated DA
df2 = df[df.duplicated('Toronto_EA',keep=False)==True]
#Find duplicated EA
df3 = df2.merge(df1, how = 'inner')
#Intersect df1 and df2
df4 = df3[df3.Weight<0.05]

df5 = df.append(df4)
final_df = df5.drop_duplicates(keep=False)
final_df.to_csv("E:/Toronto_classification/0518/2006re2.csv")
```

Reallocation:

```
df = pd.read_csv("E:/Toronto_classification/0518/2006re4_3.csv")

df['new_population'] = df.Weight2*df.Population
new_df = df.groupby('EAUID')['new_population'].sum().reset_index(name='Population')
df1 = df.groupby('EAUID').apply(lambda x:
sum(x.Weight2*x.Census_family)).reset_index(name='Census_family')
new_df['Census_family'] = df1['Census_family']
df1 = df.groupby('EAUID').apply(lambda x:
sum(x.Weight2*x.Couple_family)).reset_index(name='Couple_family')
new_df['Couple_family'] = df1['Couple_family']
df1 = df.groupby('EAUID').apply(lambda x:
sum(x.Weight2*x.One_person)).reset_index(name='One_person')
new_df['One_person'] = df1['One_person']
df1 = df.groupby('EAUID').apply(lambda x:
sum(x.Weight2*x.Total_private)).reset_index(name='Total_private')
new_df['Total_private'] = df1['Total_private']
df1 = df.groupby('EAUID').apply(lambda x:
sum(x.Weight2*x.Owner)).reset_index(name='Owner')
new_df['Owner'] = df1['Owner']
```

```
df1 = df.groupby('EAUID').apply(lambda x:
sum(x.Weight2*x.Renter)).reset_index(name='Renter')
new_df['Renter'] = df1['Renter']
df1 = df.groupby('EAUID').apply(lambda x:
sum(x.Weight2*x.Total_tran)).reset_index(name='Total_tran')
new_df['Total_tran'] = df1['Total_tran']
df1 = df.groupby('EAUID').apply(lambda x:
sum(x.Weight2*x.Car_driver)).reset_index(name='Car_driver')
new_df['Car_driver'] = df1['Car_driver']
df1 = df.groupby('EAUID').apply(lambda x:
sum(x.Weight2*x.Car_passenger)).reset_index(name='Car_passenger')
new_df['Car_passenger'] = df1['Car_passenger']
df1 = df.groupby('EAUID').apply(lambda x:
sum(x.Weight2*x.Public)).reset_index(name='Public')
new_df['Public'] = df1['Public']
df1 = df.groupby('EAUID').apply(lambda x:
sum(x.Weight2*x.Walked)).reset_index(name='Walked')
new_df['Walked'] = df1['Walked']
df1 = df.groupby('EAUID').apply(lambda x:
sum(x.Weight2*x.Bicycle)).reset_index(name='Bicycle')
new_df['Bicycle'] = df1['Bicycle']
df1 = df.groupby('EAUID').apply(lambda x:
sum(x.Weight2*x.Other)).reset_index(name='Other')
new_df['Other'] = df1['Other']

def multiple(x):
    try:
        return
sum(x.Weight2*x.Ave_people*x.Census_family)/sum(x.Weight2*x.Census_family)
    except ZeroDivisionError:
        return 0
df3 = df.groupby('EAUID').apply(lambda x:
multiple(x)).reset_index(name='Ave_people')
new_df['Ave_people'] = df3['Ave_people']
def multiple1(x):
    try:
        return
sum(x.Weight2*x.Ave_bedroom*x.Total_private)/sum(x.Weight2*x.Total_private)
    except ZeroDivisionError:
        return 0
df3 = df.groupby('EAUID').apply(lambda x:
multiple1(x)).reset_index(name='Ave_bedroom')
new_df['Ave_bedroom'] = df3['Ave_bedroom']
def multiple2(x):
    try:
        return sum(x.Weight2*x.Ave_income*x.Population)/sum(x.Weight2*x.Population)
```

```
    except ZeroDivisionError:
        return 0
df3 = df.groupby('EAUID').apply(lambda x:
multiple2(x)).reset_index(name='Ave_income')
new_df['Ave_income'] = df3['Ave_income']
def multiple3(x):
    try:
        return
sum(x.Weight2*x.Ave_dwelling*x.Total_private)/sum(x.Weight2*x.Total_private)
    except ZeroDivisionError:
        return 0
df3 = df.groupby('EAUID').apply(lambda x:
multiple3(x)).reset_index(name='Ave_dwelling')
new_df['Ave_dwelling'] = df3['Ave_dwelling']
new_df.to_csv("E:/Toronto_classification/0518/EA_2006.csv")
```

Curriculum Vitae

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Conferences:

Sun, X., Mok, D., and Wang, J. (2019). "Examining Urban Sprawl in the 11 Census Metropolitan Areas Using Sentinel-2 Imagery and the Monocentric Model", presented at the Association of American Geographers Annual Meeting, April 3 – 7, 2019.

Sun, X., Mok, D., and Wang, J. (2019). "Examining Urban Sprawl for the Toronto Census Metropolitan Area between 1986 and 2016 Using Remote Sensing Images and the Monocentric Model", presented at the Canadian Association of Geographers Annual Meeting, May 27 – 31, 2019.