

Associations between Greenspace and street Crimes in Toronto: Evidence from a spatial analysis study at dissemination area level

by

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A thesis

presented to the University of Waterloo

in fulfilment of the

thesis requirement for the degree of

Master of Science

in

Geography

Waterloo, Ontario, Canada, 2020

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Introduction: Earlier criminologists have explored various factors generating or attracting crime in urban cities coupled with crime studies focusing on the influence of social, built and natural environments in urban centres. According to Statistics Canada (2019), the Crime severity index of Canada and Toronto has been on the rise since 2014, which found the violent crime severity index showing higher trends than non-violent crime severity. This study, first, examined the crime trends and seasonality in Toronto. Next, the association between greenspace variables and street crime rates across the city at the dissemination level using the spatial statistical methods were explored. Previous crime studies have also investigated the relationship between the crime rate (property and violent) and greenspace, albeit this study only focused on analyzing crime that usually occurs outdoors, namely “street crimes.” There are two schools of thought concerning the association between crime rates and greenspace. The first belief suggests greenspace facilitates criminal activities because it conceals the offender from the victims/bystanders, while the second belief insists that greenspace deter criminal activities.

Methods: Street crime considered for this research included assault, auto-theft and robbery crime. This study explored the association between greenspace variables and street crime rates across the City of Toronto. Crime data were extracted from the Toronto Police Service public safety data portal; the greenspace data were obtained from Toronto Open Data, and sociodemographic data were exported from the 2016 Census Data collected from Statistic Canada. Street crime trends and seasonality were first, and they were carried out using crime data from the year 2014 to 2018 to generate a line graph depicting yearly, monthly and seasonal crime trends in the study area. Greenspace variables (stem density; basal area density and tree density) were estimated from tree inventory data. The sociodemographic variables considered were median household income, lone

parent, unemployment rate, high school degree holders, owner-occupied housing and renter-occupied housing. Spatial distribution maps for the dependent and independent variables were generated to show the geographical variation of the data. The Global Moran's I and Local Indicator of Spatial Association (LISA) statistics were carried out on the street crime data to detect the spatial autocorrelation and clustering in the dependent variables. The spatial regression analyses were then carried out using the spatial lag model and the spatial error model on street crime rates, greenspace and sociodemographic variables.

Results: There were changing crime trends and seasonal variation of the three-street crime occurrences. Consequently, the street crime rates indicated spatial clustering with the locations of hot and cold spots for assault and robbery crime rates similar. In contrast, auto-theft crime rates emerge in different locations across the City of Toronto. Results from the spatial regression analyses show that the stem density and tree density are negatively associated with street crime rates after controlling for specific sociodemographic factors. Also, the basal area density was not significant in the spatial regression analyses on street crime rates. The six sociodemographic indicators (median household income, unemployment rate, lone parent, high school degree holders, housing units occupied by owners and renters) were significantly associated with the three street crime rates in this current study.

Conclusion: This thesis contributes to the existing literature by using a spatial-statistical approach to estimate greenspace variables and explored their relationship with street crime rates. This study draws attention to the use of specific sociodemographic factors with street crime types, and the influence parts of a tree (greenspace) could have on street crime rates across the City of Toronto. Limitations of the data were discussed, future studies concerning the recommendation of different tree species and the influence of weather on greenspace were discussed.

Acknowledgement

I would like to start by acknowledging my supportive supervisor Dr. Jane Law for her patience and encouragement throughout my master's program at the University of Waterloo. Thank you so much for your guidance, time, dedication, resources, inspiration and understanding during my master's program. Your words will forever echo in my ears that "thesis is like cooking; you have to gather all the ingredients before cooking the food." I am grateful to Su-Yin Tan and Peter Deadman for willing to accept to serve on my research committee.

My gratitude goes to my big brother Olufemi Onifade; you have been my rock and motivator since day one. Thank you, Egbon. I will like to appreciate my Aunt Foluke Ogunro and Cousin Ayodele Ogunro, for their support since I started my master's program. Above all, I want to give glory to God for seeing me through my program. Thank you, God.

I am also grateful to my friends, lecturers and Profs: Oladotun Alade, Pelumi Onarinde, Linda Ihome, Victor Agbo, Ngone Gaye, Babatunde Adubiobi, Mr & Mrs. Adesola Adesoji, Olukayode Awe, Oluwafemi Safe, Max Salman, Toluwalope Bashorun, Jaydeep Mistry, Neomi Jayaratne, Manpreet Singh, Ernest Agyemang Duah, Remi, Bernard, Adewumi Adepoju for being there through the good and hard times. I'm grateful to Prof. Brent Doberstein (for giving me my first winter jacket), Mike Belfry, Yu Huang, Scott MacFarlane, Olusola Popoola, Olumuyiwa Akinbamijo, Michael Oyinloye, the Geospatial Centre, the Department of Geography and Environmental Management, the Faculty of Environment, Toronto's Urban forest management, Toronto Police Service and Statistics Canada for their support and the various roles they played in making my thesis a success. Thank you, all.

I want to appreciate my Uncle Barrister & Mrs. Gbadebo Olabode for believing in me even when I did not believe in myself. I'll like to thank Dr. Amelia Clarke, and Catherine Bernard for your motherly support and assurance that everything is will be fine. I will like to thank Counselling Services (especially Emmanuel Ugwuegbula and Shelley Huisken) for kind words during the demise of my late mother. Big shout out to the Onifade, Olabode, Akintunde and Ajibawo's Families for their moral support over the years.

Dedication

Dedicated to the memory of my Mother **Modupe Anike Onifade (Nee Akintunde)**, who always believed in my ability to be successful in the academic arena. You are gone, but your belief in me has made this journey possible.

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Chapter 1 Introduction

1.1 Introduction

According to Statistics Canada, the crime rate and its measurement of the severity of the crime was up two percent in the year 2018, which resulted in the fifth straight year of increment, beginning in the year 2014. Another publication by Statistics Canada acknowledged the prevalence of crime, and its severity remains 17 percent lower than the year 2008. They maintained that Canada's crime rate peaked in the year 1991, with a decline of more than 50 percent until the year 2014. Crime rate provides information on the number of police-reported incidents that have occurred for a given population. The crime rate is a count of all criminal incidents reported to and by police divided by the population of interest. The crime rate is used to facilitate comparisons among geographic areas as well as over-time, while police-reported crime has traditionally been expressed as a rate per 100,000 population. Crime rate does not provide information on the overall seriousness of crimes reported by police, and the crime rate is heavily influenced by fluctuations in high-volume, less serious offences, which serves as its limitation (Statistics Canada, 2017).

Meanwhile, the Crime Severity Index (CSI) monitors the severity level of police-reported crime. The CSI measures the overall seriousness of crime by tracking both the prevalence of crime and the seriousness of the crimes committed in a community. Crime Severity Index (CSI) also enables Canadians to track changes in the severity of police-reported crime from year to year. CSI takes account of both the change in volume of a crime and the relative seriousness of that crime in comparison to other crimes. Furthermore, the CSI includes all reported crimes, unlike the traditional crime rate, which excludes traffic and drug offences as well as Federal Statutes (Statistics Canada, 2017).

A recent study by Statistics Canada (2019) found crime rates in Canada were reported at 5,334 incidents per 100,000 inhabitants with violent crime at 1,098 incidents and property crime at 3,245 incidents (per 100,000) in the year 2017. The overall crime decreased by 23% between the year 2007 to 2017, with all provinces experiencing a decrease in crime (up to 34%). The study established that the spike in gang-related violence and shootings has contributed to a peak in violent crime since a decade ago. These led to the rates of other serious offences, including attempted murder, sexual assault, robbery and aggravated assault peaking in the year 2018, as well as the use of guns in violent crimes (Lee, 2018). Thus, the increase in sexual assault, shoplifting, fraud and theft contributed to high crime severity in the year 2018 in Canada (Statistics Canada, 2019).

The World population projection is expected to increase with more people living in the urban centre than ever before compared to decades ago. Overpopulation and urbanization have contributed to the increase in crime trends all over the World. Bhatta (2010) acknowledged that urban growth in many cities is a result of an increase in population. Also, the low mortality and fatality rate recorded among the people, coupled with increased migration to urban centres, contributed to urban growth. A study by Statistics Canada (2019) accounted for the degree of urbanization in Canada from the year 2008 to 2018, where they established that 81.41 percent of the population in Canada lived in urban cities. They also maintained urbanization has contributed to the steady decline of people living in rural areas over the past 160 years in Canada. The United Nations projected that about 86% of the developed world and 64% of the developing world would be urbanized by 2050. Whereas, another study by Statistics Canada (2018) estimated that the population growth in Canada from the year 2018 to 2068. They proposed the Canadian population could reach between 44.4 million and 70.2 million populaces by the year 2068. They compared

the future population projection with the current population (37.1 million people in the year 2018). They also suggested that the majority of the Canadian populaces will be living in urban areas in the future.

Conversely, urbanization has brought about the growth of urban sprawl in major cities, mostly because of its unrestricted growth in the cities, which intersect with the urban design carried out by urban planners (Madlener & Sunak, 2011; Fouberg, 2012). Consequently, urbanization has contributed to deprivation in urban cities, which had often led to increasing crime occurrences. Gumus (2004) suggested that factors such as income inequality, unemployment rate, population size, overcrowding, housing crisis could influence the high occurrence of crime (property and violent crime) in urban areas. Whereas, a study by Bruinsma (2007) established that criminal activities tend to cluster in city centres. According to Boggs (1965), high-income communities tend to attract different types of crime, with the crime target communities well-known to the offenders. Thus, the presence of pattern found in criminal activities makes crime activities to be predictable (Brantingham & Brantingham, 1981).

Eck & Weisburd (2015) emphasized the concept of understanding the importance of places in crime pattern studies noting some facilities can act as crime attractors/generators (e.g. bars), which might lead to the absence of criminal activities in other locations. The study argued that crime prevention in high prevalence communities might lead to criminal activities in ‘unprotected’ communities. However, they recognized that “instead of crime displacing, the benefits of the prevention efforts diffuse to unprotected locations.” Crime occurrences are not random because they tend to cluster in some areas than others, which brought about the term crime hot spot. It is

used to identify areas with a high prevalence of crime occurrences over time (Weisburd & Green, 1994; Block & Block, 1995; Eck & Weisburd, 1995).

The current mapping technologies have directed scholarly attention to spatial and temporal studies. For instance, longitudinal data were utilized in recent studies by Cheng et al. (2018) on traffic crash; Ogneva-Himmelberger (2019) on drug poisoning death; Bunting et al. (2017) on crime patterns; and Carter et al. (2019) on property crime. The study by Bunting et al. (2017) found that the hotspots for larceny are more distributed across the study area than aggravated assaults, which exhibited clustering in the northern and southern part of the Miami-Dade County, Florida. They suggested that the utilization of geospatial analyses by law enforcement agencies can target appropriate prevention programs for violent and property crime. Contreras et al. (2019) carried out a study on the longitudinal association between drug activity and crime rates. They found that “drug activity increases assaultive violence and serious acquisitive crime rates on structurally advantaged blocks.” Another study was carried out by Cowen et al. (2019) in Miami-Dade County, Florida, where they investigated the association between neighbourhood crime rates (larceny and aggravated assault), land use and walkability using long-term data from the year 2007 to 2015. They found that land-use diversity is associated with both larceny and aggravated assault, while a high level of walkability is positively associated with aggravated assault. The study also found that the neighbourhood crime rates peaks at a different time of the day, larceny and aggravated assault crime peaks during daytime and late-night periods, respectively.

Criminologists have associated crime rates with various factors such as land use (Wuschke et al., 2016; Twinam, 2017; Quick et al., 2019; Cowen et al., 2019), urban layout (Alexander, 2020), street lighting (Painter et al., 2001; Steinbach et al., 2015), alcohol establishments (Brit et al., 2005; Toomey et al., 2012), bus stops (Levine et al., 1986; Kooi et al., 2013) and so on. Apart from the

environmental association with crime rates, existing studies have also focused on the natural environment. For instance, the relationship between greenspace and crime rates, mostly in urban cities evidenced by previous crime studies (Loosle, 2016; Schusler et al., 2018). According to the Environmental Protection Agency, greenspace is regarded as a “land that is partly or completely covered with grass, trees, shrubs, or other vegetation.” Greenspace could also be regarded as parks, community gardens, vacant lots, playgrounds and cemeteries. However, this current study considered greenspace as trees. Three greenspace variables were considered in this study, and they are stem density, basal area density, tree density. Stem density was the total number of trees divided by the area size of each land area (Figure1.1). Basal area and crown area were derived from DBH and crown diameter, respectively (Figure1.2 & 1.3). The basal area density and the tree density of each DAs were obtained by dividing the aggregate basal area and crown area, respectively, by the area size of each dissemination area (DuPlissis & Russell, 2019; Megalos, 2019). Thus, diameter at breast height, or DBH, is a method of expressing the diameter of the trunk of a standing tree. Tree trunks are measured at the height of an adult's breast, which is defined differently in different countries and situations (Figure1.4). In many countries, DBH is measured at 1.3 m (4.3 ft) above the ground (Feldpausch et al. 2011).



Figure1. 1: The street lined with trees (Source: City of Toronto’s Forestry department)

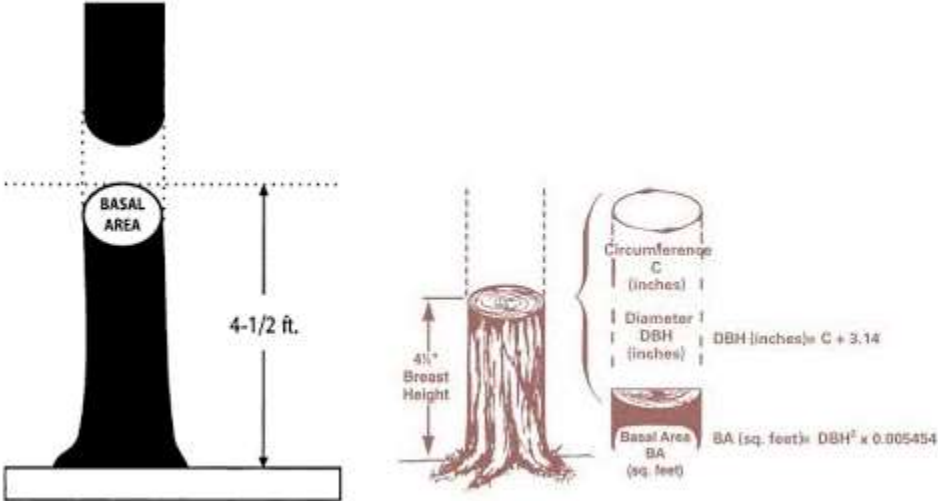


Figure1. 2: The basal area of a tree Measurement of the circumference, diameter, and basal area of a tree (DuPlissis & Russell, 2019; Megalos, 2019)

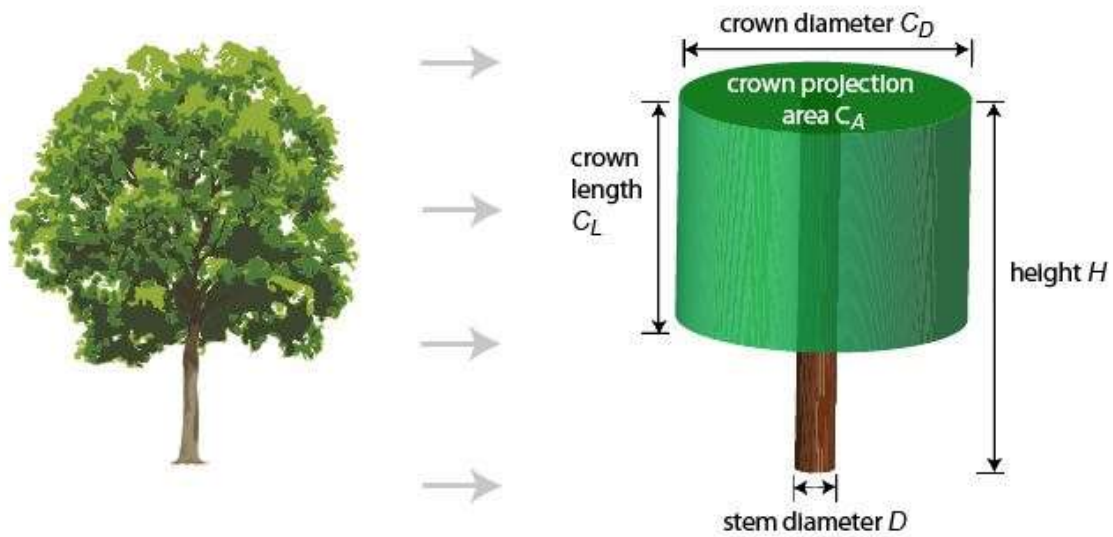


Figure1. 3: Crown projection area (Source: www.formind.org)

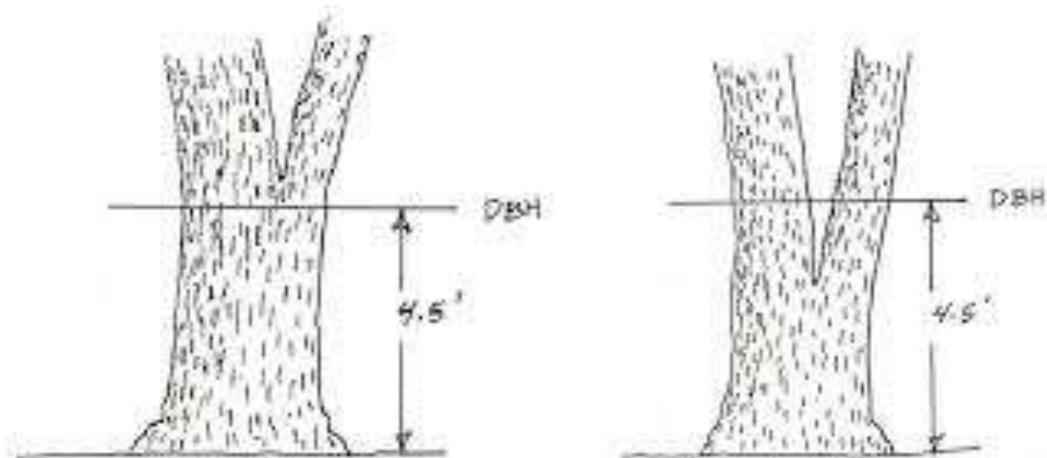


Figure1. 4: On forked trees, measure as one tree if a fork occurs at or above 4.5' (left). Measure as two trees if a fork occurs below 4.5' (right) (DeYoung, 2019)

Existing literature has examined the importance of greenspace in urban areas. For instance, a study by Akbari et al. (2001) explored how greenspace could help reduce the costs of cooling a home as well as slows down the formation of urban smog. Another study by Herzog & Chernick (2000)

concluded that tree canopy could reduce the feelings of danger, while Hartig et al. (1991) acknowledged that trees promote a sense of wellness and tranquillity. Previous crime studies emphasized that the presence of urban trees has its disadvantages, and they are often tied to levels of criminality (Troy et al., 2012; Scopelliti et al., 2016). Dense tree canopy areas could be used by criminals to hide and identify crime victims (Michael et al., 2001). However, numerous crime studies have maintained that there is a negative relationship between crime levels and the presence of tree canopy or vegetation in urban cities (Kuo & Sullivan, 2001; Troy et al., 2012; Loosle, 2016; Escobedo et al., 2018).

Several factors influenced the crime rate in urban areas such as population density, unemployment rate, poverty level (Weisburd et al., 2012), lone parent, streetlight and graffiti (Chen et al., 2016) and alcohol establishment (Pain et al., 2006). According to Shaw & McKay (1942), the social disorganization theory established that there are three ecological predictors of criminal activities, namely poverty, ethnic heterogeneity and residential mobility. These predictors promote criminal activities by increasing social disorganization. Most crime types are associated with poverty levels, according to Wolfe & Mennis (2012). A strong inverse relationship between employment and crime was established by Wang & Minor (2002) in their study.

Existing literature on the association between greenspace and crime rate have been carried out at varying geographical scales and methodology. In particular, a study by Chen et al. (2016) investigated the influence of tree coverage (LiDAR data) and road network density on property crime in Vancouver, BC. The study was carried out with the use of a small area unit of scale (dissemination area) and spatial regression analyses (OLS, Spatial Lag and GWR). Another study by Schusler et al. (2018) explored the association between tree canopy, parks and crime rates in Chicago, IL. The census tract was considered as the unit of geographical analysis in the study, and

linear regression analysis (negative binomial regression) was used to explore the influence of tree canopy and parks on both property and violent crime rates in the study area.

This current study was carried out in the City of Toronto with the study focusing on street crime data extracted from police records from the year 2014 to 2018. This current study examined three types of street crime, which are assault, auto theft and robbery crime. Assault crime is regarded as the act of inflicting physical harm or unwanted physical contact upon a person or a threat or attempt to commit such an action. In contrast, auto-theft crime is regarded as the act of taking/stealing another person's vehicle while robbery crime is considered as the act of taking property from another person or business using force or intimidation in the presence of the victim.

These street crime data were associated with the greenspace variables while controlling for specific sociodemographic factors (i.e. median household income, unemployment rate, lone parent, high school degree, tenure owner and tenure renter). The above sociodemographic factors were examined because they were considered in previous crime studies, and they are all significant to specific crime types in this current study. The greenspace variables were estimated from tree inventory data in this current study, taking a different approach in the estimation of greenspace variables from existing studies. For instance, previous studies considered LiDAR data (Chen et al., 2016), NDVI (Du et al., 2015), among others. While this study estimated the greenspace variables (stem density, basal area density and tree density) from tree inventory data and spatial regression analyses were considered in this study. The dissemination area was considered as the unit of geographical analysis, and multivariate regression analyses (spatial lag and spatial error) were carried out on the outcome and explanatory variables.

1.2 Research Questions

Various studies have been carried out to investigate the association between greenspace and crime rate in Canada and other parts of the World. Few studies have been explored in Canadian cities, and researchers tend to focus on both property and violent crime. Although, there are two categories of crime, namely property crime (non-violent or crime against property) and violent crime (crime against a person). This study aims to investigate the association between street crime rate and greenspace variables in the City of Toronto. The research questions of this study are listed below:

1. Is there a variation in yearly and monthly street crime trends? Does seasonal variation influence street crime in Toronto?
2. What is the association between street crime rate types and greenspace variables after controlling for sociodemographic indicators?

The objectives of this study are 1) to explore the trends and seasonal variation of street crime; 2) to determine the association between the three types of street crime above and greenspace.

1.3 Study Rationale

Limited research has been carried out on the influence of greenspace on crime rates in Canadian cities with some exceptions in previous studies by Du et al. (2015) in the Kitchener-Waterloo, Ontario, Chen et al. (2016) in Vancouver, British Columbia and so on. The majority of crime studies were carried out in the United States of America (U.S.A) and Europe. High crime occurrences might have influenced crime research in the U.S.A and European cities compared to low crime occurrences in Canadian cities.

Several studies focused on the association between greenspace and property crime (Chen et al., 2016), violent crime (Troy et al., 2012; Schusler et al., 2018; Escobedo et al., 2018) and combination of property and violent crime (Wolfe et al., 2012; Eckerson 2012; Gilstad-Hayden et al., 2015). Whereas numerous studies have utilized (Landsat imageries, aerial photo and tree inventory) for various measurements of greenspace. The sociodemographic indicators considered to control the outcome and explanatory variables are further discussed in the literature review section.

This current research primarily focused on the association between street crime rates and greenspace in Toronto. This study took a different approach from previous crime studies on the selection of the crimes considered. This current study considered street crimes that occur outdoors, and the presence of trees in the street could obstruct the view of bystanders or guardians. While existing crime studies mainly focusing on tree canopy for the measurement of greenspace, this current study considered different parts of trees (greenspace) and estimated three greenspace variables associated with street crime rates while controlling for specific sociodemographic factors. Also, the sociodemographic factors considered to control for the association between the street crime types and greenspace were different from the existing crime studies approach. The assault and robbery crime were classified as a violent crime. In contrast, auto-theft crime was classified as a property crime. Six sociodemographic factors were considered as cofounder factors for the street crime types (assault, auto-theft and robbery crime).

One of the goals of this study is to examine the trends (yearly and monthly) of the street crime types as well as seasonal variations. The main goal is to analyze the association between street crime rates and greenspace variables while controlling for specific sociodemographic factors in the City of Toronto. Dissemination area data facilitated control for median household income,

unemployment rate, lone-parent families, high school degree holders, owner-occupied housing units and renter-occupied housing units. This current study was carried out using spatial regression analyses (spatial lag and spatial error models). Findings from this study will be compared with results from existing crime studies (Donovan & Prestemon, 2012; Gilstad-Hayden et al., 2015; Escobedo et al., 2018), where a negative relationship between crime rates and greenspace were found.

Chapter 2 Literature Review

2.1 Crime Studies in Toronto

Increasing crime rate in urban cities is a result of various socioeconomic, built, natural and environmental factors. These phenomena led to a spike in the existing literature focused on crime studies by criminologists all over the world (Brennan-Galvin, 2002). A recent study on the property and violent crime were examined by Wang et al. (2019), where they explored the social patterning of property and violent crime in Toronto neighbourhoods. They utilized crime data from police records (from the year 2014 to 2016) and census-based Ontario marginalization index as the socioeconomic factors for their study. They found a cluster of property crime in Northwestern of the city and clusters of violent crime in Downtown Toronto. Existing literature on both property and violent crime studies have been investigated in various urban centres such as San Antonio, Tx (Cancino et al., 2007), New Haven, CT (Gilstad-Hayden et al., 2015), Kitchener-Waterloo, ON (Du et al., 2015) and so on. These studies found a different spatial distribution of crime occurrences across their respective cities.

Furthermore, a study carried out by Charron (2011) examined the statistical relationship between fifteen (15) neighbourhood characteristics and crime across the City of Toronto. They subdivided the 15 neighbourhood characteristics into five groups, namely: economic aspects of residents, cultural characteristics of residents; demographic characteristics of residents; urban characteristics of neighbourhoods and economic activities of neighbourhoods. Multivariate spatial regression analyses were carried out to explore the association between crime (property and violent crime) and the neighbourhood characteristics in the study area. The author found both crime types were associated with several neighbourhood characteristics in different proportions across the City. For

instance, dwellings requiring major repairs, economic vulnerability, access to socio-economic resources and urbanization were all associated with violent crime.

In contrast, centrality and commercial activity are closely associated with property crime. Although, Wang et al. (2019) argued that limited studies had been carried out in Canadian cities on spatial patterns of crime and the determinants of the social demographic factors specific to a crime type. They also suggested that limited crime studies might be due to the low crime occurrences in Canada compared to other countries.

Crime rates tend to be higher in urban areas than in rural, where the neighbourhood size might influence the crime rates. An increase in crime occurrences from police records in Canada was measured by the Crime Severity Index (CSI), which has peaked since the year 2014 to 2018. The higher property crime rate was observed in urban areas, while a higher violent crime rate was recorded in rural areas (Statistics Canada, 2019). However, crime occurrences were higher in urban areas because it attracts crime offenders (Statistics Canada, 2019). A study by Shover (1988), reiterated that similar urban-rural crime rate difference was found in Australia, England, Canada and the Netherlands.

