

**Investigating the Influences of Tree Coverage and Road Network  
Density on Property Crime: A Case Study in the City of Vancouver,  
British Columbia, Canada**

by

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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. I understand that my thesis may be made electronically available to the public.

## **Abstract**

With the development of Geographic Information Systems (GIS), crime mapping becomes an effective approach to investigate the spatial pattern of crime in a defined area. Understanding the relationship between crime and its surrounding environment can reveal possible strategies that can reduce crime in a neighbourhood. The relationship between vegetation density and crime has been under debate for a long time. On the one hand, dense vegetation is usually used as shield by criminals when committing crime. On the other hand, green spaces can attract people to spend time outdoors and thus create nature surveillance around the area. The convenience of road network is another important factor that can influence criminal's selection of locations. This research investigates the impacts of tree coverage and road network density on crime in the City of Vancouver. Temporal analysis was conducted based on detected vegetation changes and crime data from 2008 to 2013. High spatial resolution airborne LiDAR data collected in 2013 provided by the City of Vancouver and road network file provided by Statistics Canada were used for the extraction of tree-covered area and the calculation of road density for cross-sectional analysis. The two independent variables were put into Ordinary Least-Squares (OLS) regression, Spatial Lag regression, and Geographically Weighted Regression (GWR) models to examine their influences on property crime rates. Other independent variables taken into consideration included population density, unemployment rate, lone-parent families, low-income families, streetlights and graffiti. According to the results, the temporal analysis provided qualitative evidence of vegetation coverage having inverse impact on property crime, and the cross-sectional analysis demonstrated statistical evidences that property crime rates had negative correlations with both tree coverage and road density, with greater influences occurred around Downtown Vancouver.

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# Table of Contents

Author's Declaration.....	ii
Abstract.....	iii
Acknowledgement .....	iv
Table of Contents.....	v
List of Figures.....	vii
List of Tables .....	ix
List of Abbreviations .....	x
Chapter 1 Introduction .....	1
1.1 Introduction.....	1
1.2 Research Questions and Objectives .....	4
1.3 Structure of the Thesis .....	5
Chapter 2 Literature Review.....	7
2.1 Crime Studies in Vancouver .....	7
2.2 Crime and Vegetation .....	8
2.3 Crime and Road Network .....	10
2.4 Crime Statistical Analysis Methods.....	11
Chapter 3 Study Area and Data .....	16
3.1 Study Area .....	16
3.2 Data Sources .....	18
3.2.1 Property Crime Data .....	18
3.2.2 Tree and Road Network.....	20
3.2.3 Ancillary Data .....	22
Chapter 4 Methodology .....	23
4.1 Geoprocessing and Temporal Analysis .....	25
4.1.1 Crime Data .....	25
4.1.2 Temporal Analysis .....	25
4.1.3 Tree Covered Area Extraction .....	26
4.1.4 Road Density Calculation .....	28
4.1.5 Demographic Factors, Street Lights, and Graffiti.....	28
4.1.6 Variables Summary and Descriptions.....	28

4.2 Analytic Techniques .....	29
4.2.1 Exploratory Spatial Data Analysis.....	29
4.2.2 Regression Models.....	31
Chapter 5 Temporal Analysis .....	34
5.1 Areas with Increased Green Vegetation Coverage .....	34
5.2 Areas with Decreased Green Vegetation Coverage.....	39
5.3 Chapter Summary .....	42
Chapter 6 Cross-sectional Analysis .....	44
6.1 Geoprocessing Results.....	44
6.1.1 Tree Covered Area and Road Density Maps .....	44
6.1.2 Independent Variables Summary.....	50
6.2 Exploratory Spatial Data Analysis.....	50
6.2.1 Data Visualization.....	50
6.2.2 Spatial Autocorrelation Analysis .....	54
6.3 Regression Models.....	58
6.3.1 Ordinary Least-Squares, Spatial Lag, and Spatial Error Models.....	59
6.3.2 Geographically Weighted Regression.....	61
6.4 Chapter Summary .....	64
Chapter 7 Discussion and Conclusions.....	65
7.1 Summary of Findings.....	65
7.1.1 Presence of Influences from Tree Coverage on Property Crime .....	65
7.1.2 Influence of Tree Coverage on Property Crime.....	66
7.1.3 Influence of Road Density on Property Crime .....	67
7.1.4 Spatial Variation of the Influences of Trees and Roads on Property Crime.....	68
7.1.5 Enlightenments on Urban Planning .....	69
7.2 Limitations and Recommendations for Future Work .....	70
7.2.1 Potential Sources of Error .....	70
7.2.2 Limitations and Recommendations for Future Work .....	71
7.3 Conclusions.....	73
References.....	75

## List of Figures

Figure 3.1 Study area: City of Vancouver, British Columbia.....	18
Figure 3.2 Kerrisdale residential area: Orthophoto imagery; LiDAR point clouds in vertical view; LiDAR point clouds in 3D view; and a legend for the attribute code. ....	21
Figure 4.1 Cross-sectional analysis workflow .....	24
Figure 4.2 Discrepancies when merging high vegetation polygons and after aggregate polygons .....	27
Figure 5.1 Orthophotos of Nicola Street and Pender Street in Downtown Vancouver .....	34
Figure 5.2 Property crime trends of the DA containing the renovated residential building in Downtown Vancouver .....	35
Figure 5.3 Orthophotos of Manitoba Street and 1st Avenue in Mount Pleasant neighbourhood. 36	
Figure 5.4 Property crime trends of the DA containing the newly built apartment in Mount Pleasant neighbourhood .....	36
Figure 5.5 Orthophotos of Heather Street and 12th Avenue in Fairview neighbourhood.....	37
Figure 5.6 Property crime trends of the DA containing the new lawn in Fairview neighbourhood .....	37
Figure 5.7 Orthophotos of Ontario Street and 15th Avenue in Mount Pleasant neighbourhood..	38
Figure 5.8 Property crime trend of the DA containing the new park in Mount Pleasant neighbourhood .....	39
Figure 5.9 Orthophotos of Cedarhurst Street and West 45th Avenue in Kerrisdale neighbourhood .....	40
Figure 5.10 Property crime trend of the DA containing the area with decreased tree coverage in Kerrisdale neighbourhood.....	40
Figure 5.11 Orthophotos of Gladstone Street and Brigadoon Avenue in Victoria-Fraserview neighbourhood .....	41
Figure 5.12 Property crime trend of the DA containing the industrial buildings in Victoria-Fraserview neighbourhood.....	42
Figure 6.1 Tree covered area and buildings extracted from 2013 airborne LiDAR data .....	45
Figure 6.2 Spatial distribution of percent tree covered area by dissemination area .....	47
Figure 6.3 Spatial distribution of road density by dissemination area.....	48

Figure 6.5 Box map and box plot of property crime rates by DA .....	51
Figure 6.6 Box map and box plot of theft rates by DA.....	52
Figure 6.7 Box map and box plot of BNE rates per by DA.....	53
Figure 6.8 Global Moran’s I plots of theft rate, BNE rate, and property crime rate by DA.....	55
Figure 6.9 2013 Vancouver LISA cluster map of property crime rates by DA.....	56
Figure 6.10 2013 Vancouver LISA cluster map of theft rates by DA .....	57
Figure 6.11 2013 Vancouver LISA cluster map of BNE rates by DA .....	58
Figure 6.12 GWR maps showing spatial variation of the local coefficients .....	63
Figure 7.1 Example of georeferencing error in the west of study area.....	71



## List of Tables

Table 2.1 Comparison of previous studies on relationship between vegetation and crime .....	13
Table 3.1 Property crime types and descriptions .....	19
Table 4.1 Dependent and independent variables list and descriptions .....	29
Table 6.1 Error matrix of tree covered area extraction result .....	46
Table 6.2 Summary statistics of independent variables.....	50
Table 6.3 Summary statistics of dependent variables.....	51
Table 6.4 Dependent and independent variables of the three models.....	59
Table 6.5 Lagrange multiplier (LM) values of the three models and their significance .....	59
Table 6.6 Coefficients and significance levels of OLS and Spatial Lag regression models .....	60
Table 6.7 Regression statistics comparison between OLS and GWR .....	62

## List of Abbreviations

BNE	Break and Enter
CPTED	Crime prevention through environmental design
CSI	Crime Severity Index
DA	Dissemination area
EDA	Exploratory data analysis
ESDA	Exploratory spatial data analysis
GIS	Geographic Information Systems
GWR	Geographically Weighted Regression
LAS	Lidar native file format
LiDAR	Light Detection and Ranging
LISA	Local Indicators of Spatial Association
LM	Lagrange multiplier
LULC	Land use and land cover
Moran's I	Moran's Index
NAD 1983	North American Datum of 1983
NDVI	Normalized Difference Vegetation Index
OLS	Ordinary Least-Squares
ROI	Region of interest
UTM	Universal Transverse Mercator
VPD	Vancouver Police Department

# Chapter 1 Introduction

## 1.1 Introduction

Urbanization as a global trend has driven urban sprawl in most metropolitan areas around the world. Thus, effective urban design strategies are required, aiming at providing citizens a prosperous, sustainable and safe living environment. To ensure the safety of the residents, crime prevention has always been a crucial part of urban planning. The study and analysis of crime mainly focus on two aspects, which are the person who commit crime and the place where crime occurs (Thangavelu et al., 2013). For the first aspect, the great complex and diverse nature of human thinking can be an obstacle for analysis and control. Thus, towards crime problems, geography researchers focus on when and where crime take place to discover crime patterns. Before the emergence and development of Geographic Information Systems (GIS) techniques, paper maps and coloured dots were used for crime analysis in the police departments (Thangavelu et al., 2013). However, when big data are used for spatiotemporal analysis and predictions, paper maps are not the best option. As Ferreira et al. (2012) summarized, GIS has been applied to a number of studies since the 1960s; meanwhile, digital crime mapping has been applied in criminology field and developed significantly in the 1980s. GIS technologies have been used in various ways including, but not limited to, monitoring alerts reported by citizens, providing visual aids for identifying crime distribution patterns, identifying, modeling and predicting crime “hotspots”. Web mapping also enables researchers as well as the public to obtain volunteer provided information for crime analysis and prevention.

The crime pattern studies since mid-19th century, whether using paper maps or digital ones, have revealed from the place perspective that, the criminal activity is highly patterned and thus

predictable (Brantingham and Brantingham, 1981). In other words, crime incidents are not randomly spatially distributed, and crime “hot spots” do exist (e.g., Cozens et al., 2005). Researchers also found that the hot spots are stable over year (Weisburd et al., 2012), thus suggesting that we can deal with crime problems by concentrating on the identified hotspots, which are within a small number of places.

Based on the fact that the distribution of crime incidents follows a pattern, the concept of crime prevention through environmental design (CPTED) has been put forwarded since 1970s, asserting that “the proper design and effective use of the built environment can lead to a reduction in the fear and incidence of crime, and an improvement in the quality of life” (Crowe, 2000). Discovering the characteristics of crime-concentrated places can support CPTED strategies planning. Empirical models are developed to summarize thesis characteristics and predictive models are built accordingly to predict high-risk crime areas (e.g., Law and Chan, 2011; Law, 2012; Fitterer et al., 2015).

Crime rate is affected by various factors, including population density, poverty level, unemployment rate, etc. (e.g., Weisburd et al., 2012). Research on crime mostly included population density as an important factor. Although showing different effects (positive or negative), this variable was highly significant when predicting crime (e.g., Anderson, 2006; Troy et al., 2012, Wolfe and Mennis, 2012; Eckerson, 2013; Patino et al., 2014). Social disorganization theory introduced by Shaw and McKay (1942) proposed that poverty, ethnic heterogeneity, and residential mobility are the three ecological predictors of crime, and they promote crime through increasing social disorganization. The following research have added several other factors to the list, including lone-parent families, structural density, urbanization etc. (Clear et al., 2003). Based on the theory, poverty is another factor that researchers usually include in their crime analysis.

Most of the crime types are positively related to poverty level (e.g., Wolfe and Mennis, 2012; Thangavelu et al., 2013). The percent of single-parent families showed a negative relationship with crime in Troy et al. (2012)'s analysis, while its influence is still uncertain in other regions. Wang and Minor (2002) showed a strong negative relationship between employment and crime in Cleveland in 1990, and the effect was greater on economic crimes than violent crimes. Similar results were shown in the study that Andresen (2006) conducted in Vancouver. The influences of educational attainment and young population were also examined by researchers. Studies of crime and physical environment were mostly focusing on the presence or absence of structures such as commercial buildings, parking lots, police stations, bus stops, etc. (e.g., Chen et al., 2004; Weisburd et al., 2012). The presence of light in the nighttime reduces people's fear of crime, as well as the possibility of criminals choosing the place to commit crime. A study in three crime hot spots in England demonstrated that the improvement in lighting reduces crime incidents in the area (Painter, 1996). Thangavelu et al. (2013) found rural crime occurs more frequently in areas with less street lights. On the other hand, prosperous regions provide more opportunities for property crime, and the number of street lights can serve as an indicator of urbanization level of an area (Fitterer et al., 2015). The criminology of place study in Seattle (Weisburd et al., 2012) indicated a positive relationship between lighting and crime. Riggs (2014) also suggested that street lights make it easier for criminals to see the contents of parked cars when stealing or to make sure there is no one around when breaking into a house. Urban layout is also proved to be related to crime (Patino et al., 2014). These factors are already proven to have impact on crime, however, there are also other influential factors that can add to the accuracy when predicting crime.

Among other potential influential factors, the relationship between vegetation density and crime has been under debate for a long time. Studies find that dense vegetation is usually used as shield

by criminals when committing crime, so that vegetation is positively related to crime incidents (e.g., Kuo and Sullivan, 2001). On the other hand, some studies indicate that vegetation relates to the decrease of crime incidents. One of the possible reason is that the green spaces attract people to spend time outdoors and thus create nature surveillance around the area (Troy et al., 2012; Garvin et al., 2013). It also can be explained by the attention restoration theory, suggesting that vegetation's mentally restorative effect may reduce violent crimes by restraining the psychological precursors to criminal acts (Donovan and Prestemon, 2012; Wolfe and Mennis, 2012; Garvin et al., 2013). Another possible explanation is related to the broken windows theory, suggesting that the green spaces in urban area indicate a well-managed society and create an atmosphere of order and lawfulness, therefore preventing crime from happening (Donovan and Prestemon, 2012).

The convenience of road network is another important factor that can influence a criminal's selection of locations. The highly accessible areas are associated with higher property crime rates, while complex road networks reduce this type of crime (Beavon et al., 1994). It can be explained by the routine activities theory that the convenient road network exposes attractive and unguarded targets to potential criminals. In addition, higher traffic flows create natural surveillance that can reduce crime rate to some extent (Beavon et al., 1994).

## **1.2 Research Questions and Objectives**

There are limited studies conducted to discover the relationship between vegetation and crime in Canadian cities. Likewise, few studies of relationship between road network and crime in Canada were documented. Urban crime is usually categorized by violent crime, also known as crime against person, and non-violent crime, also known as crime against property or property crime. Based on the available data, this study aimed to discover the statistical relationships between urban

property crime and high-vegetation coverage, and between urban property crime and road network density in the city of Vancouver. Non-violent property crime types, including break and enter (BNE), theft, and mischief, were analyzed. The research questions of this thesis are listed below:

- 1) Is property crime influenced by tree coverage and road density?
- 2) How do the spatial distributions of different property crime types relate to high-vegetation coverage and road density?
- 3) Do the influences of tree coverage and road density on property crime vary spatially? If so, how?
- 4) How to predict potential crime “hot spots” and develop crime prevention strategies for these places based on the conclusions of the first three questions?

The objectives of this study are: 1) to understand the spatial patterns of property crime; 2) to understand the spatial influences of tree coverage and road density on property crime; 3) to explore the spatial variation of the influences of the two factors on property crime; and 4) to support decision making in urban property crime prevention and reduction strategies.

### **1.3 Structure of the Thesis**

This thesis consists of seven chapters. The rest of the chapters can be summarized as follows.

Chapter 2 reviews recent crime studies exploring the relationships between vegetation and crime, and between road density and crime. Previous crime studies in Vancouver are also reviewed.

Chapter 3 describes the study area, Vancouver, and data source.

Chapter 4 details the research methodology designed towards the objectives, including preprocessing of the original datasets, temporal analysis, and cross-sectional analysis using linear and spatially adjusted regression models.

Chapter 5 presents the results of the temporal analysis using data collected from 2008 to 2013, which qualitatively investigated the relationship between vegetation and property crime.

Chapter 6 presents the results of the cross-sectional analysis on data collected from 2013, including tree coverage extraction results, exploratory spatial data analysis results, and the outcomes of the regression models.

Chapter 7 summarizes the main findings and interpretations of the results, points out the sources of errors as well as their potential impact to the analysis results, and indicates the potential contribution of this study. Limitations are also summarized and further research is proposed accordingly.



## **Chapter 2 Literature Review**

### **2.1 Crime Studies in Vancouver**

As a metropolitan area with a high crime rate, Vancouver has recently drawn the attention of criminologists. Crime trajectory analysis using crime data of Vancouver from 1991 to 2006 was conducted by Curman et al. (2014). The study indicates that there is a notable concentration in criminal activity with half of them occurred only on about 5% of street blocks. Similar to the pattern found in other major cities such as Minneapolis, MN (Sherman et al., 1989) and Ottawa, ON (Andresen and Linning, 2012). For individual crime types, the concentration of crime can be even greater (Andresen and Malleson, 2011; Andresen and Linning, 2012). The crime pattern of the street segments was relatively stable over the 16 years in Vancouver. In addition, the crime hotspots mostly showed a peak crime rate in centre and a decreased rate away from the centre.

Fitterer et al. (2015) developed a model for Vancouver BNEs crime spatial prediction. Commercial and residential BNEs were studied separately and two regression models were built for each of them with one model using only BNE crime data, and the other using crime data and other ancillary data including ambient and disaggregated census population, graffiti rate, road density, number of street lights, and land values. The study found a stable spatial pattern of BNEs. The occurrence rate of BNEs also has a daily pattern, with the peaks occurring at 8:00, 12:00, and 18:00. The authors have not completed the validation to prove the performance of the predictive model. However, they did find that the model which includes ancillary social context data can increase the spatial resolution of the predicted results. The improved model can be used to police patrolling activities and thus to reduce BNE rates. Due to the complex nature of crime, more research has to be done to develop an accurate predictive model.

## 2.2 Crime and Vegetation

As mentioned in Chapter 1, various studies have been done to examine the physical and social environment around the crime hotspots. In terms of the physical surrounding environment, the presence of parking lots and commercial buildings, facilities (e.g., bus stop, police station, street lighting, etc.), urban layout, and graffiti are found to be related to the concentration of crime. However, few studies looked at the effect of vegetation. In some of the studies, presence of vegetation was used as an indicator to classify the land use of the study area (e.g., Chen et al., 2004). According to Chen et al. (2004), the percent non-vegetated area is found able to increase the accuracy of prediction of crime hot spots, and it is directly related to the occurrence of crime.

A few studies concentrated on identifying the relationship between vegetation and crime, most of which were conducted in the United States. Bogar and Beyer (2015) reviewed 10 studies from 2001 to 2013 to understand the relationships among urban green space, violence, and crime in the US. The authors found that the study methodology varies and so do the results; thus, they suggested standardization in designs and measurements. Below are the most recent and related studies.

Gorham et al. (2009) studied 11 community gardens and their surrounding area in Houston, TX, comparing the numbers of crime incidents in 2005 in the areas surrounding the gardens and in areas randomly selected in the city. Results showed no significant difference between the numbers of property crimes in the community gardens' surrounding area and other areas in the city. In other words, the studied community gardens in Houston do not have a strong effect on property crime.

