# Crime Seasonality: Exploring the Annual Temporal and Spatial Patterns of Property Crime in Vancouver, BC and Ottawa, ON

**by**

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## Abstract

It is in the best interest of policy makers to understand not only which crime prevention methods are most effective, but also when and where they are appropriate to apply. This study investigates whether seasonal variation exists temporally across different property crime types and whether these same offences possess micro-spatial patterns that vary substantially over the calendar year. A series of OLS regressions and spatial point pattern tests were employed to examine the corresponding temporal and spatial patterns of crime in two Canadian cities with differing climates, namely Vancouver, BC and Ottawa, ON. Overall, results suggest that: (a) property crimes exhibit distinct temporal peaks in humid continental climates (i.e. Ottawa) and not in temperate ones (i.e. Vancouver); (b) regardless of climate, micro-spatial patterns of property crime remain relatively constant throughout the year; and (c) the seasonal variations of crime should be studied at a disaggregate level.

**Keywords**: crime seasonality; climate; weather; property crime; routine activities theory; spatial point pattern test

*To my parents, Rob and Tania, and my brother Connor. You have shown me that I am stronger than I ever could have imagined. None of this would have been possible without your love and encouragement.*

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***Doc****: You ever think about quitting?*

***Sully****: Only about 25 times a day.*

***Doc****: Why don't you?*

***Sully****: Day's not over yet.*

*-Third Watch, Season 1, Episode 2*

*"Anywhere But Here"*

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# Chapter 1.

# Introduction

The study of crime seasonality has many functions in the criminological literature. Given some of the widely accepted environmental criminology theories, the knowledge of when and where crimes occur became increasingly important to criminologists. While some theories such as crime prevention through environmental design (CPTED) (Jeffery, 1969), routine activities theory (Cohen & Felson, 1979), geometric theory of crime (Brantingham & Brantingham, 1981), rational choice theory (Clarke & Cornish, 1985) and crime pattern theory (Brantingham & Brantingham, 1993) emphasize the importance of immediate spatial and temporal convergence, an understanding of overall patterns throughout the year provide additional insight into the causes of crime. Acknowledging not only the presence of temporal fluctuations, but also the causes of such variations can have pragmatic policy implications.

One of the strengths of many environmental criminology theories is the practicality of their subsequent crime prevention methods. Theories that date as far back as social disorganization have emphasized the idea that there are not generally problem people, but instead problem places that foster the adoption of deviant behaviour (Shaw & McKay, 1942; 1969). More recently, criminologists have thus argued that it is easier to change problem places as opposed to problem people (Sherman, Gartin & Buerger, 1989; see also Eck & Weisburd, 1995). Policy has since been implemented based on the notion that by altering the environment and “manipulating opportunities” that a potential offender enters into, s/he may decide to desist from crime (Clarke, 1980, p.140).

Because a particular environment can have such a dramatic impact on adapting human behaviour, the proper understanding of why seasonal fluctuations in crime do (or do not) occur is crucial. As Andresen and Malleson (2013) have explained, it is, therefore, in the best interest of policy makers to understand not only which crime prevention methods are most effective, but where they are appropriate to use. Furthermore, it is crucial to know when certain initiatives are supposed to impact crime thus emphasizing the importance of knowing when to evaluate the effectiveness of a crime prevention method (Andresen & Malleson, 2013, p. 32; see also Block, 1983). While the majority of crime seasonality literature has focused on patterns of assault, other literature has emerged more recently assessing temporal fluctuations of other crime types. What has gone largely understudied, however, is how the respective spatial patterns are impacted over time (Brunsdon, Corcoran, Higgs & Ware, 2009, p.906; Andresen & Malleson, 2013, p.25). Such information may prove helpful in contributing to more crime-specific prevention models (see Clarke, 1980). As such, this thesis will explore both the temporal and spatial aspects of crime seasonality.

# Chapter 2.

# Theoretical Trends in Crime Seasonality

Crime peaks, particularly in the summer months, have been demonstrated many times in the literature, however, there is continued debate over which specific crime types experience such phenomena and when (Uittenbogaard & Ceccato, 2012, p.150; McDowall, Loftin & Pate, 2012, p.407). Research on this topic dates back to the work of Quetelet (1842) who observed that property offences were higher in the winter months whereas crimes against persons peaked in June. Quetelet (1842) argued that this pattern was likely due to the fact that winter months brought about more difficult conditions thus evoking criminal activity of necessity (i.e. stealing goods). In the summer months, however, he believed that crimes against persons were precipitated by higher temperatures that lead to increased discomfort and aggression as well as increased "collisions" with other people (Quetelet, 1842, p.56). During the summer, the former implied that higher temperatures brought on violent behaviour due to physical discomfort, while the latter involved the principles of environmental criminology namely that the more people come into contact with one another, the more likely they are to cross paths with a potential offender and/or victim.

## 2.1. Temperature Aggression Theory

Temperature aggression theory hypothesizes that because higher temperatures act as "psychological causal mechanisms" in persons, increased temperatures lead to greater aggression thus increasing crime rates particularly in the summer months (Hipp, Bauer, Curran & Bollen, 2004, p.1338). Furthermore, recent research has shown that a relationship does exist between aggression and temperature (see Baron & Bell, 1976; Anderson & Anderson, 1984). However, based on the principles of temperature aggression theory, it is only able to account for the increase in violent crime in warmer months. Research has since found that seasonal peaks exist for other crime types, such as property crime (Hipp et al., 2004, p.1363). When analyses were run testing the impact of temporal and weather variables on homicide, for example, all of the temporal variables were statistically significant and explained more of the variance in the model whereas only a limited number of the weather variables, namely temperature, were able to contribute to the explanatory capacity of the model (Ceccato, 2005, p.317). In a study of seven different crime types between 1977 and 2000, McDowall et al. (2012) found that monthly temperatures "have clear importance in generating seasonal crime cycles [but that there is] little support for the notion that temperature variations can fully explain the seasonal effects" (McDowall et al., 2012, p.399). The importance of a temporal component provides support for the use of the routine activities theory that suggests fluctuations in crime rates are the result of the change in activities that people engage in over the course of the year (Cohen & Felson, 1979). Routine activities theory posits that as temperatures change, so do the activities of people. As such, routine activities theory is capable of predicting the occurrence of many crime types, not just those involving aggressive behaviour.

Despite some of the evidence discrediting the temperature aggression theory, researchers have also concurred that the impact of temperature cannot be completely ruled out (Hipp et al., 2004, p.1365; McDowall et al., 2012, p.399). Some have argued that an interaction effect between temperature and temporal variation may exist (Ceccato, 2005, p.317). It can also be seen as a contributing factor to routine activities theory in two ways. First, it can provide enough physiological discomfort that it elicits aggressive behaviour and motivates an offender. Second, it can encourage the departure from the home to engage in outdoor activities thus increasing the convergence of potential offenders and victims as well as leaving homes unguarded (Andresen & Malleson, 2013, p.25). Due to its ability to explain violent and property crime (Cohn & Rotton, 2000), routine activities theory will be examined and, subsequently, applied to the present research.