It is a well-known fact that Toronto has a reputation as one of the safest major cities in North America because of the city's low crime rate compared to other cities in North America. In the year 2007, Toronto's robbery rate ranks low, with 207.1 robberies per 100,000 people, and it has a comparable rate of auto theft to various major cities in North America (TPS, 2008; FBI, 2008). A study carried out by Boritch & Hagan (1990) used time-series analysis on crime data from 1859 to 1955 to compare male and female arrest rates in the city of Toronto. The study found a decline in female arrest rate during the late nineteenth and early twenties centuries due to the role of "first-

wave feminists. Likewise, patterns were found in major cities like Philadelphia (Steffenmeier et al., 1996), Kansas City (Alarid et al., 2000), among others.

Charron (2009) explored the spatial distribution of crime data from police records in the city of Toronto, where the author also examined the relationship between neighbourhood characteristics and crime rates using spatial regression analyses. The study investigated the property crime (break and entering, auto theft and shoplifting) and violent crime (homicide, sexual assault and assault) separately to understand the influence of both crime types. The author found Toronto's rate of property crime was average, but its rate of violent crime was slightly above the Canadian crime severity index average. The author also found that violent crime rates were associated with specific neighbourhood characteristics (i.e. densely populated areas with a high percentage of dwellings, renters, single-parent families, low-income earners and visible minorities). Equally important, the author acknowledged that property crime occurs close to major shopping centres and higher bar density in the study area. Property crime was prevalence in neighbourhoods where there were presences of high-income earners, half of the resident have University degrees, and the percentage of visible minorities are below average. The study established that several neighbourhood characteristics are associated with the two crime types but in different proportions. For instance, socioeconomic resources are related to violent crime, while property crime rates are related to commercial activities.

Quick (2013) investigated the expressive (violent) and acquisitive (property) crime occurrences in Toronto using spatial regression analysis (Ordinary least square and Geographically weighted regression) at census tract level (unit of geographic analysis). The author found both social disorganization and non-residential land uses were associated with violent crime (expressive crime). In contrast, the acquisitive crime occurrences were associated with both social

disorganization and routine activity theories in the study area. However, existing literature has considered different social theoretical frameworks for their crime studies with varying findings as a result of the significance of the socioeconomic factors. The social theoretical framework of crime studies will be discussed further in these literature reviews.

2.2 Previous research on street crime in urban settings

Street crime comprises of both property and violent crime, and they often occur in the public space with or without the presence of bystanders (Hanslmaier, 2013; Lynch et al., 2020). Khalid et al. (2015) explored the street crime hotspots in Faisalabad City in Pakistan, where they focused on four street crime types (bike theft, car theft, robbery, and snatching). The crime data were extracted from police records, and the kernel density estimation analysis was used to investigate the street crime occurrences while controlling with specific socioeconomic factors. They found that the unemployment rate was associated with a high prevalence of street crimes across the study area. They also established that bike theft has the highest occurrence. High prevalence of both bike and car theft occurs in the commercial zones along the major roads, and the robbery crime occurs in the residential area across the city. They noted that snatching crime occurs in both residential and commercial areas in the Faisalabad city.

Shiode (2011) examined two street crime (robberies and drug activity) by extracting the street crime data from calls-for-service records (911 emergency call records). The author used the network-based method to analyze the street crime data in Downtown Buffalo, New York. The author found that illegal drug activity has a higher occurrence than robbery crime in the study area. A recent study by Heywood et al. (2019) investigated the influence of University-provided transit on street crime in the neighbourhood around the Milwaukee School of Engineering in Milwaukee, Wisconsin. They extracted crime data from police-reported records, and they analyzed the street

crime data using a series of difference-in-difference estimates. They found bus services deter crime occurrences in the University neighbourhood.

Another recent study by Han et al. (2019) investigated the crime patterns around the Universal Studios Florida theme park. They extracted the crime data (assault, robbery, burglary, theft, motor vehicle theft and narcotic) from police records. At the same time, they analyzed the crime data using spatial statistical analyses (LISA and negative binomial regression) in their study. They found a positive association between the Theme parks and the crime types explored in their research, where they also found high crime concentration near the Theme park. They suggested the Theme parks act as crime-generating or attracting facilities that attract a high population, which might also encourage criminal activities inside and around the Theme parks.

2.3 Seasonality of Crime

Existing literature on crime seasonality has maintained that crime types reveal varying seasonal variation in crime across various cities like Minneapolis, MN (Cohn & Rotton, 2000); Vancouver, BC (Andresen & Malleon, 2013); Ottawa, ON (Linning, 2015); and Toronto, ON (Quick et al., 2017). The first study on crime seasonality dates back to the 19th century, which was carried out by Adolphe Quetelet (1842) in France. The author investigated the influence of seasonal changes on both property and violent crime, and he found that property crime often peaks during the winter season. He established that property crime occurrences were usually influenced by a lack of basic needs of people. The author also maintained that violent crime occurs more frequently in the summer months.

Conversely, a study by Lewis & Alford (1975), which was inspired by Quetelet's (1842) study of crime seasonality, rejected the findings that seasonal change is directly associated with crime

occurrences. In their study, the authors argued that temperature could not directly influence assault crime. They analyzed the monthly assault crime occurrences for fifty-six municipalities in the United States, and they found no evidence of the higher event of assault crime in cities with warmer temperatures. Lewis & Alford (1975) emphasized that warmer temperature leads people to spend time outdoors, and the temperature does not necessarily impact the seasonal variation of assault crimes in their study area. However, early literature reveals that the fluctuating seasonal patterns of crime are often influenced by routine activities of both victims and offenders than the weather condition of the study area (Andresen & Malleon, 2013; Linning, 2015; Chang, 2019).

Harries et al. (1984) adopted Lewis & Alford (1975) study of crime seasonality, where they considered the spatial context across all the neighbourhoods. They found that there was a peak in assault crime occurrences during the summer months for the low-status communities than middle-status and high-status neighbourhoods. They also maintained assault crime has a higher prevalence within the apartment buildings and streets of the lower status neighbourhoods. The authors pointed out the impact of both physical and social environments on crime patterns in Dallas, Texas. Another study by Field (1992) examined the annual, quarterly, and monthly crime data in both England and Wales to investigate the influence of temperature on both crime types. The author found that temperature had a positive relationship with violent and property crime types, while robbery crime was not significant in the study. Field (1992) also emphasized that the routine activity of people has more influence on property crime than the temperature or level of aggression by people (which occurs in the summer months).

A crime seasonality study by de Melo et al. (2018) in Campinas, Brazil, investigated the spatial and temporal patterns of crime (homicide, rape, robbery, burglary, and theft.). They considered seasons, months, days and hours on the criminal events that occurred between 2010 to 2013. The

authors found seasonal variation in homicide crimes but not rape, robbery, burglary and theft crime, and they acknowledged that the summer vacation period is associated with rape in the study area. They, however, concluded that the lack of seasonal patterns of the crime types might be due to the low-temperature variation in Campinas, Brazil. (de Melo et al., 2018). Michel et al. (2016) explored the trauma data collected from trauma patients provided by Johns Hopkins Hospital as well as crime data (2008-2013) obtained from the Baltimore City Police Department. They examined the influence of weather conditions on both crime and trauma incidents using the negative binomial regression method. They found that daily temperature is positively associated with homicides, violent and total crime in the study area.

In an African context, Badiora et al. (2017) investigated the seasonal patterns of assault and break-ins using the residents' perception in two Nigerian cities with different weather conditions. They found seasonal variations for violent crime (assault) in Minna, Niger State, Nigeria, which has a warmer climate. The authors acknowledged that seasonal changes of property crime (break-ins) were present in Benin City, Edo State, Nigeria, with colder weather. The study also found that high-status communities in Minna experienced high occurrences of break-ins compared to the low-status communities in Benin City. However, existing literature reveals different seasonal patterns of crime in urban centres and indicates weather conditions do not necessarily influence seasonal crime variation. Previous crime studies acknowledged the impact of social theoretical frameworks on crime seasonality, and these frameworks will be discussed extensively in the next section.

2.4 Theories Associated with spatial analysis of Crime

Social disorganization theory and routine activity theory are the two theories often considered by criminologists. They both support the social theoretical framework of crime studies (Andresen, 2006). Social disorganization theory, on one hand, expounds that “location matters” and influence the likelihood of crime occurring in a neighbourhood. The criminal events are related to five known factors (demographic, economic, social, family disruption and urbanization) of social disorganization theory, according to Shaw & McKay (1942).

Previous studies have related crime rates with a measure of neighbourhood stability (rental units and single parents), unemployment rates, high school dropouts, poverty, population density, and education attainment. In most cases, poverty usually has a more significant influence on crime rates, especially in urban centres (Wolfe et al., 2012; Chen et al., 2016; Schusler et al., 2018). In some cases, youths from disadvantaged communities might lean toward criminal activities because of their social status, which might also lead to delinquency in urban centres (Shaw & McKay, 1942).

Furthermore, a multilevel study of collective efficacy was first introduced by Sampson et al. (1997) in Chicago by surveying 8782 residents in 343 neighbourhoods. They engaged community residents to ‘police’ the community by monitoring the neighbourhood activities and confronting individuals who disturb public spaces. They found that an increased level of collective efficacy in neighbourhoods reduced crime rates in the areas in Chicago over time. Existing literature reveals the importance of social disorganization theoretical framework in investigating both property and violent crime rates in urban centres (Sampson et al., 1997; Du et al., 2015).

In contrast, routine activity theory, on the other hand, is regarded as a crime of opportunity, which was first introduced by Cohen & Felson (1979). According to (Cohen & Felson, 1979; Felson, 2003), routine activity theory is considered under some conditions which facilitate crime occurrences and the conditions are (1) suitable targets for the criminals (2) motivated offenders and (3) lack of witness or bystanders. The basis of routine activity crime is that the theory disagrees with the assertion that crime is influenced only by social factors such as poverty, inequality and unemployment. They argued that crime could also be influenced by other social factors like urbanization, college enrolment, female labour participation, and so on (Cohen & Felson, 1979).

Routine activity theory diverts criminologists from just criminal offenders focused on social disorganization theory. It relates crime occurrences to its environment and the required opportunity that will enable criminal activity at a given location (Cohen & Felson, 1979). A study by Miethe et al. (1987) examined the routine activities and victimization suggested by routine activity theory. They found that routine activity theory is more suited for property crime in their study because its conditions do not usually suit violent crime where the crime is often a spontaneous activity.

The integration of both social disorganization and routine theory has been considered by criminologists to control for the confounding factors that influence both property and violent crime rates in urban cities (Rice & Csmith, 2002; Quick et al., 2013; Du et al., 2015; Carter et al., 2019). However, existing literature found that the social disorganization and routine activity theories do not necessarily correlate with crime rates, but their influence varies according to the crime types (Gilstad-Hayden et al., 2015; Chen et al., 2016). Therefore, this current study considered specific sociodemographic factors to control for the property crime rates (auto-theft crime) and violent crime rates (assault and robbery crime).

2.5 Crime and Greenspace

Existing studies have considered greenspace as vegetation (Kuo & Sullivan, 2001; Wolfe & Mennis, 2012); urban parks (Gilstad-Hayden, 2015); tree density (Kardan et al., 2015; Lee et al., 2019); tree canopy cover (Troy et al., 2012; Gilstad-Hayden et al., 2015; Chen et al., 2016); urban trees (Donovan & Prestemon, 2012; Kondo et al., 2017) and so on. Before proceeding with the association between greenspace and crime rate, it is essential to briefly discuss the importance of the natural environment (greenspace) in urban cities (See Figure 2.1). Numerous studies have been carried out about the benefit of greenspace in urban areas. For instance, Kardan et al. (2015) examined the association between greenspace and the general health of the resident across the city of Toronto. They found that neighbourhoods with a high density of trees have higher health perception and less cardio-metabolic conditions reported. The study also established that a high density of trees tends to be abundant in neighbourhoods with higher socioeconomic status. A similar study by Maas et al. (2006) in the Netherlands found there is also a positive association with areas with dense greenspace and good health conditions reported. Whereas several studies have elaborated on the recreational value of greenspace in urban cities. The presence of greenspace encourages physical activities, reduces stress levels and lower the risk of depression as well as its relationship with good mental health state (Hartig, 2007; van den Berg et al., 2010; Astell-Burt et al., 2013; Mitchell, 2013; Doll et al., 2018). The presence of greenspace also helps control flow of stormwater (Wolch et al., 2014; Hoang & Fenner, 2016), mitigates urban heat island effects (Oliveira et al., 2011; Doick et al., 2014), increases property values (Xiao et al., 2016) and deters crime rates in some areas (Bogar & Beyer, 2016). (See Figure 2.1).

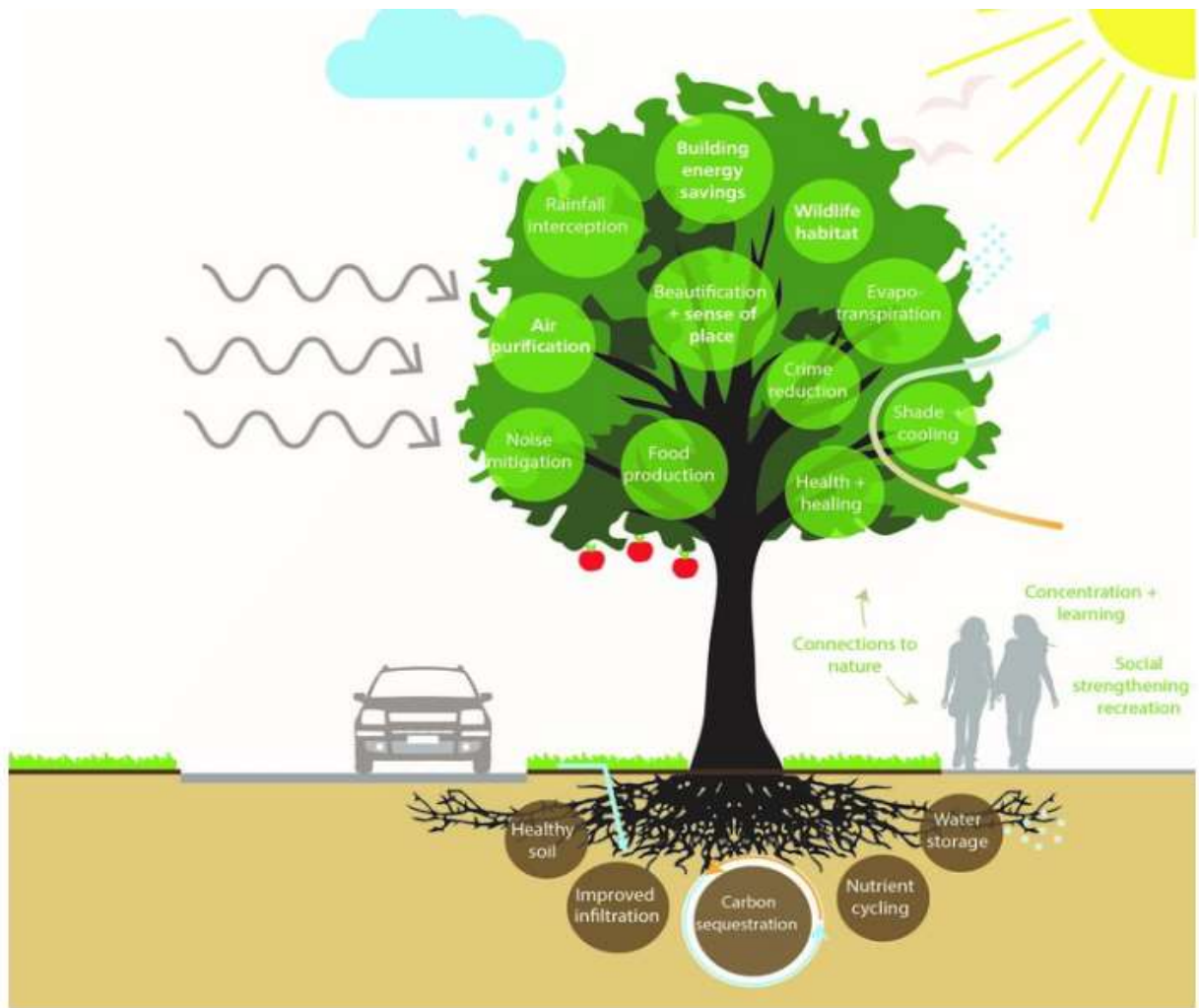


Figure2. 1: Importance of greenspace in urban space. (Source: Diamond Head Consulting,2017)

There are, however, two schools of thought concerning the association between greenspace and crime rate. The first belief is a traditional view that suggested greenspace facilitates crime activities and perceived crime risk because it hides perpetrators from potential victims and bystanders (Newman, 1978; Shaffer & Anderson, 1985; Nasar & Fisher, 1993). For instance, a study by Stoks (1983) found that rape scenes are positively associated with dense vegetation because they conceal criminal activities. Another study by Hull et al. (2001) emphasized how criminals in parks used dense vegetation to hide their criminal activities, especially when stealing from a motor vehicle or

the motor vehicle, as reported by the park police officers. These studies suggested that crime occurrences will reduce if vegetations or greenspace were removed. However, these studies did not account for crime occurrence in their analyses and findings, which fails to show the “big picture.”

The concept of crime prevention through environmental design (CPTED) was coined in the 1970s to address the need to manipulate the environment to conceive a safe community. According to Crowe (2000), CPTED is defined as “the proper design and effective use of the built environment which can lead to a reduction in fear of crime and the incidence of crime, and an improvement in the quality of life.” Previous crime studies reveal that the deterrent to crime could be achieved by appropriate environmental design, which will increase the perceived likelihood of detection and apprehension (Jeffery, 1971; Crowe, 2000). Existing literature also suggested, “certainty of being caught is a major deterrence for criminals not the severity of the punishment so by raising the certainty of being captured, criminal actions will decrease” (Jeffery, 1977; Atlas, 2008). Equally important, the broken windows theory by Wilson & Kelling (1982) revealed that a neighbourhood with overgrown or unkempt vegetation reflects social disorder, and this, in turn, will foster an environment for the crime of opportunity by criminals.

The second belief suggested that the abundance of greenspace deters criminal activities (Kuo & Sullivan, 2001; Gilstad-Hayden et al., 2015; Chen et al., 2016; Escobedo et al., 2018). Moreover, various crime studies (Table 2.1) have examined the influence of vegetation and greenspace on crime rates in urban centres using different crime types, measurement of greenspace and number of years (Wolfe & Mennis, 2012; Du et al., 2015; Schusler et al., 2018). According to Wolfe & Mennis (2012), vegetation abundance is associated with lower rates of assault, robbery and burglary, but it was insignificant for auto theft. The study was carried out by utilizing vegetation

coverage calculated by NDVI using Landsat image as its measurement of greenspace at the census tract level. With the auto-theft crime, not significant in their study, the crime rate (aggravated assault, robbery and burglaries) were associated with the remotely sensed vegetation while controlling for some socioeconomic indicators. They found violent crimes have the strongest negative association with vegetation in their study area. They also suggested that vegetation should be considered in urban crime prevention strategies by crime analysts, urban planners and decision-makers. A similar measurement of vegetation was adopted by Du et al. (2015) in their study. They examined the relationship between crime rates (property and violent crime) and vegetation cover in Kitchener-Waterloo, ON. The authors found that vegetation cover was negatively associated with both crime types in the study area. However, there is some criticism with the use of the NDVI method for the measurement of vegetation. NDVI technique does not differentiate between trees and shrubs, which might influence the findings in their studies (Chen et al., 2016).

Troy et al. (2012) investigated the relationship between tree canopy and crime rate in the greater Baltimore region, which comprises Baltimore City and Baltimore County, MD. The study region covered various land use and land cover types, which included dense urban areas and agricultural areas. The authors accounted for different effects of trees (located in private and public land) on the crime rates. The study analyzed crime data from the year 2007 to 2010 and vegetation data (aerial photo & LiDAR-derived tree canopy area) while the datasets were aggregated into census block groups. The datasets were then examined to determine the relationship between crime rates and vegetation. The authors found an inverse relationship between crime rates and vegetation in the study area.

Similarly, Donovan & Prestemon (2012) examined the relationship between urban trees and crime aggregates (all crime, violent crime and property crime) as well as two individual crimes (burglary

and vandalism) in Portland, Oregon. They found that the relationship between crime rates (2005 - 2007) and urban trees (aerial photo) reveals different outcomes. For instance, the authors found that trees in the public right of way are associated with lower crime rates while trees on a house's lot show mixed results. They suggested that smaller, view-obstructing trees are associated with an increased crime while larger trees are related to reduced crime. The authors speculate that trees may "reduce crime by signalling to potential criminals that a house is better cared for and, therefore, subject to more effective authority than a comparable house with fewer trees" (Donovan & Prestemon, 2012).

Eckerson (2012) explored the association between crime rates and vegetation in Minneapolis, MN, where the author analyzed crime data from the year 2010 to 2012 using OLS and GWR model. The author found a negative relationship between crime rates and tree canopy coverage in the study area. Gistad-Hayden et al. (2015) conducted a study in New Haven to examine the influence of tree canopy cover and urban parks on crime rates (property and violent). Tree canopy coverage (measured through high-resolution aerial imagery), urban parks, crime rates (violent and property) and socio-economic variables (educational attainment, median household income, ethnic composition, population density, vacancies and renter-occupied housing) were included in their study. They found an inverse relationship between crime rates and tree canopy cover. Similarly, Chen et al. (2016) explored the association between tree coverage and property crime in Vancouver, Canada, where they carried out the study using spatial regression analyses and geographically weighted regression (GWR). They also found a negative relationship between tree coverage and property crime, which agrees with existing literature on crime studies.

Table 2. 1: Comparison of previous studies on the influence of Greenspace on crime

Reference	Location	Crime data source	Type of Crime	Type of greenspace	Measurement of greenspace	Unit of analysis	Time	Models
Branas et al. (2011)	Philadelphia, Pennsylvania, USA.	Police Department	Property and Violent	Greened and non greened Vacant lots	Converted vacant lots to greened lots	Census tract	(1999-2008) Ten years	cross-sectional time-series linear regression models
Ekerson (2012)	Minneapolis, Minnesota, USA	Police Department UCR	Property and Violent	Tree canopy	LiDAR-derived tree crown area	Neighbourhood	(2010-2012) Three years	OLS & GWR
Phillips (2013)	AUSTIN, TEXAS, USA	Police Department	Property and Violent	Tree canopy	Aerial photo	Census Tract	(2006-2010) Five years	Linear regression
Gilstad-Hayden et al. (2015)	New Haven, Connecticut, USA.	Police Department UCR	Property and Violent	Tree canopy cover	Im-Aerial imagery	Block groups	(2008-2012) Five years	OLS, Spatial Lag
Chen et al. (2016)	Vancouver, British Columbia, Canada	Police Department	Property	Tree canopy	LiDAR-derived tree crown area	Dissemination areas	(2013) One year	OLS, Spatial Lag, GWR
Kondo et al. (2016)	Philadelphia, Pennsylvania, USA.	Interview with gunshot victims	Violent	Tree canopy cover	Aerial imagery	N/A	(2008-2011) Four years	Conditional logistics regression
Locke et al. (2017)	New Haven, Connecticut, USA.	Police Department	Property and Violent	Tree point data	Tree inventory	Block face (Census block group)	(1996-2007) Twelve years	Negative binomial regression
Schusler et al. (2018)	Chicago, Illinois, USA.	Chicago Data portal	Property and Violent	Tree canopy	Aerial photo	Census Tract	(2009-2013) Five years	Negative binomial regression
Escobedo et al. (2018)	Bogota, Colombia	Center for studies on safety and drugs (CESED)	Violent	Tree inventory	Trees = > 30cm	Census sector level	(2003-2004) Two years	Generalized linear model (GLM), GWR

Furthermore, a recent study by Escobedo et al. (2018) took a different approach with the measurement of greenspace by estimating the treescape variables from tree inventory data, which contain DBH, basal area, crown area and tree height size in Bogota, Columbia. The authors examined the relationship between crime rates and the treescape variables (tree height, basal area, crown area). They found a negative correlation between treescape variables and the homicide rate in the study area. Similar studies on the measurement of greenspace were carried out by Kardan et al. (2015) on health in Toronto, ON and most recently by Lee (2019) on social inclusiveness in a housing estate in Hong Kong (See Table 2.2). In the Canadian context, there are limited crime studies carried out to explore the association between crime rates and greenspace.

Table 2. 2: Previous studies that utilized tree inventory data

Reference	Location	Study	Tree inventory	Greenspace Variables
Kardan et al. (2015)	Toronto, Ontario, Canada	General Health	Estimated crown areas	Tree density
Escobedo et al. (2018)	Bogota, Colombia	Homicide rate	Tree height, basal area of each tree, tree density and crown area	Average basal area, crown area, tree density
Lee et al. (2019)	Hong Kong	Social inclusiveness	Estimated from the number of trees and DBH values	Stem density, basal area, crown area density

Chapter 3 Study Area and Data Sources

3.1 Study Area - City of Toronto

Toronto, Ontario is the most populous Canadian city with a population of over 2.7 million people in the 2016 Canadian census. It is located on the northwestern shore of Lake Ontario, and it is also the core of the Greater Toronto Area (GTA). In essence, it is the most populous census metropolitan area (CMA) in Canada, with a population of over 5.9 million people in 2016. Toronto is the core of the GTA, along with four other regions, namely Durham, Halton, Peel, and York makes up the Greater Toronto Area (OECD, 2009). According to Vipond (2017), Toronto is known as the centre of business, arts, finance and culture. It is also known as one of the most multicultural and cosmopolitan cities in the world as it serves as one of the first arrival city for immigrants. The city is made up of over 50% immigrant populace, and it is also known as a global nature because of her population's cultural diversity across the city of Toronto. It is considered a global city as it represents a significant economic hub in the global economy (Foreign Policy, 2008).

The city of Toronto was formerly divided into six different municipalities: Etobicoke, East York, North York, York, Scarborough and former Toronto before its amalgamation in 1998. It comprises of these municipalities, the names of these former municipalities are often used by residents who live in respective areas as an easy geographic reference when discussing the locations within the City (City of Toronto, 2019). The Economist (2017) ranked Toronto as the fourth safest major city in the world and safest major city in North America, which indicates that crime occurrences in Toronto are low compared to other major cities around the world. Although Statistics Canada (2019), reveals the Crime Severity Index (CSI) has been on the rise since the year 2014 to 2018 across the study area. They noted that the Crime severity index in Toronto rose from 45.07 to 53.64 for five years from the year 2014 to 2018.

Existing literature in the city of Toronto has explored the association between crime rate and crime risk factors (Quick et al., 2013), housing price and dwelling density (Chen et al., 2015) and social patterning (Wang et al., 2019). Also, previous studies have been carried out in Toronto to support crime prevention and programmes. These have enabled the Toronto Police Service (TPS) to create crime applications and maps, which encourages victims of crime to report criminal activities in the community to the Police. The primary purpose of the crime apps and maps was to inform residents of Toronto of the crime types in their respective neighbourhoods. Datasets and maps can be found on the TPS public safety open data portal. They contain datasets like assault, auto-theft, break-in and enter, homicide, theft over and bicycle thefts - this open data is available to the public and researchers (TPS, 2019a).

Toronto was selected as the study area because it is the largest municipality in Canada by population with a diverse resident, and the high criminal activities were taken into consideration. Previous crime studies in Toronto have focused on spatial patterning and concentration in the social framework (Quick et al., 2013; Quick et al., 2019; Wang et al., 2019). However, there is limited knowledge about the association between greenspace and crime rate in Toronto compared to studies mostly carried out in the United of America, Europe and other parts of the World. Toronto as 140 neighbourhoods, as shown in Figure 3.1.