Troy et al. (2012) conducted a study in the greater Baltimore region, which includes Baltimore City and Baltimore County, MD. The study area covered a variety of land use and land cover (LULC) types, including both dense urban areas and agricultural/forested rural areas. So the study

had taken into account the different effects of trees located in public or private land on crime. The vegetation data and crime data from 2007 to 2010 were summarized by census block groups, and analyzed using Ordinary Least-Squares (OLS) regression, Spatial Lag regression (three models for each regression method), and finally Geographically Weighted Regression (GWR) model to determine the spatial non-stationarity of crime. The models all showed a reverse relationship between crime rate (robbery, burglary and shooting) and vegetation density. Roughly a 20% decrease in crime is expected when there is a 10% increase in tree cover. And there is evidence that the effect of tree canopy varies between public and private land. Planting trees in public lands can result in higher crime-reduction benefits. However, some areas demonstrate a direct relationship between trees and crime, probably because the trees are mostly unmanaged, providing concealment for criminals.

Garvin et al. (2013) evaluated the influence of green space on crime by conducting an experiment in Philadelphia, PA. Comparing the crime rate before and after the greening of chosen vacant lots, the results suggested a reduction in crime, but this was not significantly related to greening. However, the greening of vacant lands does significantly increase residents' sense of security.

Another study conducted in Philadelphia (Wolfe and Mennis, 2012) showed similar results. The researchers conducted spatial analysis of crime from 2005 to 2009, at census tract level. The same analytic models were implemented in this study, which are OLS model and Spatial Lag model. The results indicated that robberies, burglaries and assaults are inversely related to vegetation coverage. The authors also found that vegetation has a greater negative effect on assault than other crime types. However, thefts does not show significant association with vegetation coverage.

According to Donovan and Prestemon (2012), in Portland, Oregon, from 2002 to 2004, the crown area of street trees demonstrates a negative effect on crime, while the number of trees on a house's lot is associated with the increasing of crime occurrence.

Eckerson (2013) conducted a similar study in Minneapolis, MN, analyzed the data from 2010 to 2012. OLS and GWR analysis tools in ESRI ArcGIS were applied to determine the relationship between crime and tree canopy coverage. The results showed a negative relationship between them.

There is limited research looking at the influence of vegetation on crime in Canadian cities. The most recent one is the investigation in Kitchener-Waterloo region, Ontario, (Du, 2015) using crime data from 2013 and applying OLS, Spatial Lag, and GWR models for different crime types. The result indicated a negative correlation between crime (both violent and non-violent) and vegetation density and the greater effect was found in urban core.

### **2.3 Crime and Road Network**

According to previous studies, road network primarily has influences on property crime, and it is less influential on crimes against persons. Road network complexity may reduce property crime because criminals who are unfamiliar with the area may spend more time finding an escape route; the convenience of a road network, however, provide criminals with opportunities to meet with suitable targets. Beavon et al. (1994) concluded that property crime rate is higher in more accessible and highly used areas. The authors also suggested that traffic barriers and road closures can be used as potential effective crime prevention techniques through the reduction of accessibility. In the statistical analysis performed by Copes (1999), road density, calculated by dividing the number of roads passing through by the area of the tract, demonstrates a direct influence to the increase of motor vehicle theft. Their result supports Beavon et al. (1994) study

that the routine activity of criminal is associated with the rate of property crime in the area, and road network is one of the quantifying methods towards the issue.

A few recent studies analyzed the relationship between road network patterns and crime. A study conducted in Tokyo, Japan by Murakami et al. (2004) investigated the pattern of the road network around five robbed convenience stores. The authors found similarities in the road environment of the five crime scenes. However, the result is not convincing due to the small sample size, and they failed to distinguish the characteristics from other road environments due to the absence of a control group. A survey conducted in Perth, Australia by Foster et al. (2013) showed an inverse relationship between the perceived crime risk and the street connectivity of the area, which was represented by the count of three-way intersections. In other words, the street connectivity actually increases residents' perception of safety within the area.

The study conducted in Kitchener-Waterloo region (Du, 2015) also looked at the relationship between road network and crime. The author used road density as an explanatory variable in the crime regression models, and concluded a positive correlation between crime and road density. Besides, the impact is greater in the urban center of the region.

The number of studies on this topic is limited, and the results are restricted to the studied areas. To understand the impact of road networks on crime in a particular area, research needs to be done using local data.

## **2.4 Crime Statistical Analysis Methods**

The reviewed crime and vegetation studies are summarized in Table 2.1. This table compared the study designs in aspects including the source of crime data, the studied crime type, the green space type and measurement, the unit of analysis, and the employed regression models.

In Troy et al. (2012), SpotCrime is a public web map application that presents the crime scene locations from police record, news reports, and user input. Other studies mostly used the data obtained from local police departments. The public provided data can be less secure and less precise, while police departments may not have all the data, since not all victims have reported the crime to the police. Nevertheless, police departments' official reports provide relatively reliable data for crime studies.

In terms of the measurement of green, some of the reviewed studies looked at selected gardens and greened vacant lots (Garvin et al., 2013; Gorham et al., 2009). The small sample size leads to unreliable results and more research was recommended. The results also indicate that the influence of low vegetation is not as significant as that of high vegetation. Wolfe and Mennis (2012) employed the Normalized Difference Vegetation Index (NDVI) for the measurement of vegetation. However, this method cannot identify different types of vegetation. Thus, the Light Detection and Ranging (LiDAR) technique is proved to be a robust means to help the extraction of tree canopy in high spatial resolution for the investigation.

Vegetation was proved to have different effects on different crime types according to Wolfe and Mennis (2012). Therefore, the impacts of vegetation on property crime, violent crime (or crime against person), and the total crime count/rate should be assessed and discussed separately, since the principle of the impacts can be distinct. However, research in different study areas have different outcomes. To be specific, vegetation has greater impact on violent crime than on property crime in Philadelphia, PA (Wolfe and Mennis, 2012), while the opposite situation was detected in the Kitchener-Waterloo region, ON, Canada (Du, 2015).

Table 2.1 Comparison of previous studies on relationship between vegetation and crime

<b>Reference</b>	<b>Location</b>	<b>Crime data source</b>	<b>Type of green spaces</b>	<b>Measurement of Green</b>	<b>Type of Crime</b>	<b>Unit of Analysis</b>	<b>Regression Models</b>
<b>Gorham et al., 2009</b>	Houston, Texas, USA	Police Department	Community Gardens	Distance to 11 community gardens	Property crime incident counts (theft and burglary)	Census Block	Linear regression
<b>Troy et al., 2012</b>	Baltimore, Maryland, USA	SpotCrime	Tree canopy	Aerial photo and LiDAR derived tree canopy area	Crime density (total of robbery, shooting, burglary, and theft)	Census Block Group	OLS, spatial lag, GWR
<b>Wolfe and Mennis, 2012</b>	Philadelphia, Pennsylvania, USA	Police Department	Green vegetation	Healthy, green vegetation coverage calculated by NDVI using Landsat image	Crime rates by different types (Assaults, robberies, burglaries, and thefts)	Census Tract	OLS, Spatial Lag
<b>Garvin et al., 2013</b>	Philadelphia, Pennsylvania, USA	Police Department	Vacant lots before and after greening	Random selected vacant lots	Total crime counts and various crime types incident counts	Half mile radius from the vacant lots	Difference-in-difference analysis
<b>Donovan and Prestemon, 2012</b>	Portland, Oregon, USA	Police Bureau	Trees	Aerial photo derived tree crown area, number of street trees	Total crime counts (assault, burglary, larceny, theft, robbery, vandalism)	Residential addresses	Poisson Models
<b>Eckerson, 2013</b>	Minneapolis, Minnesota, USA	Police Department UCR statistics	Tree canopy	LiDAR derived tree crown area	Crime rate (total of various crime types including thefts, robberies, homicides, burglaries, etc.)	Neighbourhood	OLS, GWR
<b>Du, 2015</b>	Kitchener-Waterloo, Ontario, Canada	Police Department	Green vegetation	Vegetation coverage calculated by NDVI using Landsat imagery	Crime rates by different types (crime against person and crime against property)	Dissemination Area	OLS, Spatial Lag, GWR

The reviewed studies also used different units of analysis, ranging from neighbourhood, census tract, census block group, to census block/dissemination area (from large to small in terms of scale). Vegetation density varies from street block to street block, and their influence on crime, by attracting people outdoors and by restraining psychological precursors of crime actions, is hypothesized to be at the micro-level. Therefore, when demographic data is available, smaller scale can provide higher resolution and larger sample size for analysis.

Based on the theory that crime incidents are clustered spatially, recent studies usually use a linear regression (e.g., OLS) followed by a spatially adjusted regression (e.g., Spatial Lag) to take into consideration the autocorrelation of crime itself. Donovan and Prestemon (2012) employed Poisson regression that is often used for count data modeling. GWR is also a robust spatially adjusted regression model for detecting spatial non-stationarity of the impacts on crime. Spatial Lag and GWR used in the reviewed studies consistently demonstrated better performances than OLS models.

The reviewed studies mostly used cross-sectional method towards the problem (Bogar and Beyer, 2015). Temporal data for change analysis can provide more evidence to test the hypothesis. To be specific, if the increase of vegetation density or coverage over time results in a decrease in crime in the same area, it infers that vegetation does have a negative effect on crime. Garvin et al. (2013) employed this method with difference-in-difference estimates. However, the small sample size limited the interpretation of their results.

The number of crime studies on road network is limited and their methodology designs vary. The characteristics of road network that were evaluated by crime analysts included road density (both in terms of number and length), accessibility, and pattern. The concentration nature of crime was



not taken into consideration in most of the reviewed studies, except in the study conducted by Du (2015).

As mentioned, the study conducted in the Kitchener-Waterloo Region (Du, 2015) was the first study conducted in Canada that looked at the crime-vegetation and crime-road relationships, taking crime spatial autocorrelation into consideration. Dissemination area was used as the unit of analysis, which is a standard geographic unit with census data and small enough to provide large sample size. The author also looked at the spatial variation of the impacts from the two variables. However, Landsat imagery with a 30-meter resolution is too coarse to capture the detailed spatial variation in vegetation (Mennis, 2011). Moreover, the calculation of NDVI does not separate trees and grass which may have different effects on crime.

In summary, extensive research has been done on crime spatial analysis. However, there is not enough insight into how crime and vegetation/road network are related. Research was inconsistently designed and focus on particular cities or regions, thus providing a limited perspective on the impacts of vegetation and road network on crime.

## **Chapter 3 Study Area and Data**

### **3.1 Study Area**

The City of Vancouver is a coastal city in British Columbia, located on the southwest corner of the province, with a size of 114 km<sup>2</sup>. Home to 603,502 residents in 2011, Vancouver is the eighth largest Canadian municipality, and the most populous city in Western Canada (Statistics Canada, 2011b). Because of its mild climate, scenic landscape, quality of life, etc., Vancouver has been ranked first on the list of the world's most liveable cities for five years (Koranyi, 2011; The Economist Intelligence Unit, 2015), thus attracting tourists and immigrants around the world. With about half of the population speaking a first language other than English, Vancouver is “one of the most ethnically and linguistically diverse cities in Canada” (City of Vancouver, 2015c).

Although voted as the most liveable city in the world, Vancouver has a high crime rate and a high Crime Severity Index (CSI) both among the top ten in the country (Perreault, 2013; Boyce et al., 2014). According to British Columbia Progress Board's report published in 2010, Vancouver had one of the highest crime rates, especially in terms of property crime, among major North American cities (CBC News, 2010). As mentioned in Chapter 1, social disorganization theory (Shaw and McKay, 1942) suggests that new immigrants can result in ethnic and racial heterogeneity within an area, which is related to the concentration of crime incidents. Therefore, the diversity of citizens in Vancouver possibly contributes to the high crime rate in the city.

As reviewed in Chapter 2, Vancouver's relatively high crime rate has drawn attention from the public and researchers. Various studies have been done to support crime prevention planning, and the crime statistics showed a progress in the field, with the calls for service to the Vancouver Police Department (VPD) decreasing from the peak in 1996 to the lowest in 2006 (Curman et al., 2014).

However, Vancouver still has a much higher property crime rate than the national average (Perreault, 2013), and the rate even increased in 2014 (Boyce, 2015). To enhance community awareness of crime, the VPD has recently launched a Web-GIS application named “GeoDash”, showing the crime incidents in the city and the map is updated every business day for Vancouver citizens to view the most up to date crime data (Vancouver Police Department, 2015c).

To sum it up, Vancouver was chosen as the study area of this research, as it provides diverse land types, populations, and enough crime incidents and types to be analyzed in the spatial aspect. It also has one of the largest urban parks in North America, named Stanley Park, locating at the north of the city. Previous studies in Vancouver provided insights on crime spatial concentration and crime attractors in social context. A predictive crime model has also been developed. However, there is a lack of knowledge on the relationships between vegetation and crime, and between road network and crime in the area.

Figure 3.1 shows the study area and the local neighbourhood boundaries. The city is divided into dissemination areas, which is the unit of analysis of this study. A dissemination area (DA) is the smallest standard geographic unit, usually with a population of 400 to 700 persons, in Canadian Census Program (Statistics Canada, 2015), similar to census block in the United States Census, as mentioned in Section 2.4. As noted before, DA as the unit of analysis provide enough of spatial details and sample size for statistical analysis. Furthermore, compared to a grid of cells with fixed areas (e.g., Fitterer et al., 2015), DA, as a predefined geographic unit, can avoid population data suppression (Statistics Canada, 2015) and there is no need to disseminate demographic factors such as population into a grid of cells, which can be erroneous. The City of Vancouver has 995 DAs as of 2011, providing a sample size  $N = 995$ .



Figure 3.1 Study area divided into dissemination areas: City of Vancouver, British Columbia.

## 3.2 Data Sources

### 3.2.1 Property Crime Data

Vancouver property crime data was obtained from the City of Vancouver Open Data catalogue, which provides free access to the city's datasets (City of Vancouver, 2008; 2013a; 2013c; 2015a; 2015b; 2015d). The original tabular data dated back to 2003 was provided by VPD. Since they have published the GeoDash web application in 2015, the geocoded ESRI point shapefiles were also made available to the public from the Vancouver Open Data catalog. The datasets provide information including crime type, year, month, neighbourhood, and coordinate. Property crime

types included in the datasets are listed and described in Table 3.1. In this study, BNE commercial and BNE residential/other were categorized as BNE, and theft from vehicle, theft of vehicle, and other theft were categorized as theft. Property crime included all the crime types listed. Violent crime types, including homicide and other crime against person, were not included in the shapefiles for privacy protection.

Table 3.1 Property crime types and descriptions

Crime Type	Description
BNE Commercial	Commercial Break and Enter. Breaking and entering into a commercial property with intent to commit an offence.
BNE Residential/Other	Residential Break and Enter. Breaking and entering into a dwelling/house/apartment/garage with intent to commit an offence.
Theft from Vehicle	Theft of property from a vehicle.
Theft of Vehicle	Theft of a vehicle, motorcycle, boat or any motor vehicle.
Other Theft	Theft of property that includes personal items (purse, wallet, cellphone, laptop, bicycle, etc.)
Mischief	A person commits mischief that willfully causes malicious destruction, damage, or defacement of property.

**Note:** Reprinted from “GeoDASH FAQs” (Vancouver Police Department, 2015b).

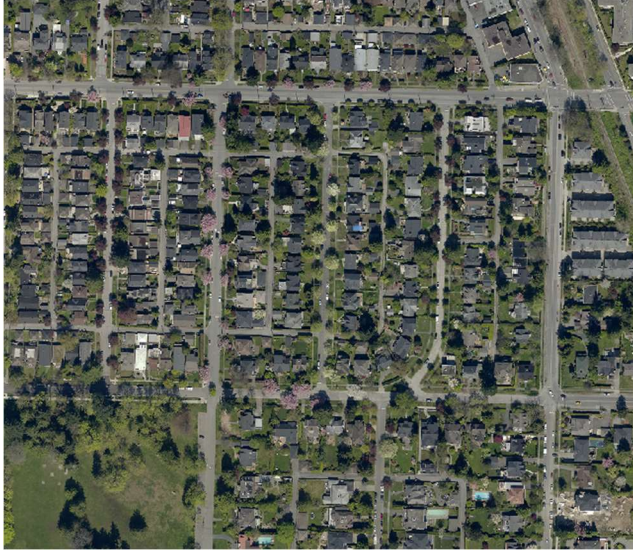
It should be noted that the data does not include all the cases reported to the police for privacy and investigation purposes, according to VPD. Moreover, the coordinates of the crime incidents were offset from the actual crime scenes, also for privacy reason. In addition, the recorded cases do not necessarily include all the criminal activities, since victims may choose not to report to the police (Luo, 2012). Despite the limitations, the most reliable and comprehensive source of crime data for the study of crime spatial-temporal pattern is the local police records (Nelson et al., 2001).

### 3.2.2 Tree and Road Network

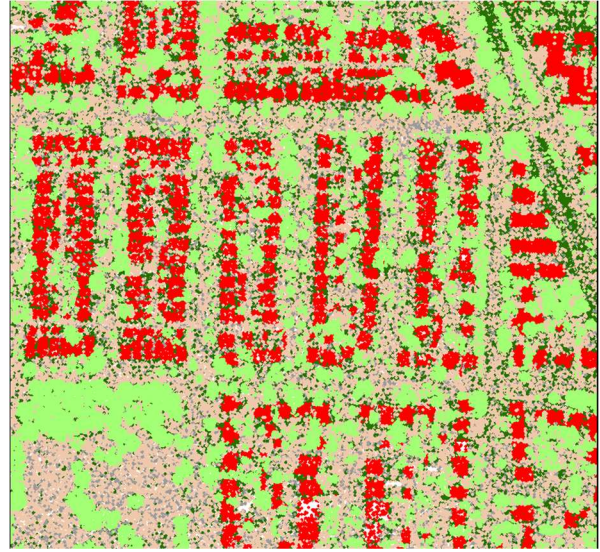
High-resolution tree crown area data was extracted from airborne LiDAR data of Vancouver, collected in February 2013. The datasets are in LAS file format and also openly available from the City of Vancouver Open Data catalogue, provided by their GIS and CADD services branch. Due to the large size of LiDAR point cloud, the dataset was divided into 168 tiles covering the jurisdiction of the city. The density of the LiDAR data is averagely 12 points/m<sup>2</sup>, reaching the vertical accuracy of 18 cm and the horizontal accuracy of 36 cm, both with 95% confidence level. A LAS file can be brought into ArcGIS platform as a LAS Dataset and viewed in 3D. Figure 3.2 shows a part of a residential area locating in Kerrisdale. The attribute code of the point cloud is presented as well in Figure 3.2. However, all of the points are classified into one of the following categories: Unassigned; ground (or bare-earth); low vegetation; high vegetation; water; and buildings. In other words, there is no point in other categories listed in the figure.

As shown in Figure 3.2, low vegetation and ground points are interspersed with the unassigned points, and comparing them to the orthophoto imagery, the distribution is erroneous. Despite the inaccurate low vegetation and ground points, LiDAR data provides high accuracy and spatial resolution for identifying high vegetation and buildings from other ground feature types. This analysis only took trees into consideration, thus LiDAR served as a perfect source for tree canopy area extraction, being able to identify all the trees in the parks, along the streets, and near residential buildings.