## 2.2. Routine Activities Theory

In their influential work, Cohen and Felson (1979) developed routine activities theory in attempt to explain the existence of a sociological paradox in the American post-World War II society, namely that the violent and property crime rate in the United States were increasing but living conditions were simultaneously improving (Cohen & Felson, 1979, p.588). As a result, they asserted that the occurrence of “direct-contact predatory” crimes were the product of the spatial and temporal convergence of three elements: “a) motivated offenders, b) suitable targets, and c) the absence of capable guardians” (Cohen & Felson, 1979, p.589). Put simply, the quotidian activities of people can influence their likelihood of involvement in a criminal event. They also argued that should one of the three elements in the model be altered (or removed) it can have a substantial impact on the opportunities for crime and possibly even prevent a criminal act altogether (Cohen & Felson, 1979, p.590). Furthermore, it should be understood that the criteria required for each of the three aforementioned elements may be different for each crime type. In other words, the criteria sought out by a motivated offender for the suitability of a target for robbery may be very different than that for break and enter. As such, we need to consider the crime-specific factors that satisfy Cohen & Felson’s (1979) model (see also Clarke & Cornish, 1986). These will likely result in different hypotheses for the study of different crime types.

It should also be noted that up until this point Cohen & Felson (1979) argued that while attention had been given to the spatial analysis of crime, less work was available on its co-dependence with temporal factors (Cohen & Felson, 1979, p.589). As a result, the authors made the case for the utility of analyzing crime at a micro-level (Cohen & Felson, 1979, p.593). Their emphasis on spatial and temporal convergence lends support for more specific/precise units of analysis required for a more thorough understanding of criminal events. Subsequent empirical work on this matter will be discussed later for contextualization of some of the analyses run in this study.

Returning to their aforementioned sociological paradox, however, Cohen and Felson (1979) argued that the increasing violent crime rate was a product of increased well-being and prosperity in the United States. As economic conditions in America were improving, people had more disposable income available to them. This, they argued, allowed people the ability to leave their households more frequently and engage in leisure activities (Cohen & Felson, 1979, p.593). The resulting effect, however, was an increase of spatial and temporal convergence with motivated offenders and suitable targets. They conclude that, ironically, increased crime is a result of the "byproduct of freedom and prosperity" brought about by an increasingly affluent American society (Cohen & Felson, 1979, p.605). This theory has since been pivotal to the continual development of environmental criminology and has also become one of the most predominant theories in the criminological literature, more generally.

## 2.3. Geometric Theory of Crime

In their influential work on geometry of crime, Brantingham and Brantingham (1981) start out by outlining the various propositions they feel contribute to criminal events. For instance, they assert the assumption that criminal motivation exists among all persons but that the strength of their motivation varies between them. They also argue that environments emit various cues that can be used for criminal purposes given sufficient motivation but that a crime can only occur provided good victims or targets are present at a specific time. These offenders will then generate a crime template of good and bad opportunities for crime that s/he consults in search of victims or targets. In other words, potential offenders consciously and unconsciously learn which environmental cues to look for in order to increase their likelihood of carrying out a crime successfully. Moreover, if a crime is completed without detection, the template is reinforced within the offender (Brantingham & Brantingham, 1981, pp.232-3).

The authors also point out that offenders spend the majority of their time engaged in legitimate activities. That is, they carry out their quotidian activities at home, school, work (referred to as nodes) and the paths they travel between these locations (Brantingham & Brantingham, 1981, p.238). As a result, offenders develop what they refer to as an action space and subsequently an awareness space. While the former consists simply of the location where offenders spends their time, the latter is a mental/cognitive understanding of these known places and their surroundings. In other words, the authors argue that individuals' areas of highest awareness are places that they have been to and/or seen. As a result, the patterns of mobility of all persons are quite predictable and relatively stable (Brantingham, & Brantingham, 1981, p.238). After all, the nodes each person frequents and the paths that we use to travel between them are bound by the design of urban planners. In other words, many of us share the same nodes and paths thus increasing our likelihood of victimization if we share them with motivated offenders (Andresen, 2010, p.20).

Given these parameters, Brantingham and Brantingham (1981) were then able to characterize the basic target selection patterns commonly employed by offenders. For instance, they argue that the selection process involves consideration for what makes a "good" target, such as level of "potential payoff and the risk of apprehension" (Brantingham & Brantingham, 1981, p.235). In order to make such determinations the offenders must be aware of the existence of the target, its location and characteristics. As a result, it will likely be present in location(s) that the offender has been. Based on the aforementioned assumptions regarding offender movement, it can then be hypothesized that the targets that will likely be selected will be close to one of the offender's nodes (e.g. his/her home, place of work, etc.). Therefore, the annual quotidian activities of motivated offenders will likely have an impact on when and where crimes are committed.

### 2.3.1. Crime Generators vs. Crime Attractors

Due to the importance that people's routine activities have on their risk of victimization and/or likelihood of offending, the concept of crime attractors and crime generators should also be discussed. Brantingham and Brantingham (1995) have argued that crime more often occurs at places where people feel relatively safe. As many studies have shown, and as predicted by routine activities theory, the likelihood of being victimized increases in areas that many people frequent such as shopping malls, parking lots and transit stops as opposed to dark back alleys (Brantingham & Brantingham, 1995, p.6). As a result, they introduced two monumental concepts to the environmental criminology literature: crime generators and crime attractors.

In their first concept, crime generators, Brantingham and Brantingham (1995) refer to locations that attract large numbers of people for purposes other than criminal activity. Such places can include shopping malls, entertainment complexes and sports stadiums. While these particular places may not be criminogenic in themselves, they create situations in which motivated offenders can act simply due to the presence of opportunity. In other words, offenders may not have necessarily set out to commit an offence at that particular time or location, but once an opportunity presents itself, they act upon it (Brantingham & Brantingham, 1995, p.7). Within the seasonality literature, there is “strong support for [the] proposition [that] entertainment establishments have a positive effect on both overall levels of crime and seasonal oscillations in crime” (Hipp et al., 2004, p.1359). This concept provides important insight and support to the principles of routine activities theory in accounting for crime seasonality (or lack thereof).

Brantingham and Brantingham (1995) also proposed the notion of crime attractors in their work. This concept refers to the particular places that possess criminally favourable characteristics that increase opportunity for motivated offenders. These locations are often conducive to crime in that they present a reduced likelihood of detection. Such locations can include “bar districts; prostitution areas; drug markets…[and] large insecure parking lots in business or commercial areas” (Brantingham & Brantingham, 1995, p.8). Because these places are so crime-friendly, the authors posit that offenders will take the time and effort to go out of their way to travel to such places in order to carry out their crimes (Brantingham & Brantingham, 1995, p.8; see also Ratcliffe, 2011). Based on the definitions of these two concepts, it becomes apparent that the spatial patterning of crime may vary depending on the type of crime being studied. Once again, further support is given to the notion of creating crime-specific models to predict criminality and try to prevent it (Clarke & Cornish, 1986, p.150). In the study of crime seasonality, it seems advantageous to study crime at a disaggregate level in order to account for potential differences in when and where different crime types are occurring.

Lastly, it should be noted that Brantingham and Brantingham (1995) also argued that cities also possess “crime-neutral areas” that act as neither crime attractors nor crime generators (p.8). Moreover, they claimed that such places were more abundant within a city and although they would experience some crime, they would not be as prolific as the crime generators and attractors (Brantingham & Brantingham, 1995, pp.8-9). More recently, these assertions have been empirically supported by research in the crime at place literature. More specifically, Weisburd, Bushway, Lum and Yang's (2004) study of micro-spatial crime patterns in Seattle revealed that the majority of street blocks experienced little to no crime. Moreover, their trajectory analyses revealed that these crime levels remained relatively stable over a 14 year period (Weisburd et al., 2004). This study was replicated using Vancouver data and generated similar results (see Curman, Andresen and Brantingham, 2014).[1] As such, it is probable that crime generators and/or attractors contribute largely to the disproportionately high levels of crime at very limited places within a city thus strongly contributing to the overall spatial patterns of offending.