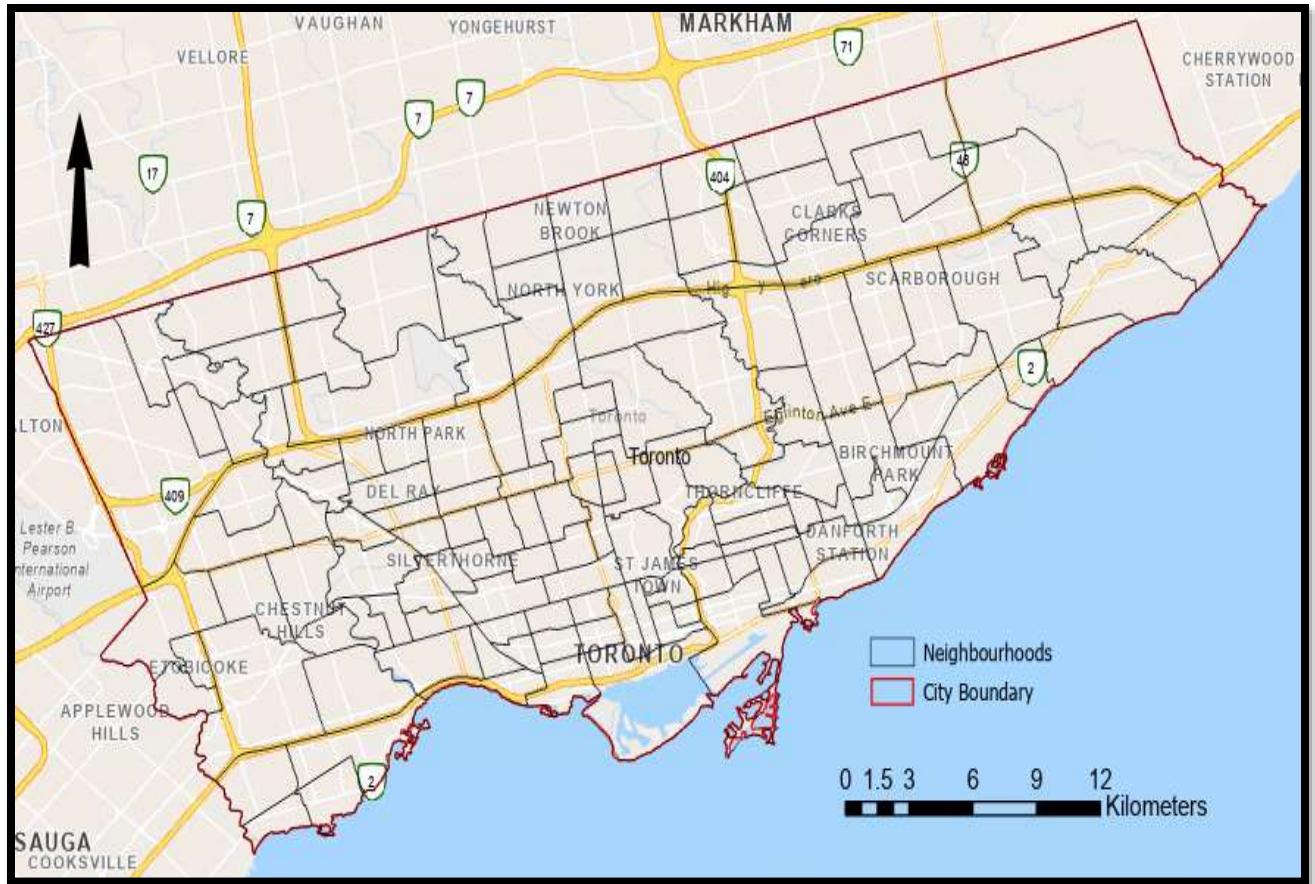


Figure 3. 1: Study area subdivided into 140 neighbourhoods: City of Toronto, Ontario, Canada

3.2 Spatial Unit of Analysis – Dissemination area (DA)

Existing literature on crime studies has considered different types of units of analysis in their research. For instance, the neighbourhood (Wang et al., 2019), census tract (Quick et al., 2013) and dissemination area (Du et al., 2015; Chen et al., 2015) were utilized in their respective studies. However, the dissemination area (DA) is the unit of analysis considered for this current study. DA is a small census geographical unit that covers the study area with each area containing 400 to 700 people (Statistics Canada, 2019). The dissemination area is preferable to larger census geographical units (i.e. Census tract) in this study because of its microanalysis of place. It is important to note that the DA was considered because of its utilization in previous studies. Hence,

a small spatial scale could grant this study to detect patterns that might be masked using large geographical units due to the aggregating of smaller areas. Figure 3.2 shows the dissemination areas in the city of Toronto. The City of Toronto has 3702 DAs as of the 2016 Canadian census program.



Figure 3. 2: Study area subdivided into 3702 dissemination areas: City of Toronto, Ontario, Canada

3.3 Data Sources

3.3.1 Outcome Variables – Crime Data

The crime data used for this study were retrieved from the Toronto police service public safety data portal, which provides free access to the city’s crime and traffic accident datasets. The available crime datasets are assault, auto-theft, break & enter, homicide, theft over and bicycle thefts (TPS, 2019a). This study focused on street crime, which is assault, auto-theft, and robbery crime. These crime variables were preferred for this study because they are more likely to occur in open spaces or outdoors with a higher chance of violence. According to Troy et al. (2012), “These crimes can benefit from concealment and be deterred by eyes on the street.” For instance, the absence of onlookers and opportunities for concealment will encourage an attempted robbery or auto-theft in an open space.

The crime datasets contain geocoded point shapefiles with the location and coordinate of the crime occurrences, which were offset from the crime scenes to the nearest intersection to protect the privacy of the victims (TPS, 2019c). The crime datasets were obtained from Police records, and according to Luo (2012), not all crime incidents are reported to the police department. However, the most reliable and comprehensive source of crime data is from local police records (Nelson et al., 2001). The crime datasets also contain information on the police division, crime type, neighbourhood, year, month, time and coordinate. The street crime types and descriptions in the datasets are listed in Table 3.1.

Table 3. 1: Street crime types and descriptions

<i>Crime Type</i>	<i>Description</i>
<i>Assault</i>	The act of inflicting physical harm or unwanted physical contact upon a person or a threat or attempt to commit such an action.
<i>Auto-theft</i>	The act of taking another person’s vehicle.
<i>Robbery</i>	The act of taking property from another person or business using force or intimidation in the presence of the victim.

3.3.2 Explanatory Variables – Greenspace Data

The greenspace data represented the individual trees data that were extracted from the City of Toronto Open Data Catalogue. They were compiled by Urban Forestry staff during inspections and tree maintenance work on trees located on City-owned street allowances (City of Toronto, 2019e). The greenspace data are openly available and are in point shapefile format. They contain over 530,000 records of trees in its database, and the City’s Urban Forestry staff annually updated them. The datasets include the location, diameter breast height (DBH), address, common and botanical names of the trees. Previous research has utilized tree inventory data to estimate greenspace variables in their studies. For example, the association between greenspace (Figure 3.3) and general health (Kardan et al., 2015); homicide rates (Escobedo et al., 2018) and social inclusion (Lee et al., 2019). This current study focused on the utilization of the number of trees per DA and diameter breast height (DBH) to estimate variables for the stem density, basal area density and tree density. Accounting for different tree species were considered for the tree density variable (See Table 3.2). Existing literature has focused mostly on the influence of tree canopy or tree density on crime rates. The exception is a study by Escobedo et al. (2018) on the relationship

between treescape (DBH, tree height, crown area, basal area, tree density) and homicide rates in Bogota, Columbia. The selected greenspace variables (stem density, basal area density, and tree density) for this current study were considered to determine if any parts of a tree might influence the street crime rate. Statistical estimation analysis was carried out on the tree inventory data to derive the greenspace variables. Figure 3.4 shows the different tree species in the study area.

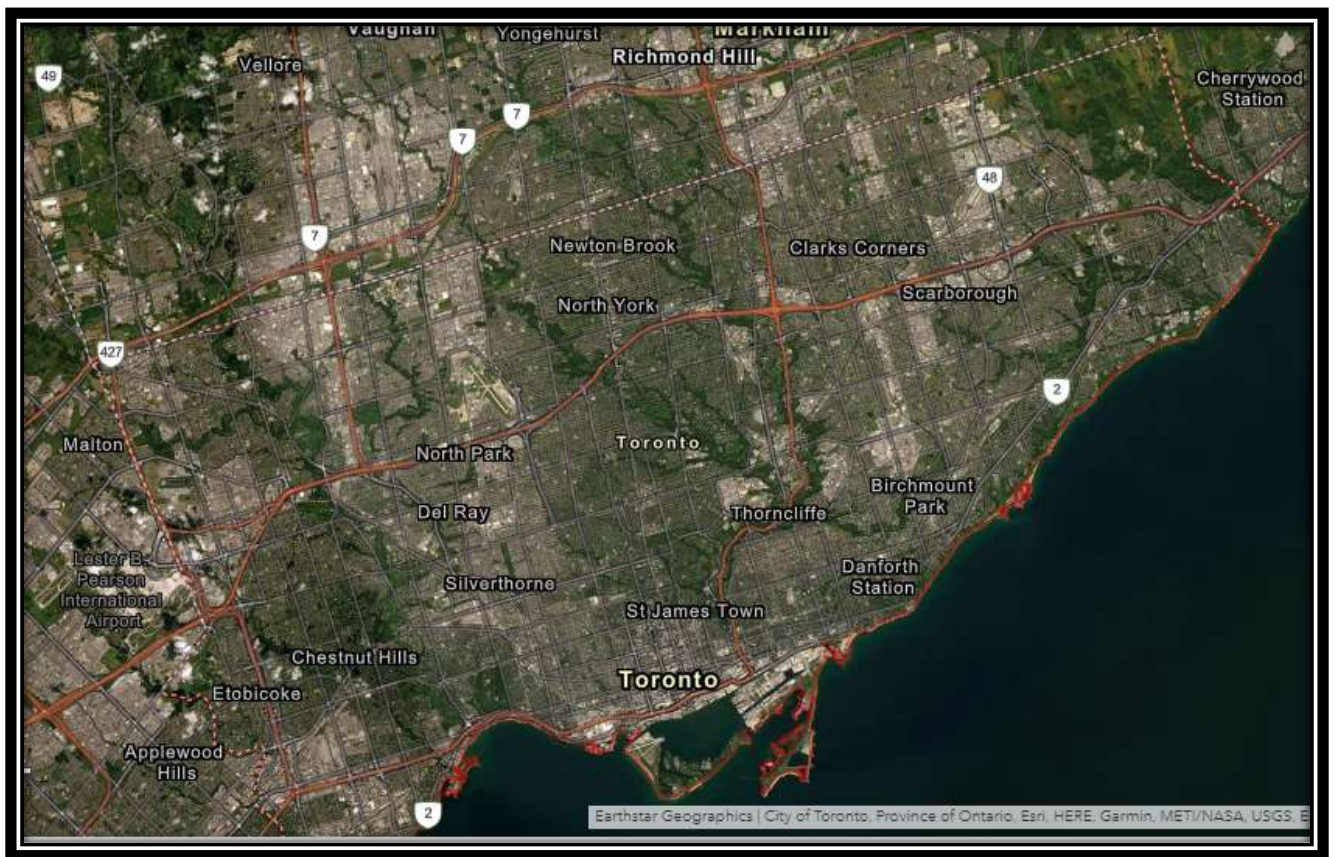


Figure 3. 3: Study area showing greenspace: City of Toronto, Ontario, Canada

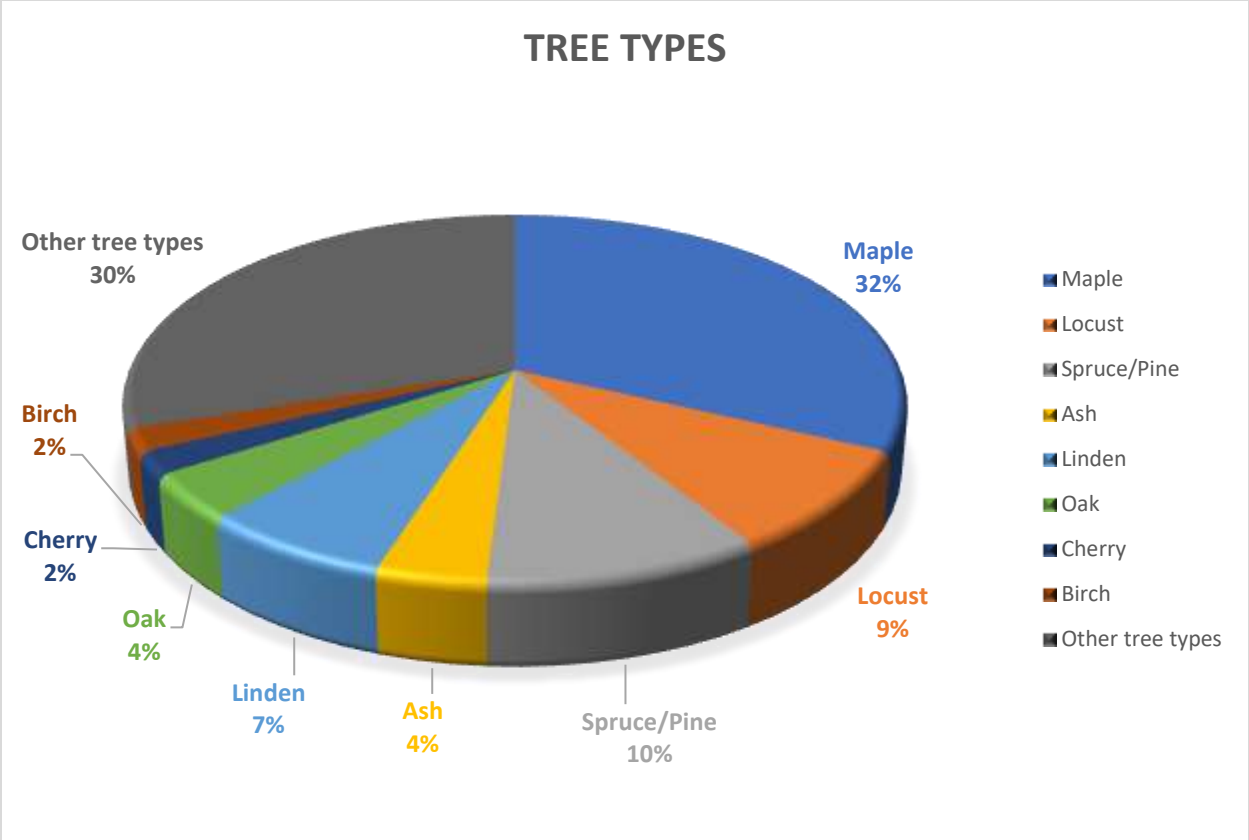


Figure 3. 4: The pie chart for the 8 known tree types and other tree types in Toronto

3.3.3 Sociodemographic Data

The sociodemographic factors used in this study were extracted from the 2016 Census data obtained from Statistic Canada. The census data were available in different units of analysis, and they contain important information about indigenous peoples, education; training and learning; ethnic diversity and immigration; families, households and housing; income, pensions, spending and wealth, labour, languages and population; and demography. The 2016 census data were extracted at the dissemination area level. The sociodemographic factors considered were median housing income, lone parent, unemployment rate, owner-occupied housing unit, renter-occupied housing unit and high school degree, which were inspired by existing literature on crime studies.

Table 3.2 shows the units of measurement for the crime rates, greenspace and sociodemographic variables

Table 3. 2: Greenspace variables, crime data variables and units

Variable	Units
Crime rates	Crime per population
DBH	cm
Median household income	\$
Tenure Owner	%
Tenure Renter	%
Lone Parent	%
High School	%
Unemployment rate	%
Area size	m ²
Trees density	m ²
Basal area density	m ² /tree
Stem density	Number of trees/ m ²

3.4 Descriptive Statistics

Table 3.3 and Table 3.4 provide descriptive statistics for the street crime rates, greenspace and sociodemographic variables at the DA level, respectively. The dependent variables (street crime rate) and independent variables (greenspace and sociodemographic variables) show apparent variation across the dissemination areas. The total crime counts and crime rate per 1000 persons were included in Table 3.3. The assault crime has the highest rate for crime incidents, while the independent variables included are the three greenspace variables estimated from tree counts and diameter breast height (dbh). Six sociodemographic factors from previous crime studies that were significant to both property and violent crimes were considered for this current study.

Table 3. 3: Summary statistics for the dependent variable (n = 3702) at the DA level

Variable name	Total Count	Rate	Min	Max	Mean	SD
Assault (per 1000 population)	18617	6.815	0	580.645	7.665	17.597
Auto-theft (per 1000 population)	4674	1.711	0	453.730	2.264	9.343
Robbery (per 1000 population)	3522	1.289	0	54.730	1.442	3.571

Table 3. 4: Summary statistics for the independent variable (n = 3702) at the DA level

Variable name	Min	Max	Mean	SD
Stem density	0	0.485	0.123	0.063
Basal Area density	0	114.795	1.234	3.357
Tree density	0	0.266	0.013	0.015
MedHouIn	0	113408	34193.272	14728.831
TenOwn (%)	0	22.55	1.586	1.514
TenRen (%)	0	31.850	1.421	2.305
Unempl rate	0	38.500	8.009	4.499
LonePar (%)	0	5.600	0.412	0.478
HighSch (%)	0	63.900	4.199	3.938

Chapter 4 Method

4.1 Data Acquisition and Preparation

The relationship between street crime rates and greenspace was carried out using statistical-spatial analysis, and it involved the use of linear and non-linear equations to estimate for the greenspace variables. Quantitative analysis was carried out using the street crime data from the year 2018, the sociodemographic factors were extracted from the Census 2016 data, and greenspace variables were extracted and estimated from the tree inventory data. In addition to these analyses, line graphs were used to investigate the trends (yearly and monthly) and the seasonal variation of street crime using crime data from the year 2014 to 2018. The street crime trends and seasonal variations were carried out to provide evidence as to changes in criminal activities over the years and to investigate the influence of seasonal change on criminal activities in the city of Toronto. Next, quantile maps were generated for some sociodemographic factors (median housing income, lone parent, owner-occupied housing and unemployment rates). Followed by box maps and cartograms for the street crime rates across Toronto. The spatial autocorrelation and spatial clustering test were carried out using Moran's I statistics. Finally, multivariate spatial regression analyses were carried out using both the spatial lag and spatial error models with a significance level of 5%.

For this study, preparation of each data component included street crimes, greenspace variables and sociodemographic factors at the dissemination area level were carried out had to obtain the dependent and independent variables. All datasets were projected to North American Datum of 1983 (NAD 1983) 17N, to avoid geoprocessing error while utilizing the spatial tool in the ArcGIS platform. The datasets preparation was carried out using the ArcGIS Desktop platform by importing the datasets into ArcMap 10.7.1 and using a spatial join tool to align all the datasets at the dissemination area level within the study area.

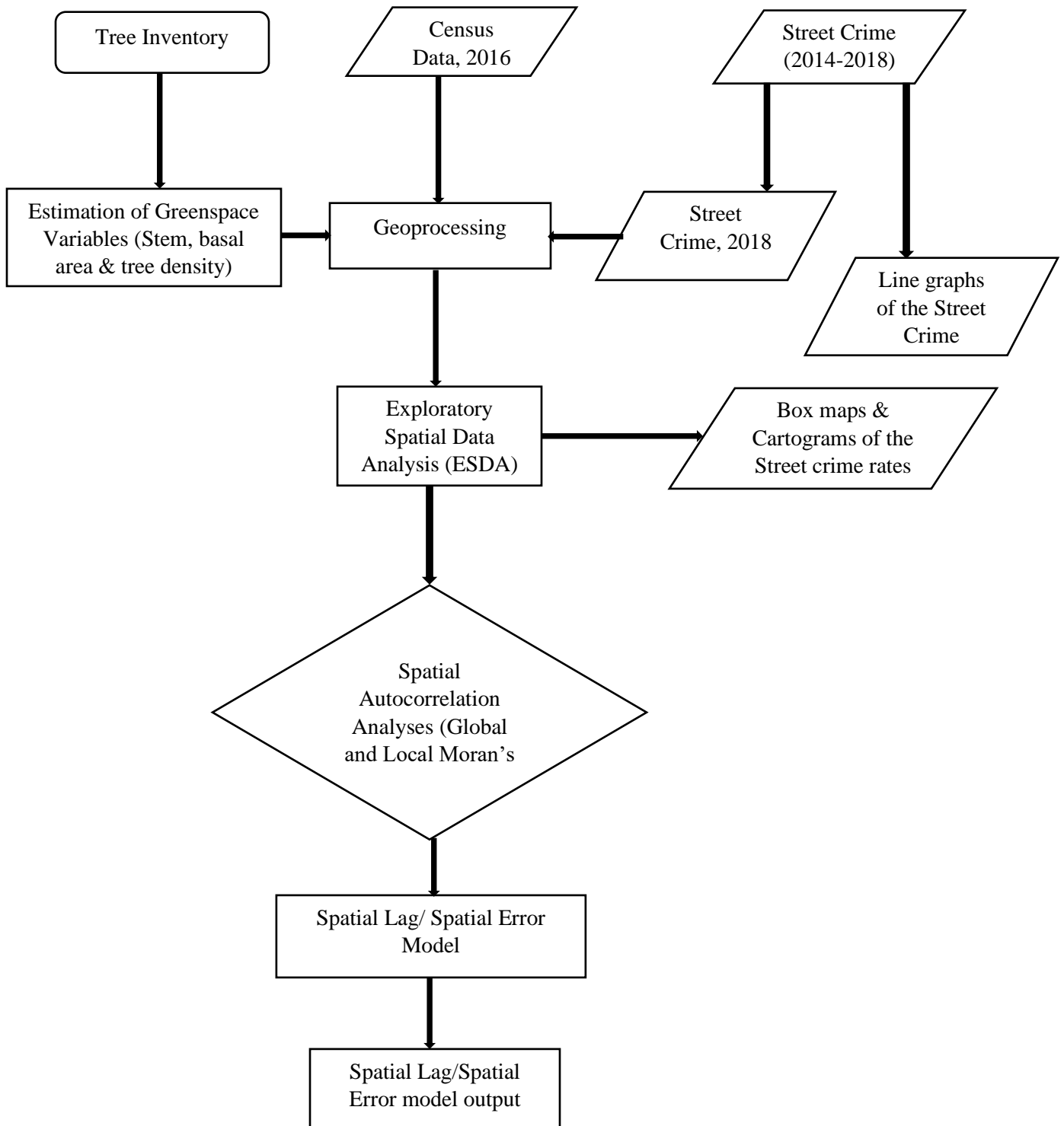


Figure 4. 1: Workflow of this study

Street crime data were obtained from the TPS open data portal, while tree inventory data was used to estimate the greenspace variables exported from the City of Toronto open data portal. The tree inventory data contains different tree types and their diameter breast height (DBH), which were used to estimate for the greenspace variables (stem, basal area and tree density). Figure 4.1 above presents the workflow.

4.2 Summary and Descriptions of Variables

Table 4. 1: Dependent and independent variables names and description

Descriptions	
Dependent Variables	
Assault (2018)	Assault rate per 1000 persons by DA
Auto-theft (2018)	Auto-theft rate per 1000 persons by DA
Robbery (2018)	Robbery rate per 1000 persons by DA
Independent Variables	
Greenspace Variables	Descriptions
Tree Density	Percent of the crown area by the area size of DA
Basal Area Density	Percent of the cross-sectional area of the tree by DA
Stem Density	Percent of the sum of trees by the area size of DA
Control Variables	
Median household income	Median household income
High school degree	Percent with high school degree by DA
Tenure owner	Percent of tenure owner by DA
Tenure renter	Percent of tenure renter by DA
Lone parent	Percent of lone-parent families by DA
Unemployment rate	Unemployment rate by DA

4.3 Geospatial Variables

4.3.1 Crime Occurrences Data

Street crime is regarded as the crime that occurs in public space, and they were represented by three dependent variables (assault, auto-theft, and robbery) in this study (see Table 4.1 for description). The street crime rate is expressed as the volume of crime to the population in a given location. This study used the 2018 street crime rate, and they were estimated using the ArcGIS platform (ArcMap 10.7.1), the crime incidents were aggregated to the DA polygons using the spatial join tool. The sum of the crime incidents in each DA polygon was the total number of the crime that occurs within a particular location. Each street crime type was estimated separately to avoid the geoprocessing error when using the spatial join tool to aggregate the street crime rate and the independent variables (greenspace variables and sociodemographic factors) into each DA. Also, the crime data from the year 2014 to 2018 for the three- street crime were used to explore seasonal variation, monthly (2018) and yearly (2014-2018) trends.

4.3.2 Greenspace variables

Statistical analyses were used to estimate the greenspace variables considered in this study. Greenspace data were obtained from the City of Toronto open data portal, and the datasets were imported into ArcMap 10.7.1 for further geoprocessing. They were estimated using the total number of trees for stem density; diameter breast height (DBH) values for the basal area density. Crown diameter and crown area (Figure 4.2) was used to estimate the tree density variable. The estimation of the basal area density and tree density was carried out separately. They were spatially joined to the DA polygon, where a new field was automatically generated with the number of trees in each DA and the tree per DA was used to estimate the stem density. Table 4.2 shows the formula used to determine the greenspace variables.

Table 4. 2: Formula used to estimate the greenspace variables, data source and reference

Greenspace Variables	Formula	Data Source	Reference
<i>Stem density</i>	Number of trees in each DA/ Area size of DA * 100	Toronto Open data (Street trees)	Lee et al. (2019)
<i>Basal Area density</i>	Basal area = $\text{Pi} * \text{DBH}^2 / 4$ Basal area density = Total basal area in each DA/ Area size of DA * 100	Toronto Open data (Street trees)	Escobedo et al. (2018); Lee et al. (2019)
<i>Street tree density</i>	<p>Crown diameter formula for 8 Known types of trees</p> <p>Crown diameter (Maple) = $0.3048 * (-0.543 + 4.691 * (\text{dbh} * 0.3937)^{0.688})$</p> <p>Crown diameter (Locust) = $0.007 + 0.825 * \log(\text{dbh}) + 0.077 * \log(\text{dbh})^2$</p> <p>Crown diameter (Spruce/Pine) = $0.3048 * (1.634 + 3.628 * (\text{dbh} * 0.3937)^{0.723})$</p> <p>Crown diameter (Ash) = $0.3048 * (-7 + 7.72 * (\text{dbh} * 0.3937)^{0.589})$</p> <p>Crown diameter (Linden) = $0.3048 * (-1.4 + 4.302 * (\text{dbh} * 0.3937)^{0.667})$</p> <p>Crown diameter (Cherry) = $1.76 + 0.1540 * \text{dbh}$</p> <p>Crown diameter (Oak) = $1.717 + 0.156159 * \text{dbh}$</p> <p>Crown diameter (Birch) = $0.975 + 0.161512 * \text{dbh}$</p> <p>Linear regression was used to determine the unknown type of trees formula</p> <p>Formula = $0.0965 * [\text{DBH_TRUNK}] + 3.6436$</p> <p>Crown Area formula</p> <p>Crown area = $3.142 * \text{Sqr}(\text{CrownDiam} / 2)$</p> <p>Street tree density formula</p> <p>Tree density = Crown Area/ Area size of DA * 100</p>	Toronto Open data (Street trees)	Kardan et al. (2015); Lee et al. (2019)

Note: Diameter Breast Height (DBH) is the measurement of the diameter of the trunk or bole of a standing tree Measurement of DBH was taken at 1.3m from the ground.