(a)

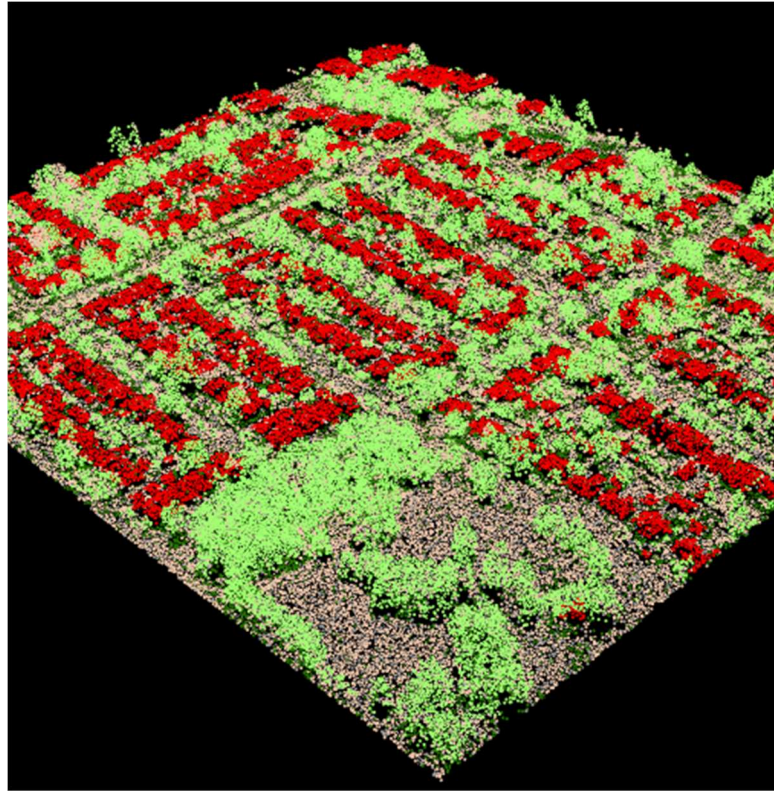


(b)

**Classification**

- 1 Unassigned
- 2 Ground
- 3 Low Vegetation
- 4 Medium Vegetation
- 5 High Vegetation
- 6 Building
- 7 Noise
- 8 Model Key/Reserved
- 9 Water
- 10 Rail
- 11 Road Surface
- 12 Overlap/Reserved
- 13 Wire - Guard
- 14 Wire - Conductor
- 15 Transmission Tower
- 16 Wire - Connector
- 17 Bridge Deck
- 18 High Noise
- 19-31 Reserved

(c)



(d)

Figure 3.2 Kerrisdale residential area: (a) Orthophoto, (b) LiDAR point clouds in vertical view, (d) LiDAR point clouds in 3D view, and (c) a legend for the attribute code.

The 2013 road network data (Road Network File, 2013) was obtained from Statistic Canada and clipped to the study area. The roads in Vancouver generally form a grid. Most streets are running north and south and most avenues are running east and west (City of Vancouver, 2016b).

### **3.2.3 Ancillary Data**

The analysis included population density, unemployment rate, percent lone parent families, percent low-income families, number of street lights, and number of graffiti as ancillary data. Census data of 2011 by dissemination area, including DA boundaries, was obtained from Statistics Canada, while point shapefiles presenting the most up-to-date locations of every street light and graffiti were provided by Vancouver Open Data catalog and downloaded in 2015. The 2011 education and labour data by DA was missing and the 2006 census data was used instead.

Orthophotos from the years of 2008 and 2013 were obtained from Vancouver Open Data catalog. The 2013 orthophoto was used for accuracy assessment of tree crown extraction, and both of the two-date orthophotos were employed in the temporal analysis.



## Chapter 4 Methodology

To investigate the relationship between crime and tree coverage, both temporal analysis and cross-sectional analysis were applied. In other words, in addition to the quantitative analysis using the data from 2013, trends analysis was also conducted using temporal data from 2008 to 2013. The temporal analysis was conducted to provide evidence of crime trends being influenced by changes of trees and vegetation in the surrounding areas, and it will be introduced in the geoprocessing section. However, only cross-sectional analysis was used to investigate the relationship between crime and road density due to the fact that the road network does not change much within a few years.

The cross-sectional analysis of this study used the data from 2013. Tree coverage was extracted and calculated using airborne LiDAR data. The OLS, spatial lag/spatial error, and GWR regressions were applied to investigate the influences of tree coverage and road density on crime. Figure 4.1 presents the workflow of this part of the methodology.

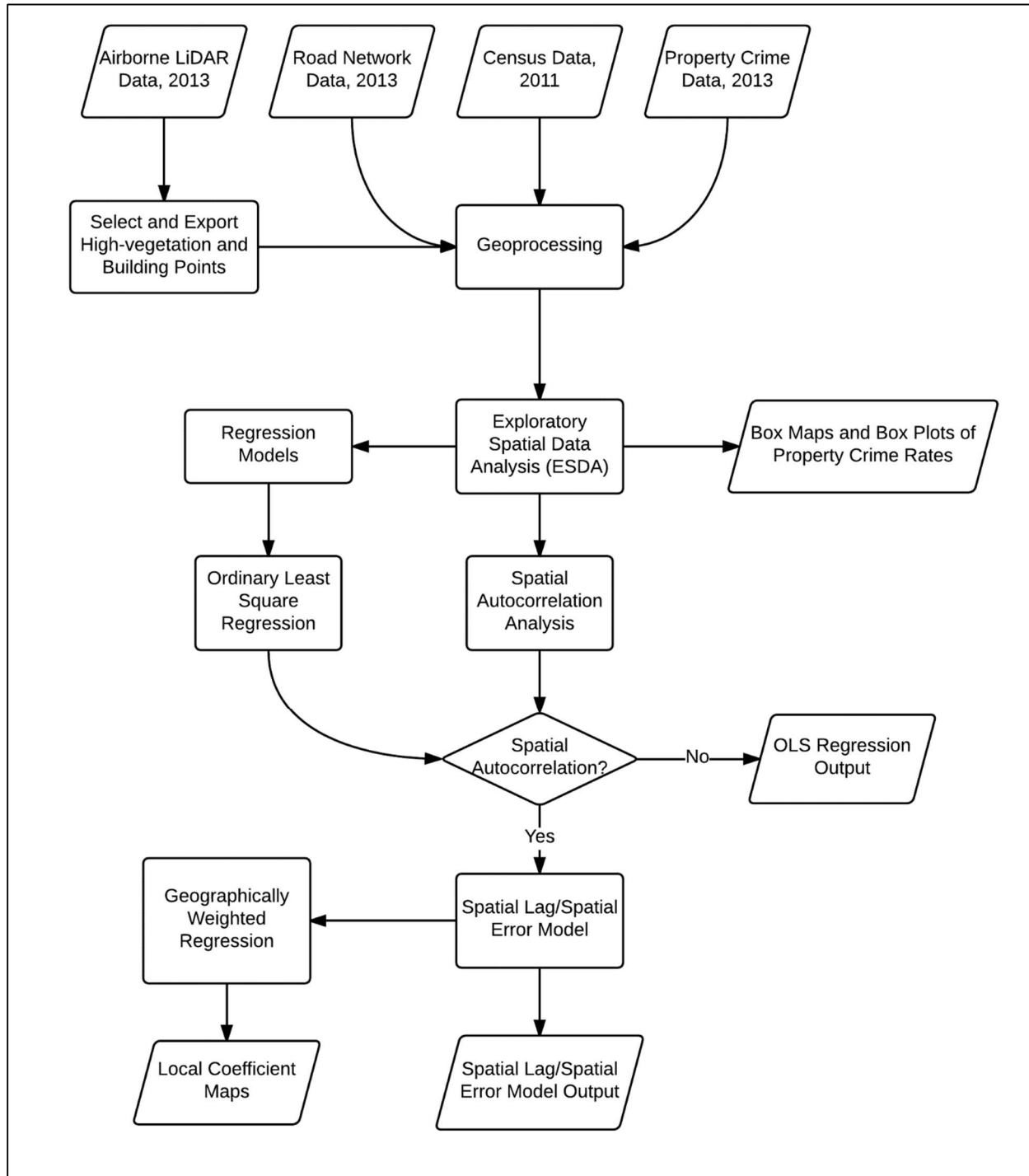


Figure 4.1 Cross-sectional analysis workflow

## **4.1 Geoprocessing and Temporal Analysis**

Before quantitative analysis, preprocessing had to be done to obtain the dependent and independent variables. All the datasets were projected to the Universal Transverse Mercator (UTM) Zone 10N and North American Datum of 1983 (NAD 1983) in order to enable calculations of length and area and to reduce georeferencing errors, especially when using the spatial join tool. The geoprocessing steps were mainly done within the ArcGIS platform.

### **4.1.1 Crime Data**

The 2013 crime rates of theft, BNE, and total property crime were the three outcome variables in this study, defined as the volume of crime in an area to the population of that area. In this study, they were expressed per 1,000 population per year. To derive the number of crime incidents for all the property crime in each DA, the points were aggregated to the DA polygons they are located in using spatial join, and the number of the points in each polygon was the volume of property crime within this area. BNE and theft crime incidents were selected and separated from the dataset, and their rates were calculated using the same method.

Yearly crime data from 2008 to 2012 was also aggregated to each DA. The crime incident counts of selected DAs were used for temporal analysis.

### **4.1.2 Temporal Analysis**

On the one hand, according to Vancouver's Greenest City Action Plan (2011-2014) implementation and update reports, Vancouver has increased the vegetation coverage of the city since 2011. As of 2013, the documents reported the planting of street trees and the development of new mini parks locating at Yukon Street and 17th Avenue, and at Main Street and 18th Avenue (City of Vancouver, 2012; 2013b). On the other hand, new buildings were built replacing green

vegetation in some of the southern areas for residential and industrial usage. Orthoimages from 2011 and from 2013 were compared at these areas for identification of changes in vegetation coverage. Yearly crime incident counts of DAs containing areas with land cover changes from 2008 to 2013 were plotted in line graphs to demonstrate the crime trends. Four sites with increased vegetation cover and two sites with decreased vegetation cover were selected for temporal crime data investigation.

#### **4.1.3 Tree Covered Area Extraction**

Percent tree cover of each DA was one of the main explanatory variables to be investigated in the cross-sectional study. Since the LiDAR points have already been classified with high accuracy in the tree and building categories, only high vegetation and building points were extracted and used in this study. The original LAS files were first converted to shapefiles using ENVI. The derived point shapefiles contained all the information needed including number of return, classification code, location, and elevation fields.

The shapefiles were then brought into ArcMap for further geoprocessing. A python script was developed to automate the process of extracting tree crowns and buildings from 168 LAS datasets. It first defined the projection of the shapefile as NAD 1983 UTM Zone 10N, which is the same as the original LAS file. Points representing trees were selected by attribute and exported, with “return number = 1 and classification= 5”. For better visualization and analysis of the study area’s LULC types, buildings (classification = 6) were extracted from LiDAR data using the same method in the code. The selected points were exported as a new shapefile for each type, and the points in each file were aggregated to polygons with the aggregation distance set to 2 m, which means points within 2 m from each other will be aggregated to the same polygon. All the temporary point shapefiles were deleted at the end of the script, leaving only the output polygon files.

The 168 parts of the study area were then merged into one for each land use type. Because the points were aggregated to polygons using the aggregate points tool, there were discrepancies at the edges of each merging part, see Figure 4.2(a). Thus, aggregation polygon tool was applied to the merged file to correct the discrepancy. The parameter was also set to 2 m for the purpose of integrity and accuracy, see Figure 4.2 (b).

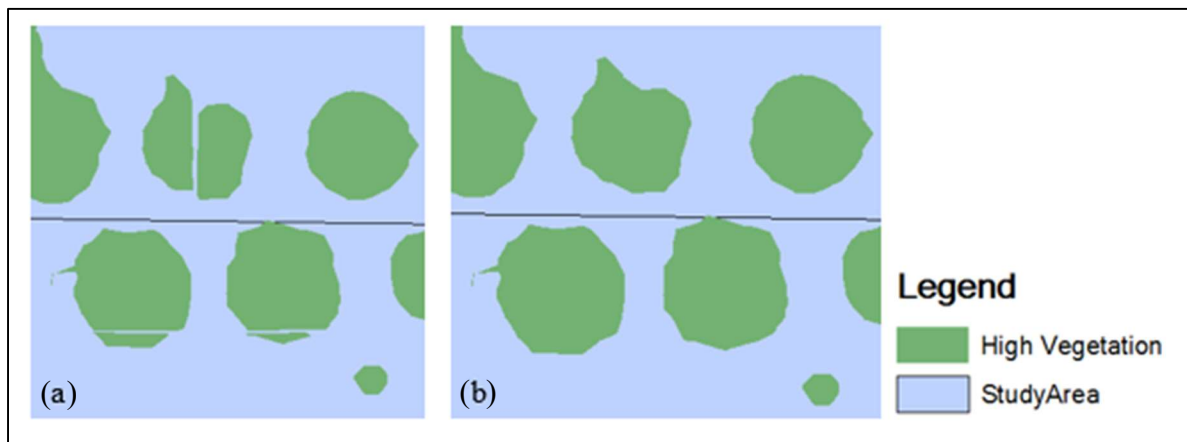


Figure 4.2 Discrepancies (a) when merging high vegetation polygons, and (b) after aggregate polygons

Accuracy assessment was conducted for the derived tree coverage map. Vancouver's 2013 orthophoto was used as the ground truth map and region of interest (ROI) was selected based on whether there were tree crown covered or not. More than 1 million random pixels (7.5 cm x 7.5 cm) were selected to be compared with the tree canopy polygons extracted from LiDAR data, and another one million pixels were selected from the land area that was not covered by tree crowns. Since the extracted tree cover and the ROI files were both polygon shapefiles, areas of the polygons were calculated and an error matrix was built accordingly, with square meter as unit. This error matrix was used to estimate the user's accuracy, producer's accuracy, and overall accuracy of the tree canopy extraction.

To calculate the percent tree cover for each DA, intersect tool was used to clip tree canopy polygons within each DA, followed by the spatial join tool that joined and calculated the sum of the tree covered area in the DAs. The percent tree covered area was then calculated as the ratio of tree covered area to the total area of each DA.

#### **4.1.4 Road Density Calculation**

Road density was the other explanatory variable investigated in this study. The same method was applied to road network data, clipping the road segments in each DA, and summing up the length of the segments. Road density was calculated as the ratio of the sum of road length to the land area.

#### **4.1.5 Demographic Factors, Street Lights, and Graffiti**

As discussed in Chapter 1, previous research has concluded that crime is significantly influenced by various factors including street lights, graffiti, and demographic factors including population density, percent of low income families, percent of lone parent families, and unemployment rate. Thus, they were included as additional explanatory variables in the regression models in order to take their effects into account.

Demographic data was found in the 2011 census dataset. They were associated to each DA and calculated accordingly. The last two independent variables, the number of lights and the number of graffiti in each DA, were calculated using the same method as processing crime data.

#### **4.1.6 Variables Summary and Descriptions**

As a summary of the geoprocessing steps, all the dependent and independent variable names and descriptions are listed in Table 4.1.

Table 4.1 Dependent and independent variables list and descriptions

<b>Description</b>	
<b>Dependent Variables</b>	
PropCrimeR	Property crime rate per 1000 population by DA
TheftCrimeR	Theft rate per 1000 population by DA
BNE	BNE rate per 1000 population by DA
<b>Independent Variables</b>	
TreeCov	Percent tree cover by DA
RoadDens	Road density (total length per 100 m <sup>2</sup> ) by DA
PopDens	Population density per 1,000 m <sup>2</sup> by DA
Unemplm06	2006 Unemployment rate (%) by DA
LowInc	Percent of low income families by DA
LoneParent	Percent of lone parent families by DA
Lights	Number of street lights per 10,000 m <sup>2</sup> by DA
Graffiti	Number of graffiti per 10,000 m <sup>2</sup> by DA

## 4.2 Analytic Techniques

The investigation of the statistical relationships between tree coverage and property crime and between road density and property crime was done through a cross-sectional analysis using the data from 2013 listed above. The two main steps for cross-sectional approach were an exploratory spatial data analysis (ESDA) followed by regression model analyses to determine the influences of the examined variables.

### 4.2.1 Exploratory Spatial Data Analysis

The first step was to explore the spatial distribution of property crime, BNE, and theft rate across the city. It was done through a series of steps of exploratory spatial data analysis (ESDA), which is an extension of exploratory data analysis (EDA). EDA is “a collection of descriptive and graphical statistical tools intended to discover patterns in data and suggest hypotheses by imposing

as little prior structure as possible” (Tukey, 1977). It provides a first insight and summarizes the main characteristics of a dataset. ESDA focuses especially on the spatial aspects of data. It can provide visualization for the spatial distribution of data, identifying spatial outliers, as well as detecting patterns of spatial association and data clustering (Anselin, 1994). Therefore, it is necessary before any testing of statistical hypotheses to avoid applying unsuitable regression models to the datasets (Symanzik, 2014). Open source GIS software GeoDa was used for its extensive range of geostatistical functionalities for ESDA (Anselin, 2003; Luo, 2012).

First, box maps and box plots of each dependent variable and the two investigated independent variables were created for visualization of the data. Box maps symbolize the map to present quantity of the variable using graduated colours. The classes are broken down using quartiles, and two additional classes highlight lower and higher outliers at the low and high extremes of the distribution accordingly. This study used a hinge of 1.5, which means an observation is regarded as an outlier if it lies more than 1.5 times the interquartile range away from the upper or lower boundary of the interquartile range (Luo, 2012). Box plot shows the characteristics of the data distribution, and also identifies the outliers (Anselin and Bao, 1997). GeoDa links the box map and box plot windows together so that user can explore the map to identify spatial outliers in the study area on the map.

Exploring maps provides us basic insights into the data. However, data visualization for human perception alone cannot provide solid evidence whether the data were spatially clustered or not (Luo, 2012). Formal statistical tests are necessary. Thus spatial autocorrelation analysis was applied for each of the studied crime types in the following step of ESDA. The presence of spatial autocorrelation suggests that an observation value is not independent from observations of nearby locations (Dormann et al., 2007).



Moran's Index (Moran's I) is the most widely used method to measure spatial autocorrelation. Its value ranges from -1 to +1, with the positive values suggesting a spatial clustering of similar values and the negative values suggesting a spatial clustering of dissimilar values (Le Gallo and Ertur, 2000). To calculate Moran's I, a weight matrix was first created for the DA polygons based on queen contiguity, in other words, based on the shared borders and common vertices (Sridharan et al., 2007). Global Moran's I tests implemented in GeoDa were then conducted over the three outcome variables of crime rates based on the weight matrix, and the results indicated the spatial autocorrelation across all records (Dormann, 2007). The significance level filter was set to 0.001, which means a 0.1% probability was allowed of rejecting the null hypothesis given that it is true (Schlotzhauer, 2007). The global Moran's I tests were followed by local Moran's I tests, results of which were presented using Local Indicators of Spatial Association (LISA) cluster map, offering an identification of the locations with significant spatial clustering, or crime hot spots in this case. The local Moran's I was estimated based on a randomization of 99 permutations, and the LISA map highlighted the significant clustering using a significance level filter of  $p < 0.05$ .

#### **4.2.2 Regression Models**

The statistical relationships between crime and tree covered area and between crime and road density can be assessed in GeoDa software using regression models. The OLS estimation was firstly applied to the examined crime types respectively, with all the dependent variables as covariates. However, as noted before from previous crime studies, crime usually has a positive spatial autocorrelation, and locations with high crime rates are usually clustered together. Using the OLS linear regression model which ignores the spatial autocorrelation of crime data can lead to erroneous results. Therefore, Lagrange multiplier (LM) tests were assessed to determine the best fit spatial regression model. It was done by comparing the significance of standard LM-Error and

LM-Lag test values. When they are both highly significant, robust LM-Error and LM-Lag test statistics are also compared. If the statistics are all highly significant, the model with a higher test value is applied. An increase in the log likelihood of spatial regression model than that of the OLS model suggests an improvement of fit of the data (Anselin, 2004).

A spatial lag model, which is a spatial autoregressive model, “assumes spatial autoregressive process occurs only in the dependent variable” (Xie et al., 2015). It can be expressed in matrix notation as below (Xie et al., 2015; Bidanset and Lombard, 2014; Kostov, 2010):

$$y = \rho Wy + X\beta + \varepsilon \quad (4.1)$$

where  $y$  is the dependent variable,  $X$  is a matrix of covariates,  $\rho$  and  $\beta$  are vectors of coefficients, and  $\varepsilon$  is an error term.  $W$  is the spatial weights matrix indicating distance relationship between observations  $i$  and  $j$ , making  $Wy$  the spatially lagged dependent variable (Bidanset and Lombard, 2014; Kostov, 2010).