## 2.4. Conclusions

The theoretical concepts described above demonstrate how changes in quotidian activities can have a drastic impact on an offender's discovery of criminal opportunities. Moreover, the locations where such crimes take place will likely fluctuate because the routine activities of victims and offenders are not static throughout the year. For instance, as discussed above, the very nature of some crime generators and attractors such as sports arenas and shopping malls have their own schedules of events that attract people seasonally and crime patterns will likely vary accordingly. As such, these theories demonstrate the importance of studying both the temporal and spatial aspects of crime simultaneously in order to assess the true nature of offending patterns.

[1] A more detailed discussion of the Weisburd at al. (2004) and Curman et al. (2014) articles can be found in chapter 5 of this thesis.

# Chapter 3.

# The Present Study

While a great deal of focus has gone into studying the temporal component of crime seasonality, far fewer attempts have been published regarding the spatial aspect of seasonality (Brunsdon, Corcoran, Higgs & Ware, 2009, p.906). Moreover, little to no empirical focus has been placed on the spatial component of seasonality at a micro-spatial scale of analysis (Andresen & Malleson, 2013, p.33-4). This study attempts to address both of these concepts by investigating the following research questions:

(1) does seasonal variation exist within property crime types?

(2) what temporal and micro-spatial seasonal crime patterns are generated in cities with differing climates?

(3) should crime data be disaggregated in the study of crime seasonality?

(4) do micro-spatial patterns of crime change with the seasons?

All of these questions are consistent with the principles of routine activities theory and should provide a greater understanding of concepts that have emerged in the field of environmental criminology. By testing for seasonal patterns in new data sets, it is hoped that additional insight can be applied to an area of research that has reached no firm consensus on the topic. Furthermore, by analyzing data at both a disaggregate and micro-spatial scale, distinct trends will likely emerge that would otherwise go unobserved. Lastly, because the above research questions can be characterized as testing either the temporal or spatial components of crime seasonality, the analyses conducted in this thesis will be divided into two distinct chapters. Following a discussion of the study settings and data sources that will be used in all analyses, the temporal chapter will describe the previous literature that has been conducted regarding crime seasonality followed by the methods, tests and results of the analyses. The subsequent chapter that considers the spatial component of these crime trends will follow a similar format.

## 3.1. Study Settings and Data Sources

The research questions were investigated using police report data from two Canadian cities, namely Vancouver, British Columbia and Ottawa, Ontario. These sources were publicly available on the Vancouver Open Data Catalogue (http://data.vancouver.ca/datacatalogue/index.htm) and Ottawa Police Department websites (http://www.ottawapolice.ca) respectively. These two cities were chosen due to their differing climates, similar national population rankings and availability of sufficient information permitting the following analyses.

### 3.1.1. Vancouver, BC

The census metropolitan area (CMA) of Vancouver, British Columbia is the largest populated metropolitan area in Western Canada and the third largest CMA in Canada (Statistics Canada, 2015a). Between the three census reports produced by Statistics Canada between 2001 and 2011, Vancouver's CMA population has been continually growing. In 2001, the population was recorded as 1.9 million persons. It grew by 2006 to approximately 2.1 million and increased again by 9.3% to 2.3 million residents in 2011. Excluding metropolitan areas, however, the city of Vancouver recorded a population of 603,502 residents in 2011. This constituted a 4.4% increase from the 578,041 residents reported in 2006. As such, Vancouver is the most populated city in British Columbia and the 8$^{th}$ most populous city in Canada (Statistics Canada, 2015a).

Vancouver is a coastal city situated on the Pacific Ocean and is located approximately 50km north-west of the Washington State border. Its latitude and longitude coordinates are 49.2°N and 123.1°W respectively (Environment Canada, 2015a). According to the Köppen-Geiger Climate Classification, Vancouver's climate has been described as moderate oceanic (Classification: Cfb). This means its main climate is characterized by warm temperatures, fully humid with high precipitation, and warm summers (see Kottek, Grieser, Beck, Rudolf & Rubel, 2006). Vancouver often experiences high levels of rainfall from October to March, warm summers and relatively warm winters with little snowfall. Moreover, the temperature fluctuations between winter and summer are relatively small. Based on 29 years-worth of historical climate data, Environment Canada (2015a) lists average daily temperatures in Vancouver that range between 3.6°C in December to 18.0°C in July and August. Extreme temperatures fell between -17.8°C and 34.4°C. Average rainfall levels are more drastic and range from 35.6mm in July to 185.8mm in November. Conversely, average snowfall amounts remain relatively low and range from 0cm in April through October and 15cm in December (Environment Canada, 2015a).

The Vancouver police-report crime data used in this study cover an 11 year period from 2003 to 2013 and provided the month of occurrence and addresses anonymized to the 100-block. In other words, the last two digits of each listed address were removed prior to their posting in the database. The dataset contained various property crime types that included: commercial break and enter, mischief, theft from vehicle and theft of vehicle. Frequency tables for this data can be found in appendix A.

### 3.1.2. Ottawa, ON

Ottawa, Ontario is the national capital of Canada and, according to the 2011 census, its CMA possesses the fourth highest ranked metropolitan population in the country[2] (Statistics Canada, 2015b). More specifically, the 2006 census reported an Ottawa-Gatineau CMA population of over 1.1 million residents and this figure subsequently grew 9.1% to 1.2 million residents in 2011. Looking solely at the residential statistics in the city of Ottawa, however, the 2011 census revealed a population of 883,391 residents. These figures make Ottawa the fourth most populous city in Canada and the second in the province of Ontario, short of Toronto (Statistics Canada, 2015b).

[2] Note: This statistic is based on the population of Ottawa-Gatineau as per data collection in the 2011 Canadian census.

The city of Ottawa is located on the south side of the Ottawa River across from Gatineau, Québec. It is situated north east of the Great Lakes and is approximately 200km west of Montreal and 450km north east of Toronto, ON. Its latitude and longitude are 45°N and 75°W respectively (Environment Canada, 2015b). The Köppen-Geiger Climate Classification lists Ottawa as a humid continental climate (Classification: Dfb). This refers to a climate consisting of snow, fully humid precipitation and warm summers (Kottek et al., 2006). Ottawa has four distinct seasons with larger magnitude differences in temperature than Vancouver. Moreover, Ottawa experiences less rainfall overall but with higher occurrence in the summer months. Winters are also colder with much more snowfall. Based on historical climate data from 1981-2010, Environment Canada lists average daily temperatures that range from -10.3°C in January to 21.0°C in July. Extreme temperatures have historically ranged between -36.1°C and 37.8°C. Average rainfall amounts range from 18.7mm in February to 92.8mm in June and average snowfall ranges from 0cm in May through September and can reach as high as 54cm in January (Environment Canada, 2015b).

The Ottawa police-report data examined in the following sections contains crime data over 3 years, namely 2006 to 2008. For each observation, information regarding the date, time, and address anonymized to the 100-block were included. For all years of data the following crime types were included: commercial break and enter, residential break and enter, robbery and theft of vehicle. From April 2007 to December 2008, data for mischief were also recorded. As such, in some cases partial analyses using mischief were possible and more specific information on their inclusion will be discussed in subsequent chapters. Frequency tables for the Ottawa data can be found in appendix B.