Stem density for each dissemination area was quantified as the total number of trees in each dissemination area over the area size of the dissemination area multiplied by 100 to be in a percentage format. The stem density varies across the dissemination area of the City of Toronto (Figure 4.3). The basal area was quantified as pi (3.142) multiply by the square of the sum of DBH in each dissemination area and divided by 4. The basal area density of each dissemination (Figure 4.4) was estimated as the total basal area in each dissemination area over the area size of the dissemination area multiplied by 100 to be in a percentage format.

The tree density for each dissemination area was estimated as the total crown area of the trees in the dissemination area over an area size of the dissemination multiplied by 100 to be in a percentage format. The crown area values were used to estimate the tree density, and it was derived from the crown diameter formula (see Table 4.2). The diameter at breast height (DBH) values was used to estimate the crown diameter of the trees. Forestry researchers fitted linear and non-linear models to relate crown diameter and DBH for different species of trees. And, to estimate the crown areas, the crown diameter was, first, estimated using formulas on the DBH for 8 known tree types (Maple, Locust, Spruce, Ash, Linden, Oak, Cherry, and Birch). These formulas were derived from forestry research (see Table 4.2). The 8 known tree species covered 398,683 (70%) of the trees, and the other unknown was 170729 (30%) of the trees. The estimation of the crown diameter for the unknown formula on the DBH was carried out using the linear regression equation on the (70%) known trees estimates. The derived equation was used to estimate the crown diameter for the unknown trees (Table 4.2). The crown areas (Figure 4.2) of the trees were quantified by assuming the crown areas were circular, and the area of circle formula (Table 4.2) was used to estimate the crown areas of the trees.

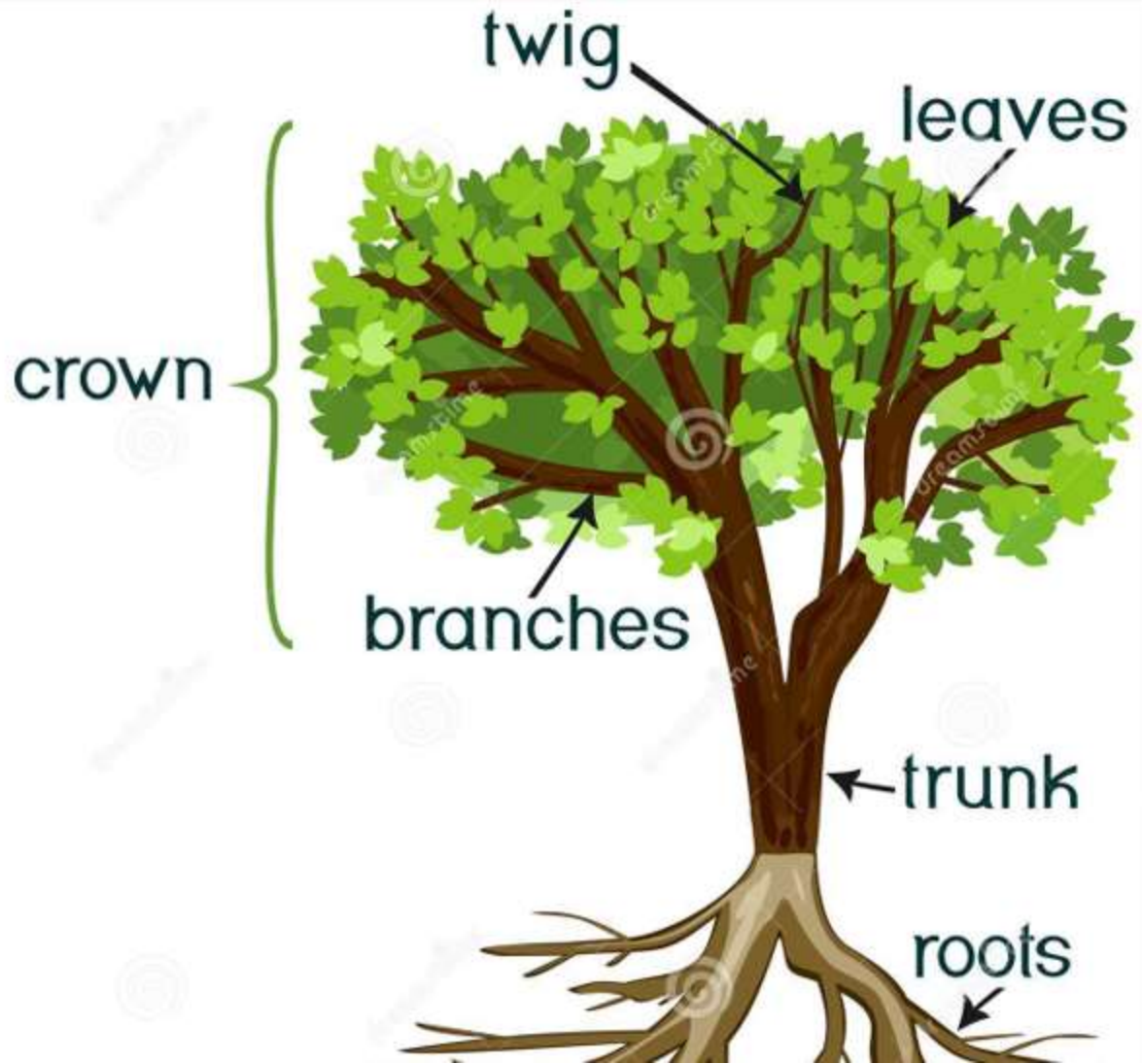


Figure 4. 2: Morphology of adult tree with green crown, root system, and titles (Source: Dreamstime, 2019)

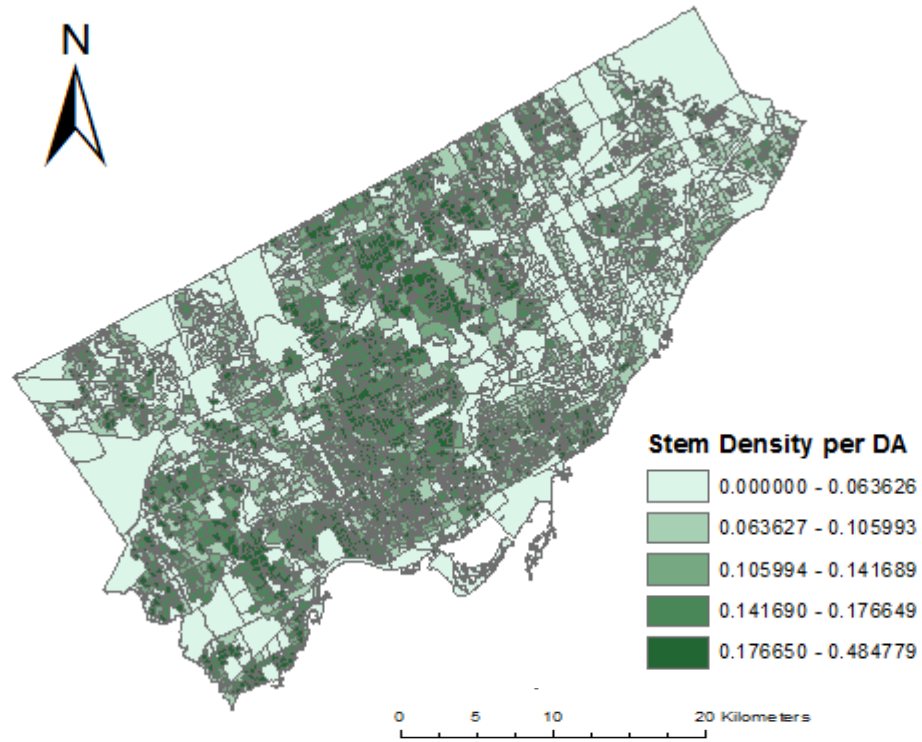


Figure 4. 3: Stem density map by DA in the City of Toronto

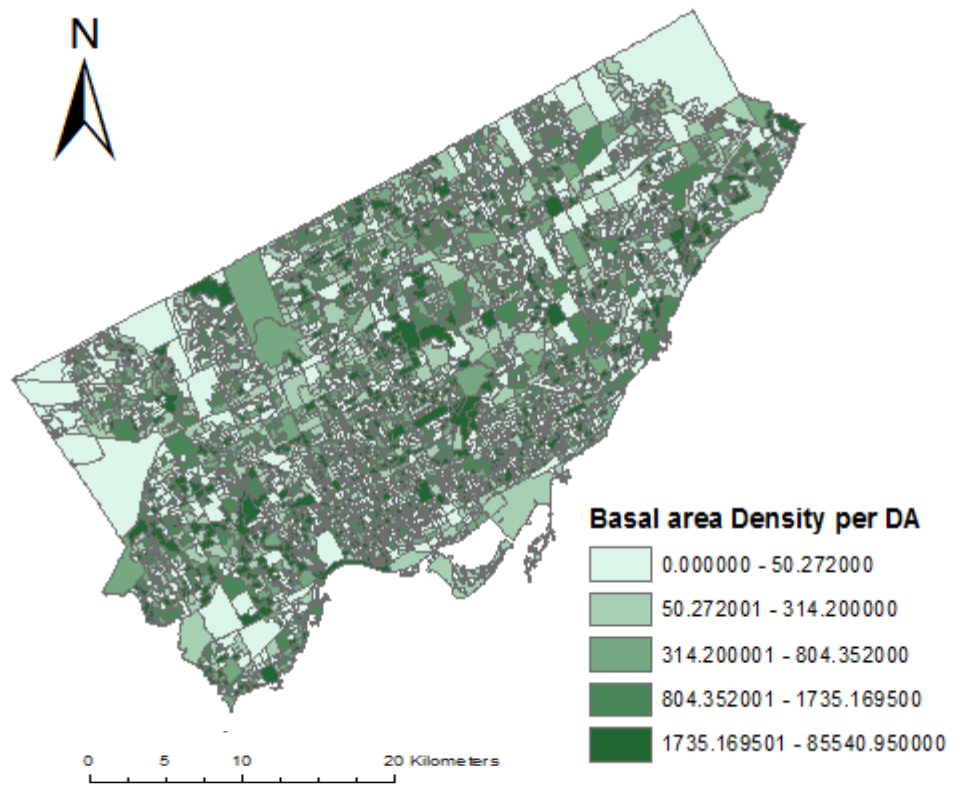


Figure 4. 4: Basal area density map by DA in the City of Toronto

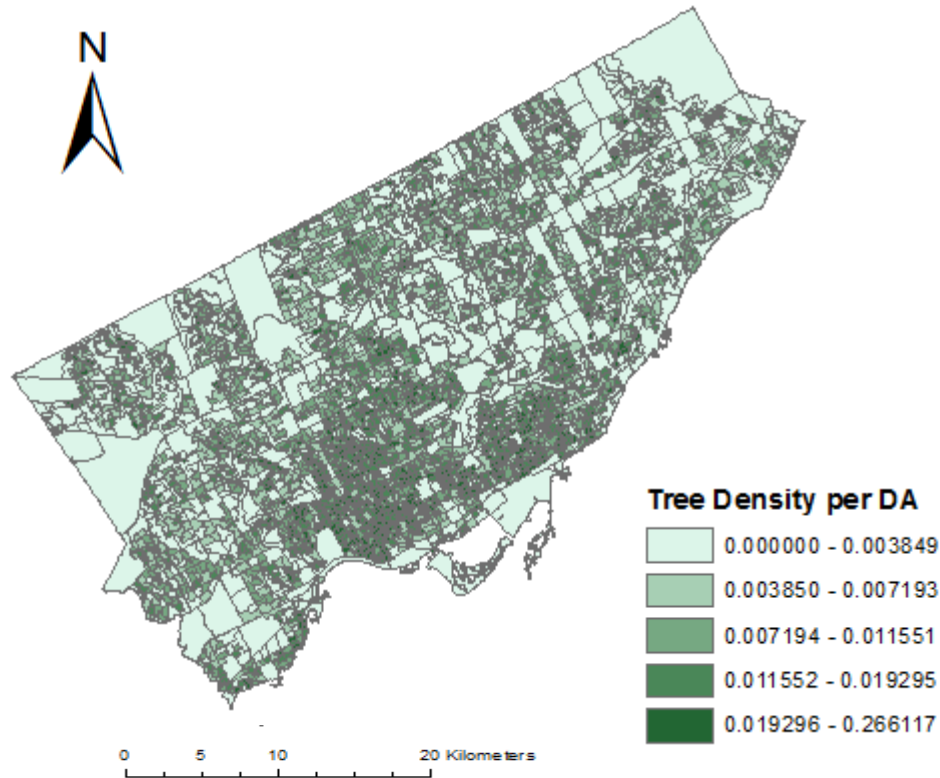


Figure 4. 5: Tree density map by DA in the City of Toronto

4.3.3 Sociodemographic factors

Previous crime studies have controlled using various sociodemographic factors in their investigation about the influence of the crime rate on greenspace in urban cities. Census 2016 data at the dissemination area level was obtained from the Geospatial center at the University of Waterloo provided by Statistics Canada. Urban areas are known to be unique and exhibit different characteristics. Urban areas are often influenced by varying sociodemographic characteristics, as evidenced by existing literature. These sociodemographic factors were exported out of the Census 2016 data at DA level and were included as independent variables considered for the multivariate regression analyses. Existing crime studies have found both social disorganization and routine activity theory framework in controlling for the sociodemographic factors with varying results as

some sociodemographic factors were significant while others were not, in their respective studies. However, this current study considered six sociodemographic factors, and they are median housing income, lone parent, unemployment rate, owner-occupied housing unit, renter-occupied housing unit and high school degree. These factors were considered because they were relevant and significant in previous crime studies (Gilstad-Hayden et al., 2015; Chen et al., 2016; Schusler et al., 2018; Escobedo et al., 2018).

4.4 Analytical Approach

A series of analyses were carried on the dependent and independent variables to determine the spatial association between the street crime types, greenspace and sociodemographic variables. Spatial distribution sociodemographic factors and of the street crime rate across the city was the first course of action. Quantile maps were generated for the four sociodemographic factors. In contrast, box maps and cartograms were created for the three street crime rates to explore the spatial distribution of the street crime rates. The spatial distribution of the street crime rate involves the use of geo-visualization analysis on the dependent variables. It focused on the spatial aspects of the data by providing the spatial distribution of the data, identifying patterns of spatial association and spatial outliers in the data (Anselin, 1994). The process is known as the exploratory spatial distribution analysis (ESDA), which lets one have a deep understanding of the phenomena of the data and lets one make better decisions relating to the data (Bivand, 2010; ESRI, 2019).

Box maps and cartograms of each dependent variable were generated for the spatial visualization of the data. Box maps are an improved version of quantile maps, which symbolizes the map using graduated colours for the quantity of the variable. It is separated using quartiles with the outliers in the first and fourth quartiles, which were highlighted separately (Anselin, 2005; Chen et al., 2016). Whereas, cartogram replaces the original spatial values with circles, and the area of the

circle is proportional to the selected variable (Dorling, 1995; Anselin, 2005). The box map and cartogram used a hinge of 1.5 and can be interpreted as when a value lies more than 1.5 times the interquartile range away from the upper or lower boundary of the interquartile range is referred to as an outlier (Luo, 2012)

The ESDA process cannot be used to determine the geographic pattern in data which can be clustered, dispersed or random pattern. Global Moran's I statistics were used to determine if spatial autocorrelation exists in the dataset to show if there is any similarity in the value at a given location and its defined neighbours (Moran, 1950; Haining et al., 1998). Global Moran's I statistics use a range from -1 to +1 with a negative value indicating a dispersed pattern between the neighbouring areas, and a positive value suggests clustered pattern between the bordering areas and zero values indicate there is no spatial autocorrelation. A weight manager was used to create a weight matrix, which was determined by the queen contiguity method, and it considers the DAs that share boundaries. The Global Moran's I tests were carried out using the GeoDa software platform with the weight matrix created for each dependent variable before the Moran's I statistics were conducted on the three street crime rates.

As the name suggests, the Global Moran's I statistic does not indicate the location of the spatial clustering in a study area. It only reveals the value, which is often positive, neutral or negative (Bivand, 2010). However, local indicators of spatial association (LISA) cluster and significance maps were generated for each dependent variable to identify the regions with significant spatial clustering, and the maps reveal the locations of the hot spots and cold spots across the study area at a significance level of 1%.

4.5 Spatial Regression Models

Previous crime studies have shown that there is usually positive spatial autocorrelation and the presence of hot spot clusters in the study area (Du et al., 2015; Chen et al., 2016). The presence of spatial autocorrelation in the dependent variable means the OLS regression will not be suitable for this study (Pfeiffer et al., 2008; Chen et al., 2016). Spatial lag and spatial error models were carried out to explore the local spatial processes with the regression analyses. (Anselin, 2003).

The multivariate spatial regression analyses were carried out to test the spatial association between the street crime rates, greenspace variables while controlling for specific sociodemographic factors. These spatial regression analyses were carried out using the GeoDa software known for its extensive package as it conducts spatial data analysis, geo-visualization, spatial autocorrelation and spatial modelling (Anselin, 2003). The multivariate spatial regression was conducted using the spatial lag and spatial error model, and the models were compared. The findings from multivariate regression analyses will be discussed in the discussion section.

4.5.1 Spatial Error and Spatial Lag Models

The classic OLS regression was not used in this study because of the presence of spatial autocorrelation in the outcome (dependent) variables. Inevitably, the multivariate spatial regression was carried out to investigate the influence of greenspace variables on street crime rates while controlling for specific sociodemographic indicators. This study used the two predominant types of the spatial regression model, which are the spatial lag model (equation 1) and the spatial error model (equation 2). These spatial econometric models have been used to explore the relationship between crime rate and greenspace in previous crime studies (Ekerson, 2012; Wolfe & Mennis, 2012; Gilstad-Hayden et al., 2015) which justify the validity of the models:

$$y = \rho W y + \sum a_i X_i + \varepsilon \quad (4.1)$$

$$y = \sum a_i X_i + u, \quad u = \lambda W u + \varepsilon \quad (4.2)$$

Where $u = \lambda W u + \varepsilon$, u is a disturbance vector that is spatially autocorrelated, and λ is a spatial error parameter. y is the dependent variable of crime rates; ρ is a spatial regression coefficient that shows the spatial dependence of the sample observations, and λ is a spatial autoregressive coefficient that reflects the spatial dependence of the residuals. W_y and W_u are spatial weight matrix W , the spatial lag operators calculated with y and the residual u respectively; X_i represents the urban form metric or control variable, and a_i is the corresponding coefficient; ε is the error term.

The spatial lag model contains the spatial dependence effects of the dependent variable y ; the spatial error model includes the spatial dependence effects of the residual u (LeSage et al., 2014; Golgher et al., 2016). The spatial lag model is regarded as a spatial autoregressive model on account that the regression coefficient is included for the weight mean value of the dependent variables as well as influence the dependent variables in neighbouring areas (Anselin, 1988).

A spatial error model infers the spatial autoregressive process that occurs only in the error term. It shows an indication that clustering reflects the influence of unmeasured variables (Messner & Anselin, 2004). In contrast (to spatial lag), the spatial error model “suggests that the amount of variance in the crime rate that is not predicted by the independent variables is due to spatially autocorrelated missing variables” (Anselin, 1988).

Chapter 5 Results

5.1 Descriptive patterns

5.1.1 Crime trends (Yearly)

Table 5. 1: Yearly crime trends for the three dependent variables

Years	Assault	Auto-theft	Robbery
2014	16375	3488	3585
2015	17705	3209	3464
2016	18475	3271	3613
2017	18973	3536	3901
2018	18617	4674	3522

The yearly crime trends for the street crime occurrences were generated with crime counts (See Table 5.1) using line graphs (See Figure 5.1). This analysis was carried out to explore the yearly (2014 - 2018) trends of assault, auto-theft and robbery crime occurrences in Toronto. According to Statistics Canada (2019), crime severity index has slightly increased for property and violent crime in Toronto. The assault crime occurrences from the year 2014 to 2018 indicates an increase in assault occurrence from 2014 to 2017 and slightly dropped in 2018 (See Figure 5.1a). The auto-theft started with an increased crime occurrence from the year 2014, slightly dropped in the year 2015, peaks in the year 2016 and 2017 and increased drastically in the year 2018 (See Figure 5.1b). Finally, the robbery crime that occurred in the year 2014 was higher than the year 2015, slightly increased in the year 2016 to 2017, and the robbery occurrences dropped in the year 2018 (Figure 5.1c). The assault crime has the highest occurrence in Toronto for five years time period.

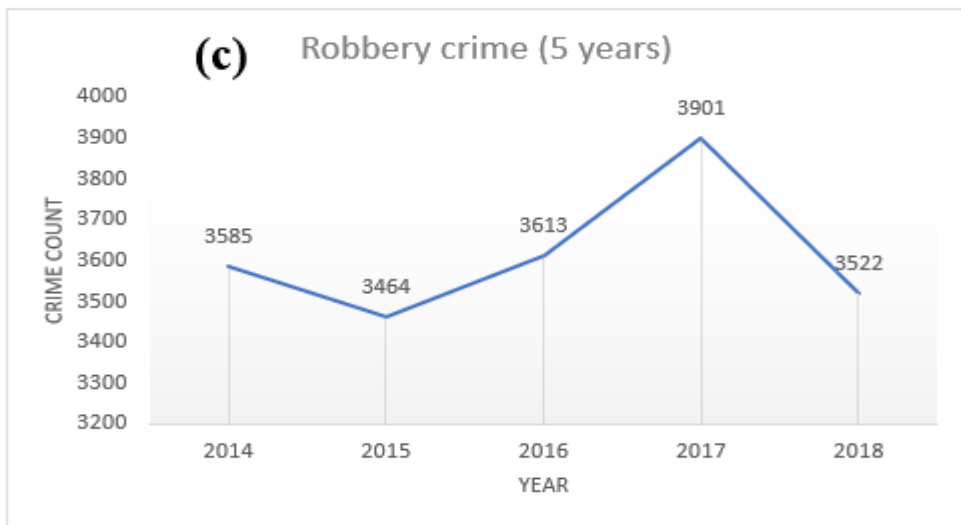
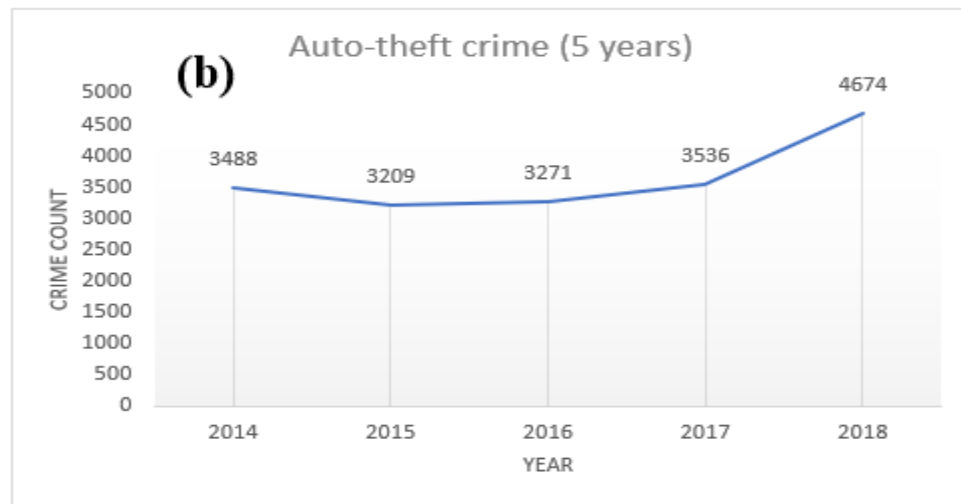
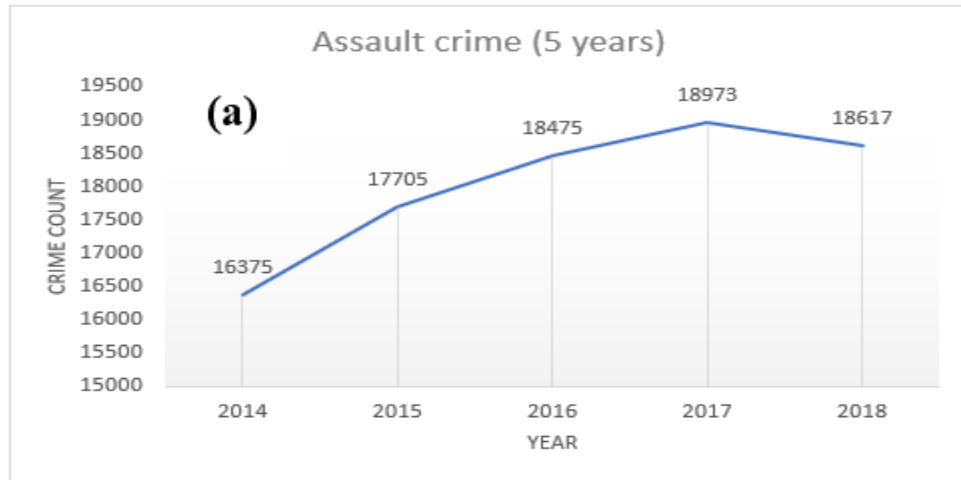


Figure 5. 1: Yearly trends in crime (a) Assault; (b) Auto-theft; (c) Robbery, Toronto, 2014 to 2018.

5.1.2 Crime Trends (Monthly)

Table 5. 2: Monthly crime trends for the three dependent variables

Months	Assault crime	Auto-theft crime	Robbery crime
January	1563	319	326
February	1320	329	283
March	1546	339	357
April	1538	340	231
May	1777	410	266
June	1654	381	268
July	1622	391	283
August	1620	410	307
September	1530	363	293
October	1566	444	299
November	1511	496	331
December	1370	452	278

Following the yearly trends discussed earlier, the monthly trends for the year 2018 crime were examined for the street crime types that occurred in the study area. Table 5.2 and Figure 5.2 shows crime counts and line graphs for each street crime type, while the monthly line graph exhibits varying patterns for the street crime types. The assault occurrence reveals a decrease in February, a slight increase in March, dropped in April, increase in May (summer month). The assault crime decreases from June to September, slightly increase in October and dropped from November to December (see Figure 5.2a). Next, the auto-theft crime occurrences uncover a different pattern, the auto-theft crime peaks from January to May, slightly dropped in June, peaks from July and August, drops in September, peaks in October and November, decreases in December (see Figure 5.2b). Finally, the robbery crime decreases in February, peaks in March, drops in April, the peak from May to August, slightly decrease in September, peak in October and November and decreases in December (see Figure 5.2c). The monthly trends of the assault and robbery crime indicate high occurrence from April to August (Summer months) while Auto-theft crime peaks in the summer months (May-August) and Fall months (October and November).