A spatial error model, on the other hand, assumes spatial autoregressive process occurs only in the error term, and it can be expressed as below (Xie et al., 2015):

$$y = \lambda Wu + X\beta + \varepsilon \quad (4.2)$$

where  $u$  is a spatially dependent error term, and  $\lambda$ , similar to  $\rho$ , is a spatial autoregressive parameter. The rest of the equation is as in spatial lag model (Xie et al., 2015).

GWR was also employed in the ArcGIS platform to test for spatial non-stationarity and to investigate the local regressions for crime in the Vancouver DAs. GWR can be expressed as below (Bidanset and Lombard, 2014):

$$y_i = \beta_0 (u_i, v_i) + \sum \beta_k (u_i, v_i) x_{ik} + \varepsilon_i \quad (4.3)$$

where  $\beta_0$  is the model intercept, or constant,  $(u_i, v_i)$  stands for the coordinates of the  $i$ th regression “point”,  $\beta_k$  is the  $k$ th coefficient,  $x_{ik}$  is the  $k$ th independent variable for the  $i$ th observation, and  $\varepsilon_i$  is the  $i$ th error term (Bidanset and Lombard, 2014).

GWR was applied to the three models in ArcGIS platform and the model performance was examined by comparing the AICc statistic with that of the corresponding OLS regression. A lower AICc value indicates a better fit of the data (ESRI, 2016).

GWR creates regressions that vary depending on locations of the observations, so each observation has its local coefficient for each covariate (Bidanset and Lombard, 2014). Symbolizing the map by the local coefficients of percent tree cover or road density, the local coefficient maps demonstrated the spatial distribution of the extent of impact from the two examined explanatory variables on crime respectively. The relatively insignificant coefficients were eliminated according to pseudo t-statistics, calculated as the ratio of the estimated coefficient to its standard error (Nakaya et al., 2005). A pseudo t value close to 0 indicates a low significance of the local coefficient.

## Chapter 5 Temporal Analysis

Temporal analysis demonstrated the trends of theft, BNE, as well as total property crime counts in selected DAs from 2008 to 2013, in correspondence to the change in vegetation coverage. After a careful comparison of orthophotos of 2008 and 2013, it was concluded that changes in LULC took place in only a few areas within the five years. Two sites with decreased vegetation coverage and four sites with increased vegetation coverage were selected. The trends were analysed with line graphs.

### 5.1 Areas with Increased Green Vegetation Coverage

Figure 5.1 shows the first chosen area with increased vegetation coverage, and it was in Downtown Vancouver. The surrounding area of a residential building in this DA (DAUID = 59153987) had been renovated with lawns in 2013 compared to 2008. Figure 5.2 shows the reported property crime incident counts from 2008 to 2013. According to the line graph, the reported property crime incidents were fewer in 2011 to 2013 than in 2008 and in 2010.

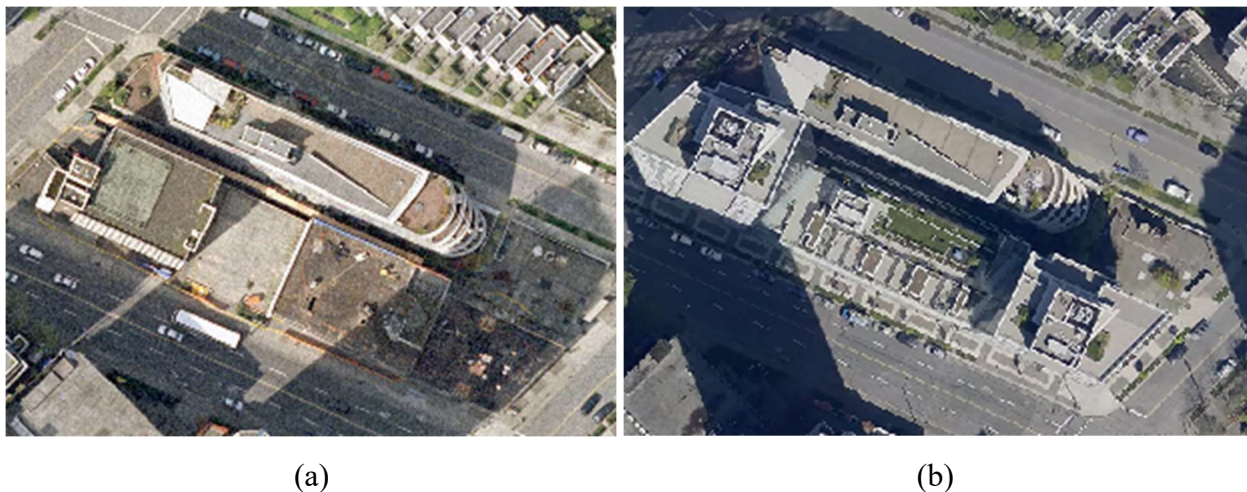


Figure 5.1 Orthophotos of Nicola Street and Pender Street in Downtown Vancouver (a) in 2008, and (b) in 2013.

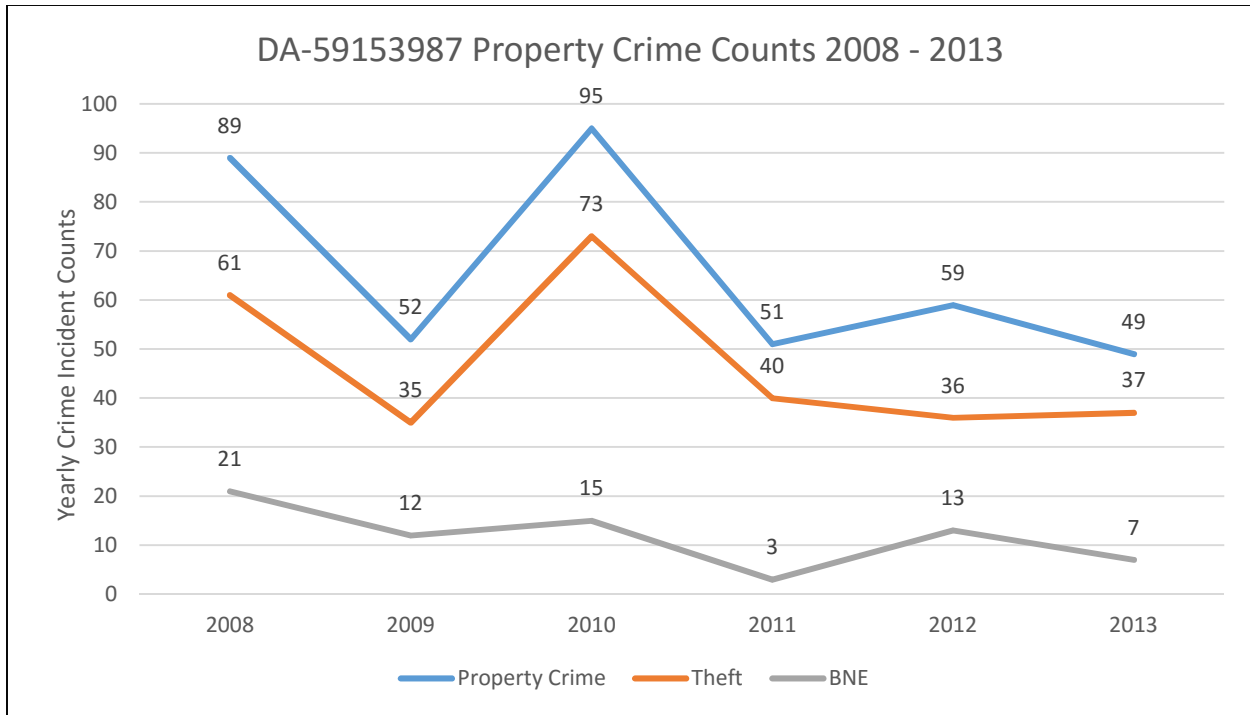


Figure 5.2 Property crime trends of the DA containing the renovated residential building in Downtown Vancouver

The second selected area was south to the first one and it was in the Fairview neighbourhood. Figure 5.3 presents the difference of the land cover in the area between 2008 and 2013. Residential buildings were built by the shoreline and surrounded by trees and lawns. However, the crime incident counts in the DA (DAUID = 59153146) experienced a constant increase from 2008 to 2013 (see Figure 5.4). Except that the BNE incident number had been relatively stable over the five years, theft incident number had been increasing, resulting in the increasing of the total property crime incidents from 622 in 2008 to 938 in 2013.



(a)



(b)

Figure 5.3 Orthophotos of Manitoba Street and 1st Avenue in Mount Pleasant neighbourhood (a) in 2008, and (b) in 2013

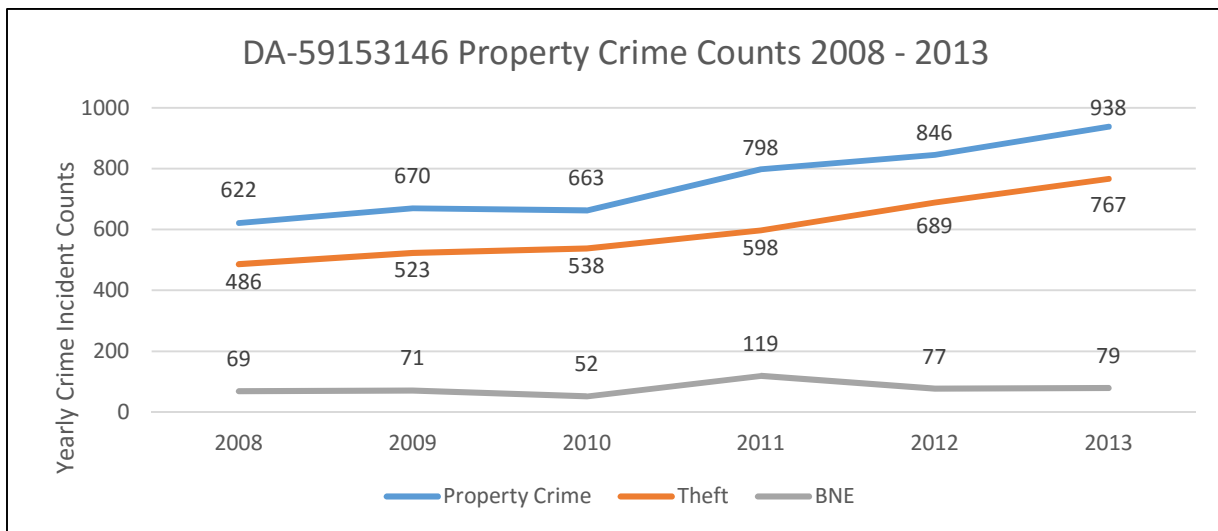


Figure 5.4 Property crime trends of the DA containing the newly built apartment in Mount Pleasant neighbourhood



The third selected area was also in Fairview neighbourhood. Figure 5.5 compares the orthoimages of the area at Heather Street and 12<sup>th</sup> Avenue in the DA with a DAUID of 59150649. In the top marked area, a building had been replaced by a lawn, and in the bottom marked area, which is a school, there was also an increase in the green area from 2008 to 2013. The property crime trends are presented in Figure 5.6.

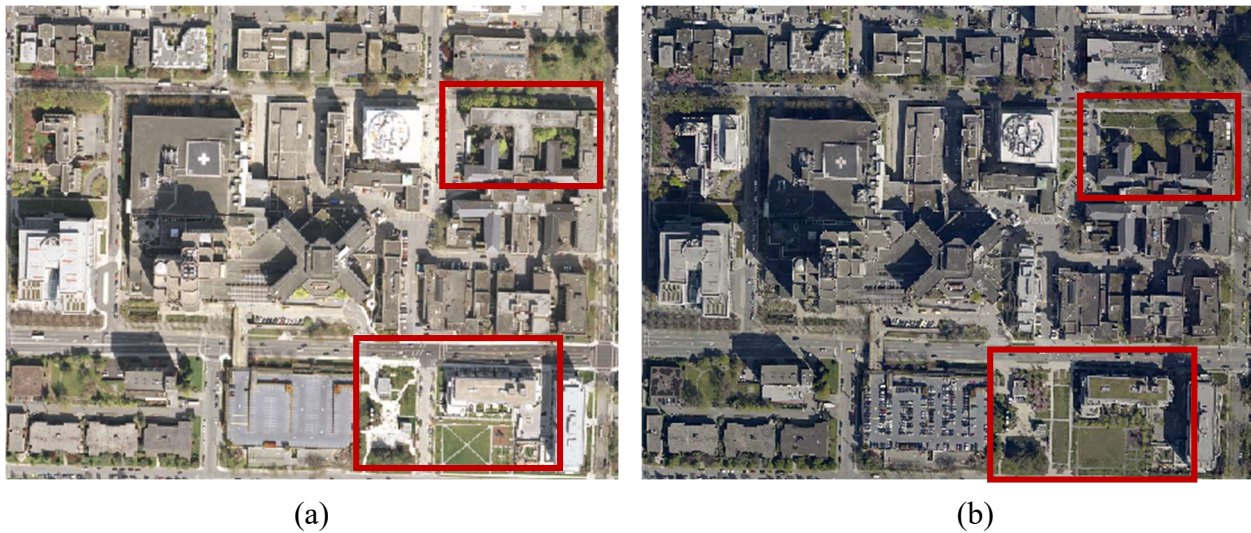


Figure 5.5 Orthophotos of Heather Street and 12th Avenue in Fairview neighbourhood (a) in 2008, and (b) in 2013

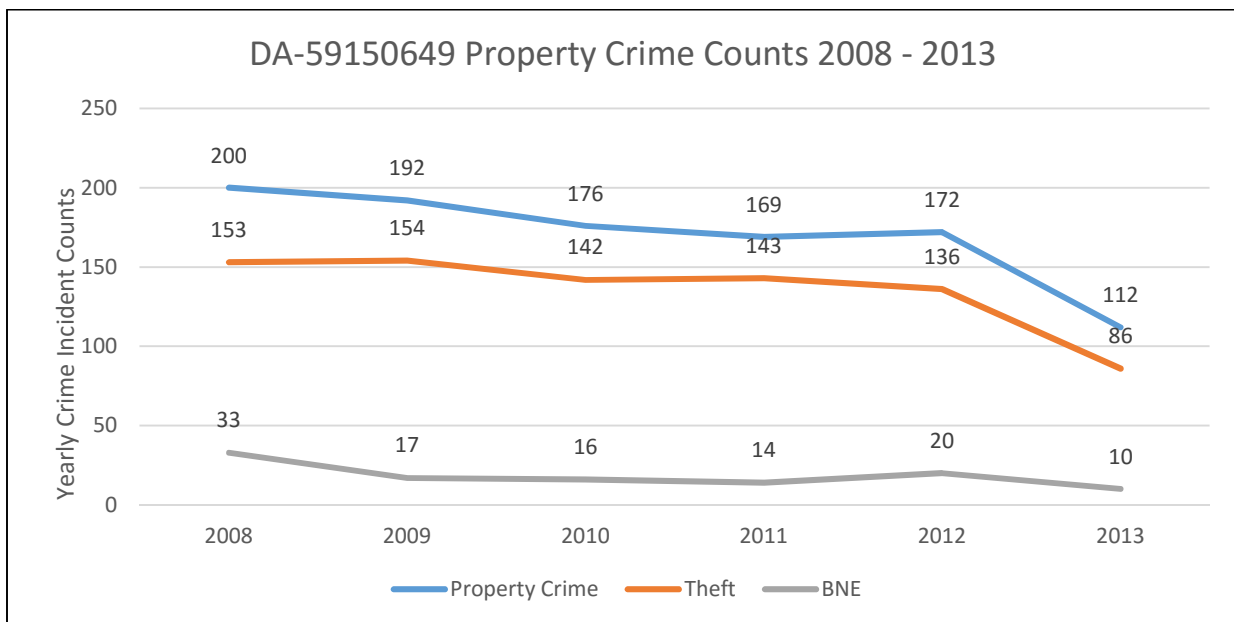


Figure 5.6 Property crime trends of the DA containing the new lawn in Fairview neighbourhood

According to Figure 5.6, all the three series had shown a decreasing trend in general, with the total reported property crime incidents having dropped from 200 to 112, theft incidents from 153 to 86, and BNE incidents from 33 to 10.

The last selected DA with increased vegetation coverage is shown in Figure 5.7. In 2013, there was a new park completed at Ontario Street and 15<sup>th</sup> Avenue, replacing the two buildings in the 2008 orthophoto. The park contributed to the increase of vegetation coverage in this DA (DAUID = 59150680). The corresponding line graph of the DA's property crime trends is displayed in Figure 5.8. BNE incidents in 2013 expressed an unusual sharp rise than in 2012. Despite this, although with some fluctuations, the reported total property crime and theft incidents number were generally decreasing.



(a)



(b)

Figure 5.7 Orthophotos of Ontario Street and 15<sup>th</sup> Avenue in Mount Pleasant neighbourhood (a) in 2008, and (b) in 2013



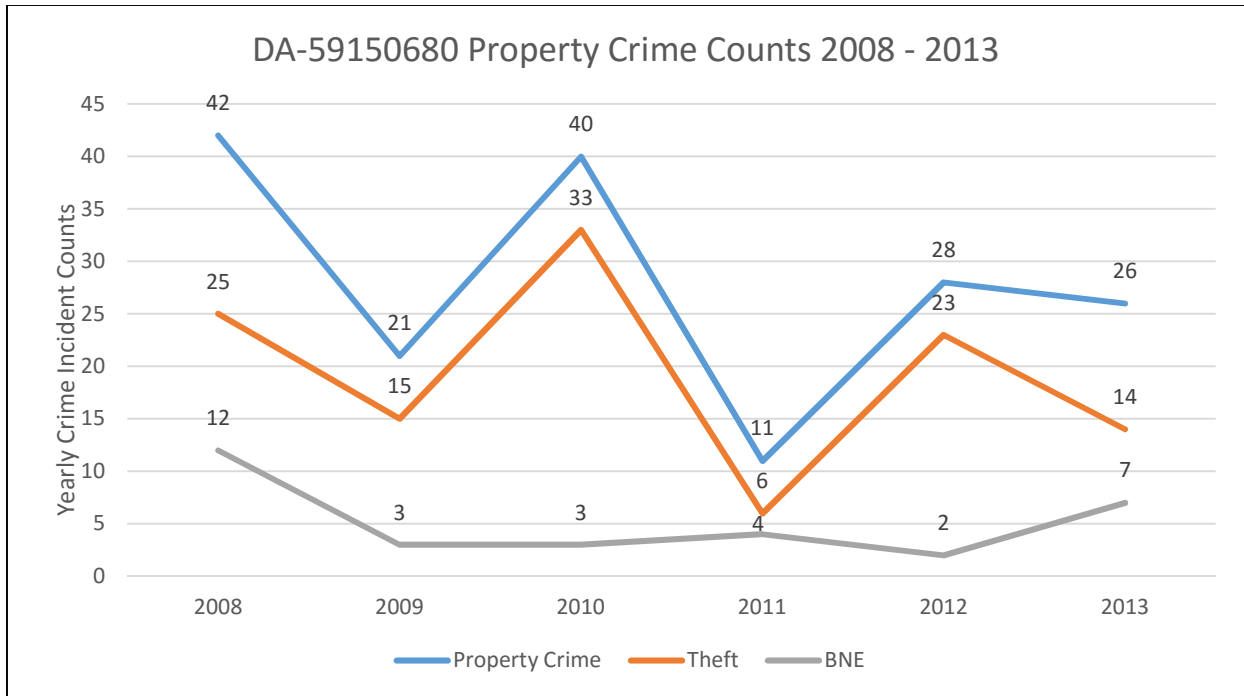


Figure 5.8 Property crime trend of the DA containing the new park in Mount Pleasant neighbourhood

## 5.2 Areas with Decreased Green Vegetation Coverage

One of the chosen DAs with decreased vegetation coverage was near the golf courses in Kerrisdale neighbourhood (DAUID = 59150954). As shown in Figure 5.9, trees were cut and buildings were built, resulting in the decrease of tree coverage in this area in 2013 compared to 2008. The reported property crime incidents for this DA were plotted in a line graph to demonstrate the trends (see Figure 5.10). Property crime incidents increased within the five years, from 12 to 21. Theft incidents has also increased, from 5 to 10. BNE incidents increased from 2 to 7, and even reached 12 in 2012.