### 3.1.3. Crime Rates in Canada, 2003-2013

Since the early- to mid-2000s, crime rates in Canada have been steadily decreasing. These trends at both the national level as well as across the four most populated census metropolitan areas can be seen in Table 3.1.[3] As previously discussed, Vancouver and Ottawa are the third and fourth most populous CMAs in Canada next only to Toronto and Montreal. Despite these decreasing crime trends from 2003-2013 and lesser population, Vancouver consistently possesses the highest overall crime rate of the four listed CMAs. In fact, its total crime rate remains more than double that of Toronto in all years. As per the Canada-wide statistics, Vancouver also experiences more crime than the national average. Interestingly, however, Vancouver has seen the largest net decrease in its crime rate over this time period. Ottawa, on the other hand, has maintained a more stable decreasing trend. Its crime rate has been consistently lower than the national average and has had a total crime rate that is approximately half of Vancouver's (see table 3.1). Given these overall trends it is, thus, unsurprising that Vancouver's rates of property and violent crime are also the highest amongst these cities and the national average. The rates of both crime classifications in Vancouver are nearly double the corresponding figures in Ottawa. Interestingly, although the property crime rates in both cities appear to decrease over time, the violent crime rates do not show similar patterns.

[3] Table 3.1 was generated by the author based on figures contained in the Canadian Socio-economic Information Management System (CANSIM) using the Computing in the Humanities and Social Sciences (CHASS), through the University of Toronto website (see http://dc.chass.utoronto.ca/chasscansim/). Official data from Statistics Canada can also be found in the following publications: Wallace, 2004; Sauvé, 2005; Gannon, 2006; Silver, 2007; Dauvergne, 2008; Wallace, 2009; Dauvergne & Turner, 2010; Brennan & Dauvergne, 2011; Brennan, 2012; Perreault, 2013; Boyce, Cotter & Perrault, 2014.

**Table 3.1. Police-reported crime rates in the 4 most populated census metropolitan areas in Canada, 2003-2013**

| | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **1. Toronto** | | | | | | | | | | | |
| 2011 Pop: 5.6 million | | | | | | | | | | | |
| **Total Crime** | **5,046** | **4,604** | **4,414** | **4,493** | **4,264** | **4,020** | **3,829** | **3,605** | **3,411** | **3,164** | **2,941** |
| Violent Crime | 1,106 | 1,050 | 1,050 | 1,054 | 1,047 | 992 | 948 | 915 | 883 | 816 | 749 |
| Property Crime | 3,404 | 3,073 | 2,909 | 3,035 | 2,853 | 2,678 | 2,554 | 2,378 | 2,248 | 2,090 | 1,936 |
| **2. Montreal** | | | | | | | | | | | |
| 2011 Pop: 3.8 million | | | | | | | | | | | |
| **Total Crime** | **6,238** | **6,007** | **6,014** | **6,037** | **5,604** | **5,588** | **5,490** | **5,065** | **4,800** | **4,582** | **4,072** |
| Violent Crime | 1,187 | 1,175 | 1,177 | 1,160 | 1,097 | 1,128 | 1,105 | 1,051 | 1,027 | 968 | 903 |
| Property Crime | 4,599 | 4,389 | 4,365 | 4,314 | 3,947 | 3,902 | 3,819 | 3,468 | 3,239 | 3,063 | 2,657 |
| **3. Vancouver** | | | | | | | | | | | |
| 2011 Pop: 2.3 million | | | | | | | | | | | |
| **Total Crime** | **11,488** | **11,407** | **10,671** | **10,052** | **9,271** | **8,622** | **8,123** | **7,645** | **7,263** | **7,195** | **6,897** |
| Violent Crime | 1,562 | 1,582 | 1,570 | 1,589 | 1,510 | 1,455 | 1,427 | 1,337 | 1,226 | 1,150 | 1,023 |
| Property Crime | 8,800 | 8,431 | 7,656 | 6,990 | 6,393 | 5,779 | 5,337 | 4,956 | 4,669 | 4,786 | 4,642 |
| **4. Ottawa** | | | | | | | | | | | |
| 2011 Pop: 1.2 million | | | | | | | | | | | |
| **Total Crime** | **6,236** | **5,569** | **5,635** | **5,575** | **5,324** | **4,739** | **4,534** | **4,266** | **4,110** | **4,103** | **3,615** |
| Violent Crime | 1,190 | 1,085 | 990 | 912 | 879 | 779 | 766 | 706 | 655 | 643 | 672 |
| Property Crime | 4,458 | 3,947 | 4,093 | 4,114 | 3,947 | 3,490 | 3,365 | 3,026 | 2,950 | 2,938 | 2,442 |
| **Canada** | | | | | | | | | | | |
| 2011 Pop: 33.5 million | | | | | | | | | | | |
| **Total Crime** | **7,770** | **7,600** | **7,325** | **7,245** | **6,908** | **6,631** | **6,461** | **6,159** | **5,779** | **5,632** | **5,190** |
| Violent Crime | 1,435 | 1,404 | 1,389 | 1,387 | 1,354 | 1,334 | 1,322 | 1,292 | 1,236 | 1,197 | 1,092 |
| Property Crime | 5,299 | 5,123 | 4,884 | 4,809 | 4,525 | 4,258 | 4,122 | 3,838 | 3,536 | 3,434 | 3,146 |

Source: Statistics Canada, Canadian Socio-economic Information Management System (CANSIM) using Computing in the Humanities and Social Sciences (CHASS), University of Toronto (see http://dc.chass.utoronto.ca/chasscansim/)
Note: Rates are calculated per 100,000 persons
Note: Total Crime = all criminal code violations excluding traffic violations

# Chapter 4.

# The Temporal Component of Crime Seasonality

## 4.1. Literature Review

Empirical testing of routine activities theory with respect to crime seasonality has predominantly focused on the patterns of assault (see Michael & Zumpe, 1983; Block, 1984; Harries, Stadler & Zdorkowski, 1984). More recently, however, research has begun to emerge regarding various crime types. The majority of these papers employ routine activities as the theoretical framework for the research. Due to the opportunity specific needs of certain crime types, a review of the literature is broken down and discussed according to specific crime types.

### 4.1.1. Assault

While much of the research on seasonality has not come to a firm consensus on the temporal trends of various crime types, the empirical literature has consistently found statistically significant peaks for assault in the summer months (Michael & Zumpe, 1983, p.884; Harries & Stadler, 1983, p.247; Cohn, 1990, p.281). Most authors attribute this trend to explanations developed via routine activities theory in that, the summer months bring about the engagement of leisure activities out of the home (Andresen & Malleson, 2013, p.25; Uittenbogarrd, & Ceccato, 2012, p.150). While this is the overarching crime trend, arguments have also been made that while violent crime (such as assault) is highest among adults in the summer, it is the greatest in the fall among youths (Carbone-Lopez & Lauritsen, 2013, p.410-1). They speculate that assaults among youths may be more prevalent in the fall due to their return to school and increased interactions with other students (Carbone-Lopez & Lauritsen, 2013, p.419). Underlying trends such as these lend support to the notion that studying different peoples' routine activities is crucial in understanding the true crime trends and lends support to disaggregating data down to different crime types as well as different populations at risk.