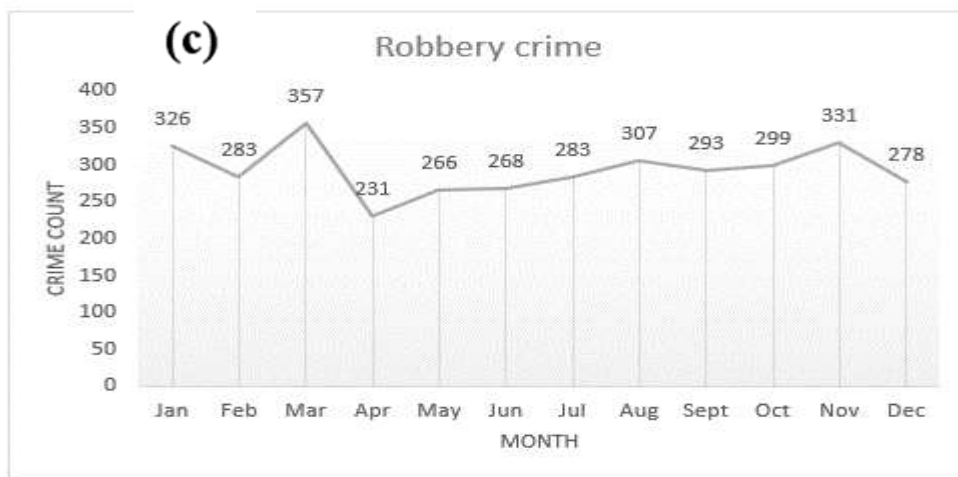
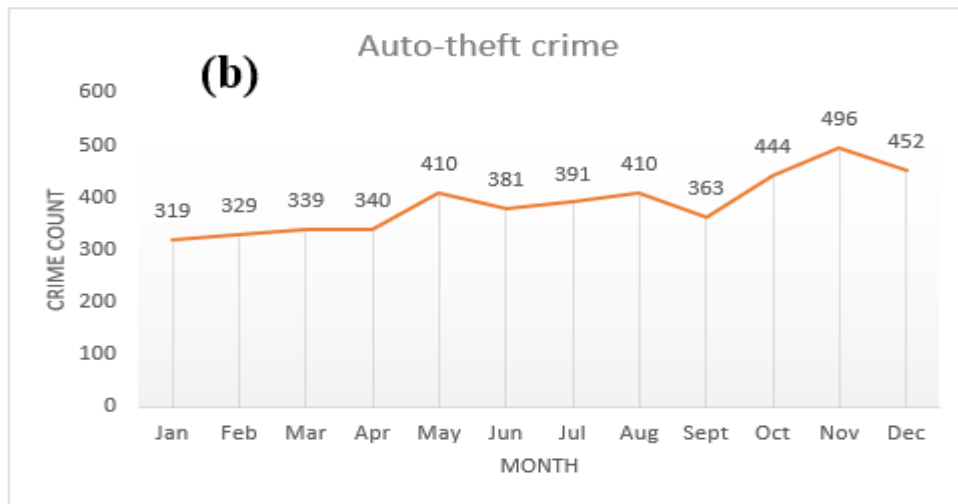
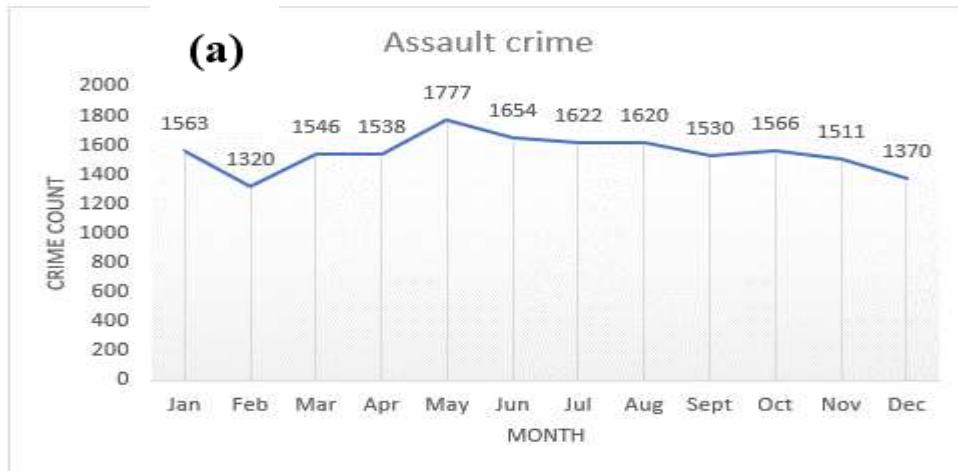


Figure 5. 2: Monthly trends in crime(a) Assault; (b) Auto-theft; (c) Robbery, Toronto, 2018.

5.1.3 Seasonal Variations of Street Crime

Table 5. 3: Seasonal crime trends for the three dependent variables

Season	Assault crime	Auto-theft crime	Robbery crime
Winter	4429	987	966
Spring	4969	1131	765
Summer	4772	1164	883
Fall	4447	1392	908

Note: Winter (Jan.- Mar.); Spring (Apr.-Jun.); Summer (Jul.-Sept.); Fall (Oct.-Dec.)

The seasonal variation and counts of the street crime types examined in Toronto were shown in Figure 5.3 and Table 5.3, respectively. The seasonal variation for assault crime indicates a drop from Spring to Summer and Fall season, while the assault crime is at the lowest in the Winter season (See Figure 5.3a). Next, the auto-theft uncovers a different seasonal variation with the auto-theft crime increasing from Spring to Summer and Fall season, the auto-theft crime has the lowest occurrence in the Winter season (See Figure 5.3b). Finally, the robbery crime reveals an increase in robbery occurrences from the Spring season to the Fall season with the highest occurrence in the Winter season (See Figure 5.3c).

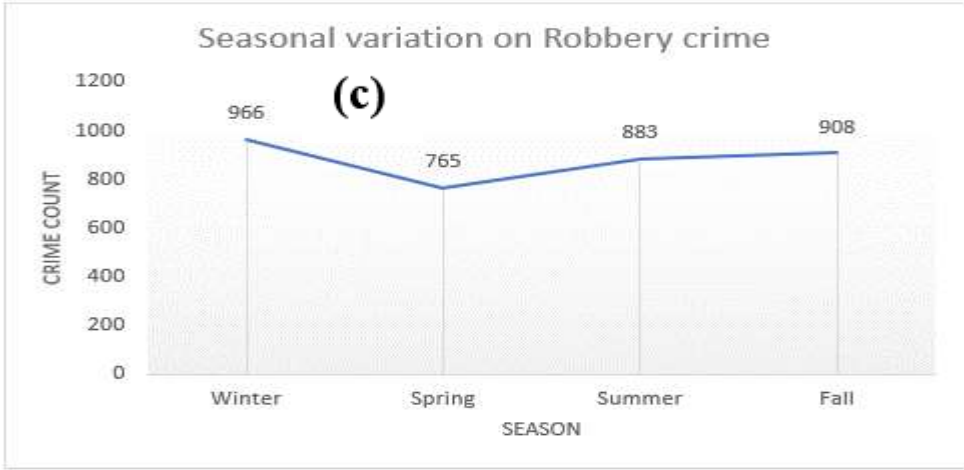
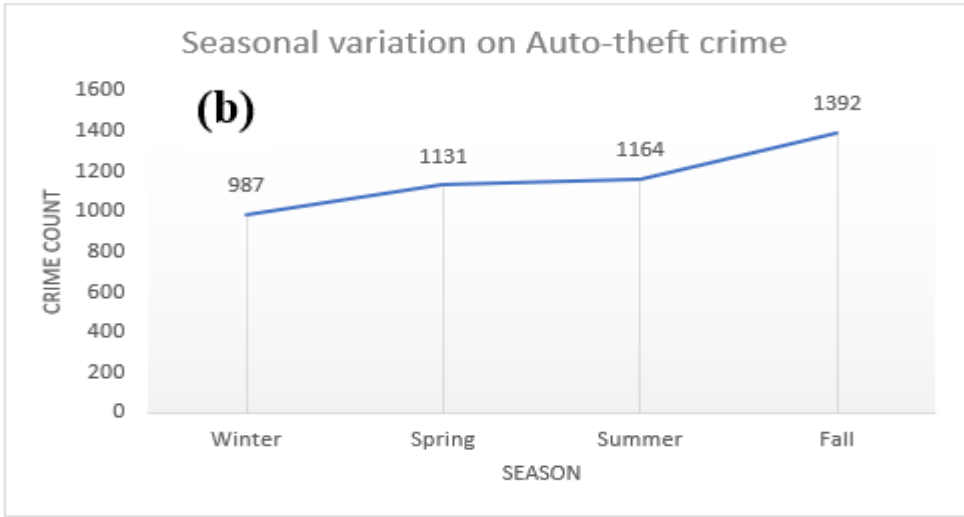
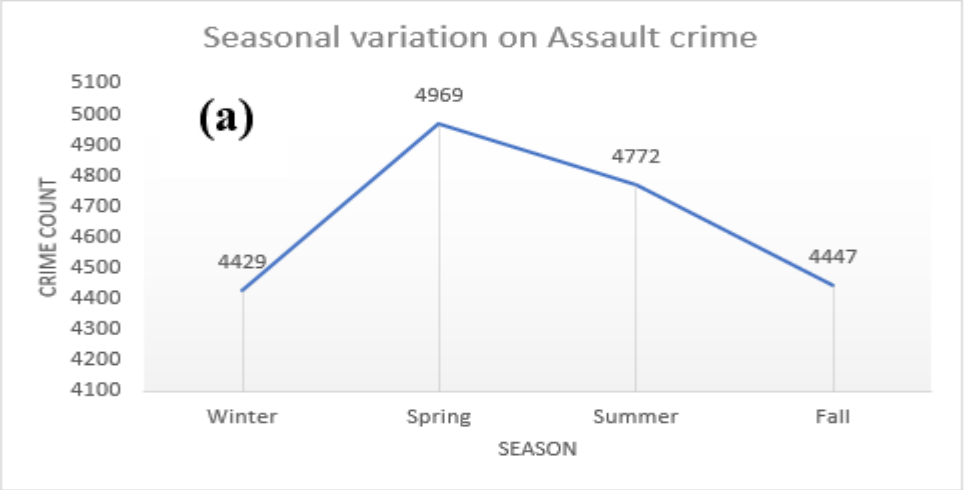


Figure 5. 3: Seasonal trends in crime (a) Assault; (b) Auto-theft; (c) Robbery, Toronto, 2018.

5.2 Spatial distribution

Quantile maps were generated to show the spatial distribution of four sociodemographic factors that were significant to the street crime rates and greenspace variables. Figure 5.4 (median household income), Figure 5.5 (lone parent), Figure 5.6 (unemployment rate) and Figure 5.7 (owner-occupied housing unit) show the spatial distribution of the varying sociodemographic factors across the city of Toronto. This method was used to indicate the spatial distribution of sociodemographic factors in the study area. The quantile maps of the sociodemographic factors reveal varying characteristics across the city.

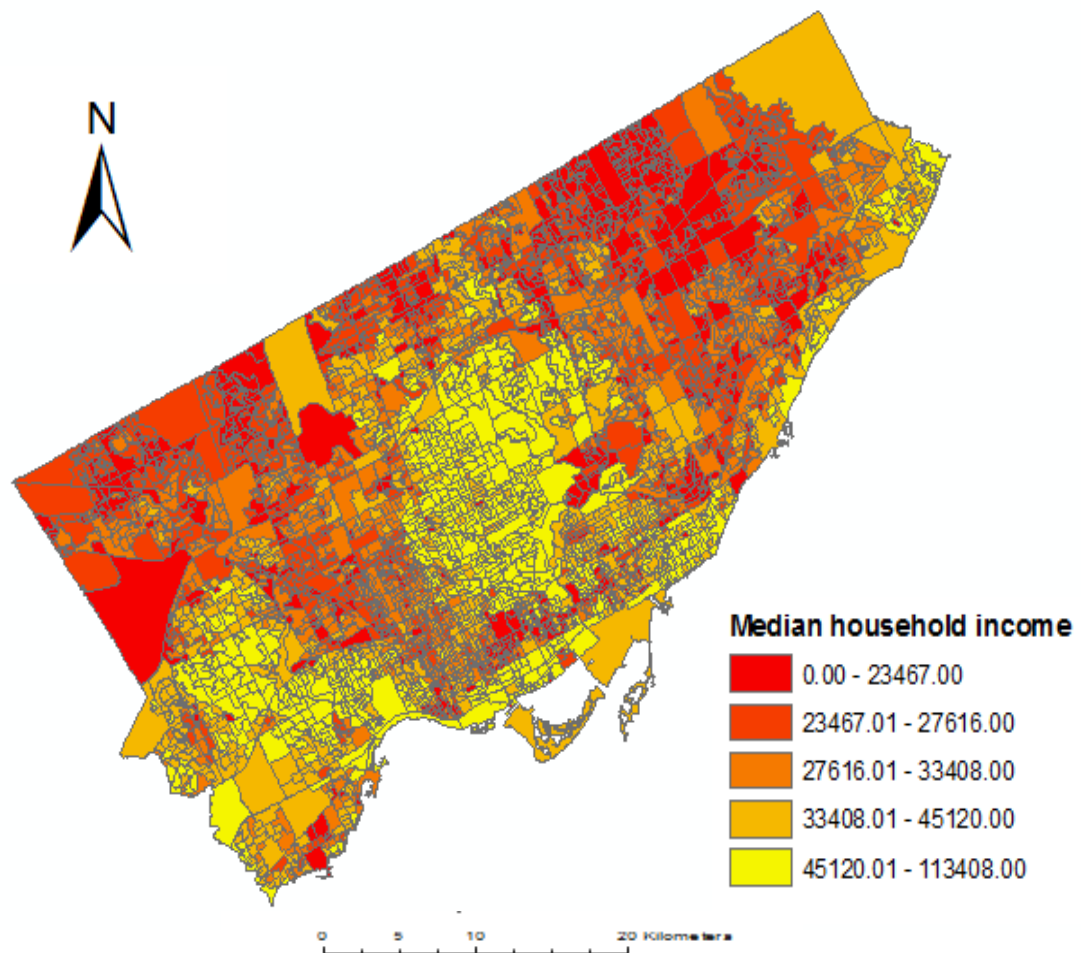


Figure 5. 4: Spatial distribution of median household income in Toronto at the DA level

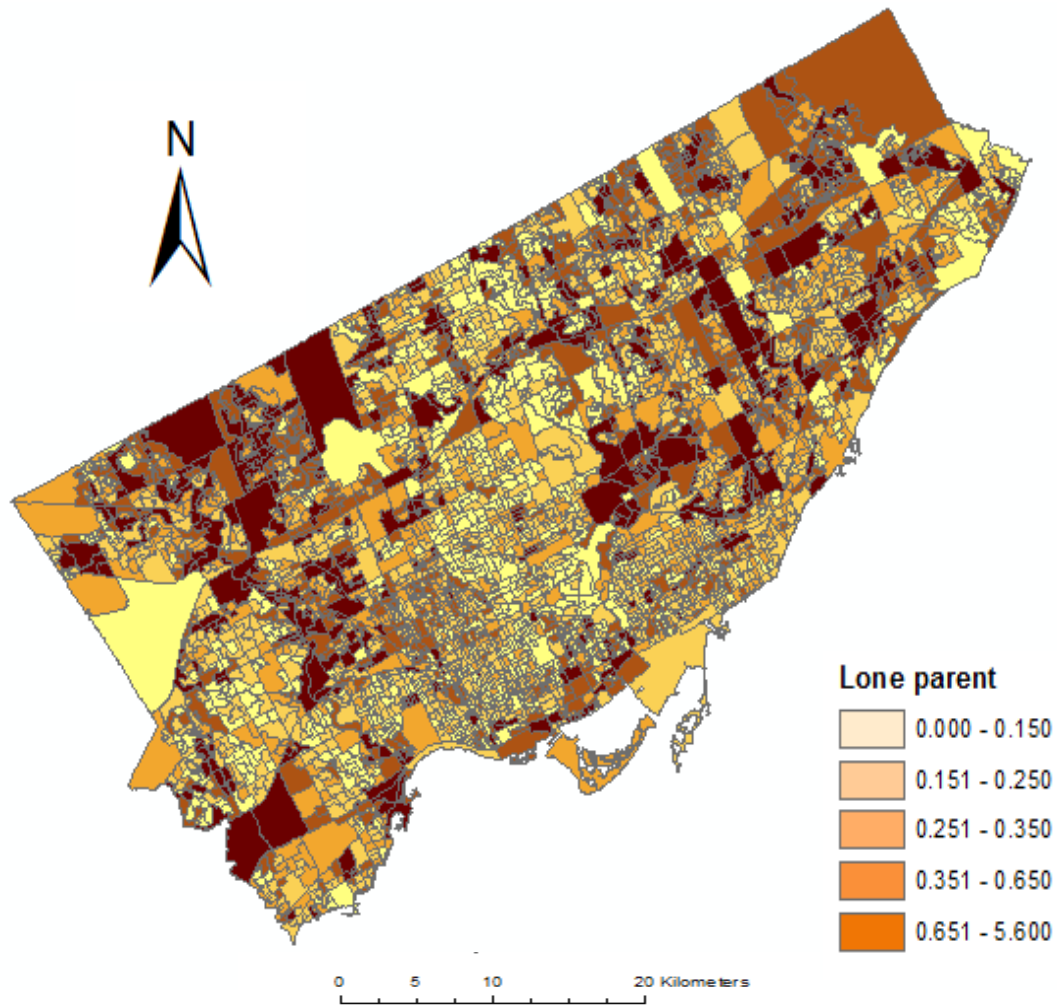


Figure 5. 5: Spatial distribution of lone parent in Toronto at the DA level

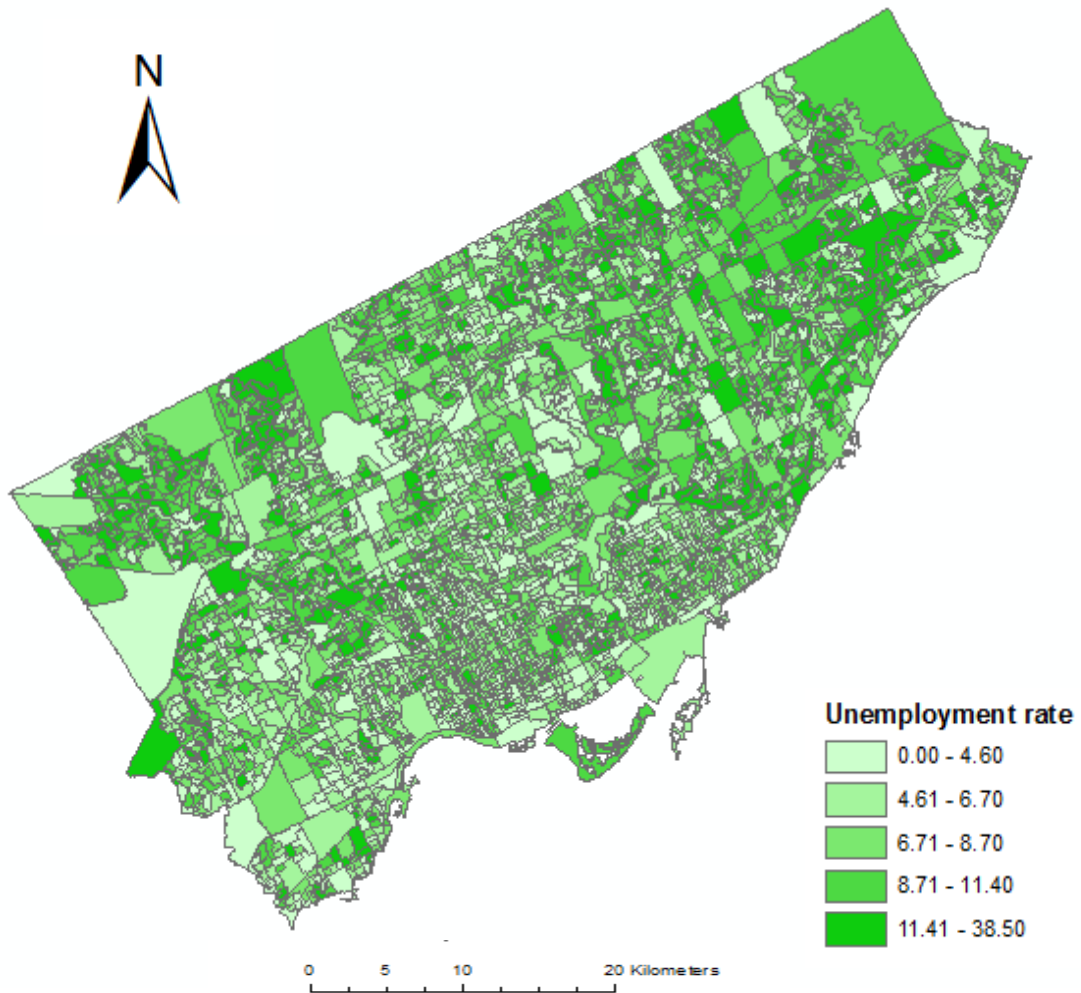


Figure 5. 6: Spatial distribution of the unemployment rate in Toronto at the DA level

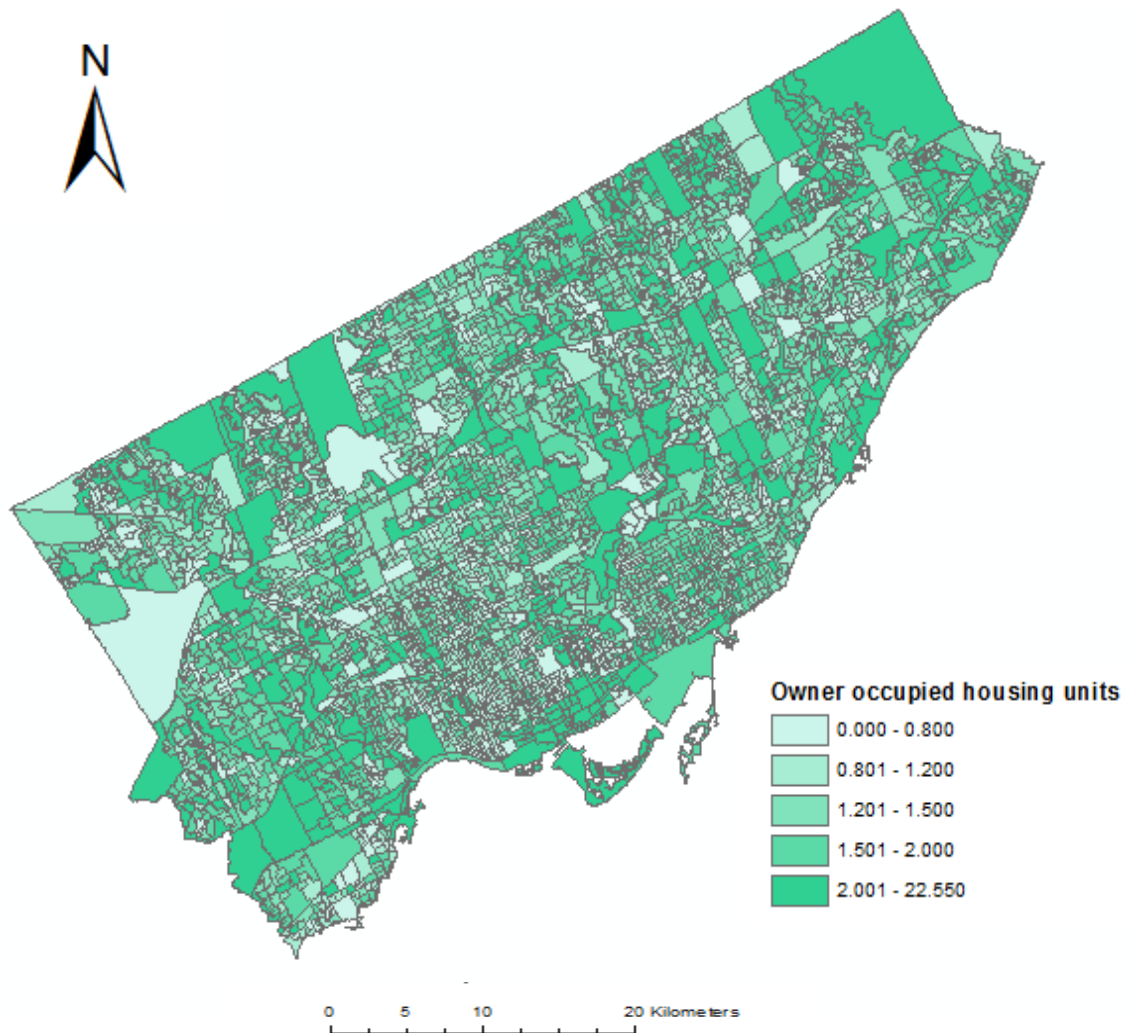


Figure 5. 7: Spatial distribution of owner-occupied housing units in Toronto at the DA level.

5.3 Exploratory Spatial Data Analysis and Geo-Visualization

This study used the ESDA method to visualize the spatial distribution of the three dependent variables, which are assault, auto-theft and robbery crime rate (Figure 5.8, 5.9 & 5.10). The Geo-visualization of the dependent variables was produced by a set of box maps and cartograms. This process was followed by spatial association analyses (i.e. spatial autocorrelation and spatial clustering analysis) carried out on the three dependent variables using Moran’s I and LISA statistics, respectively.