(a)

(b)

Figure 5.9 Orthophotos of Cedarhurst Street and West 45th Avenue in Kerrisdale neighbourhood (a) in 2008 and (b) in 2013

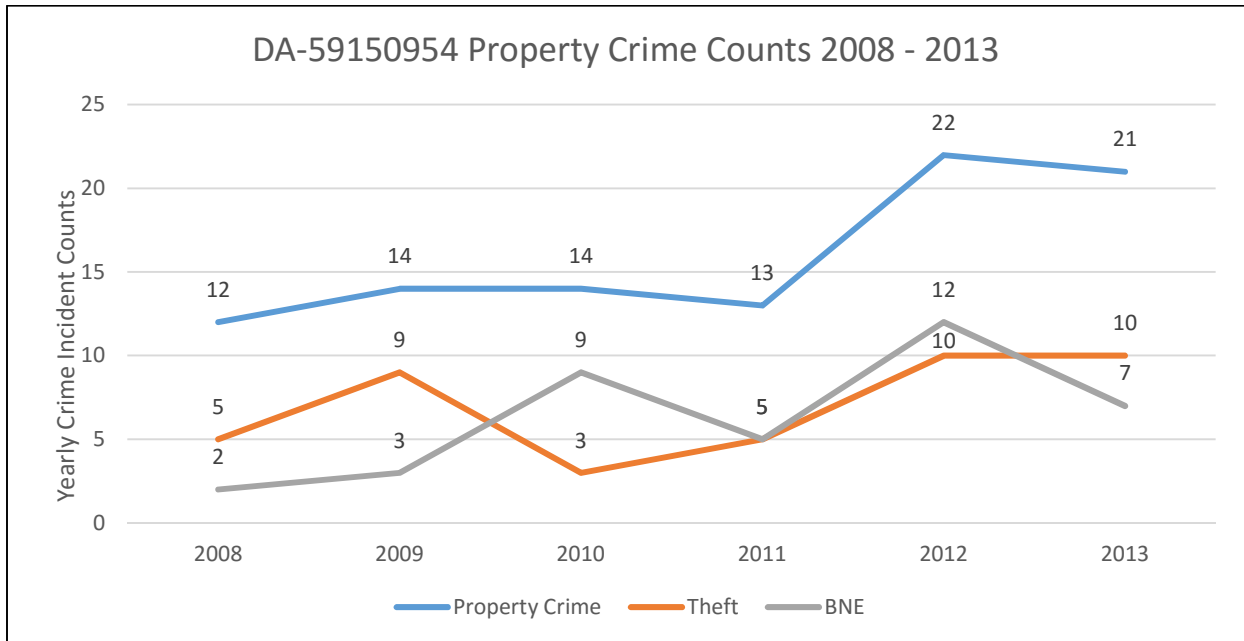
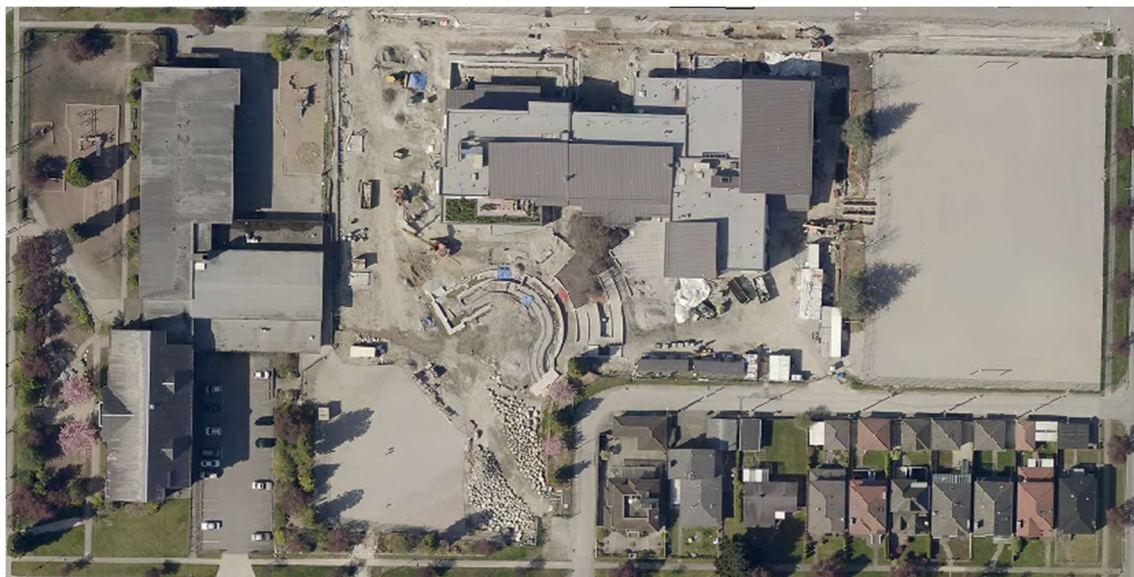


Figure 5.10 Property crime trend of the DA containing the area with decreased tree coverage in Kerrisdale neighbourhood

The last examined area was in the Victoria-Fraserview neighbourhood. Industrial buildings were built over a vacant plot at Gladstone Street and Brigadoon Avenue, wiping out the vegetation in the plot (see Figure 5.11). Some of the houses nearby also had less trees in yard in 2013 (not included in the figure). This DA (DAUID = 59150454) had lost a large area of vegetation.



(a)



(b)

Figure 5.11 Orthophotos of Gladstone Street and Brigadoon Avenue in Victoria-Fraserview neighbourhood (a) in 2008, and (b) in 2013



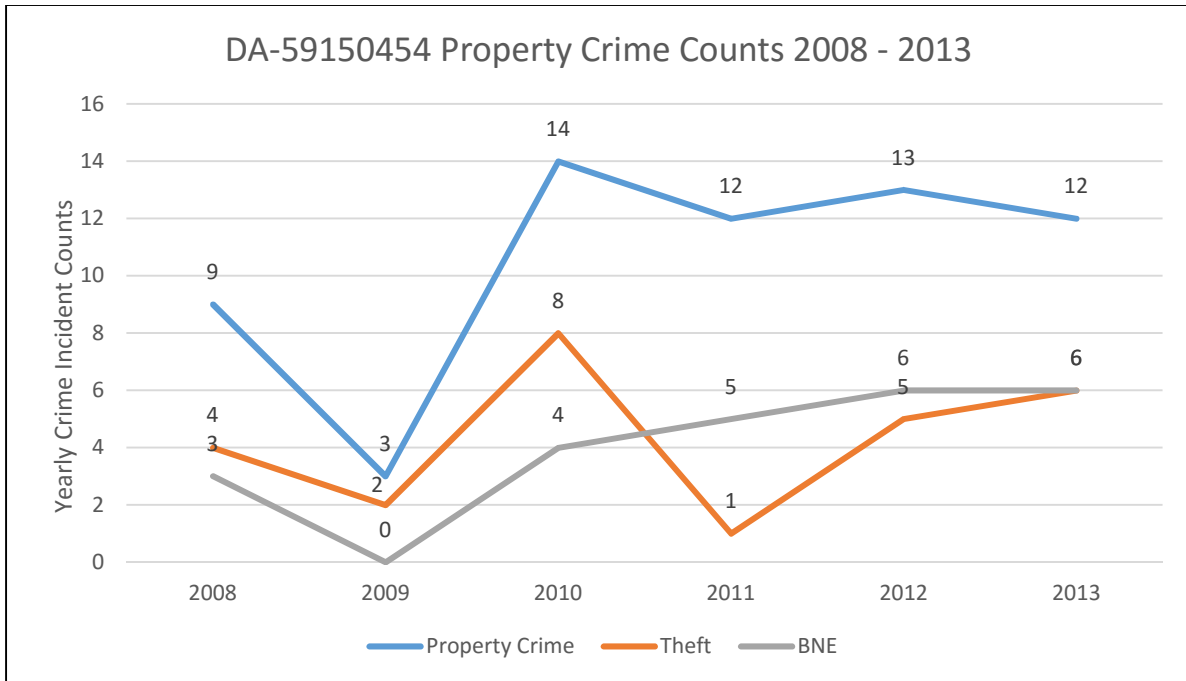


Figure 5.12 Property crime trend of the DA containing the industrial buildings in Victoria-Fraserview neighbourhood

As shown in Figure 5.12, property crime incidents in this DA dropped in 2009, however increased the following years. Therefore, according to the figure, the general trends of theft, BNE, and total property crime increased over the five years.

### 5.3 Chapter Summary

This chapter has shown the results of temporal analysis on crime trends in selected areas from 2008 to 2013, and estimated their possible relationships to the change of vegetation coverage. Most of the chosen DAs with an increased vegetation coverage had experienced a drop of property crime, while the identified DAs with a decreased vegetation coverage had suffered an increase of property crime incidents. The only exception was the DA with a DAUID of 59153146 in Fairview neighbourhood, where a number of multi-family residential buildings were built after 2008. The

reported crime incidents number increased, even though new vegetation was planted around the buildings.

Five of the six selected spots had provided evidence that the change in property crime counts was probably related to the change in the green vegetation in the surrounding environment.

Yet the temporal analysis result described in this chapter was not enough for the estimation of relationships between trees and property crime. Accurate measurements, a larger sample size, and advanced statistical calculations are needed to quantitatively investigate the effect from trees on theft, BNE, and property crime in total. In addition, road networks did not change in the city over the five years, thus the temporal analysis was not suitable.

## **Chapter 6 Cross-sectional Analysis**

This chapter presents the results of cross-sectional analysis, from preprocessing, ESDA, and regression models. The results of geoprocessing provided insights and summaries of the two examined independent variables, which were percent tree cover and road density. Other explanatory variables were also summarized. ESDA provided an insight in the dependent variables, which were property crime rate, theft rate, and BNE rate. Finally, the regression model results revealed the relationships between crime rate and percent tree coverage and between crime rate and road density.

### **6.1 Geoprocessing Results**

#### **6.1.1 Tree Covered Area and Road Density Maps**

Percent tree covered area was one of the investigated explanatory variables in this study. Figure 6.1 shows the extracted tree coverage map of Vancouver in 2013, which indicates the presence of trees all over the city, particularly in the western neighbourhoods and in the southeast of Killarney. Stanley Park, as one of the largest urban parks in North America (City of Vancouver, 2015c), was almost fully covered by trees and vegetation. On the contrary, there were less trees in the downtown area and the Sunset neighbourhood.

The accuracy of tree crown area extraction from LiDAR datasets directly influences the performances of the regression models based on it. Therefore, accuracy assessment was conducted using 2013 orthophoto, and the result is presented in Table 6.1. As it indicates, the tree covered area extraction had a producer's accuracy of 96.9% and a user's accuracy of 99.9%. The overall accuracy of tree covered area extraction is 98.4%. In conclusion, the results indicated a high accuracy of tree covered area extracted from LiDAR datasets.



Figure 6.1 Tree covered area and buildings extracted from 2013 airborne LiDAR data

Table 6.1 Error matrix of tree covered area extraction result

Classification	Ground Truth		Total area
	Area covered by trees	Area not covered by trees	
Area covered by trees (m <sup>2</sup> )	5878.6	3.2	5881.8
Area not covered by trees (m <sup>2</sup> )	185.5	6015.4	6,200.9
Total area (m <sup>2</sup> )	6064.1	6018.6	12082.7
Accuracy Calculations:			
Producer's accuracy (trees) = $5878.6/6064.1 * 100\% = 96.9\%$			
User's accuracy (trees) = $5878.6/5881.8 * 100\% = 99.9\%$			
Overall accuracy (trees) = $(5878.6+6015.4)/12082.7 * 100\% = 98.4\%$			

The map shown in Figure 6.2 is symbolized by percent tree covered area of each DA. The values were divided by quartiles and the upper outliers were highlighted as shown in the legend. There was no value in the range of lower outlier. The map generally agreed with that shown in Figure 6.1, with the western part of the city showing a higher percentage covered by trees. Most of the DAs in the Downtown neighbourhood had a tree coverage lower than 10%. The northern and western shorelines were mostly industrial areas, and they also contained DAs with lower tree coverage.

A road density map was created using the same symbolization method with tree coverage map. Figure 6.3 presents the map that divided road density values by quartiles with both lower and upper outliers highlighted. Unlike percent tree cover, road density by DA showed a relatively random spatial pattern within the study area. The DAs with shorelines and parks had lower road density, while some of the one-family residential areas had higher road density.



Since population density is a significant influential factor of crime, another map was created using the 2011 population density data. Figure 6.4 presents the spatial distribution of population density across the city.

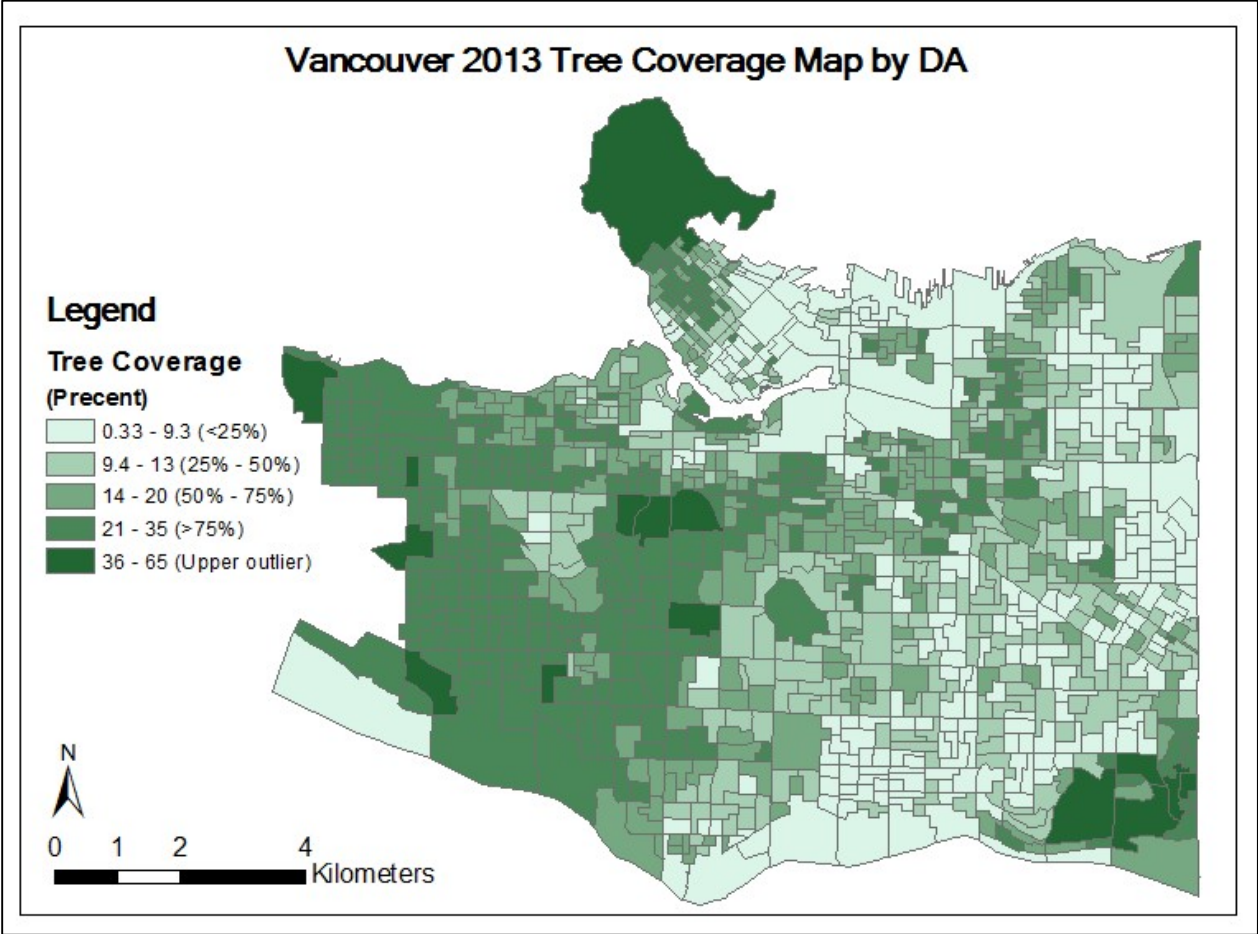


Figure 6.2 Spatial distribution of percent tree covered area by dissemination area