### 4.1.2. Sexual Assault/Rape

Research into the seasonality into sexual assault is limited and, of the literature that exists, there seems to be no firm consensus on any distinct annual rhythms for the offence. Some studies have found significant peaks for rapes in the summer months (Michael & Zumpe, 1983, p.884; Perry & Simpson, 1987, p.84). Others, however, have not found statistically significant relationships between rape and higher temperatures (DeFronzo, 1984, p.198-9). Later on, Cohn (1993) discovered that in three years worth of data, rapes were not significantly related to months, but were instead affected by the presence of light and temperature. She speculates that seasonality may not be present for rapes due to the premeditation that is often involved in such offences (Cohn, 1993, p.80). This characteristic can, thus, impact the temporal and spatial trends of sexual offending. For instance, it is far more likely for the offender and victim to know one another prior to the offence (Maguire & Brookman, 2009, p.517). As such, it is very probable that these sexual offenders are able to assault their victims at locations, such as their homes, regardless of the season (Leclerc, Wortley & Smallbone, 2010, p.649). Furthermore, it has also been found that in order to increase criminal achievement, many sexual offenders opt to find one victim and assault him or her on multiple occasions as opposed to attempting to find multiple victims (Lussier, Bouchard & Beauregard, 2011, p. 441). Therefore, in some cases, these crimes may not necessarily be brought about by victims and offenders coming into contact with one another because of overlapping routine activities, but are instead occurring at a steadier rate over the year. However, in the case of serial rapists, other empirical research has demonstrated that initial contact locations between the offender and victims are often directly related to the “activity nodes and routine pathways” of those involved (Beauregard, Proulx & Rossmo, 2005, p.584; see also Brantingham & Brantingham, 1995; Alston, 1994).[4] It should thus be noted that these differences may be dependent on whether the offender

[4] Many of the examples used for the spatial analysis of serial rape have examined cases when the involved parties were strangers.

is known to the victim (see Alston, 1994; Rossmo, 1994; Rossmo, 2000). As a result, very different annual temporal and spatial patterns will likely emerge depending on the relationship between the parties involved. This could provide some explanation for the discrepancy within the seasonality research.

### 4.1.3. Homicide

Research on the seasonal fluctuations of homicide is also inconsistent (Cohn, 1990, p.286). In McDowall et al.'s (2012) analysis of multiple crime types, they found that while homicide was highest in the summer months, its peak was not significantly greater than the peak that emerged in December (McDowall et al., 2012, p.399). In her study of homicides in Brazil, Ceccato (2005) also found that the greatest number of homicides occurred in the summer (Ceccato, 2005, p.312). These trends were attributed to the fact that increased numbers of people were travelling to crime generators, such as festivals and gatherings, and coming into contact with one another thus increasing the likelihood of conflict. Returning to the temperature-aggression vs. routine activities theory debate, Ceccato (2005) found that temporal variables "make a more significant contribution to explaining the variance in the models" than the weather variables employed (Ceccato, 2005, p.317).

Studies using data from both the United States and Canada, however, have found no evidence for any consistent seasonal trends in homicides (Michael & Zumpe, 1983, p.884; Dagum, Huot & Morry, 1988, p.130). Moreover, an analysis of homicides in Israel revealed little support for the presence of any sort of seasonal fluctuations (Landau & Fridman, 1993, p.177). In these cases, the authors tended to focus on the fact that murder was accompanied by various motives and that the victims were often known to the offenders (Landau & Fridman, 1993, p.169). In Canada it has been reported that "most victims knew their killer" and that the "majority of accused persons [were acquaintances] followed by family members" (Mahony, 2011, p.10; see also Salfati & Dupont, 2006, p.128). Once again, it appears as though the consideration of the relationship between victim and offender can impact the time and place of an offence, in this case homicide. A case could also be made to consider whether a homicide was instrumental (i.e. premeditated) or not when trying to assess seasonal variations.

However, Woodworth and Porter (2002) found that in a Canadian context premeditation is a factor that is largely characteristic of homicides committed by psychopaths (over 90%). The non-psychopaths in their sample committed instrumental homicides in 48.4% of cases (see Woodworth & Porter, 2002, pp.440-441). Although the prevalence of premeditation among psychopaths was staggering, it should be remembered that such individuals only make up approximately 1% of the general population (see Hare, 1996, p.26). Therefore, premeditation may not serve as the best indicator and/or explanation for seasonal variations in homicides, particularly in Canada.

### 4.1.4. Break and Enter/Burglary

In a test designed to contrast the explanatory capacities of temperature aggression and routine activities theory, Hipp et al. (2004) generated a hypothesis based on temperature aggression theory stating that because seasonal variation is due to higher temperatures that lead to violent behaviour, “there [would] not be a seasonal effect for property crime rates” because the offence is not aggressive in nature (Hipp et al, 2004, p.1338). After applying the latent curve model to their three years worth of uniform crime report data, they found statistically significant oscillations for both violent and property crimes (Hipp et al., 2004, p.1352). Such results provided further support for routine activities theory as well as evidence for the existence of crime seasonality for property crimes. Other studies have also found that burglaries tend to peak during the summer months (Cohn & Rotton, 2000, p.263; McDowall et al., 2012, p.399; Andresen & Malleson, 2013, p.25; Chimbos, 1973, p.322). Such temporal patterns have often been attributed to the fact that summertime leisure activities of people remove them from their homes thus eliminating capable guardianship of their property. This provides ideal target selection for motivated offenders (Andresen & Malleson, 2013, p.25; Chimbos, 1973, p.322). Furthermore, one of the most effective crime prevention techniques for burglary is to lock the doors and windows of one’s home, but in the summer months, these are more often left open due to higher temperatures (Hamilton-Smith & Kent, 2009, p.425). Such actions provide offenders with easier access to homes. Despite these findings, other research in England has indicated that residential burglary drops to the lowest annual levels in the summer months and is instead at its highest in February and March (Farrell & Pease, 1994, p.492). What should be noted, however, is that Farrell & Pease’s

(1994) work focused solely on residential burglaries as opposed to a more routinely used aggregate burglary variable. Unfortunately little work has been done with disaggregated burglary data. As such, less is known as to whether residential burglaries experience the same seasonal trends as commercial burglaries. Contrary to the issue of unlocked doors and windows of houses in the hotter months, many businesses operate consistently throughout the year thus eliminating a particular prime time to commit such an offence (see also Sherman et al., 1989, p.46).

### 4.1.5. Robbery

Robbery has also been characterized by an inconsistency in the empirical literature. In their analysis of three years worth of data for Minneapolis, Minnesota, Cohn and Rotton (2000) found that robberies peaked during the summer months (Cohn & Rotton, 2000, p.263). Conversely, McDowall et al. (2012) found that all crimes except for robbery peaked in the summer months. More specifically, they observed that robberies were highest in December, but that there was also a peak in the summer (McDowall et al., 2012, p.396). In Michael and Zumpe's (1983) study of sixteen American cities, they found that only five of the sixteen locations had statistically significant rhythms for robbery and that they peaked in November-December (Michael & Zumpe, 1983, p.884). Finally, Landau & Fridman (1993) found that in Israel, robberies peaked in the winter months and attributed these findings to monetary motives based on increased unemployment and necessities such as food, clothing and shelter. Moreover, they explained that the colder weather present in winter months reduced the number of people in the streets (i.e. capable guardians) thus increasing the suitability of targets who were present. They also argued that shortened daylight hours put potential victims at an increased likelihood of victimization (Landau & Fridman, 1993, p.168-9).

On the other hand, the winter months provide increased opportunities due to peak shopping times for the Christmas holidays (Andresen & Malleson, 2013, p.31). Therefore, robberies may be largely attributed to "the intensity of activity on the street" (Loukaitou-Sideris, 1999, p.397). However, it appears that there is a fine line for robbers regarding the volume of persons in an environment. More specifically, Loukaitou-Sideris

(1999) related some of Shlomo Angel's (1968) original assertions about more ideal places for robbers to take advantage of:

> As intensity of activity increases from very low to low, enough potential victims are on the street to warrant the attention of potential offenders, but there are not enough people to provide for adequate surveillance. According to Angel (1968), this is a "critical intensity zone" (p. 16) in which most crimes take place. With higher levels of activity, crime falls because there are enough people to assure informal surveillance of the site (Loukaitou-Sideris, 1999, p.397; see also Angel, 1968).