5.3.1 Geo-Visualization of the Street Crimes

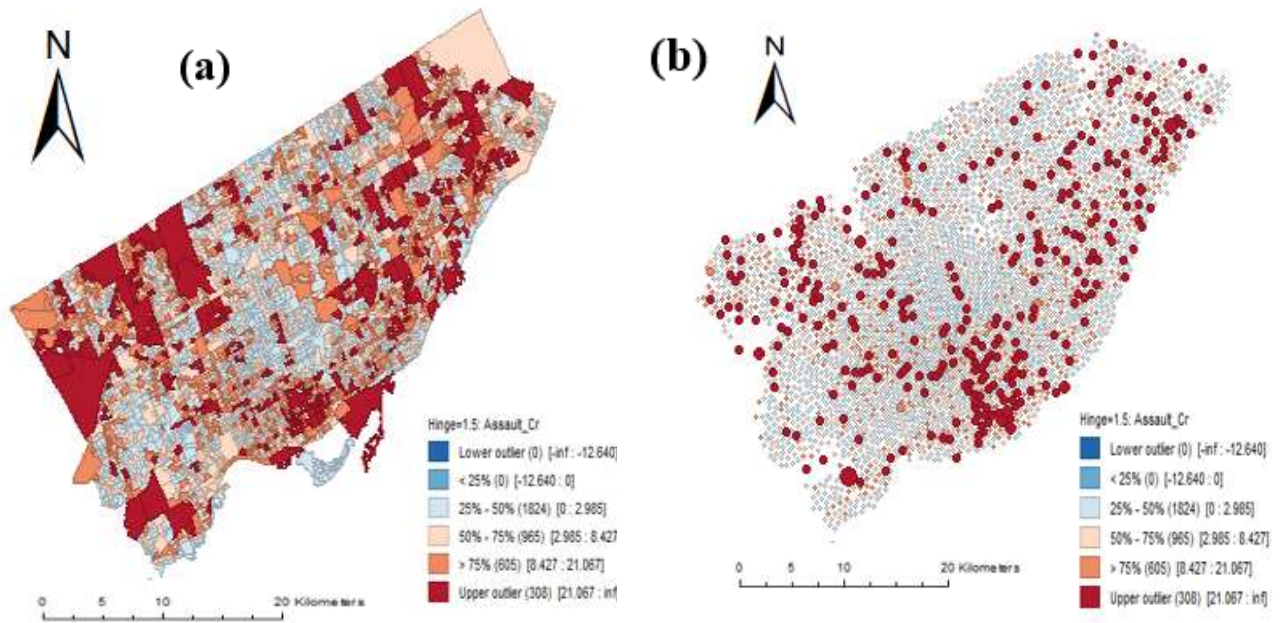


Figure 5. 8: Box map (left) and Cartogram (right) of Assault crime rates per 1,000 persons by DA in 2018, with a hinge of 1.5

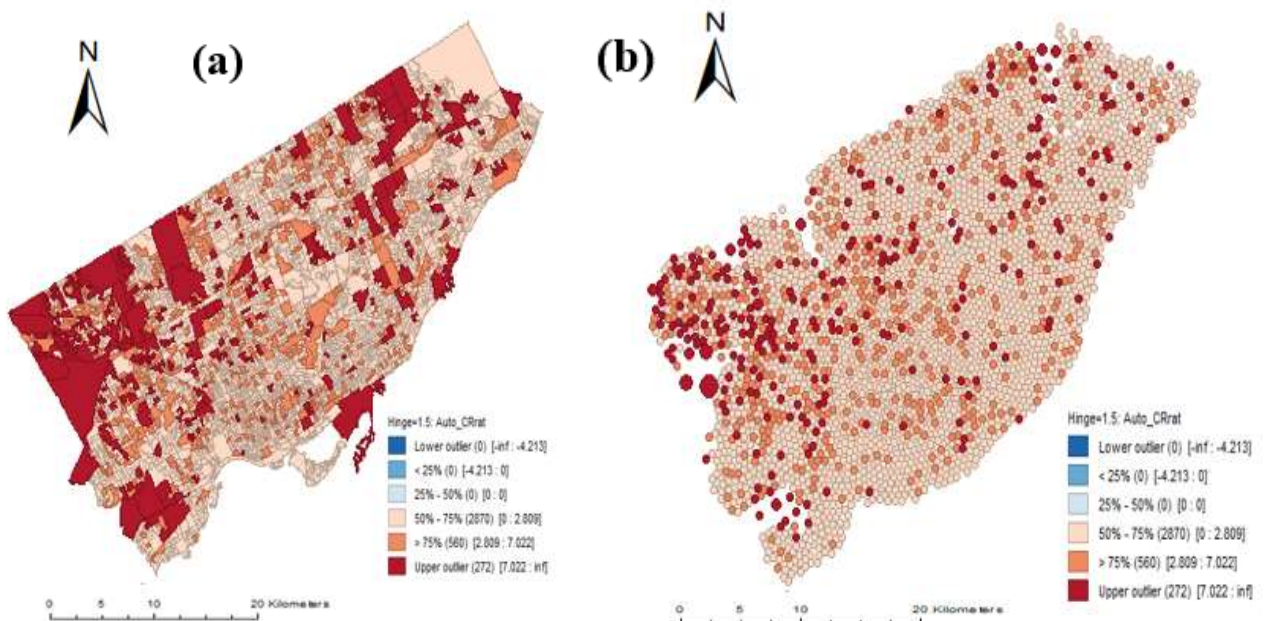


Figure 5. 9: Box map (left) and Cartogram (right) of Auto-theft crime rates per 1,000 persons by DA in 2018, with a hinge of 1.5

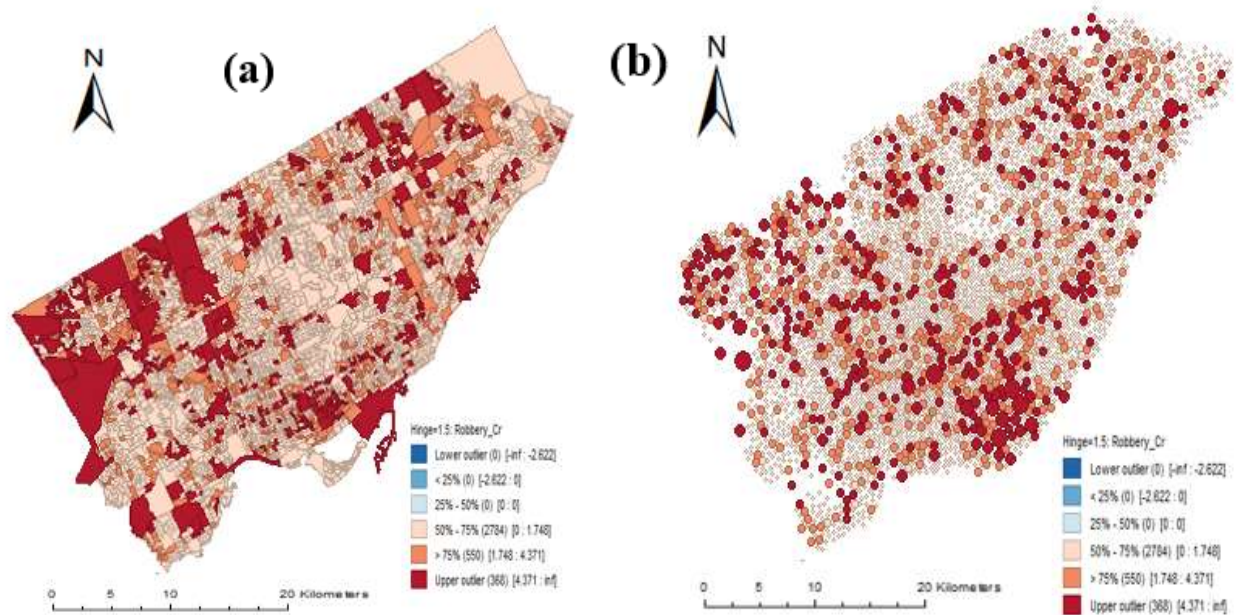


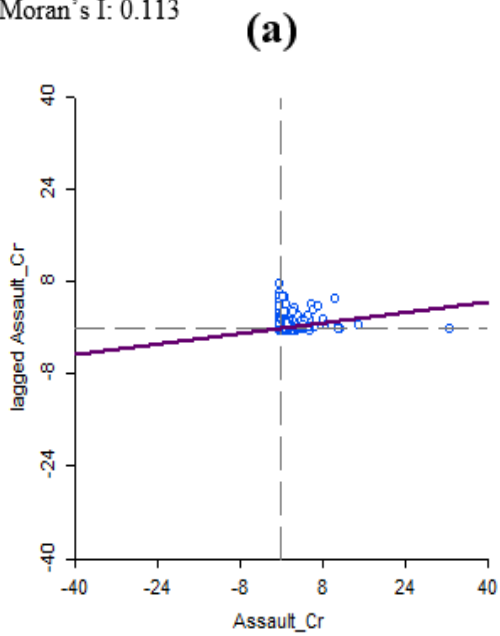
Figure 5. 10: Box map (left) and Cartogram (right) of Robbery crime rates per 1,000 persons by DA in 2018, with a hinge of 1.5

5.4 Spatial Association

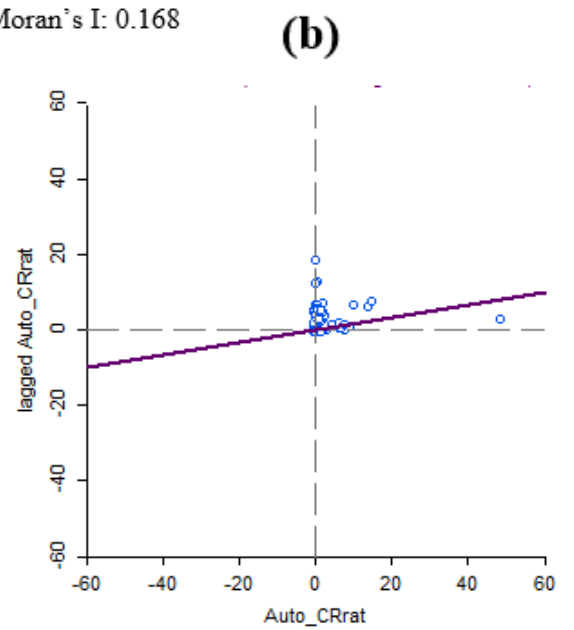
5.4.1 Spatial Autocorrelation Analysis

Figure 5.11 shows the Moran's I scatterplot for dependent variables plotted in the GeoDa software. Box maps and cartograms were used to visualize the street crime rate spatial distribution. However, the box map and cartograms do not account for the spatial association of neighbouring DAs. The Global Moran's I tests were used to establish the existence of spatial autocorrelation in the dependent variables (street crime rates). The Global Moran's I statistics of assault, auto-theft and robbery crime rate at a significance level of 1% are 0.113, 0.168 and 0.156, respectively. The values from the Moran's I statistics are positive, indicating the presence of spatial autocorrelation in the dependent variables.

Moran's I: 0.113



Moran's I: 0.168



Moran's I: 0.156

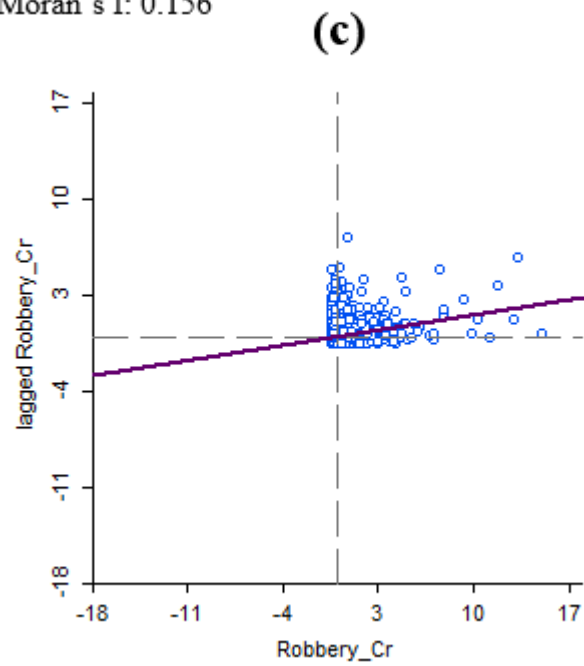


Figure 5. 11: Global Moran's I scatterplot for crime rates (a) Assault (b) Auto-theft (c) Robbery crime rates

5.4.2 Spatial Clustering Analysis

LISA statistics were used to identify the locations of spatial clustering by carrying out the Local Moran's I test on the three dependent variables. Three LISA cluster and significant maps were generated for the dependent variables (Figures 5.12, 5.13 and 5.14) with the DAs highlighted with relatively high and low significance for the three dependent variables. The neighbouring DAs were grouped into low-low, low-high, high-low and high-high, showing the spatial association between neighbouring DAs.

Each dependent variable exhibits varying cluster maps. The assault crime map (Figure 5.12) reveals high-high clusters in South Riverdale, Moss Park, Annex, Church-Yonge Corridor, Regent Park, Bay Street Corridor, Kensington-Chinatown, University, Niagara, Stonegate-Queensway, Mimico, West Humber-Clairville, Rexdale-Kipling, Humber Summit, Mount Olive-Silverstone-Jamestown, Humbermede, Thistletown-Beaumont Heights, Woburn, Morningside and West Hill neighbourhoods. The assault crime map reveals low-low clusters in Kingsview Village-The Westway, Weston, Humber Heights-Westmount, Mount Dennis, Banbury-Don Mills, Lawrence Park North, Englemount-Lawrence, Yonge-Eglinton, Leaside-Bennington, Thorncliffe Park, Forest Hill South and Yonge-St.Clair neighbourhoods. Figure 5.13 uncovers that the auto-theft crime is prevalent in Islington-City Centre West, Mimico, Alderwood, Black Creek, Glenfield-Jane Heights, Downsview-Roding-CFB, West Humber-Clairville, Rexdale-Kipling, Mount Olive-Silverstone-Jamestown, Thistletown-Beaumont Heights, Milliken and Agincourt North neighbourhoods. In contrast, the low-low clusters for the auto-theft crime were found in New Toronto, Mimico, South Parkdale, Niagara, Junction Area, Weston-Pellam Park, Morningside and Woburn neighbourhoods. Figure 5.14 reveals the robbery map with the high-high clusters were found in Kensington-Chinatown, University, Bay Street Corridor, Church-Yonge Corridor, Moss

Park, Regent Park, Cabbagetown-South St.James Town, Humber Summit, Black Creek, Humbermede, York University Heights, Glenfield-Jane Heights and Morningside neighbourhoods. In contrast, low-low clusters for the robbery crime were in Lawrence Park North, Lawrence Park North, Yonge-Eglinton, Englemount-Lawrence, Princess-Rosethorn, Edenbridge-Humber Valley, Centennial Scarborough and West Hill neighbourhoods.

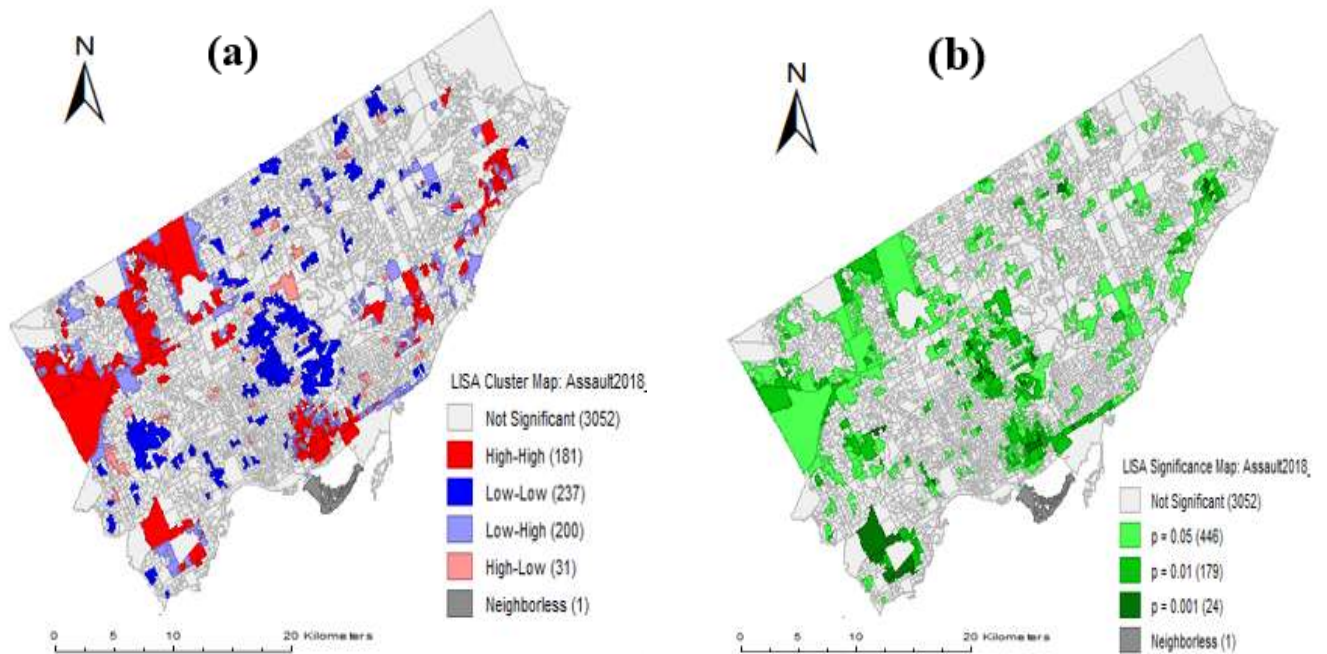


Figure 5. 12: LISA cluster (left) and significant map (right) of assault crime rates by DA, based on 999 permutation

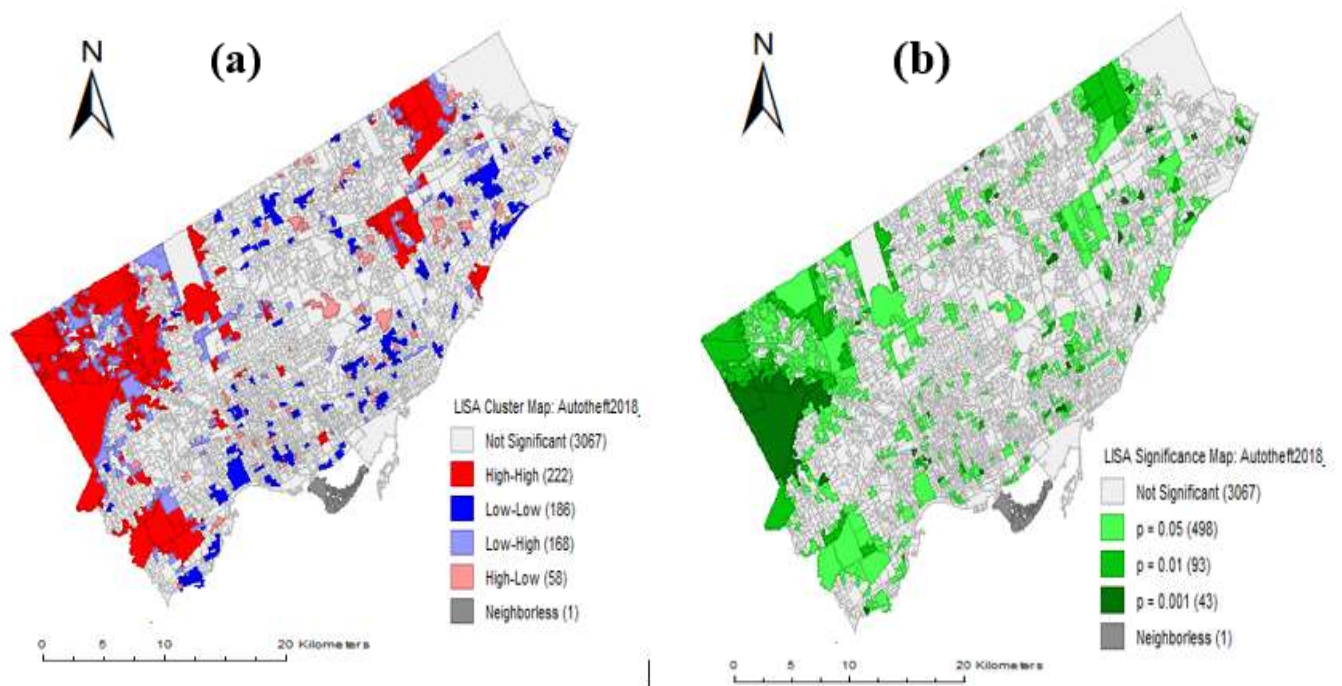


Figure 5. 13: LISA cluster (left) and significant map (right) of auto-theft crime rates by DA, based on 999 permutation

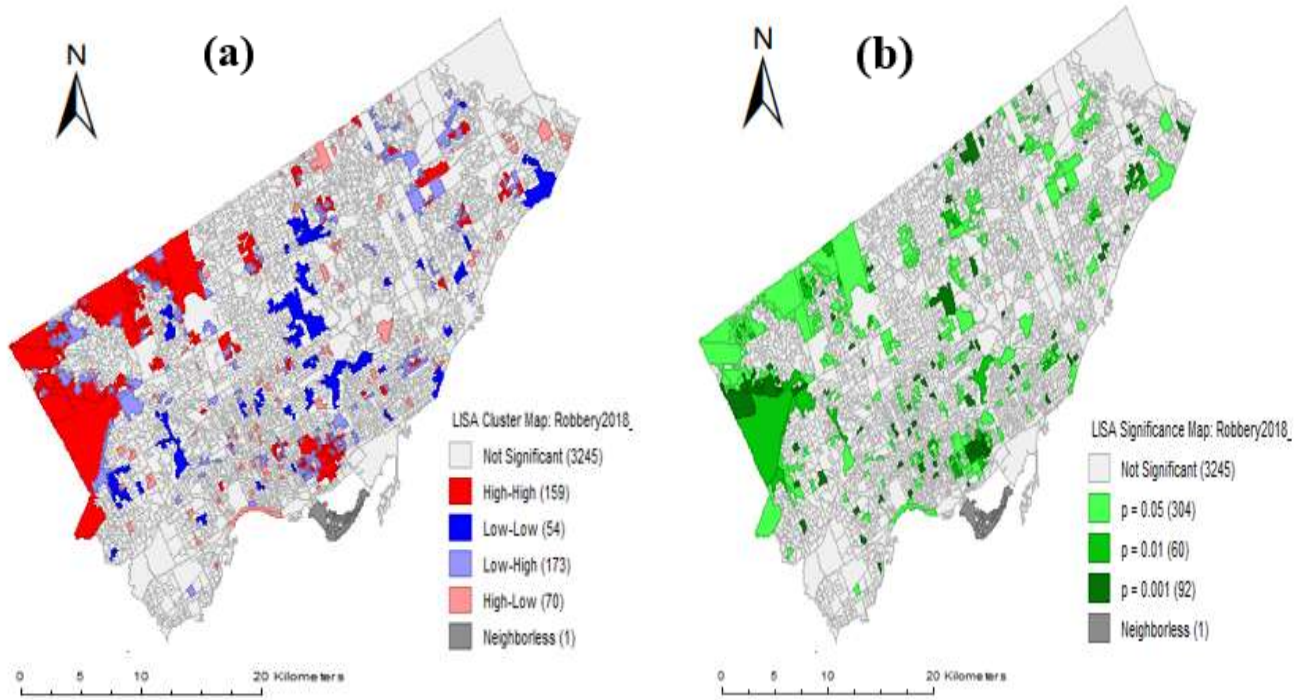


Figure 5. 14: LISA cluster (left) and significant map (right) of robbery crime rates by DA, based on 999 permutation

5.5 Spatial Regression Analyses

Spatial Lag and Spatial Error Models

OLS regression was not used in this current study because of the presence of spatial autocorrelation in the dependent variables. Spatial regression analyses were carried out on the street crime rate types, greenspace variables and sociodemographic factors using the spatial lag and spatial error regression analyses. The influence of stem density on the dependent variables was first investigated while controlling for specific sociodemographic factors that are significant at a 5 % level. Followed by tree density influence on street crime rate while the spatial lag and spatial error regression analyses were carried out with the results compared.

Basal area density was not significant to the street crime rate types in the spatial regression analyses; however, the stem density and tree density were both significant to the street crime rates. Basal area density was excluded from this section because it was not significant in the analyses (See Appendix II). Table 5.4 shows the results of spatial regression analyses for the stem density variable on the three dependent variables (assault, auto-theft and robbery crime rate) while controlling for specific sociodemographic variables for each street crime rate. Table 5.5 shows the results of the spatial regression analyses for the tree density variable on the three dependent variables (assault, auto-theft and robbery crime rate) while controlling for specific sociodemographic variables for each street crime rate.

5.5.1 Spatial regression results for the Stem Density on Crime Rates

Table 5.4 reveals the results from the spatial lag and spatial error models exploring the association between street crime rates and greenspace variables while controlling for specific sociodemographic factors. Results from the spatial lag and spatial error were consistent with the spatial error models, while the stem density had a statistically significant relationship with assault crime rate (coeff = -42.539, $p < 0.001$), auto-theft rate (coeff = -13.225, $p < 0.001$) and robbery rate (coeff = -5.392, $p < 0.001$) after controlling for specific sociodemographic factors.

The spatial error model slightly outperformed the spatial lag model because of its lower AIC values in each dependent variable. The spatial error model, R² and lag coefficient, is marginally higher than the spatial lag model. For, assault crime rate (Table 5.4), there was a significant negative association between stem density and assault crime rate ($p < 0.001$) as well as median household income and lone parent. Whereas, there was a positive association between tenure owner and assault crime rate. While the auto-theft crime rate, the spatial lag model and the spatial error model reveal (Table 5.4), there was a significant negative association between stem density and auto-

theft crime rate as well as with median household income, owning unit occupied by renter and unemployment rate ($p < 0.001$). There was a positive association between high school degree holders and the auto-theft crime rate ($p < 0.001$). Finally, the spatial lag model and spatial error model (Table 5.4) indicate a negative association between stem density and robbery crime rate as well as median household income, unemployment rate and lone parent ($p < 0.001$). There was a positive association between the unit occupied by the owner and the robbery crime rate ($p < 0.001$).

Table 5. 4: Spatial regression results for the stem density model on crime rates

Variables	Assault		Auto-theft		Robbery	
	Spatial Lag	Spatial Error	Spatial Lag	Spatial Error	Spatial Lag	Spatial Error
Constant	14.305**	16.445**	4.294**	5.266**	2.663**	3.317**
Stem density (%)	-39.967**	-42.539**	-12.055**	-13.225**	-4.504**	-5.392**
Median household Income	-9.106e-5**	-0.000**	-1.296e- 5***	-1.959e- 5***	-2.250e-5**	-2.549e-5**
Tenure Owner (%)	0.678**	0.738**			0.105*	0.119*
Tenure Renter			-0.523**	-0.603**		
Unemployment rate			-0.114**	-0.117**	-0.0395*	-0.043**
Lone Parent (%)	-3.142**	-3.516**			-0.607**	-0.697**
High School Degree (%)			0.188**	0.219*		
Lag coeff. (Rho)	0.175**		0.2696**		0.295**	
Lag coeff. (Lambda)		0.180**		0.274**		0.303**
R ²	0.057	0.058	0.072	0.074	0.079	0.082
Log likelihood	-15769.500	-15768.629	-13408	-13406.892	-9838.72	-9835.22
AIC	31550.900	31547.300	26831.1	26825.8	19691.4	19682.4

p < 0.05*, p < 0.001, p < 0.1*****

5.5.2 Spatial Regression results for the Tree Density on Crime Rates

Table 5.5 reveals the results from the spatial lag and spatial error models exploring the association between the street crime rates and greenspace variables while controlling for specific sociodemographic indicators. Results from the spatial lag and spatial error regression reveal that the spatial error models show the tree density had a statistically significant association with three street crime rates. For example, assault crime rate (coeff = -109.67, $p < 0.001$), auto-theft rate (coeff = -41.061, $p < 0.001$) and robbery rate (coeff = -20.09, $p < 0.001$) after controlling for specific sociodemographic factors.

The spatial error model slightly outperformed the spatial lag model because of its lower AIC values in each dependent variable. The spatial error model, R^2 and lag coefficient, is marginally higher than the spatial lag model. For, assault crime rate (Table 5.5), there was a significant negative association between tree density and assault crime ($p < 0.001$) as well as median household income and lone parent. There was also a positive association between tenure owner and assault crime. Next, for the auto-theft crime rate, the spatial lag model and the spatial error model indicate (Table 5.5), there was a significant negative association between tree density and auto-theft crime. As well as with median household income, tenure renter and unemployment rate ($p < 0.001$). There was a positive association between high school holders and auto-theft crime ($p < 0.001$). Finally, for the robbery crime rate, the spatial lag model and spatial error model (Table 5.5) reveal a negative association between tree density and robbery crime rate as well as with median household income, unemployment rate and lone parent ($p < 0.001$). There was a positive association between the housing unit occupied by the owner and the robbery crime rate ($p < 0.001$).

Table 5. 5: Spatial regression results for the tree density model on crime rates

Variables	Assault		Auto-theft		Robbery	
	Spatial Lag	Spatial Error	Spatial Lag	Spatial Error	Spatial Lag	Spatial Error
Constant	12.105**	14.426**	3.842**	4.748**	2.518**	3.167**
Tree density (%)	-97.688**	-109.67**	-39.395**	-41.061**	-17.128**	-20.09**
Median household Income	-0.000**	-0.000**	-3.264e-5*	-4.064e-5**	-2.973e-5**	-3.437e-5**
Tenure Owner (%)	0.685**	0.732**			0.098*	0.1095**
Tenure Renter			-0.4198*	-0.509**		
Unemployment rate			-0.1034*	-0.109*	-0.036*	-0.0402*
Lone Parent (%)	-2.062*	-2.526**			-0.508**	-0.592**
High School Degree (%)			0.171*	0.204*		
Lag coeff. (Rho)	0.190**		0.2688**		0.297**	
Lag coeff. (Lambda)		0.198**		0.273**		0.306**
R ²	0.048	0.0495	0.070589	0.072	0.079	0.082
Log likelihood	-15788.7	-15786.859	-13412.2	-13410.921	-9839.04	-9835.680
AIC	31589.4	31583.7	26838.3	26833.8	19692.1	19683.4

p < 0.05*, p < 0.001, p < 0.1*****

Chapter 6 Discussion

In this chapter, the trends and seasonal variation of the street crime were, first, summarized and discussed. Next, the association between greenspace variables and street crime rates after controlling for specific sociodemographic factors were discussed. The best greenspace variable out of three variables was suggested and supported with evidence from existing studies. Finally, the chapter concludes with the limitations, contributions, impact and future direction.