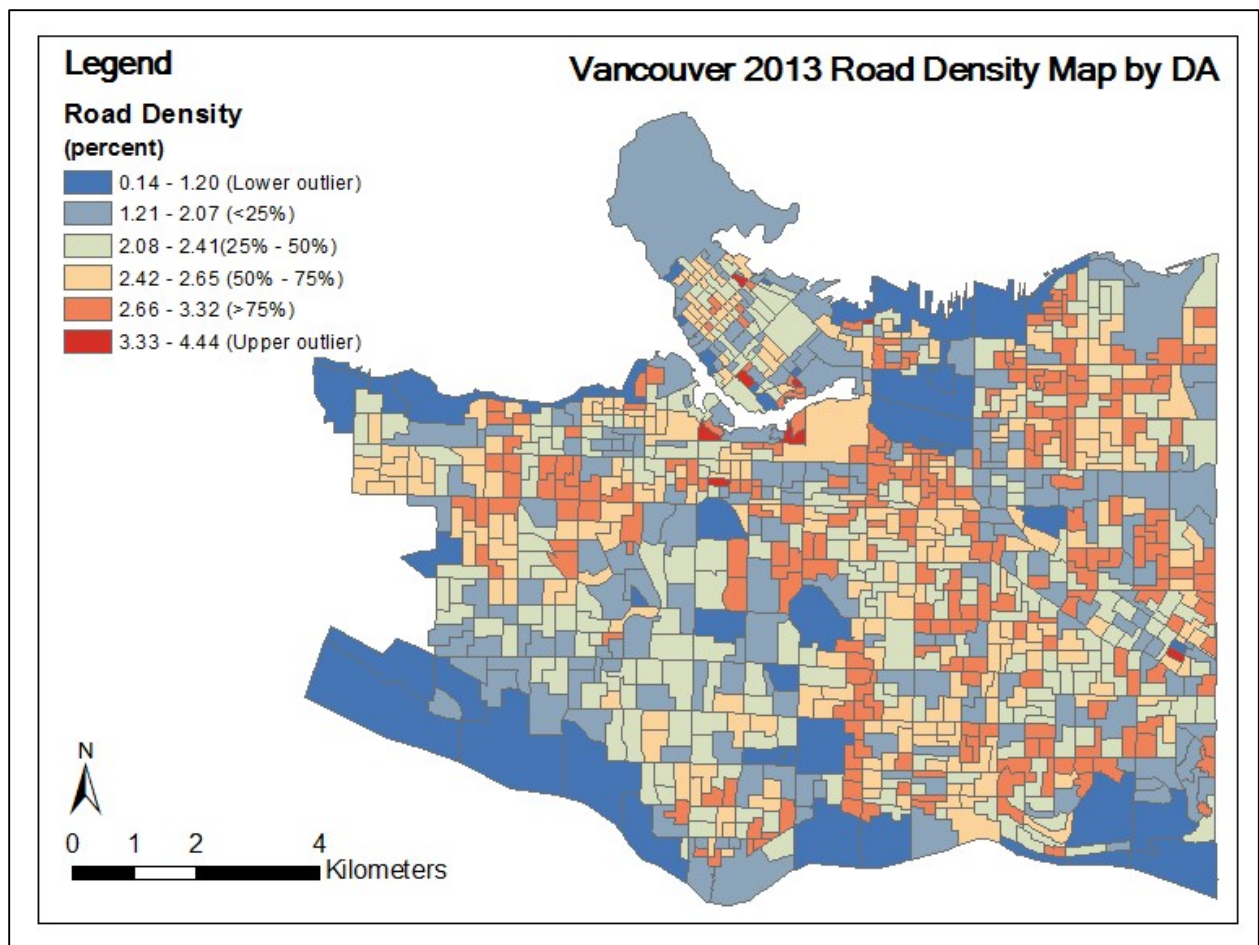


Figure 6.3 Spatial distribution of road density by dissemination area

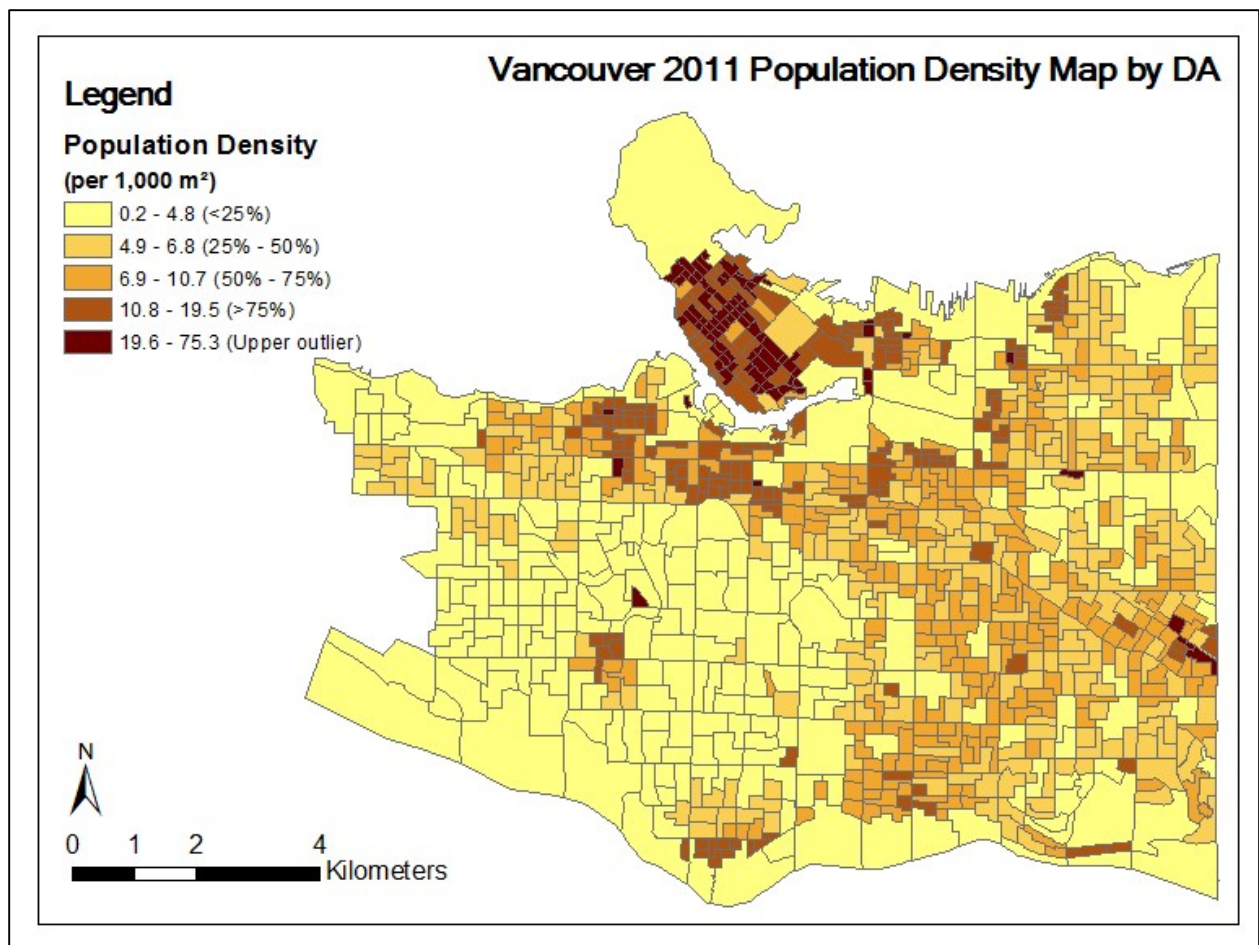


Figure 6.4 Spatial distribution of population density by dissemination area

### 6.1.2 Independent Variables Summary

Six variables proved to be important in crime analysis were included in addition to the two investigated variables, tree coverage and road network density. Table 6.2 includes a statistical summary of the eight explanatory variables.

Table 6.2 Summary statistics of independent variables

<b>Variable Names</b>	<b>Min</b>	<b>Max</b>	<b>Mean</b>	<b>SD</b>
TreeCov (%)	0.33	65.08	14.97	7.56
RoadDens (%)	0.14	4.44	2.32	0.51
PopDens (per 1,000 m <sup>2</sup> )	0.19	75.29	9.59	9.21
Unemplm06 (%)	0	20.25	5.84	2.44
LowInc (%)	0	92.11	19.87	12.43
LoneParent (%)	0	42.86	6.95	8.19
Lights (per 10,000 m <sup>2</sup> )	0	29	6.04	4.54
Graffiti (per 10,000 m <sup>2</sup> )	0	100.49	3.20	9.13

## 6.2 Exploratory Spatial Data Analysis

The ESDA of this study focused on the three outcome variables, which are property crime rate and the rates of two common types of property crime, theft and BNE. Data visualization was provided by a series of box maps and box plots, and spatial autocorrelation analyses of the three dependent variables were done using Moran's I statistics.

### 6.2.1 Data Visualization

Theft in this study included the reported incidents of theft from vehicle, theft of vehicle, and other theft. BNE included both commercial and residential BNEs reported to the police. And property crime included theft, BNE, and mischief. A statistical summary of the 2013 crime rates in the city is provided in Table 6.3.

Table 6.3 Summary statistics of dependent variables

Dependent Variables	Min	Max	Mean	SD
PropCrimeR (per 1,000 population)	0	1.44e+5	4.87e+3	8.33e+3
TheftCrimeR (per 1,000 population)	0	1.23e+3	33.61	68.51
BNE (per 1,000 population)	0	87.17	7.91	7.65

The spatial distributions of property crime, theft, and BNE rates are shown in the three box maps below, and the box plot corresponding with each crime category was on the right of the crime box map (Figures 6.5, 6.6, and 6.7). The maps were symbolized by crime rates that were divided by quartiles, and the outliers were highlighted.

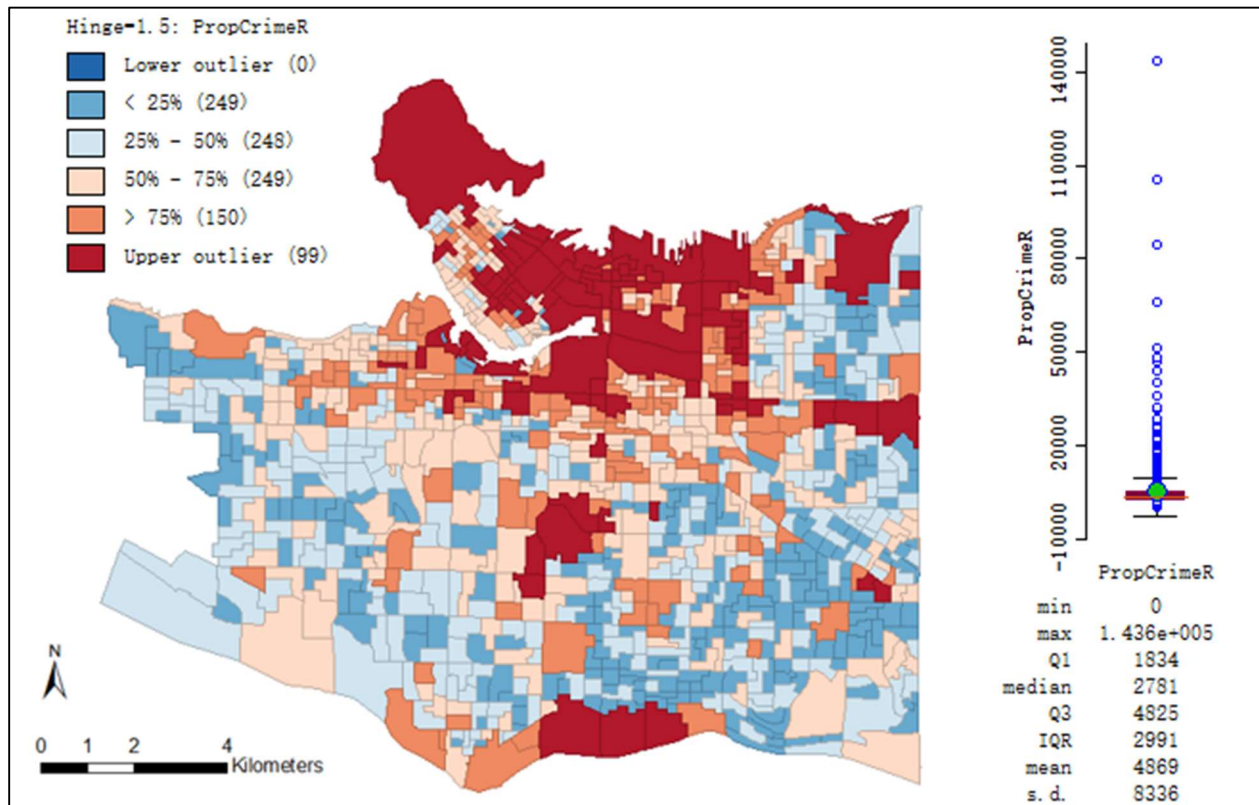


Figure 6.5 Box map (left) and box plot (right) of property crime rates per 1,000 population in 2013 by DA, with a hinge of 1.5 (In box plot, orange line: median; green dot: interquartile range)



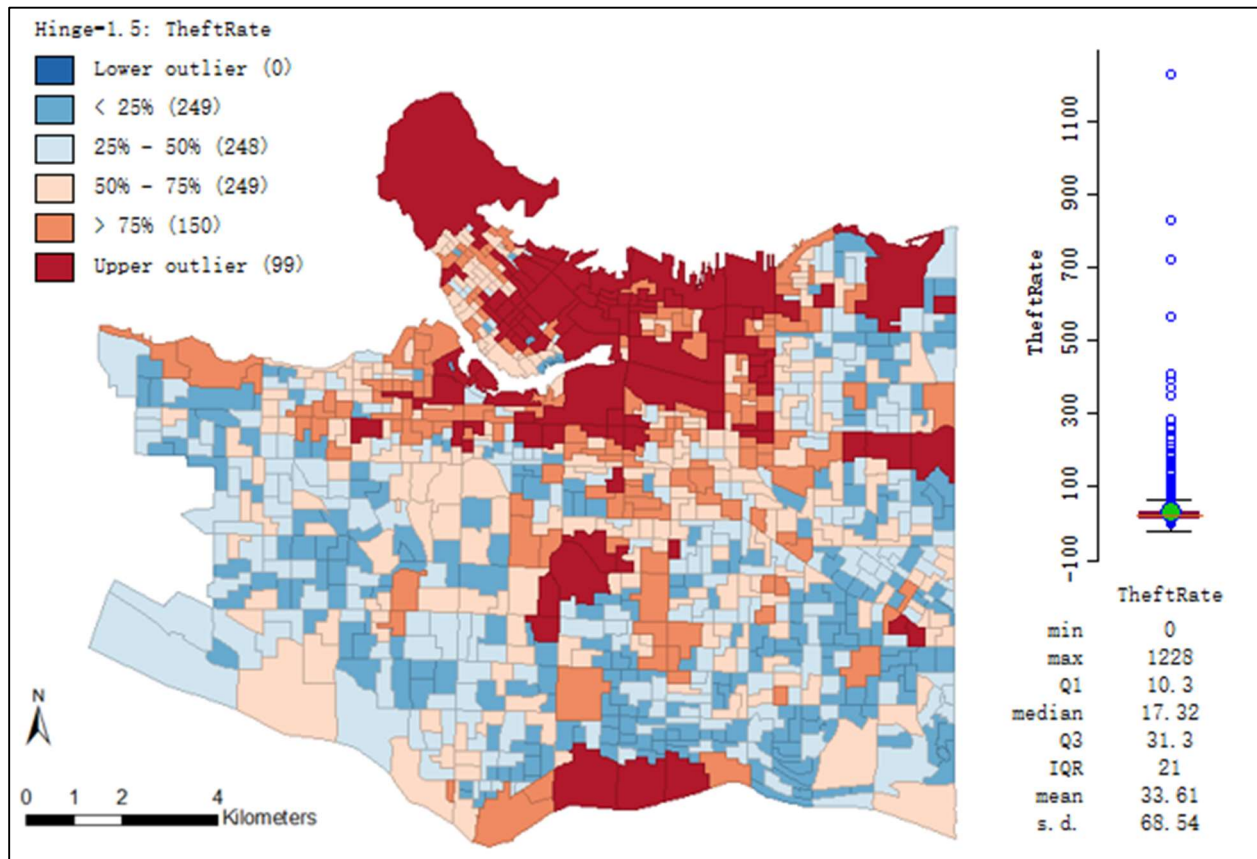


Figure 6.6 Box map (left) and box plot (right) of theft rates per 1,000 population in 2013 by DA, with a hinge of 1.5 (In box plot, orange line: median; green dot: interquartile range)

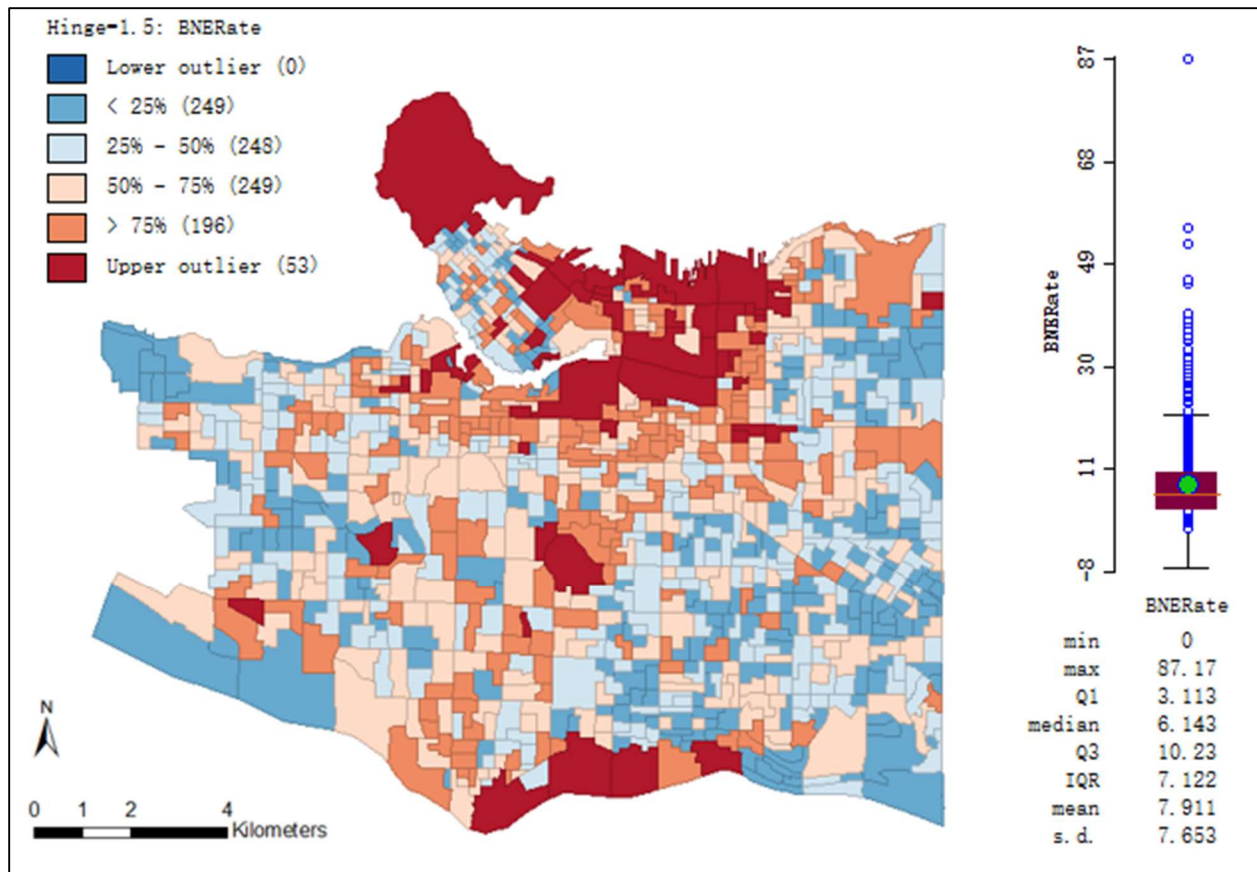


Figure 6.7 Box map (left) and box plot (right) of BNE rates per 1,000 population in 2013 by DA, with a hinge of 1.5 (In box plot, orange line: median; green dot: interquartile range)

An overall exploration of the box maps indicated the total property crime, theft, and BNE rates were not uniformly distributed in the study area. Instead, the high crime rate DAs were clustered within a few neighbourhoods, showing a highest concentration in downtown area. In addition, the western neighbourhoods exhibited a lower crime rates level than the southern shoreline and the northern shoreline, including the Downtown and Strathcona neighbourhoods. The distribution pattern demonstrated a correspondence with the spatial distribution of trees presented in Figure 6.2. However, an obvious exception was Stanley Park, suffering a high property crime rate while having the highest percent tree cover. Moreover, the Downtown and West End neighbourhoods also had a high population density (see Figure 6.4). Only by exploring and comparing crime, tree

coverage, and population density maps cannot distinguish the effects from the two independent variables on crime. Therefore, statistical analyses were needed.

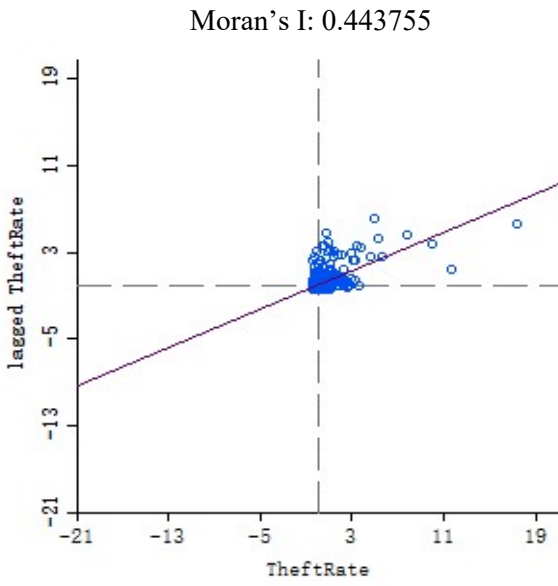
Theft and BNE rates generally demonstrated a similar pattern as total property crime rate. However, the West End neighbourhood and some of the downtown DAs had moderate BNE rates compared to their high theft rates and total property crime rates.

The corresponding box maps and box plots provided further information of the crime statistics through linked selection. The maximum of all the three variables were in the city's northern shoreline within downtown area, while the minimum values of theft and total property crime rates scattered in one-family residential areas, mostly in the southern part of the city. There were a number of DAs that had a BNE rate of zero. Most of these DAs were located in the residential area in southern area of the study area as well, but there were also ones located near the downtown core, in the West End neighbourhood. Some of the DAs with parks had a limited number of residential or commercial buildings, and they also had low BNE rates.