Given these arguments, both the time of day and year appear to be critical in our understanding of robbery offending patterns. Moreover, even the slightest changes in environmental factors can lead to temporal variations thus providing some account for why various empirical studies on robberies may not converge but still provide support for routine activities theory in their explanations of the trends that emerged from their data.

### 4.1.6. Motor Vehicle Theft

Fewer seasonality studies have managed to incorporate variables concerning automotive crime such as theft from and theft of vehicle. Moreover, when such variables are included in analyses, they are often aggregated into larger property crime variables thus thwarting efforts to assess motor vehicle theft individually (for example, see Hipp et al., 2004, p.1343). Of the existing literature, however, mixed results have been found. Using data from 1988 to 1990 in the United Kingdom, Farrell and Pease (1994) found no distinct seasonal trend for motor vehicle theft. Instead, they only observed a drop in calls for service to police in 1988 that they attributed to a "change in recording practices" (Farrell and Pease, 1994, p.492). Likewise, Cohen, Gorr and Durso (2003) discovered a "cancelling-out effect" in their assessment of vehicle thefts (Cohen et al., 2003, p.21). More specifically, the statistically significant predictor variables[5] demonstrated opposing impacts on the dependent variable thus annulling any annual peaks (Cohen at al., 2003, p.21).

[5] The two variables deemed statistically significant from the authors' principle components analysis were the presence of retail establishments (e.g. department stores, check cashing, etc.) and higher presence of young persons and transient populations (Cohen et al., 2003, p.21).

More recently, McDowall et al. (2012) found distinct seasonal peaks for motor vehicle theft over a 24 year period across 88 American cities. The months that the crime count spiked, however, differed once average monthly temperatures were controlled for. When solely using the raw crime data, offences peaked in August and reached their lowest in February. However, when temperature was accounted for in the model, motor vehicle thefts were highest in December/January and lowest “in the spring and early summer” (McDowall et al., 2012, p.399). Lastly, when exploring trends within each of the 88 American cities, McDowall et al. (2012) found much larger magnitude changes in the percentage difference between peaks and troughs in cities with generally colder climates. In other words, cities that experience large annual temperature changes (e.g. Minneapolis, MN) exhibited more distinct seasonal trends for motor vehicle theft than cities with more consistent ambient temperatures (e.g. Honolulu, HI) (McDowall et al., 2012, p.402). This provides strong support for the need for additional comparisons of cities with differing annual climates.

### 4.1.7. Non-Criminal Factors that Impact Annual Differences in Temporal Offending Patterns

In addition to assessing the annual variation of crime trends in a given city, other non-criminal variables should be considered. Given the empirical importance of how peoples’ routine activities can impact crime fluctuations (Hipp et al., 2004), studies have also explored the influence of school schedules and holidays on offending patterns (Carbone-Lopez & Lauritsen, 2013; Cohn & Rotton, 2003). Because families often plan vacations around school breaks, it can increase the number of persons at popular tourist destinations as well as decrease populations in suburban areas (Butler, 2001, p.7). Moreover, the presence of children and youth increases in the community when school is not in session. Seeing as young persons, particularly teenagers and young adults, are the most criminogenic demographic (Bell, 2007, p.107; see also Hirschi & Gottfredson, 1983), elimination of their supervision from school allows them the independence to engage in alternative activities, sometimes criminal. In 2010, the United States alone had approximately 55 million children and youth enrolled in both public and private school who subsequently escape its supervision for summer break (Snyder & Dillow, 2013, p.63).

Carbone-Lopez & Lauritsen (2013) recently investigated what impacts such a large influx of young persons might have on the US crime trends. After an extensive review of data from the National Crime Victimization Study of persons twelve years and older, the authors made comparisons to those of police report data. They found that cases of serious violence[6] were relatively similar to the police data, but that cases of simple assault differed in their seasonal trends. More specifically, while assaults traditionally peak in the summer months, the victimization data for young persons indicated that simple assaults were highest in the fall (Carbone-Lopez & Lauritsen, 2013, p.418). The authors attribute this to a restructuring of social statuses at the beginning of the school year thus increasing the volume of assaults. Furthermore, they found that if the crimes were reported, they were more likely to be received by school officials. As a result, the offences were unknown to the police (Carbone-Lopez & Lauritsen, 2013, p.418). At a spatial level, they discovered that violence on the street was highest in the summer, but remained relatively stable throughout the year for commercial areas and within households (Carbone-Lopez & Lauritsen, 2013, p.419).

While breaks in the school calendar provide changes in many individuals' routine activities, the influence of calendar holidays should also be considered. Cohn and Rotton (2003) explored the influence of major and minor holidays on crime in Minneapolis, Minnesota. What set their study apart from others was the fact that they disaggregated annual holidays in their analysis. Past research had found that holidays did not significantly impact crime trends, but it was readily noted that the variables included were aggregated for analysis (Cohn & Rotton, 1997, p.1332). When analyzed individually, different crime types were statistically significant on different holidays. As a general trend, greater fluctuations in crime were observed on major holidays whereas crime remained relatively unaffected on minor holidays (Cohn & Rotton, 2003, p.358). The authors concluded that holidays that involved changes in routine activities lead to the greatest increases in crime. For instance, the data revealed that

> …assaults significantly increased on New Year's Day, disorderly conduct increased on Independence Day and decreased on Christmas Day, and

[6] Serious violence was an aggregate variable that included rape and sexual assault, robbery and aggravated assault (Carbone-Lopez & Lauritsen, 2013, p.407).

> there were significantly more complaints about domestic violence on Thanksgiving Day and Christmas Eve. Analyses on property crimes that controlled for weather and temporal variables found that theft decreased on Independence Day, Thanksgiving Day, and Christmas Day, burglaries declined on Independence Day, and robberies declined on Thanksgiving Day and Christmas Day (Cohn & Rotton, 2003, p.358).

These findings provide very telling results with respect to routine activities theory by demonstrating the impact on crime resulting from one day of change in peoples' general activities. While some studies have found that robberies generally increase in the winter months around the Christmas holidays (Landau & Fridman, 1993; Andresen & Malleson, 2013), these results suggest that robberies decline on the actual holiday itself (Cohn & Rotton, 2003, p.358). As a result, studies such as this provide additional and telling information that would have otherwise gone undetected at a month-level. Future analyses should, therefore, explore the impact of such variables whenever possible.

## 4.2. Temporal Hypotheses

Based on this literature and on the proposed research questions, the following hypotheses were generated regarding the temporal aspects of crime seasonality:

(1) Property crime seasonality will be more prominent in cities with more distinct weather seasons.

(2) Different crime types should be examined individually because each offence type will exhibit different temporal patterns.

(3) Different weather variables will have greater impacts on particular property crime types due to the situation-specific characteristics needed to carry out the offences.