6.1 Key Findings

6.1.1 Trends and Seasonal Variations of Street Crime

This study examined the street crime (assault, auto-theft and robbery) trends and seasonal variation of street crime in the City of Toronto using longitudinal data from the year 2014 to 2018. For the yearly crime trends, the street crime data from the year 2014 to 2018 were utilized. Whereas, 2018 street crime data was used to analyze the monthly trends and the seasonal variations of the street crime types. Line graphs were used to investigate trends and seasonal variations of the street crime types in the city of Toronto.

Street Crime Trends

The crime trend analysis for the longitudinal data from the year 2014 – 2018 was inspired by the findings from Statistics Canada's crime severity index reports. They found an increase in violent and property crime in Canada from the year 2014 to 2018 (Statistics Canada, 2019). This current study was carried out to investigate the yearly and monthly street crime trends from the year 2014 to 2018 in the city of Toronto. Table 5.1 and Figure 5.1 shows the variation in the yearly crime trends for street crime occurrences. The findings from this current study uncover changing yearly trends in the assault, auto-theft and robbery crime occurrences in the study area. This current study,

however, classified assault and robbery crime as a violent crime while the auto-theft crime was regarded as property crime.

The yearly street crime trends reveal that the assault, auto-theft, and robbery crime occurrences are slightly in agreement with the crime severity index reports over five years period. Notwithstanding, the auto-theft crime peaked in the year 2018, unlike both assault and robbery crimes that dropped in the same year. The assault crime has the highest occurrence and might have been influenced by the high population, the presence of bars and night clubs (crime attractor facilities), especially in Downtown Toronto. The auto-theft crime occurrences are slightly higher than the robbery crime occurrences in the study area. The yearly trends of street crime are slightly in agreement with the crime severity index reports. This current study acknowledges the validity of the crime severity index reports. It also draws attention to how routine activities and social disorganization of Toronto's populace could play a part in the varying street crime trends in Toronto.

The finding on yearly crime trends is followed by the 2018 monthly street crime trends, which were motivated by the previous studies by Andresen & Malleson (2013) and Linning (2015) on seasonality of crime. They investigated the frequency and seasonal variations of crime. The study by Andresen & Malleson (2013) draws attention to the varying monthly frequency of crime occurrences in Vancouver, BC. Whereas, the study by Linning (2015) compared the monthly frequency of crime occurrences in Vancouver, British Columbia and Ottawa, Ontario (two cities with different weather conditions). The study acknowledges the peak in vehicle theft in Ottawa, ON from May to August (Summer months), a spike in vehicle theft in Vancouver, BC, from February to May and slightly peaked again from July to September.

For the monthly street crime trends, this current study reveals there were monthly variations in street crime occurrences for the year 2018 (See Table 5.2 & Figure 5.2). The assault crime occurrences peaked in May, auto-theft crime peaked in May and November while robbery crime peaked in March, August and November. A study by Quentent (1842) pointed out that violent crime tends to peak during summer months while property crime peaks during winter months. Another study on assault crime occurrence across 56 cities (with varying weather conditions) in the United States of America by Lewis & Alford (1975). They argued that the routine activities of people in the study areas are more influential than the annual temporal fluctuations of weather conditions on assault crime. The findings suggest weather conditions might influence the spike in street crime occurrences in the city of Toronto. As line graphs were utilized to determine the monthly variations, it is crucial to note that weather condition is not the only factor that contributes to crime seasonality. This section focused on the trends for the yearly and monthly crime while the next section will elaborate more on seasonal variation of the street crime occurrence in the city of Toronto.

Seasonal Variations of the Street Crime Types

This current study followed a similar crime seasonality approach by Andresen & Malleon (2013) and de Melo et al. (2018). They investigated the seasonality of crime types. This current study carried out the crime seasonality analysis to investigate the seasonal variations of street crime occurrences in the city of Toronto (See Table 5.3 and Figure 5.3). The study by Andresen & Malleon (2013) adopted the spatial point pattern test to investigate the seasonal variation of crime across the city of Vancouver. They found different seasonal changes for the crime types. Whereas, for this current study, only line graphs were used to investigate the seasonal variation of street crime occurrences in the city of Toronto. The findings reveal varying seasonal variation for the

three street crime occurrence similar to results by previous crime seasonality studies (Andresen & Malleson, 2013; Linning 2015; de Melo et al., 2018).

This study reveals a peak in assault crime during the Spring and Summer seasons, while assault crime occurrences were at its lowest during the Winter season (See Figure 5.3a). Next, the auto-theft crime peaked from the Spring season to the Fall season with the highest auto-theft crime occurrence in the Fall season (See Figure 5.3b). Finally, the robbery crime peaked from Spring to Fall season (See Figure 5.3c) with the highest occurrence of robbery crime occurring during the Winter season.

Findings from this current study drew attention to exiting reviews on temperature and crime (Anderson, 1987; Field, 1992; Gamble & Hess, 2012; de Melo et al., 2018). These studies reveal hotter weather conditions influence violent crime in urban cities. Existing literature on crime seasonality also suggested that the change in routine activities of the victims and offenders during warm weather could impact crime occurrences in urban cities. However, findings in this current study reveal assault peaked in the Spring season, auto-theft crime peaked during the Fall season, and robbery crime rose during the Winter season. Existing literature reveals violent crime often peaks during the warmer months while property crime peaks during the colder months (Quentent, 1842). The findings from this current study reveal assault and auto-theft crime occurrences were at their lowest during the Winter season while the robbery crime is at its lowest during the Spring season. Although the assault and auto-theft crime occurrences agree with existing literature, robbery crime occurrences uncover a different trend. The seasonal variation of street crime occurrences might be influenced by other factors other than weather conditions. It could also be as a result of different built or environmental characteristics in the study area like the presence of

bars, night club, access to sidewalks, presence of streetlight, abundant or lack of greenspace in some neighbourhoods, and so on.

6.1.2 Association between Greenspace and Street Crime Rates

This study first, used quantile maps to show spatial distribution and variation of the sociodemographic factors across the city of Toronto. Next, the geo-visualization process was used to measure the spatial distribution of street crime rates across Toronto. The box maps and cartograms revealed different crime hot spot locations for the three dependent variables with the assault crime prevalent in South Riverdale, Moss Park, Annex, Church-Yonge Corridor, Regent Park, Bay Street Corridor, Kensington-Chinatown, University and Niagara neighbourhoods. In contrast, the robbery crime was prevalent in Regent Park, Moss Park, Church-Yonge Corridor, Bay Street Corridor, Kensington-Chinatown, University, Cabbagetown-South St. James Town and South Riverdale neighbourhoods. While auto-theft crime seems to be more prevalent in West Humber-Clairville, Mount Olive-Silverstone-Jamestown, Thistletown-Beaumont Heights, Rexdale-Kipling, Elms-Old Rexdale and Kingsview Village-The Westway neighbourhoods.

The next step involved testing the spatial dependency in the street crime rate types, and these tests were carried out using the Global Moran's I statistics to measure the presence of spatial autocorrelation in the dependent datasets. The Global Moran's I value was 0.113, 0.168 and 0.156 for assault, auto-theft and robbery, respectively, with significance level at 1%, providing an observed indication of spatial clustering in the study area. Then, the Local Moran's statistic test uncovers the presence of clusters (hot spot and cold spot) while identifying their locations and their comparable statistical significance level at 1% for the dependent variables. The association between greenspace variables (tree density, stem density and basal area density) on street crime rates were discussed in the next section.

Tree density and Street Crime rates

A recent study by Mouratidis (2019) investigated the impact of tree canopy cover on a perceived fear of people in 45 neighbourhoods in the Oslo Municipality, Norway. The study used quantitative and qualitative techniques to collect tree cover data (from satellite data measuring tree height ≤ 5 m) and perceived safety data (from residents randomly through questionnaires), respectively. The author revealed that “neighbourhoods with higher tree cover are perceived as safer than those with lower tree cover” (Mouratidis, 2019). Although Mouratidis’s study did not account for crime occurrence in his study, the author reported the perceived feelings of the neighbourhood’s residents to the abundant tree canopy.

Consequently, in this current study, the spatial-statistical association between greenspace variables and street crime rate were analyzed. This current study explored the association between street crime rate types and tree density (estimated from tree inventory data) after controlling for specific sociodemographic factors. The estimation of the greenspace variable in this current study is similar to the study carried out by Escobedo et al. (2018), where they investigated the influence of treescapes on homicide rates in Bogota, Columbia. Another example was a study carried out by Kardan et al. (2015) on the relationship between greenspace and general health in Toronto, Ontario, Canada.

Tree density was negatively associated with the three street crime rates in Toronto DAs at a significance level of 5%. This current study supports existing literature findings on the negative association between crime rates and greenspace at various geographic scales (Donovan & Prestemon, 2012; Gilstad-Hayden et al., 2015; Chen et al., 2016; Escobedo et al., 2018). The finding from this current study is similar to a study carried out by Wolfe & Mennis (2012), where they explored the association between aggravated assault, robberies and burglaries on vegetation.

However, NDVI was the measurement of vegetation in their study. They found that the abundance of vegetation is associated with lower rates of assault, robbery and burglary crime, but the theft crime was not significant in their study.

The negative coefficient (-20.09) observed for the robbery crime rates is lower than the negative coefficient (auto-theft: -41.06; assault: -109.67) for both auto-theft and assault crime rates. This finding reveals that tree density might have a small magnitude of influence on both **robbery and auto-theft crime rates** in the city of Toronto because of their lower coefficient. The presence of abundant tree density in Toronto could deter street crime types. Although **assault crime** is regarded as brazen because it is usually a spontaneous action and often involved familiar faces, abundance tree density could play a part in deterring assault crime in Toronto. For the **assault crime reduction**, the pros and cons of proactive policing or neighbourhood policing programs should be discussed with community leaders to determine if the crime prevention programs will be suitable for the communities in Toronto. The **auto-theft and robbery crimes** are known as a crime of opportunity because it usually involved taking someone else properties with permission either with forces or lack of bystanders or witnesses. Tree density might influence both **auto-theft and robbery crime rates** because tree density could conceal criminal activities. These street crimes (auto-theft and robbery) could be deterred by initiating proactive policing and neighbourhood watch programs in the affected neighbourhoods. Tree density might influence the three-street crime in the city of Toronto, tree planting programs should be encouraged by policymakers and with more emphasis on neighbourhood policing and surveillance to curb the criminal activities in Toronto's neighbourhoods.

Stem density and Street Crime rates

This current study was inspired by the greenspace equity study carried out by Lee et al. (2019), where they uncovered the injustice of greenspace in a public housing estate in Hong Kong. The authors estimated three greenspace variables (stem, basal area and crown area density) from the tree inventory data. They found housing estates with high concentrations of greenspace have high population density and young residents, while housing estates with a low concentration of greenspace have an ageing population (Lee et al., 2019). Greenspace inequality was also reported by Kardan et al. (2015) in Toronto, where high economic status neighbourhoods have higher tree density abundance than the low financial status neighbourhoods. A similar measurement of greenspace estimation was carried out in the violent crime study by Escobedo et al. (2018) in Bogota, Columbia. They estimated the greenspace variables for basal area, crown area, tree height and density from tree inventory data, and they explored the association between homicide rates and greenspace variables (treespaces).

Stem density was inversely associated with the **three street Crime rates (assault, auto-theft and robbery)** in this current study in Toronto dissemination areas at a 5% significance level. In a South American study, Escobedo et al. (2018) reported that “higher tree density and larger size (i.e. tree density, basal area and tree height) were associated with lower homicide rate in their study.” There are limited studies on the association between stem density and crime rates. Previous crime studies have mostly focused on the use of remotely sensed data (Wolfe et al., 2012; Ekerson, 2012; Chen et al., 2016) and vegetation cover (Du et al., 2015). and recently on tree inventory data (Escobedo et al., 2018). The use of different measures of greenspace in existing literature ignores the different influence parts of a tree could have on crime studies. For instance, Escobedo et al. (2018) confirmed tree abundances are associated with violent crime in Bogota, Columbia. Although the

stem density consists of the total number of trees in each dissemination areas in Toronto, this current analysis was carried out to explore the association of the stem density on the **three street Crime rates** in Toronto.

The findings from the multivariate regression analyses for the association between stem density and street crime rates mirror the association discussed in the previous section (tree density and street crime rates). According to Table 5.4, there was a negative correlation between **three street Crime rates (assault, auto-theft and robbery)** and stem density in Toronto. The **auto-theft and robbery crime rate** also have a lower negative coefficient (auto-theft: -13.225; robbery: -5.392) than the coefficient (-42.539) of **assault crime rates**. The lower negative coefficient and AIC values reported for this multivariate regression analysis (association between stem density and street crime rates) reveal the stem density has more influence on the street crime rates than the tree density variable. The **robbery crime rates** have the lowest negative coefficient in the multivariate regression analyses, which reveals the total number of trees could influence robbery crime in Toronto. As discussed in the previous section, **auto-theft crime** also has a low negative coefficient than the **assault crime**, and this implies that the stem density might have a small magnitude of influence on both **robbery and auto-theft crime rates** in the study area. As suggested in the previous section, the importance of collaboration between policymakers, community leaders and law enforcement agencies cannot be understated. However, stem density has a small influence on **street Crime rates**. It is important to note that the stem density estimation does not account for the size or types of the tree, which could have influenced its low coefficient correlation with the street crime types. Policymakers should encourage tree-planting programs by providing incentives to the neighbourhoods with lower greenspace to achieve greenspace equity. Crime prevention

programs should be initiated by community leaders, law enforcement, policymakers, government and non-government agencies for the collective goal of sustainable development.

Basal area density and Street Crime rates

Few studies have been carried out to examine the association between basal area density and crime rates because it is not usually captured by the utilization of aerial photos or Landsat imageries for the measurement of greenspace (Du et al., 2015; Chen et al., 2016). A recent study by Escobedo et al. (2018), where they investigated the influence of treescapes on homicide rates in Bogota, Columbia using a tree inventory, which was discussed in the previous sections. They revealed the importance of exploring the different parts of a tree that could influence violent crime rate. They investigated the association between basal area and homicide rate, where they found trees with higher basal areas are associated with fewer homicide rates in Bogota, Columbia.

Finding from this current study reveals that basal area density is not a significant predictor of street crime rates (See Appendix II). Due to the inconsequential influence of basal area density on the street crime rates, the findings are not discussed extensively. In summary, the results from both multivariate regression analyses reveal basal area density is not significant to the **three street Crime rates (assault, auto-theft and robbery)** in the city of Toronto. It might be due to the fewer trees in some parts of the City of Toronto with an estimation of about 27% tree canopy coverage for the city (City of Toronto, 2019b). Although the other **two greenspace variables (tree density and stem density)** were significant predictors of the street crime rates, there may be other underlying factors that contributed to the insignificant association found between basal area density and street crime rates.

6.1.3 Sociodemographic Factors Associated with the Street Crime Types

Median Household Income

Median household income was found to be negatively associated with the three **Street Crime (assault, auto-theft and robbery)** in Toronto at the Dissemination area level. The low negative coefficient (-0.00) at a significance level of 5% reveals the median household income is associated with the three Street crime rates in the study area. In a greater Baltimore region study, Troy et al. (2012) reported that median household income was positively associated with robbery, burglary, theft and shooting crime at the Census block group level. Although, the Census block group (with 600 – 3000 people) is larger than the Dissemination area (with 400 – 700 persons). The unit of analysis selection did not impact the findings in this current analysis. For instance, a study in Vancouver by Chen et al. (2016) reported that low income was positively associated with theft at the DA level. Although Chen's study used low income as a confounder, this current study considered median household income as it serves as a better cofounder because median household income considers the high- and low-income earners. The median income is defined as “the amount that divides the income distribution into two equal groups, half having income above that amount, and half having income below that amount.” The median household income considers both the high and low-income earners, which could be related to the victims and offenders. However, some underlying factors also play critical roles in criminal activities in a given neighbourhood.

Furthermore, the median household income could influence neighbourhoods in different ways, usually in the form of social inequality. High-income earners tend to live far away from low-income earners. For instance, the household below the median income could cultivate crime offenders because of their low economic status. In contrast, the household above the median income could attract criminal activities because of their high financial status. Existing literature

reveals that economically disadvantaged neighbourhoods reported more criminal activities (Morenoff & Sampson, 1997; Schnell et al., 2017). Assault crime could be a result of the presence of alcohol establishments, night clubs and bars in Toronto, which usually attract crime offenders with the motivation to commit a crime. Youth gangs also contribute to assault crime in Toronto, with the fight over territories among gang members leads to assault against other members and residents.

At the neighbourhood level, for households with high income, proactive policing should be encouraged to disable criminal activities. In contrast, for households with low income, policymakers should consider investment in the youth-at-risks programs, which will provide alternative means of events, and it will discourage young adults from low-income families from joining gangs or engage in criminal activities. Law enforcement and Policymakers should collaborate on community programs that will deter criminal activities in the City of Toronto.

Housing Unit Occupied by Owners

The housing units occupied by owners was positively correlated with **two street Crime rates (assault and robbery)** in Toronto at DA level. Assault and robbery crimes were regarded as violent crimes in this current study. According to Census Bureau (n.d.), a housing unit occupied by owners is considered as where “the owner or co-owner lives in the unit, even if it is mortgaged or not fully paid for.” The previous study by Troy et al. (2012) revealed an inverse relationship between the housing unit occupied by owners and crime (robbery, burglary, theft and shooting). Although Troy et al. (2012) reported a negative relationship, the authors stated the housing units occupied by the owner’s indicator were expected to be associated with reduced criminal activities due to the prominent low economic status in the greater Baltimore region.

Furthermore, the low positive coefficient (assault: 0.732; robbery: 0.109) for assault and robbery crime reveals there was a positive association between **street crime (assault and robbery)** and owner-occupied homes. **Assault crime** is spontaneous and could occur between neighbours and residents of a neighbourhood. In contrast, **robbery crime** is usually a crime of opportunity, which often involves the use of a weapon or threats. Socially disadvantaged communities could have contributed to this association, and it is important to note that there is more percentage of owners occupied homes compare to homes occupied by renters in the city of Toronto. Neighbourhood watch programs should be implemented in the affected neighbourhood, and surveillance equipment could be acquired to monitor the neighbourhoods. Previous studies have confirmed the importance of surveillance on crime prevention in urban cities (Goodstein & Shotland, 1980; Piza et al., 2019; Circo & McGarrell, 2020). Collaboration between the neighbourhood representatives, law enforcement, decision-makers and policymakers is vital to be able to come up with feasible crime prevention programs for the neighbourhoods.

Housing Unit Occupied by Renters

The housing units occupied by renters were found to be negatively associated with the **auto-theft crime rate** in Toronto's dissemination areas. As this current study only associated significant sociodemographic factors to street crime rates, the housing units occupied by renters were significantly and inversely associated with only the auto-theft crime rate. Housing units occupied by the renter is regarded as a housing unit occupied if a person or group of persons is living in the house temporarily with monthly or yearly payment obligation to the landowners or agents in charge of the building (Census Bureau, 2020). A positive correlation between crime rates and housing units occupied by renters were reported in previous studies (Gilstad-Hayden et al., 2016; Schusler et al., 2018). According to Gilstad-Hayden et al. (2016), a more significant percentage of

renter-occupied housing was associated with both higher violent and property crime rates in New Haven, CT. In this current study, a low negative coefficient (-0.509) was confirmed as the association between **auto-theft crime rate** and housing unit occupied by renters in Toronto's DA at a 5% significance level.

Housing units occupied by renters are associated with **auto-theft crime** because of the low coefficient reported in this current study. Toronto is known for its multi-storey buildings and condo without an adequate parking space, which leaves cars and vehicles parked on the street. Auto-theft crime is a crime of opportunity; crime offenders will be encouraged to commit vehicle thefts with the availability of parked vehicles on the road and the absence of witnesses and bystanders. Car owners should get anti-theft security that would prevent car thefts. As suggested earlier, the proactive and neighbouring policing program will put more eyes on the street, which would dissuade auto-theft in Toronto.

Unemployment Rate

The unemployment rate is inversely associated with two **street Crime rates (auto-theft and robbery)** in the city of Toronto at the dissemination area level. The negative coefficient (auto-theft: -0.109; robbery: -0.040) observed were relatively low (See Table 5.4 & Table 5.5), which indicated that the unemployment rate is associated with both **auto-theft and robbery crime rates** in the study area. Although a study by Chen et al. (2016) reported an insignificant relationship between property crime and the unemployment rate in Vancouver, and this might have been as a result of the lack of census data. The authors used 2006 census data for the unemployment rate and 2013 property crime data, which might have influenced the insignificant association between property crime and the unemployment rate in Vancouver, BC. Moreover, a positive relationship

between percent unemployed and crime rates (assault, burglary, homicide and robbery) was confirmed by Schusler et al. (2018) in Chicago.

The unemployment rate is an important indicator of criminal activities because it motivates crime offenders to seize opportunities to survive. Unemployment and underemployment factors could be associated with low economic status because it impacts the income one earns. The unemployment rate is associated with **auto-theft and robbery crime rates** because these crimes are usually a crime of opportunity with the aid of stealing or taking someone else's property to enrich themselves. According to Chappelow & Barnier (2020), the unemployment rate is defined as the percentage of unemployed people in the total labour force. The authors acknowledge unemployment influence the income of families, which could encourage the affected families to find other means of income. Social programmes should be organized in the neighbourhood that will inspire and empower people with entrepreneurship skills with the collaboration between various agencies like policymakers, decision-makers, government and non-governmental agencies.

Lone Parent Family

Lone parent family was negatively associated with two **street Crime rates (assault and robbery)** in the city of Toronto at DA levels. Low negative coefficient (assault: -2.526; robbery: -0.592) were observed for the two street crimes, which indicated that the lone parent indicator has more influence on the robbery crime than the assault crime in Toronto. Lone parent family is also regarded as a single-parent family; it is defined as a family that contains only one parent with his or her child(ren) who does not have a spouse or live-in partner (Statistics Canada, 2020). In the Kitchener-Waterloo study, Du et al. (2015) confirmed single-parent family households boost criminal activities in the study area. The authors reported the single-parent family household to

have more influence on property crime than violent crime in the Kitchener-Waterloo region. Alternatively, a study by Chen et al. (2016) reported a negative relationship between lone parent family and property crime rates (theft and BNE) in Vancouver. Although the negative coefficient (-0.68) observed in the study by Chen et al. (2016) was low. Previous studies revealed that lone-parent families have more influence on property crime than violent crime (Du et al., 2015; Chen et al., 2016).

Lone parent family is associated with both assault and robbery crime in Toronto as evidenced by the low negative coefficient recorded in this current study. The robbery crime, which encompasses taking someone else property, reveals that the condition in a single-parent household (such as low income, overcrowding, etc.) could motivate the crime offenders to engage in criminal activities. Street gangs often contain youths from the socially disadvantaged neighbourhood who engage in violent crime across Toronto (Gaetz et al., 2010; Charron, 2011). Social program initiatives such as youth-risk and mentorship program should be implemented to dissuade youths from criminal activities, which in turn will reduce crime in Toronto. Law enforcement, policymakers and politicians should collaborate to implement preventive crime programs to make the neighbourhood safer.

High School degree holders

High school degree holders are positively associated with auto-theft in Toronto at DA level. The two street Crime rates (assault and robbery) were not considered for high school degree holders' indicator because first, they are both regarded as violent crime, and the factor was not significant to the violent crime. A low positive coefficient (0.204) was observed in this current study, which indicated that high school degree holders could influence auto-theft crime in Toronto.

Previous studies have considered a different sociodemographic factor in their studies. For instance, previous studies have considered, no high school diploma (Schusler et al., 2018), high school degree (Gilstad-Hayden et al., 2016), educational attainment (Wolfe & Mennis, 2012) and population above 25 years without secondary school degree (Eckerson, 2013). A positive relationship between crime and high school degree holders were reported in previous studies (Eckerson, 2013; Schusler et al., 2018). Although the study carried out in Chicago by Schusler et al. (2018) considered people without a high school diploma, the authors indicate this factor influences the crime (assault, battery, burglary, homicide, narcotics and robbery) in their study.

Educational attainment status usually plays a crucial role in the socioeconomic status of a person because it can influence the economic status one belongs to in the community. Education plays a significant factor in job opportunities, which might put the person in underemployed or unemployed status. According to Statistics Canada, educational attainment refers to the highest level of education that a person has completed. In contrast, a high school degree holder relates to people with a high school diploma. Economically disadvantaged people are more susceptible to engage in criminal activities, which could influence auto-theft crime in a neighbourhood. Entrepreneurship training and programmes should be implemented to encourage people to be self-employed, and proactive policing should be discussed to alleviate auto-theft crime in Toronto's neighbourhood.

6.1.4 Recommendation for the best out of the three greenspace variables

There are limited studies on the relationship between street crime rates and greenspace done in Canadian cities. For example, Chen et al. (2016) analyzed the association between property crime (theft and BNE) and tree coverage in Vancouver, BC. They focused only on property crime rates, and LiDAR point data was used for the greenspace measurement. Another example, Du et al.

(2015), examined how vegetation coverage influenced crime rates in the Kitchener-Waterloo region, using NDVI (satellite imagery) as the vegetation indicator. They considered both property and violent crime in their study. This current study focused on street crime rates (assault, auto-theft and robbery) and greenspace, which corresponds with the crime occurrences and the presence of trees in the street. The majority of existing literature on the association between crime rate and greenspace was carried out in the United States of America (Troy et al., 2012; Donovan & Prestemon, 2012; Eckerson, 2013; Loosle, 2016). This is because there were higher criminal activities and populations in America's cities compared to the reported criminal activities in Canadian cities.

Three greenspace variables (stem density, basal area density and tree density) were explored in this current study, with their limitations discussed in the next section. The three greenspace variables considered in this study were estimated from the tree inventory data, and they contain values used for the estimation of different parts of a tree. There are limited studies done on the utilization of the total number of trees and DBH values to estimate for the stem density, basal area and tree density variables. Donovan & Prestemon (2012) and Escobedo et al. (2018) studies reveal that trees with larger basal areas deter crime rates in their respective studies.

Considering the **stem density and basal area density variables** did not account for different tree types in their respective estimation of greenspace variables considered in this current study (Figure 6.1). The **tree density variable**, however, accounted for the eight (8) known tree types in this current study. At the same time, linear regression analysis was used to derive the formula to estimate the unknown tree types/species. The best greenspace variable for this study is the tree density variable because it also supports previous studies' consideration of tree density estimation from tree inventory data (Kardan et al., 2015; Escobedo et al., 2018; Lee et al., 2019).