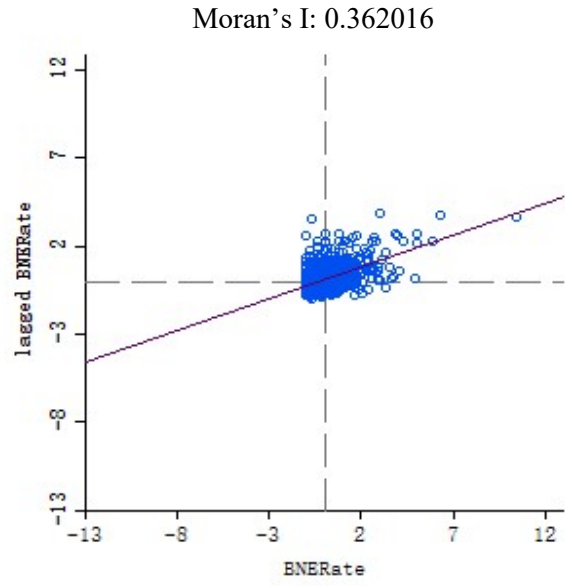
### **6.2.2 Spatial Autocorrelation Analysis**

The box map provided a first insight into the crime rate spatial distribution. Yet it did not consider the spatial association of neighbouring DAs (Luo, 2012). Therefore, statistical tests taking the crime rates of nearby DAs into account were needed to further prove the presence of spatial autocorrelation of the independent variables. The global Moran's I plots generated using GeoDa are shown in Figure 6.8. The Moran's I statistics of theft rate, BNE rate, and property crime rate were 0.44, 0.36, and 0.46 respectively, all with the significance level of 0.001. The three positive values indicated the presence of spatial autocorrelation of the examined variables.

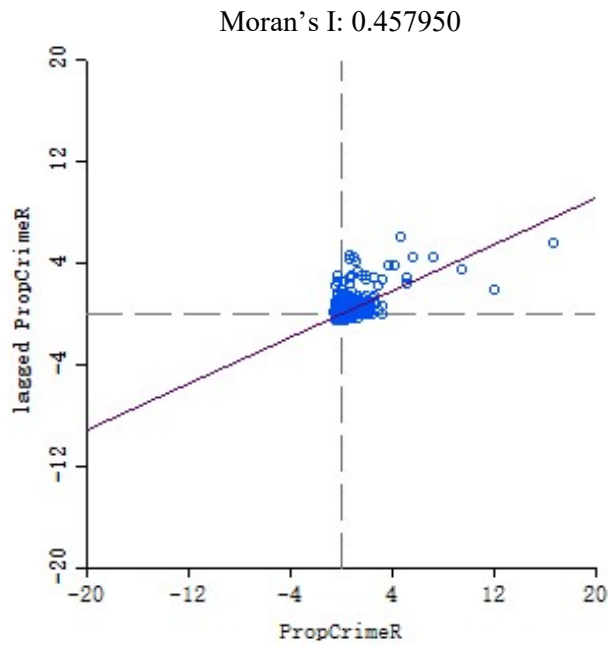




(a)



(b)



(c)

Figure 6.8 Global Moran's I plots of (a) theft rate by DA, (b) BNE rate by DA, and (c) property crime rate by DA.

Local Moran's I tests for the three dependent variables were then conducted and presented using LISA cluster maps to indicate the locations of spatial clustering. The LISA cluster maps (see Figures 6.9, 6.10, and 6.11) highlighted DAs with significant (with a significance level of 0.05) spatial association with their neighbours and categorized them into high-high, high-low, low-high, and low-low. High-high means high values surrounded by high values, and the others can be interpreted similarly. As figures 6.9, 6.10, and 6.11 exhibit, the high-high spatial association type was concentrated in the downtown core and the neighbourhood bordering it to the east (Strathcona). Theft rate and the total property crime rate shared similar clustering pattern with the low-low spatial association existing in the western and southeastern of the city. For BNE rate, low-low DAs were clustered in West Point Grey and Killarney neighbourhoods with the presence of urban forests, and there were more high-low and low-high spatial association types existed.

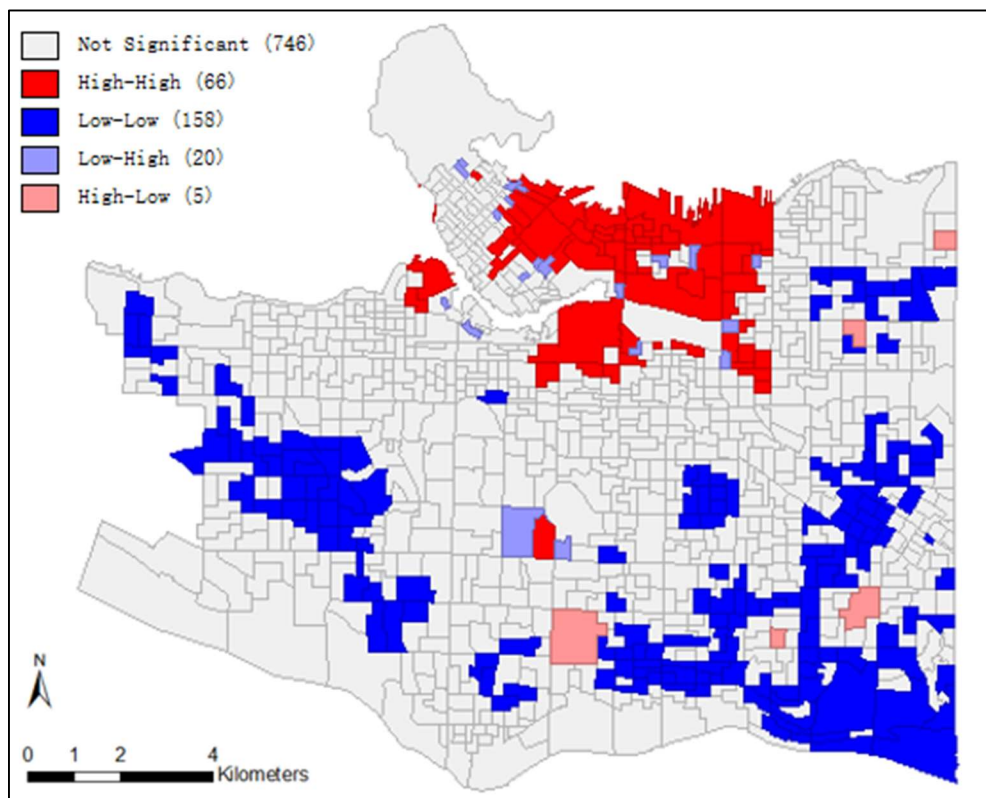


Figure 6.9 2013 Vancouver LISA cluster map of property crime rates by DA, based on 99 permutation and a significance filter of  $p < 0.05$

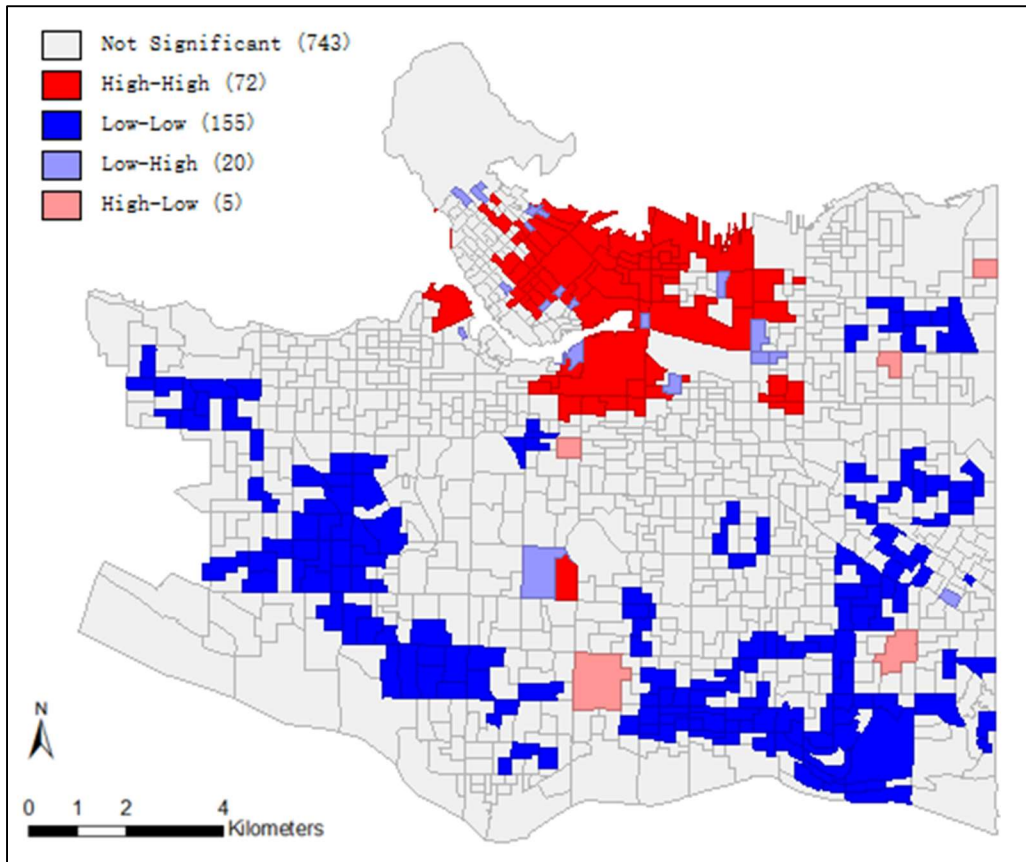


Figure 6.10 2013 Vancouver LISA cluster map of theft rates by DA, based on 99 permutation and a significance filter of  $p < 0.05$

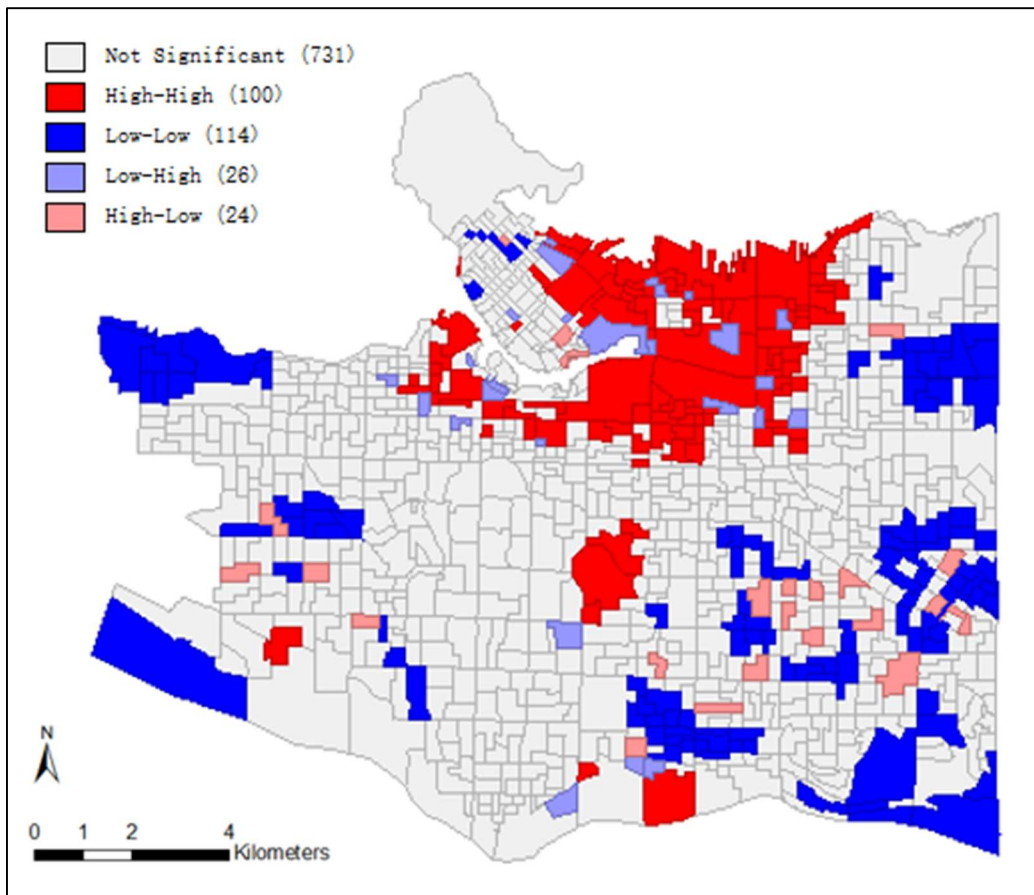


Figure 6.11 2013 Vancouver LISA cluster map of BNE rates by DA, based on 99 permutation and a significance filter of  $p < 0.05$

### 6.3 Regression Models

The ESDA described in the last section provided a first insight into the crime data distribution. Moreover, by comparing the percent tree cover map and the crime distribution maps, there was potentially a negative correlation between crime and tree coverage in City of Vancouver, yet the relationship between crime and road density was still uncertain. To statistically estimate the influences of tree coverage and road density on property crime and on different types of property crime, multiple regressions were applied to three models (see Table 6.4).

Table 6.4 Dependent and independent variables of the three models

Models	Dependent Variable	Independent Variables
A	Property Crime Rate	<b>1) TreeCov; 2) RoadDens;</b> 3) PopDens; 4) LowInc; 5) LoneParent; 6) Unemplm06; 7) Lights; 8) Graffiti.
B	Theft Rate	
C	BNE (Break and Enter) Rate	

### 6.3.1 Ordinary Least-Squares, Spatial Lag, and Spatial Error Models

OSL regression was first applied to the three models and the results are shown in Table 6.6. Percent tree coverage and road density both demonstrated significant (with 0.01 significance level) negative correlations with theft, BNE, and total property crime rates.

However, according to the results, the adjusted  $R^2$  values of all the three models were notably low. Additionally, the Moran's I tests in ESDA had concluded the presence of spatial autocorrelation of the three outcome variables. Therefore, OLS as a linear regression was not suitable for the models. The results of LM tests were examined. Since they were all highly significant, the values are listed in Table 6.5 and compared. According to the LM test results, spatial lag had higher values which means spatial lag regression is more likely to be the best fit of the data. Therefore, spatial lag regression was then applied to each model, and the results are also shown in Table 6.6 to be compared with the OLS results.

Table 6.5 Lagrange multiplier (LM) values of the three models and their significance

Models	Standard LM		Robust LM	
	LM-Error	LM-Lag	LM-Error	LM-Lag
A (Property Crime)	200.49***	318.44***	29.77***	147.72***
B (Theft)	221.10***	325.75***	26.95***	131.60***
C (BNE)	190.40***	242.78***	7.53**	59.91***

p<0.01\*\*, p<0.001\*\*\*

Table 6.6 Coefficients and significance levels of OLS and Spatial Lag regression models (model A: property crime; model B: theft; model C: BNE)

Variable	Model A Coefficients		Model B Coefficients		Model C Coefficients	
	OLS	Spatial Lag	OLS	Spatial Lag	OLS	Spatial Lag
<b>Constant</b>	1.28e+4***	8.04e+3***	98.26***	60.32***	12.96***	8.29***
<b>TreeCov</b>	-151.48***	-92.64***	-1.21***	-0.69***	-0.08**	-0.07**
<b>RoadDens</b>	-2.92e+3***	-1.94e+3***	-23.04***	-14.76***	-1.66***	-1.13***
<b>PopDens</b>	-84.47***	-165.47***	-0.58**	-1.33***	-0.14***	-0.15***
<b>LowInc</b>	54.33***	28.51*	0.48***	0.29**	0.03	0.008
<b>LoneParent</b>	-143.89***	-86.89***	-1.12***	-0.68***	-0.14***	-0.09***
<b>Unemplm06</b>	7.64	6.90	-0.57	-0.23	0.12	0.07
<b>Lights</b>	142.79**	93.59*	1.17**	0.74*	0.05	0.03
<b>Graffiti</b>	2.91e+4***	9.93e+3***	214.28***	66.38***	22.70***	12.51***
<b>W_CrimeRate</b>		0.64***		0.66***		0.51***
<b>Adjusted R<sup>2</sup></b>	0.203		0.171		0.140	
<b>Pseudo R<sup>2</sup></b>		0.452		0.436		0.321
<b>Log Likelihood</b>	-10277.4	-10139	-5520.11	-5378.38	-3357.24	-3269.39

p < 0.1\*, p < 0.05\*\*, p < 0.01\*\*\*

A new dependent variable, “W\_CrimeRate”, was included in each model when applied spatial lag regression. It is a spatial term representing a spatially lagged variable for weight matrix generated based on queen contiguity. Pseudo R<sup>2</sup> of spatial lag regression result is not a real R<sup>2</sup> and not comparable with the adjusted R<sup>2</sup> of OLS regression, thus the performances of the regression models were estimated through the comparison of the log-likelihood.

As noted before, log-likelihood is used to estimate the fit of the model with a higher value (less negative) indicating a better fit. As shown in Table 6.6, the spatial lag regression increased the log-likelihood values for all of the three models, from -10 277.4 to -10 139 for total property crime, from -5 520.11 to -5 378.38 for theft rate, and from -3 357.24 to -3 269.39 for BNE rate. The high significance of the spatially lagged dependent variable and the enhanced log-likelihood value both confirmed previous analysis that the dependent variables had significant spatial autocorrelation. Moreover, the estimated coefficients of both percent tree cover and road density decreased in

magnitude when applied spatial lag regression for all three models. For instance, the estimated coefficient of percent tree cover in model A was -151.48 using OLS regression, while the value was -92.64 using spatial lag regression. This suggested weaker influences of independent variables on crime rates when applying spatially lagged method.

The results of spatial lag regression indicated a significant inverse relationship between the three outcome variables and road density. The negative correlations were also significant between property crime rate and percent tree cover, between theft and percent tree cover, and between BNE rate and percent tree cover ( $p < 0.05$ ).

Other independent variables mostly showed significant influence on property crime. Population density and percent lone parent families had inverse relationships with property crime and each of the two categories of it, while percent low income families, number of street lights, and number of graffiti demonstrated direct relationships with theft and total property crime. The direct influences were not significant in model C (BNE), except for that from graffiti density. Unemployment rate showed insignificant relationships with all the three dependent variables.

### **6.3.2 Geographically Weighted Regression**

The next step involved applying GWR to the three models. Given the evidence that the independent variable unemployment rate did not show significant influence on crime, it was eliminated when applying GWR. Compared to the OLS regression results, GWR results, with lower AICc statistics and enhanced adjusted  $R^2$ s, proved the significance of spatial non-stationarity of the crime-tree and crime-road relationships (see Table 6.7).

The output DA polygons from GWR tool had their local coefficients for the tested explanatory variables, and the variation of the local coefficients for percent tree covered area and road density

in each model were mapped respectively (see Figure 6.12). Pseudo t-statistics were calculated and the DAs which had pseudo t-statistics close to 0 were regarded to have non-significant regression results thus symbolized by colour grey in the maps. The significance thresholds were set as  $|t| > 0.5$  for percent tree cover and  $|t| > 1$  for road density.

Table 6.7 Regression statistics comparison between OLS and GWR (unemployment rate variable eliminated from all three models)

Statistics	Model A		Model B		Model C	
	OLS	GWR	OLS	GWR	OLS	GWR
AICc	20490.2	20297.4	10968.7	10844.8	6721.8	6523.1
Adjusted R <sup>2</sup>	0.266	0.444	0.242	0.372	0.148	0.346

As shown in the property crime GWR maps (Figures 6.12(a) and (b)), coefficients of percent tree cover were becoming more negative in DAs that are closer to the downtown core of Vancouver, expressing greater effects on property crime rates in the downtown area and the Strathcona neighbourhood. On the other hand, Stanley Park and some residential DAs in the Kensington-Cedar Cottage neighbourhood showed a positive correlation between tree coverage and property crime rate, with a lower effect. Road density indicated a greater negative effect also in the downtown area and the northeast region to the Hastings-Sunrise neighbourhood, and the variation was relatively less than the coefficients of tree coverage. The theft GWR maps (Figures 6.12(c) and (d)) showed similar trends of coefficients for both of the dependent variables, with relatively smaller actual values.