## 4.3. Data

The data for Vancouver and Ottawa were both employed to test the proposed hypotheses. The dependent variables for Vancouver are police incident data that were retrieved from the Vancouver Open Data Catalogue website (http://data.vancouver.ca/datacatalogue/index.htm) and contained information pertaining to location and month of occurrence on four crime types over an 11 year period (2003-

2013). The crime classifications include: commercial break and enter, mischief, theft from vehicle and theft of vehicle. Appendix A provides the total and seasonal frequencies of these variables. Similarly, dependent variables for the city of Ottawa were taken from police incident data posted on the Ottawa Police Service website (www.ottawapolice.ca). Those data contained information regarding the specific dates and times as well as locations of offences that occurred between 2006 and 2008. The crime classifications that included data throughout this entire three year period include: commercial break and enter, residential break and enter, robbery and stolen vehicle (see Appendix B). Records of mischief incidents began consistently being reported in April 2007 until December 2008 (see Appendix B). As such, the use of mischief will be discussed further when its inclusion could be justified in certain analyses. Lastly, it should be noted that these data apply exclusively to the cities of Vancouver and Ottawa, not their census metropolitan areas.

The independent variables concerning climatic conditions were obtained from two sources. All data representing weather variables including temperature, rain, snow and precipitation were retrieved from the Environment Canada historical climate data webpage (http://climate.weather.gc.ca/). Similarly, all information regarding the times and hours of illumination were obtained from the National Research Council of Canada website (http://www.nrc-cnrc.gc.ca/eng/services/sunrise/advanced.html). Tables 4.1 & 4.2 provide the descriptive statistics for these weather and illumination variables relevant to Vancouver and Ottawa, respectively. Lastly, IBM's Statistical Package for the Social Sciences (SPSS) was used to calculate additional trend variables including month and month squared, as well as various dummy variables. The month variable was assigned sequential values (1, 2, 3,…12) for each month and each crime type and month squared is simply the square of month. Because the Vancouver data were identified only by month, variables for the number days in the month as well as the number of weekend days in a month were created. Dummy variables were created to control for the annual seasons and the seasons themselves were defined as the following: winter (January – March), spring (April – June), summer (July – September), and fall (October – December). In the case of Ottawa, however, information regarding the specific day were available and, thus, trend variables for day of the year and day of the entire dataset were included. Moreover, dummy variables for major and minor holidays were created because they could be identified in the dataset. The dummy variables for the seasons remained the same as those of Vancouver in order to remain consistent.

**Table 4.1. Descriptive Statistics for independent and dependent variables used in temporal regression, Vancouver, 2003-2013**

| | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|
| **Dependent Variables:** | | | | |
| Commercial Break and Enter (month) | 194.4 | 58.2 | 91 | 377 |
| Mischief (month) | 418.5 | 74.3 | 291 | 691 |
| Theft from Vehicle (month) | 999.4 | 328.6 | 486 | 1799 |
| Theft of Vehicle (month) | 253.9 | 163.3 | 57 | 638 |
| Total Crime (month) | 1866.2 | 583.6 | 1028 | 3225 |
| **Independent Variables:** | | | | |
| Maximum Temperature (°C) | 19.5 | 6.4 | 8.5 | 34.4 |
| Average Temperature (°C) | 10.5 | 5.4 | 0.9 | 19.7 |
| Maximum Rain (mm) | 21.7 | 14.3 | 0.0 | 91.6 |
| Average Rain (mm) | 3.0 | 2.1 | 0.0 | 10.3 |
| Total Rain (mm) | 92.4 | 63.2 | 0.0 | 308.0 |
| Maximum Snow (cm) | 1.6 | 5.3 | 0.0 | 44.6 |
| Average Snow (cm) | 0.1 | 0.3 | 0.0 | 2.9 |
| Total Snow (cm) | 2.6 | 9.4 | 0.0 | 89.4 |
| Total Illumination (hrs) | 13.4 | 2.8 | 9.5 | 17.6 |
| Twilight (hrs) | 1.2 | 0.1 | 1.1 | 1.4 |

Although the data provide the counts of crime in a given month (Vancouver) or day (Ottawa), the multiple years of data allowed for configuration into a more seemingly continuous format. For example in the case of Vancouver, N = 132 because there are 132 months present within the data set representing the months between January 2003 to December 2013. However, the number of actual criminal events in the Vancouver dataset is n = 246,342. This means that nearly 250,000 crimes (of the types previously specified) were committed during the 11 year time period. Because the Ottawa data contained the day that was associated with each offence, the dataset was configured in a continuous manner according to the days of the year. This means that the Ottawa dataset contains N = 1096 days to represent all data from January 2006 to December

2008. In the case of mischief, however, N = 645 because the data began in April 2007 and continued until December 2008. The number of offences captured in these data are n = 20,108 for all crime excluding mischief and an additional n = 14,024 for the mischief offences producing a total of 34,132 crimes examined within.

**Table 4.2. Descriptive Statistics for independent and dependent variables used in temporal regression, Ottawa, 2006-2008**

| | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|
| **Dependent Variables:** | | | | |
| Commercial Break and Enter (day) | 3.9 | 2.5 | 0 | 15 |
| Residential Break and Enter (day) | 6.0 | 3.3 | 0 | 22 |
| Robbery (day) | 2.0 | 1.6 | 0 | 10 |
| Theft of Vehicle (day) | 6.5 | 3.3 | 0 | 20 |
| Total Crime (day) | 18.4 | 6.4 | 0 | 41 |
| Mischief (day; 2007-8) | 21.7 | 8.7 | 2 | 61 |
| **Independent Variables:** | | | | |
| Maximum Temperature (°C) | 11.9 | 12.4 | -18.1 | 36.3 |
| Average Temperature (°C) | 6.8 | 11.6 | -21.6 | 29.3 |
| Total Rain (mm) | 2.2 | 5.6 | 0.0 | 68.0 |
| Total Snow (cm) | 0.8 | 2.9 | 0.0 | 35.6 |
| Total Illumination (hrs) | 13.3 | 2.4 | 9.9 | 16.9 |
| Twilight (hrs) | 1.1 | 0.1 | 1.0 | 1.3 |

The weather and illumination variables for Vancouver that were created from the historical data represent monthly trends. In the case of temperature, the average temperature variable contains the mean temperature in the given month while the maximum and minimum temperature variables provide a value for the highest and lowest temperatures that occurred on any day within that month. Both of these variables were included to account not only for average trends during the month but also extreme cases, such as a heat wave, that may have been unusual in that particular month. Similarly, variables for average, maximum, minimum and total rain and snow were included for analysis. The first three variables were derived in the same fashion as the temperature variables and total rain is simply a sum of the accumulation of rain and snow in each month, respectively. Lastly, illumination variables were incorporated to represent three factors at a monthly level: the mean number of hours between sunrise and sunset, the mean number of twilight hours, and the mean total number of hours of illumination (i.e. sunrise to the end of twilight). Although other variables such as minimum temperature, minimum rain, minimum snow and the mean number of hours between sunrise and sunset were initially included, preliminary tests in IBM'S Statistical Package for Social Sciences (SPSS) indicated high levels of multicollinearity with other variables. A series of Partial-F tests were conducted to determine if their removal could be justified and not impose omitted variable bias. The variables that remained in the full regression models can be found in appendices E & F.

The creation of weather and illumination variables for the Ottawa data differed from the Vancouver equivalent because the data were compiled on a daily, not monthly basis. As such, average, maximum and minimum daily temperatures were included, but only variables representing the total daily accumulations of rain and snow were generated. Lastly, because the Ottawa data were not limited to monthly aggregates, the illumination data represent the actual number of hours of daylight. The variables for number of hours between sunrise and sunset, twilight duration and total illumination are thus not monthly averages and are instead counts of those hours of occurrence during the given day.