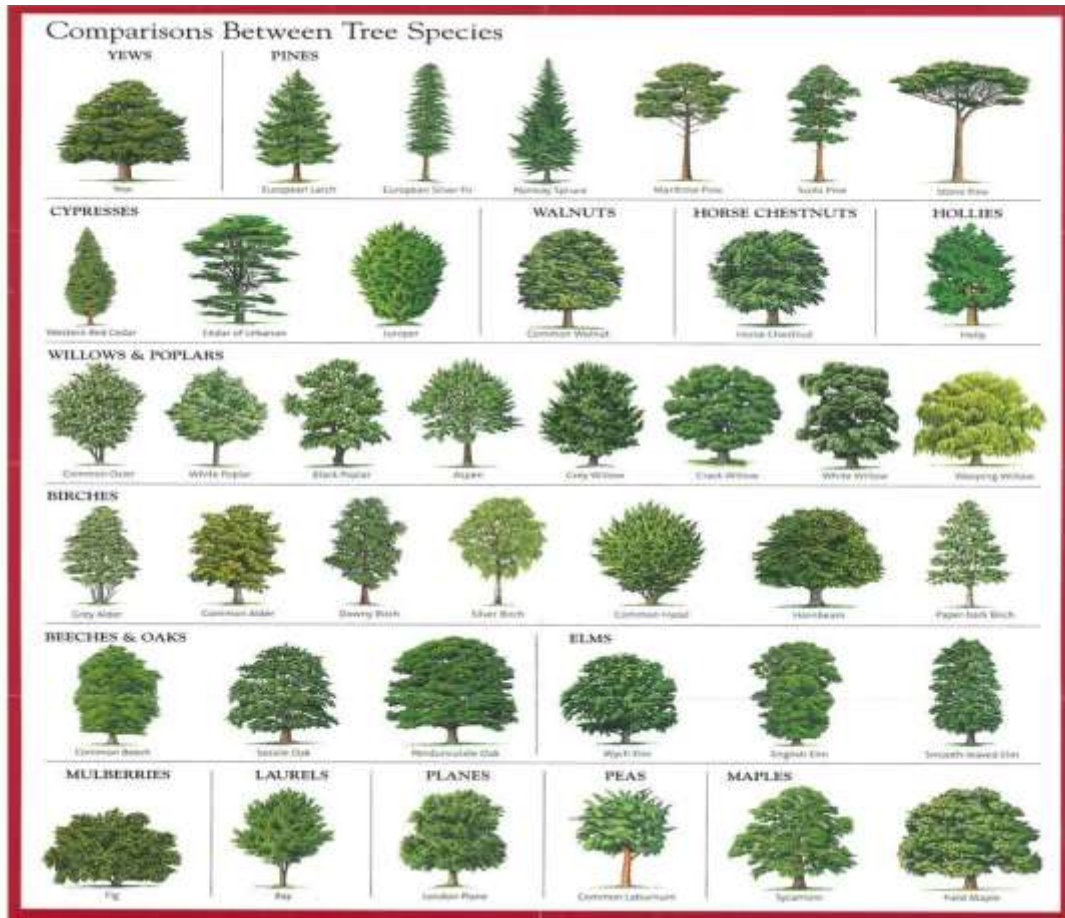


Figure 6. 1: Comparison between tree species – image showing different shapes and sizes of trees (<https://www.pinterest.co.uk/pin/19562579615151388/>)

6.2 Limitations

Street crime data have limitations. First, the street crime data were obtained from the Toronto police service record. They were data from police records from the year 2014 to 2018 with Police reported crime datasets been subjected to under-reporting due to various reasons by victims or bystanders/witnesses. For example, reasons like insecurity, fear of retaliation by the offender, shame and stigma could influence reporting a crime to the police (Lakhani, 2012; Moreau, 2019). As such, the street crime data used in this study might be underrepresented. Street crime data were offset to the nearest intersection to protect the privacy of the crime victims (Toronto Police Service,

2019c). The street crime data were point data that were aggregated to the DA level with the possibility of geoprocessing error occurring because of the aggregation process. Next, the unit of analysis used in this current study was the dissemination area (DA), and the spatial join tool was used to spatially join the street crime point dataset to DA polygon with the possibility of geoprocessing error occurring in the study.

The greenspace data comes with its limitations too. They were obtained from the City of Toronto open data, and they pertain to Toronto City-owned trees located on road allowances (City of Toronto, 2019c). The greenspace data are point data that have been geocoded to the parcel address with a similar potential geoprocessing error to the crime rate discussed earlier. With over 530,000-point datasets representing different tree species across the City of Toronto, statistical estimation was carried out before aggregating the greenspace variables at DA level. The stem density variable was derived by using the spatial join tool to aggregate the trees' data at the DA level, which automatically generated the total tree count per DA. In short, the stem density and basal area density did not account for the influence of different tree types on the street crime rate (See Figure 6.2).

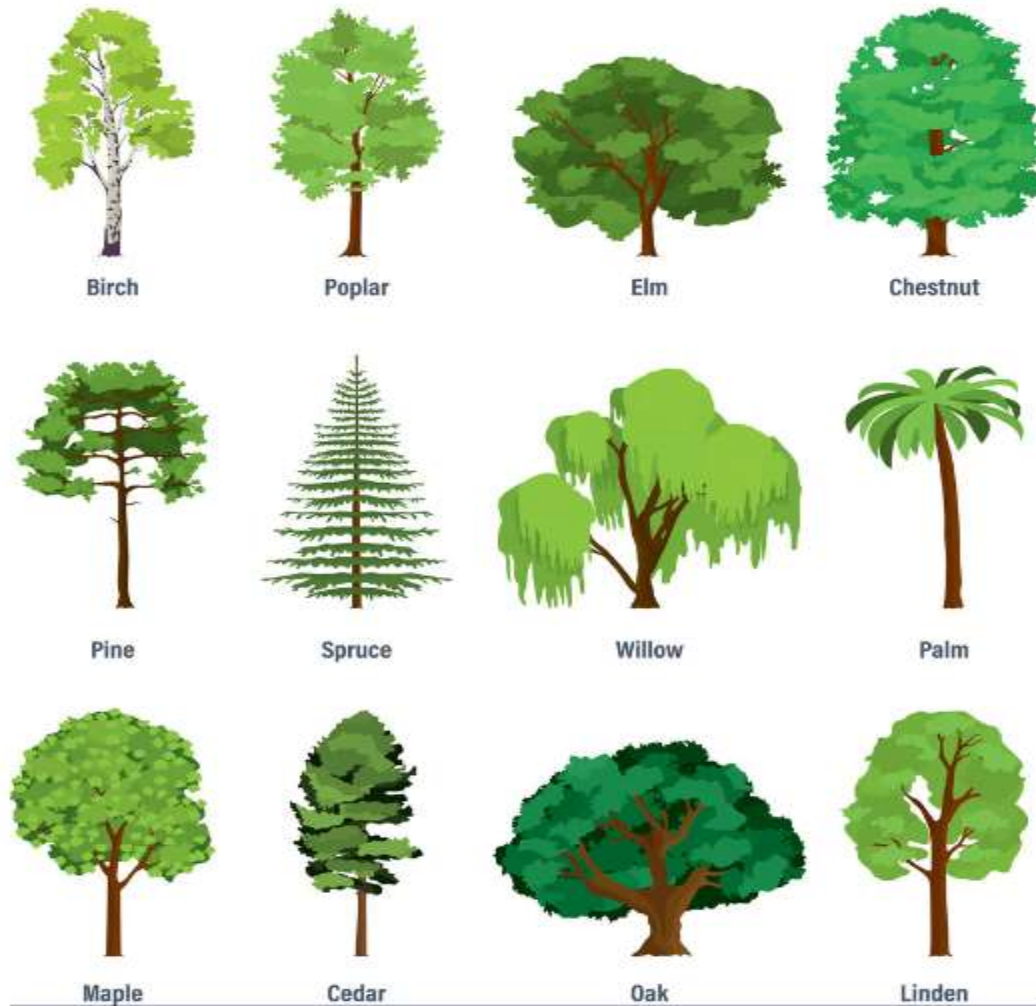


Figure 6. 2: Collection of Different types of trees (<https://www.vectorstock.com/royalty-free-vector/collection-of-different-kinds-of-trees-vector-18852923>)

The tree density variable was estimated using a similar method Kardan et al. (2015) utilized to associate the influence of neighbourhood greenspace on general health in Toronto. The tree density was calculated from the tree inventory data by using the formula for eight (8) known tree types (See Table 4.2). Estimation of the crown diameter of the known tree types was carried out. In contrast, the estimation of unknown tree types was carried out by using linear regression on the results of known tree types crown diameter. A formula was derived from the linear regression to estimate the crown diameter of unknown tree types. The limitation in this process is that the tree

inventory data contains 70% of the known tree types and 30% of the unknown tree types, which includes various tree species. Also, the assumption that all trees are circular when the area of circle formula was used to estimate the crown area (See Figure 6.3) and the tree density variable was calculated using the crown areas of the trees. The linear regression formula and assumption that trees are circular might influence the findings in this current study. Statistical processes were used for the estimation of the three greenspace variables (stem density, basal area density and tree density). The spatial tool was used to aggregate the greenspace variables at the DA level. The crime rates and sociodemographic variables are also at the DA level. As discussed earlier, with the use of the spatial tool on different sources of data, these processes can sometimes result in potential georeferencing errors.

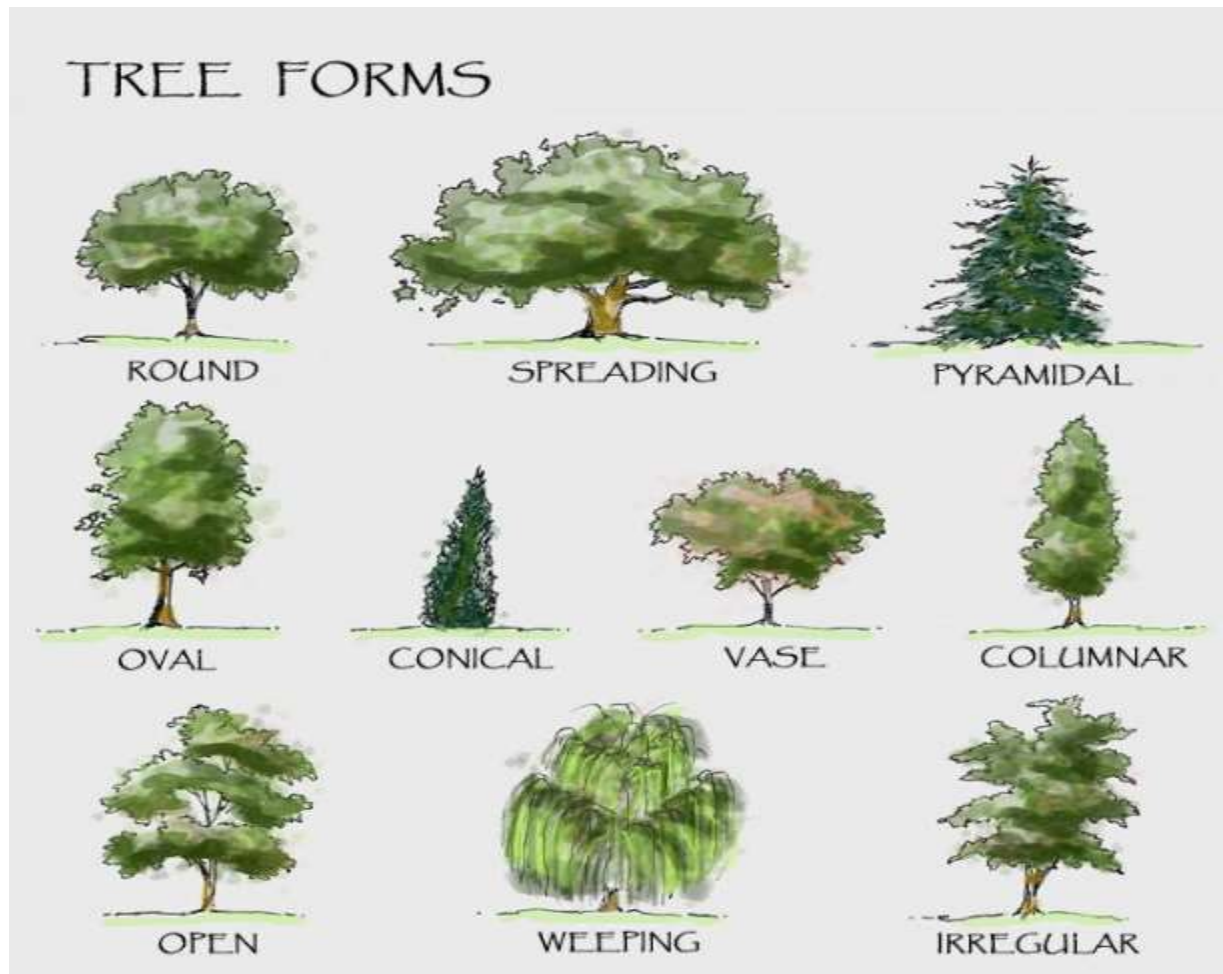


Figure 6. 3: Tree forms (<https://www.pinterest.com/pin/712272497295995748/>)

Finally, the modifiable areal unit problem (MAUP) is a major concern that can influence findings from aggregated data. It can cause statistical bias and affects the scale and shape of the aggregation unit (ESRI, 2019). The areal units (zonal objects) used in many geographical studies arbitrary, modifiable and subject to the whims and fancies of whoever is doing, or did, the ‘aggregating’ (Openshaw, 1984). Two problems could arise as a result of MAUP, and they are zoning and scale effect. The zoning effect occurs when the locations of boundaries are altered, which may influence data aggregated (Arbia & Petrarca, 2011). The scale effect occurs when data are aggregated into a fewer or larger entity (Openshaw, 1984). This study was carried out to explore the influence of

greenspace on the street crime rate at a micro spatial scale using greenspace variables and street crime data that were aggregate to the DA level. A previous study by Chen et al. (2016), where the authors aggregated property crime, greenspace and socio-economic data at the DA level, produce similar findings to this current study.

6.3 Research Contribution, Impacts and Future Direction

Research Contribution

Despite those limitations, this study contributes to the Canadian literature on crime studies by investigating the association between street crimes and greenspace after controlling for specific sociodemographic factors. Previous Canadian studies on the association between crime rates and greenspace have considered various crime types. For instance, a study carried out in Kitchener-Waterloo, ON by Du et al. (2015), considered both property and violent crime while Chen et al. (2016) study in Vancouver, BC, examined property crime for their respective studies. In contrast, this current study considered three street crimes. It classified them into property and violent crimes with street crimes having a higher chance to occur on the street where the majority of urban trees are located across the City of Toronto.

Furthermore, existing literature on crime and greenspace utilized random selected vacant lots (Garvin et al., 2013), NDVI using Landsat imagery (Wolfe & Mennis, 2012; Du et al., 2015) and Aerial photo & LiDAR data (Troy et al., 2012; Donovan & Prestemon, 2012; Chen et al., 2016) for measurement of greenspace. This study used spatial statistical analysis to estimate its greenspace variables, which are similar to past studies on the relationship between greenspace and health (Kardan et al., 2015) and homicide rates (Escobedo et al., 2018). Whereas, this current study estimated three greenspace variables (stem density, basal area density and tree density) from tree

inventory data. This current study investigated their association with street crimes that depart from past crime studies, which usually focus on tree canopy/vegetation cover association with crime types.

Besides, several crime studies have controlled for the same socioeconomic factors with different crime types (property and violent crimes). The sociodemographic factors studied; all have a significant association with street crime barring the insignificant coefficient of median housing income on auto-theft in stem density analyses. This current study also considered sociodemographic factors that are significant to violent (assault and robbery) and property (auto-theft) crimes to control for confounding factors. Due to the presence of spatial autocorrelation in the dependent variables, this study did not consider the classical OLS regression. The spatial regression analyses were adopted in this current study with two spatial regression analyses (spatial lag and spatial error) that account for spatial dependency in their analyses, unlike the OLS regression.

Impact of the study

This current study explored the associations between greenspace and street crimes after controlling for significant sociodemographic factors in Toronto. With greenspace estimated from tree inventory, which contains DBH, locations and botanical name. Sociodemographic indicators were inspired by existing literature with a focus only on the significant indicators for both property and violent crime. This current study will encourage criminologists to explore various parts of the tree and its relationship with crime studies. It will also inspire criminologists to investigate alternative methods for the measurement of greenspace and how it might be applicable in crime studies.





























The findings from this study reveal that greenspace deters street crime in the city of Toronto. The sociodemographic factors studied, which all have a significant association with street crime, should warrant further investigation for the reduction of street crime. As suggested in the discussion section, the importance of tree planting and crime prevention programmes can not be understated in Toronto's neighbourhoods. The crime prevention through environmental design (CPTED) strategies reliance on the ability to influence offender decisions before the criminal acts. Previous studies have emphasized the advantages of implementing CPTED for the built environment, which deters criminal activities with the manipulation of the built environment (Moffat, 1983; Crowe, 2000). Elimination of escape routes, correct use of streetlights, improvement of pedestrian and bicycle lanes, planting of trees and shrubs have been recommended to architects and urban planners. The application of CPTED measures has shown reduced criminal activities in various studies (Cozens, 2002; Stafford et al., 2007; Atlas, 2008).

Future Direction

This study focused on the association between greenspace variables and street crime rates in the City of Toronto owing to its high population in Canada without considering the Greater Toronto Area (GTA), which consists of neighbouring cities. Further crime studies should be carried out to investigate the association between street Crime rates and greenspace in the GTA. Also, similar research should be carried out in other urban areas to validate the association between street crime rate and greenspace. With the current advancement in technology, future research should consider longitudinal data analysis using a spatiotemporal methodology (i.e. Emerging hot spot analysis) to investigate the spatial patterns of street Crime over time. This current study was carried out using a cross-sectional approach.

Likewise, future studies should compare greenspace data extracted from LiDAR or aerial imagery and greenspace variables estimated from tree inventory data (DBH, basal area, and so on). The comparison should be carried out between different types of measurement of greenspace, which will provide insight for future studies on crime and greenspace. A study by Escobedo et al. (2018) reported an inverse relationship between tree height and homicide rates in Bogota, Columbia. Further studies should be carried out to validate the relationship between street crime rates and tree height (greenspace) in urban cities. Again, future studies should consider examining the influence of tree types (evergreen and deciduous) on street crime rates over some time (See Figure 6.4). Additionally, this current study focused on the use of specific sociodemographic factors, and they all have a significant association with street crime. These should warrant further investigation for the reduction of street crime.

Further investigation can be carried out on the effect of weather season (Winter, Spring, Summer and Fall) on trees and street crime in urban cities. It can be carried out by investigating the influence of weather conditions on different tree species (e.g. Maple) and if there are any street crime variations during different weather seasons of the year. Findings from a study by Linning (2015) on spatial patterns of property crime between two different cities (Ottawa and Vancouver) with differing climates shows there are distinct temporal peaks in Ottawa than in Vancouver and regardless of different climates. Research studies should be done to examine the seasonal spatial patterns of street crime in urban cities to plan appropriately for different seasons and inform law enforcement planners, urban planners and decision-makers on effective resource management.

OAK		Smooth Toothed	Opp.	D	OSIER WILLOWS		Smooth Toothed	Alt. Alt.	D D
BEECH HORNBEAM		Shiny Toothed	Alt.	D	SALLOW CRAB APPLE		Smooth Toothed	Alt. Alt.	D D
BIRCH		Smooth Toothed	Alt.	D	PINE		Pairs	-	E
ALDER		Rough Toothed	Alt.	D	CEDAR LARCH		Bunches	- -	E D
LIME HAZEL		Smooth Toothed Rough Toothed	Alt.	D	SPRUCE		Brush	-	E
ELM		Rough Toothed	Alt.	D	YEW		Spiky	-	E
ASH ROWAN		Smooth Toothed	Opp.	D	HOLLY HOLMOAK		Shiny leathery	Alt. Alt.	E E
SYCAMORE		leathery	Opp.	D	BOX		Shiny	Opp.	E
Field MAPLE		Smooth	Opp.	D	WHITE BEAM		Toothed Waxy under	Alt.	D
MAPLE PLANE		Smooth leathery	Opp. Alt.	D	WALNUT ELDER		Smooth Toothed	Opp. Opp.	D D
SWEET CHESTNUT		Shiny Toothed	Alt.	D	CHERRY BLACKTHORN		Smooth Toothed	Alt. Alt.	D D
HORSE CHESTNUT		Toothed	Opp.	D	MULBERRY		Shiny Toothed	Alt.	D
WHT. POPLAR		Waxy under	Alt.	D	MEDLAR		Downy under	Alt.	D
BLK POPLAR ASPEN		Smooth Toothed	Alt. Alt.	D D	HAWTHORN		Shiny	Alt.	D

Opp.=Opposite Alt.=Alternate E= Evergreen D=Deciduous

Figure 6. 4: Evergreen and deciduous tree types - images showing the different types of tree species (<https://www.pinterest.com/pin/559642691179011618/>)

Chapter 7 Conclusion

In this study, crime data from police records were utilized as the outcome variable. Street crime was classified into property and violent crime. The study investigated the trends, seasonal variations of street crimes. It explored the association between street crime rates and greenspace after controlling for specific sociodemographic factors (as covariates) in the city of Toronto. Also, it investigated (street) crime that often occurs due to concealment or “deterred by eyes on the street” (as outcome variables), including violent crime (assault and robbery) and property crime (auto-theft). The greenspace variables were estimated from tree inventory data (as explanatory variables).

This current study identified trends and seasonal variations in street crime occurrences in Toronto. Street crime reveals varying yearly trends in crime occurrence in Toronto with a peak in assault crime in the year 2017 and 2018; the auto-theft peaked in 2018 while robbery peaked in 2017. This finding is somewhat in agreement with the crime severity index reported by Statistics Canada in 2019. The monthly trends of the three street crime occurrences vary as the assault crime peaked in May, the auto-theft crime peaked in May and November while the robbery crime peaked in March, August and November. Next, the seasonal variation of assault, auto-theft, and robbery crime rose during Spring, Fall and Winter season, respectively. Geo-visualization analysis reveals the spatial distribution of street crime rates across the city of Toronto with assault crime rates prevalent in South Riverdale, Moss Park, Annex, Church-Yonge Corridor, Regent Park, Bay Street Corridor, Kensington-Chinatown, University and Niagara neighbourhoods. Auto-theft rates uncovered a high occurrence in the West Humber-Clairville, Mount Olive-Silverstone-Jamestown, Thistletown-Beaumont Heights, Rexdale-Kipling, Elms-Old Rexdale and Kingsview Village-The Westway neighbourhoods. In contrast, the robbery crime rate was prevalent in Regent Park, Moss

Park, Church-Yonge Corridor, Bay Street Corridor, Kensington-Chinatown, University, Cabbagetown-South St. James Town and South Riverdale neighbourhoods.

Spatial autocorrelation was present in the dependent variables. The multivariate spatial regression analyses were then carried out on street crime rates, greenspace and sociodemographic factors with comparable findings from both spatial lag and spatial error analyses. This study utilized tree inventory data, and this study differentiates itself from past studies that employed remotely sensed data or satellite imageries for the measurement of greenspace. The estimation of greenspace variables was carried out using spatial statistical techniques (used formulas to estimate the greenspace variables). Also, specific sociodemographic factors were used to control for the different street crime types, which depart from the social theoretical framework considered in the existing literature on crime studies.

The multivariate regression analysis findings support existing literature that reveals a significant negative association between the street crime rates and greenspace after controlling for specific sociodemographic factors. It is important to note that greenspace varies in different seasons because of the influence on the weather condition on greenspace (trees) and the presence of different tree species (evergreen and deciduous). The multivariate regression analyses reveal that stem density analyses have a lower negative coefficient compared to the tree density analysis's influence on street crime rates. The stem density has an influence on street crime in the city of Toronto. However, finding reveals that the robbery crime rate has a lower negative coefficient compared to its counterparts (assault and auto-theft) in both spatial regression analyses. At the same time, basal area density was not significant to the street crime rates in this study.

The findings from this study contribute to Canadian literature on crime studies by exploring the associations between greenspace variables and street crime rates in the city of Toronto, Ontario. This study also drew attention to the influence different parts of a tree (i.e. stem, basal area and tree density) might have on street crime rates in urban cities. In this current study, the stem density (total number of trees) has more influence on street crime than the tree density, while the basal area density was not significant to street crime rates in Toronto. The sociodemographic factors studied, which all have a significant association with street crime, should warrant further investigation for the reduction of street crime. Further investigation of significant sociodemographic factors should be encouraged to ensure crime prevention programmes that target the root causes (i.e. low economic status) of criminal activities in neighbourhoods in Toronto. The importance of green space in urban cities cannot be understated. Law enforcement planners, urban planners, and landscape architects should collaborate to achieve a collective goal of sustainable development as well as greenspace equity.

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Appendix I

Relationships between crown diameter and DBH

“The formula was extracted (some of the coefficients are changed due to converting the original formula to metric measures)” (Kardan et al., 2015).

Crown diameter (Maple) = $0.3048 * (-0.543 + 4.691 * (dbh * 0.3937)^{0.688})$. (Reference -Troxel et al., 2013).

Crown diameter (Locust) = $0.007 + 0.825 * \log(dbh) + 0.077 * \log(dbh)^2$. (Reference -Troxel et al., 2013).

Crown diameter (Spruce/Pine) = $0.3048 * (1.634 + 3.628 * (dbh * 0.3937)^{0.723})$. (Reference -Troxel et al., 2013).

Crown diameter (Ash) = $0.3048 * (-7 + 7.72 * (dbh * 0.3937)^{0.589})$. (Reference -Troxel et al., 2013).

Crown diameter (Linden) = $0.3048 * (-1.4 + 4.302 * (dbh * 0.3937)^{0.667})$. (Reference -Troxel et al., 2013).

Crown diameter (Cherry) = $1.76 + 0.1540 * dbh$. (Reference - Hemery et al., 2005).

Crown diameter (Oak) = $1.717 + 0.156159 * dbh$. (Reference - Hemery et al., 2005).

Crown diameter (Birch) = $0.975 + 0.161512 * dbh$. (Reference - Hemery et al., 2005).

Appendix II

Basal Area Density

Spatial regression results for the basal area density model and crime rates

Variables	Assault		Auto-theft		Robbery	
	Spatial Lag	Spatial Error	Spatial Lag	Spatial Error	Spatial Lag	Spatial Error
Constant	10.224*	12.229*	3.145*	3.981*	2.164*	2.721*
Basal area density (%)	-0.033***	-0.037***	-0.049***	-0.040***	0.016***	0.0189***
Median household Income	-0.000*	-0.000*	-2.978e- 005*	-3.674e-005*	-2.820e- 005*	-3.189e-005*
Tenure Owner (%)	0.826*	0.882*			0.128*	-0.141*
Tenure Renter			-0.524*	-0.592*		
Unemployment rate			-0.102*	-0.108*	-0.037*	-0.041*
Lone Parent (%)	-1.806*	-2.254*			-0.455*	-0.544*
High School (%)			0.233*	0.258*		
Lag coeff. (Rho)	0.188*		0.274*		0.295*	
Lag coeff. (Lambda)		0.190*		0.277*		0.301*
R ²	0.041	0.041	0.0676	0.0684	0.074	0.076
Log likelihood	-15801.4	-15801.708	-13418.9	-13417.85	-9848.47	-9847.24
AIC	31614.9	31613.4	26851.8	26847.7	19710.9	19706.5

p < 0.001*, p < 0.05, p < 0.1*****