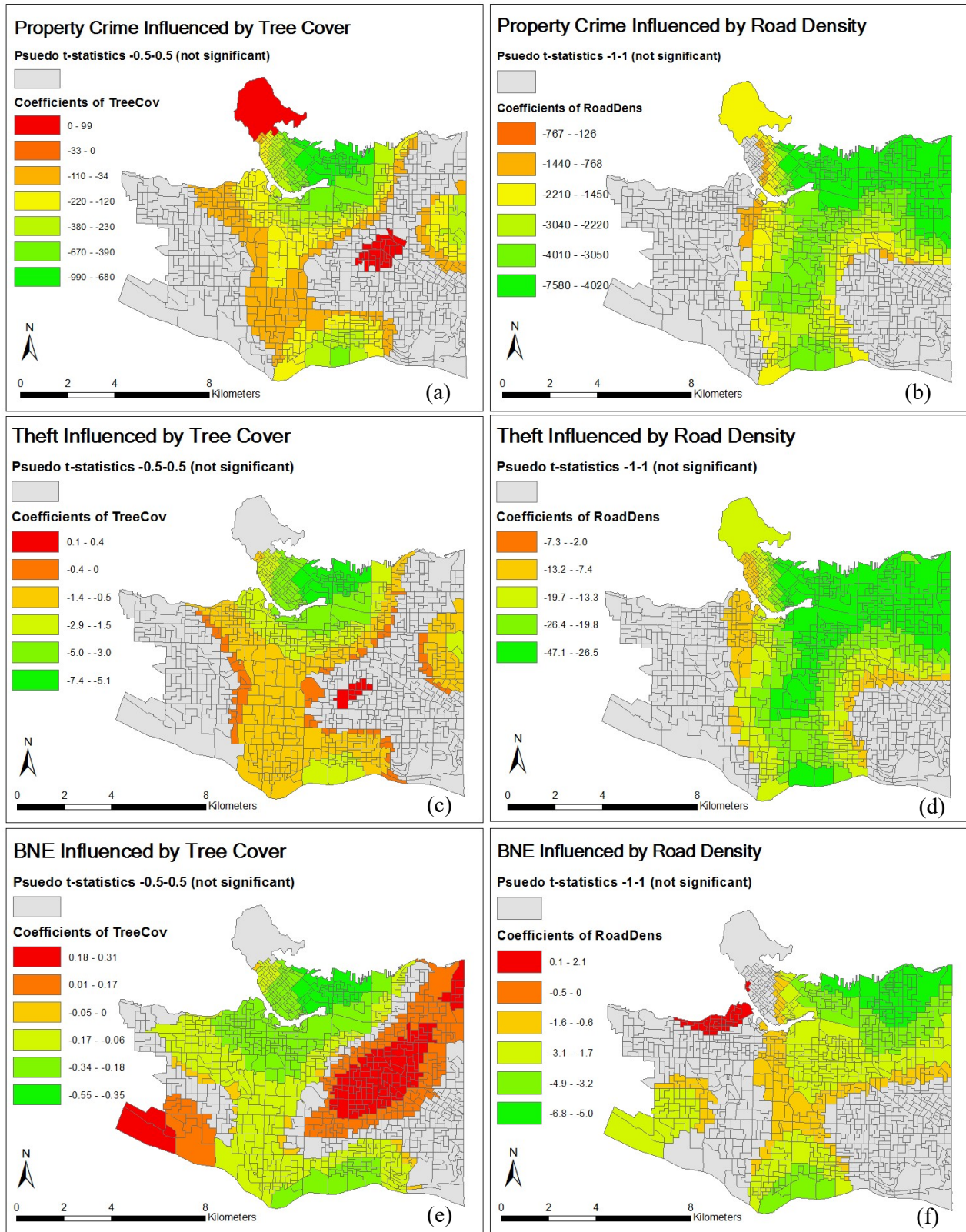


Figure 6.12 GWR maps showing spatial variation of the local coefficients

The BNE GWR maps (Figures 6.12(e) and (f)) were different from those of property crime and theft. The negative effects from percent tree cover on BNE rate were still greater in downtown Vancouver and the Southern shoreline, but much more DAs had demonstrated positive effects that were significant. Due to the low crime rate of BNE, the magnitude of effects from tree coverage and road density on BNE was much lower than that on theft and total property crime. In the north of the Kitsilano neighbourhood, some of the DAs had a positive coefficient of road density against BNE rate.

## **6.4 Chapter Summary**

This chapter has presented the results of the cross-sectional analysis on investigating the statistical relationship between tree coverage and crime, as well as between road density and crime. The ESDA provided evidence of possible negative impact from tree coverage on property crime and the presence of spatial autocorrelation of crime variables. And the following analysis using regression models had supported the findings with statistics. The spatial lag regression generated a better fit of the model data and the estimated coefficients of percent tree cover were all negative values for the three models against total property crime rate, theft rate, and BNE rate respectively. Although the ESDA showed no sign of relationship, road density also had negative coefficients with high significance in spatial lag regression results, demonstrating significant inverse relationship with property crime rate, theft rate, and BNE rate as well. The further examination using GWR had shown that percent tree cover and road density both had greater impact on property crime, theft, and BNE crime rates in downtown Vancouver.

## **Chapter 7 Discussion and Conclusions**

This chapter interprets the results and summarizes the key findings of this study by answering the original research questions posed in Chapter 1. The limitations of this study are then discussed and future work is proposed accordingly. The chapter finally concludes with notable implications and potential contributions of this study.

### **7.1 Summary of Findings**

#### **7.1.1 Presence of Influences from Tree Coverage on Property Crime**

The temporal analysis investigating the relationship between trees and property crime was inspired by the difference-in-differences approach comparing crime statistics in neighbouring area before and after the greening of selected vacant lots in Philadelphia, USA (Garvin et al., 2012). The study reported a non-significant decrease of violent crime after vacant lot greening, while this study focused on the impact of green vegetation against property crime. As it was summarized in the end of Chapter 5, five of the six examined DAs demonstrated an inverse relationship between vegetation coverage and property crime incidents, with the other one experienced increased property crime incidents when its vegetation covered area had also increased.

The DA which showed agreement between directions of vegetation coverage change and property crime count change does not necessarily suggest a direct relationship between the two variables. The increase of reported theft and BNE incidents might be the result of the completing of an apartment complex near downtown, increasing the residential population in the DA. In this case, the increase of crime incident count does not mean an increase in crime rate.

Moreover, the fluctuation in property crime counts in DAs with DAUID = 59153987 and DAUID = 59150680 indicates the uncertainty in crime trend. Complex social aspect is involved in crime

changes over time. In other words, crime is influenced by various factors such as population, social disorganization, etc., even crime itself in the neighbouring area. The variation of yearly property crime counts cannot all be considered a result of the change in vegetation coverage in the surrounding environment. Therefore, this temporal analysis approach only serves as a qualitative method. The results provide supportive evidence for the quantitative analysis using cross-sectional approach.

### **7.1.2 Influence of Tree Coverage on Property Crime**

The cross-sectional analysis has provided solid evidence of the inverse relationship between trees and property crime rate in Vancouver City. Firstly, airborne LiDAR data served as a reliable source of deriving tree crown areas and their spatial distribution in the city, with an overall accuracy of 98.4%. Compared to 30 m resolution Landsat imagery, LiDAR data provided details of tree crowns beside buildings and along city streets. Having set a parameter of 2 m when applying aggregate points, the extracted tree crown polygons from LiDAR points can be considered as having a spatial resolution of 2 m. In addition to the use of a small unit of analysis which was dissemination area, the high resolution and accuracy of tree-covered area extraction and calculation led to the precision in estimating its relationship with property crime.

ESDA was a useful technique to explore the general spatial patterns of crime data. Being compared with the tree coverage map, the spatial distributions of theft, BNE, and total property crime in Vancouver in 2013 exhibit evidence of crime rates relating to the spatial distribution of tree coverage. The outliers of crime variables were identified, with maximum values mostly locating in Downtown Vancouver, where there were less area covered by trees.

Further ESDA employing statistical tests proved the presence of spatial autocorrelation of property crime rates, suggesting that the property crime rate in a DA can be affected by the rate of neighbouring DAs. The high value clusters were locating in downtown core of the city, showing a pattern similar to many other municipalities in North America (e.g. Luo, 2012; Eckerson, 2013). Given the existence of spatial autocorrelation of the dependent variables, spatially adjusted regressions (spatial lag and GWR) were applied to provide a better estimation. For each model, spatial lag regression did generate a better fit for the data with a less negative log-likelihood value than that was in OLS regression results. GWR also proved its performance by lower AICc values. Therefore, only results generated from spatial lag regression and GWR are discussed.

Spatial lag regression models proved the qualitative findings with significant negative coefficients in regression results. According to Table 6.6 with the spatial lag regression results, BNE had a less negative coefficient in spatial lag result, which means a small magnitude of influence from trees. Moreover, the explanatory power of the BNE model, denoted by pseudo  $R^2$ , was smaller than the other two models. The first finding could be due to the fact that BNE has a smaller incident number than theft. The possible cause of the smaller explanatory power of the BNE model is that BNE rate is affected by other factor(s) which may have little influence on other property crime types. For example, the BNE rate is more likely related to the distribution of building types and numbers, as well as average income of the families, security facilities, etc.

### **7.1.3 Influence of Road Density on Property Crime**

A highly significant negative correlation was detected between road density and property crime, which disagree with the results of the study conducted in Kitchener-Waterloo region, Ontario (Du, 2015). Due to the limited number of researches published on this topic, we cannot conclude that whether this disagreement is the result of variation in the situation of different study area.

On the other hand, road density is somehow related to road complexity, with high road density probably suggesting a large number of road segments and a high level of complexity of the road network. For instance, as the research conducted in Tokyo, Japan (Murakami et al., 2004) denoted, residential areas usually have more number of roads and greater road density than commercial areas. As mentioned in Section 2.3, researches on road network and crime found that complex road network can reduce the number of property crime. The methodology in this study only found the statistical relationship between road density and property crime. More verifications needs to be done on the road characteristics in order to find the reason for their effects on crime, and this will be described in detail in Section 7.2.

#### **7.1.4 Spatial Variation of the Influences of Trees and Roads on Property Crime**

GWR provided more information into the research questions. Most importantly, it demonstrated the spatial variation of the tree and road densities' effects on property crime. Some notable findings are discussed below.

Tree coverage and road density not only have inverse influence on property crime, but also have different magnitudes of influence on property crime in different area in Vancouver. In terms of tree coverage, as presented in Chapter 6 (Figure 6.12), significant negative correlations existed in the central area of the city, and the magnitude of influence becomes greater in the downtown core of the city. However, unlike other DAs, Stanley Park DA and some of the Kensington-Cedar Cottage DAs demonstrated a positive correlation between property crime and trees. On the other hand, road density has less spatial variation in central Vancouver with most of the DAs showing a great inverse influence on property crime (Figure 6.12).

According to the tree coverage map (Figure 6.2), some of the DAs in Kensington-Cedar Cottage neighbourhood had high tree coverage in 2013. And according to the property crime distribution map (Figures 6.5, 6.6, and 6.7), these DAs also had relatively high property crime rate. However, as one of the most ethnically diverse neighbourhood in east Vancouver (City of Vancouver, 2016a), its high crime rate can be a result of a high social disorganization level rather than a high tree coverage of the neighbourhood. Stanley Park had a high property crime rate most likely because that it is a tourist attraction, which makes it vulnerable to theft and mischief. Therefore, for these exceptions, high crime rates are explained by other factors rather than merely depending on trees and road network.

The standard residuals of the local regressions estimated using GWR were also reviewed. The underestimated and overestimated results should be randomly scattered over the map, and clusters in the map indicate that there are factors that were not taken into the account in the model (ESRI, 2016). However, the high regression residuals were concentrated in the northern area of the city including Stanley Park and downtown area. Moreover, on exploring the local  $R^2$  values of GWR results of property crime model, it is noticed that lower local  $R^2$  values below 0.2 were clustered in Renfrew-Collingwood and Kerrisdale neighbourhood. These are also the results of variations in the social aspect among different neighbourhoods. Other important factors other than the included variables may be involved.

### **7.1.5 Enlightenments on Urban Planning**

The findings have inspired the strategies planning on urban design for property crime prevention. The inverse correlation between tree coverage and property crime suggests that the Greenest City Action Plan carried on in Vancouver can not only create beautiful views and clean air, but also reduce city property crime rate and provide a safe living environment for residents. In addition,

downtown core of the city is usually a place with high crime rate. According to the GWR maps, since the tree coverage has greater influence on property crime in downtown Vancouver, tree planting projects should be carried on in the downtown core commercial areas in order to reduce property crime rate.

The inverse relationship between road density and property crime suggests that urban planners can design complex road networks with more road segments and higher road density within the urban area to reduce property crime. In regions with lower tree coverage and lower road density, which are likely regions with high property crime rates, more police resource can be assigned for crime prevention purpose.

## **7.2 Limitations and Recommendations for Future Work**

### **7.2.1 Potential Sources of Error**

Despite the high accuracy of tree-covered area extraction, potential errors exist in the calculation of percent tree cover. One of them was georeferencing error. For instance, as shown in Figure 7.1, the borders of the two datasets offset each other. Dataset obtained from different sources may originally have had different projections, and this sometimes results in georeferencing errors. The methodology used in this study was less sensitive to this situation, attributing to the use of point crime data and spatial join rather than aggregated polygon crime data.

In addition to the fact that the crime data does not include all the crime incidents that took place in the city, crime data has another source of error due to the offsets of police-provided data. For privacy protection purposes, crime incidents were offset to the nearest road segment. Since the DA boundaries usually overlap with roads, a number of crime points were in the boundary lines of the DA polygons. Therefore, when using contains as the match option for spatial join, a point on the



boundaries or vertexes were counted multiple times, and resulting in overestimation of the crime rate in some of the DAs. It was also possible that a crime incident was offset into a nearby DA.

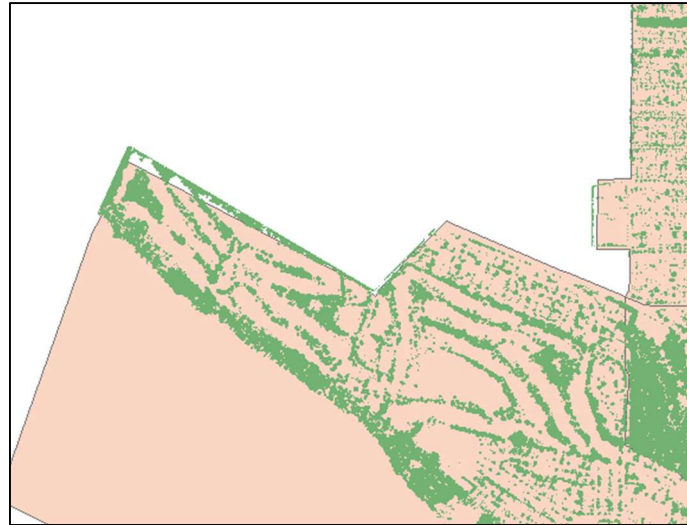


Figure 7.1 Example of georeferencing error in the west of study area

Social and economic developments are fast and unexpected (Ferreira et al., 2012). The use of 2006 unemployment rate data led to some error in the regression models. Among the 8 selected independent variables, unemployment rate was not significant in any of the three regression models, thus eliminated in GWR models. Compared to 2006 census data, 2011 census data is the most up to date demographic data source for this study, however, the actual statistics could be different in 2013.

### **7.2.2 Limitations and Recommendations for Future Work**

First of all, the study area of this study was limited to the City of Vancouver, and some of the results are representative within the city (e.g., the spatial variation of influences of trees and roads on crime). The study of the greater Vancouver area would possibly reveal more patterns and information. Also, similar research should be conducted in other municipalities in Canada to verify

the hypotheses. Besides, this study did not differentiate urban trees along streets and beside buildings from trees in parks. The capacity of reducing urban property crime by planting trees in these different locations is still uncertain. Detailed crime analysis needs to be done on urban parks and urban trees respectively.

Temporal analysis was done using readily available data from orthophotos and police provided crime data. Because of the restricted data availability, this study only focused on a period of 5 years. Due to the limited changes occurred in the city over a short period, the temporal analysis in this study has the same problem with the one that was conducted in Philadelphia (Garvin et al., 2012), with a rather small sample size which is insufficient in detecting statistically significant changes in crime. To improve the temporal analysis on vegetation-crime relationship, future research can be done by controlling greening projects in various locations and monitoring crime trends in their surrounding areas over a longer period. Quantitative analysis can also be conducted by calculating the yearly percent changing in vegetation coverage and crime rate. Population change in the studied area, as a major influential factor of crime, should also be monitored.

Furthermore, due to the restriction of violent crime data usage, this study did not include the analysis of violent crime data. However, as noted before, Vancouver also has a high Crime Severity Index (CSI) taking into account the seriousness of crime incidents as well, and violent crime consequences are usually more serious than property crime. Furthermore, vegetation and trees are likely to prevent violent crime by mentally restorative effects that restraining the psychological precursors to crime acts. Thus theoretically it has greater influence on crime types involving violence. The result of another study in Philadelphia (Wolfe and Mennis, 2012) indicated that burglaries and robberies, which are both violent crime, have a significant inverse relationship with trees while theft does not. Therefore, future work may be conducted to investigate the influence of

vegetation and road network on violent crime as well. The newly launched GeoDash web application enables the collection of homicide and crime against person incidents data.

In this study, road density was calculated according to its definition provided by the World Bank. However, the calculation method ignored the other characteristics of road network such as width and complexity, which are also correlated to road length. Therefore, the correlation between road density and property crime can be a result of property crime being influenced by other road network factors. Further studies are needed to take these factors into consideration. Road complexity can be quantified by the number of intersections in the road network, and road segments can be assigned different weights based on their widths or traffic volumes.

Lastly, the use of LiDAR dataset in this study was limited to the extraction of classified tree points. The average height of high vegetation can be derived from the dataset and used as another explanatory variable to investigate if crime rate is related to tree height. In addition, such high-spatial resolution LiDAR data with three-dimensional information has the potential for the construction of 3D models for further development of crime prevention applications.

### **7.3 Conclusions**

This study contributes to the Canadian literature on crime prevention through environmental design (CPTED) by investigating the influences of tree coverage and road density on property crime in the city of Vancouver, British Columbia. More specifically, temporal analysis on tree-property crime relationship was done by associating the trends of property crime from 2008 to 2013 to the change of vegetation coverage in the area, and cross-sectional analysis on tree-property crime and road-property crime relationships employed spatially adjusted regression models to

estimate the correlation between tree coverage and property crime and between road density and property crime using data from 2013.

The key findings of this study are that, temporal trend of property crime in a defined area has an inverse relationship with the vegetation coverage change in this area; and spatially, property crime and its two main categories, namely theft and BNE, have significant inverse relationships with both percent tree coverage and road density. Moreover, while road density has a relatively stable influence on property crime across the city, the influence of tree coverage varies spatially, with the greater influences concentrated in Downtown Vancouver and its surrounding neighbourhoods.

These notable findings provide supports for decision making in urban planning. Planting trees and developing new urban parks can reduce property crime in Vancouver, especially in its downtown core. And allocating police force in neighbourhoods with low tree coverage and low road density can be an effective way of saving police resources while also keeping the city safe.

Green vegetation can provide not only beautiful views, but also clean and fresh air, and well-developed road network can provide residents with convenience in life. The findings from this study also suggests that property crime reduction is a potential benefit of urban trees. In conclusion, urban planners and city police can work together in environmental sustainable development and crime reduction simultaneously.

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