## 4.4. Methods

In order to operationalize and test the aforementioned temporal hypotheses, a series of descriptive evaluations and ordinary least squares (OLS) regressions[7] were conducted on the Vancouver and Ottawa data using R: The Project for Statistical Computing (http://www.R-project.org). Eleven distinct models were run on each of the independent variables (both aggregate and disaggregate) in the Vancouver and Ottawa data. Initial tests checking for OLS assumptions were conducted and revealed that error

[7] Although these are count data, the longitudinal nature of the available data allowed for the data to act more continuous in nature thus justifying the use of OLS regressions. Moreover, the monthly and daily nature of the data resulted in little to no zero values in the independent variables thus justifying the exclusion of Poisson modeling for these analyses.

terms in all models were not independently, identically or normally distributed. In fact, both autocorrelation and heteroscedasticity were present in the data. As such, robust covariance matrix estimators were incorporated into the regression analyses using the *vcovHAC* function in R.

Once the initial model had been run and assessed, a testing down method was employed. This means that the statistically most insignificant variables were removed one at a time until a final model of statistically significant predictor variables remained. With each variable that was removed, a 'partial' F statistic was also calculated and compared to its corresponding critical F value to test for joint significance of variables. In other words, while an independent variable may be statistically insignificant at the 95% level, it may possess joint significance with another variable in the model thus justifying its retention in the final model. Once these statistics were calculated and compared to the critical F values for each independent variable, a final regression model was run.

## 4.5. Results

### 4.5.1. Descriptive Patterns

Although all data and results will be discussed, for ease of legibility, this section of the thesis will only show tables and figures for the descriptive patterns in both cities in 2008. This year was selected because it includes the most amount of information, including a full year worth of mischief data in Ottawa. Additional tables and figures can be found in appendices C through F for reference. The counts and percentages of crime in Ottawa and Vancouver grouped into the previously defined seasons[8] are shown in Tables 4.3 & 4.4 for 2008 and again in appendices A & B for the remaining years. Not surprisingly, seasonal crime trends appear more apparent in Ottawa, a city that experiences more distinct seasonal weather, than in Vancouver. Percentages of the frequencies of crime in Vancouver range from 21.3% to 28.3% and do not appear to fluctuate very much throughout the year. Conversely, the frequency of crime in Ottawa

[8] Winter (January – March); Spring (April – June); Summer (July – September); Fall (October – December)

exhibits its highest levels in the summer months upward of 30% and its lowest in the winter months almost consistently below 20%. However, it should be noted that these seasonal trends in Ottawa are not quite as prominent in the preceding years (see Appendix B). As such, OLS regression analyses were conducted (see next section) to determine whether the seasonal trends/differences were truly statistically significant.

**Table 4.3. Frequencies of crime types, by season, counts and percentages, Vancouver, 2008**

| | Winter | | Spring | | Summer | | Fall | | Total |
|---|---|---|---|---|---|---|---|---|---|
| Commercial B&E | 647 | (28.30) | 578 | (25.3) | 565 | (24.7) | 494 | (21.60) | 2284 |
| Mischief | 1484 | (26.90) | 1476 | (26.8) | 1280 | (23.2) | 1267 | (23.00) | 5507 |
| Theft from Vehicle | 2737 | (24.00) | 2859 | (25.1) | 2846 | (24.9) | 2969 | (26.00) | 11411 |
| Theft of Vehicle | 636 | (26.30) | 675 | (27.9) | 591 | (24.5) | 514 | (21.30) | 2416 |
| All Crimes | 5504 | (25.50) | 5588 | (25.8) | 5282 | (24.4) | 5244 | (24.20) | 21618 |

Note: Percentages are in parentheses, were rounded to the nearest tenth and thus may not add evenly to 100.

**Table 4.4. Frequencies of crime types, by season, counts and percentages, Ottawa, 2008**

| | Winter | | Spring | | Summer | | Fall | | Total |
|---|---|---|---|---|---|---|---|---|---|
| Commercial B&E | 272 | (19.5) | 385 | (27.6) | 426 | (30.5) | 312 | (22.4) | 1395 |
| Residential B&E | 359 | (18.8) | 494 | (25.8) | 629 | (32.9) | 431 | (22.5) | 1913 |
| Robbery | 133 | (19.1) | 181 | (25.9) | 224 | (32.1) | 160 | (22.9) | 698 |
| Theft of Vehicle | 390 | (20.7) | 497 | (26.4) | 596 | (31.6) | 401 | (21.3) | 1884 |
| Total Crime (w/o mischief) | 1154 | (19.6) | 1557 | (26.4) | 1875 | (31.8) | 1304 | (22.1) | 5890 |
| Mischief | 1215 | (18.2) | 1754 | (26.2) | 2227 | (33.3) | 1490 | (22.3) | 6686 |
| Total Crime (w/mischief) | 2369 | (18.8) | 3311 | (26.3) | 4102 | (32.6) | 2794 | (22.2) | 12576 |

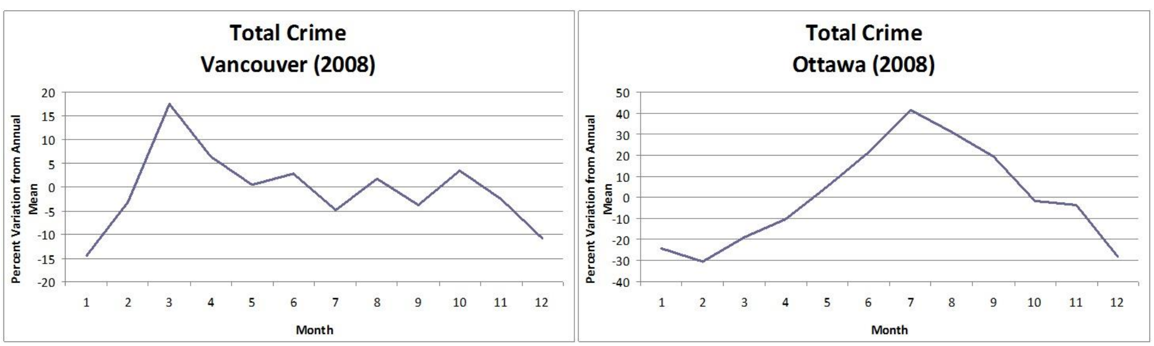
Note: Percentages are in parentheses, were rounded to the nearest tenth and thus may not add evenly to 100.

Considering the monthly graphs in Figures 4.1 - 4.3[9] generated from these same frequencies, the above trends are undoubtedly distinct (for graphs/figures in other years

[9] Note: Figures 4.1 - 4.3 provide graphs of the frequency data's percent variation from the annual mean so as to provide a more standardized view of the shapes of the crime trends.

see appendices C & D). Moreover, a monthly view of the data demonstrates individual crime-specific trends that could have gone unnoticed using only the aforementioned seasonal frequency tables as well as aggregate total crime variables. Such trends are particularly likely to occur if some of the crime types occur more frequently and thus mask the differing patterns of others. For instance, the total crime graph for Ottawa shows crime rising steadily early in the year to a peak in July and then decreasing almost as steadily into December (Fig. 4.1). Graphs for mischief and residential break and enter exhibit very similar curvilinear shapes as well (Fig. 4.3). Moreover, mischief and residential break and enter are the two crime types that occurred the most frequently in the data so it is thus not surprising that their trends are reflected in the aggregate total crime graph. However, the figures for robbery and theft of vehicle display very different relationships (Fig. 4.3). In fact, July had one of the lowest counts of robbery in the year and thefts of vehicle appear to increase in the winter months. Interestingly, commercial break and enter exhibit a distinct seasonal peak but slightly later in the year than the overall aggregate (Fig. 4.3).

**Figure 4.1. Monthly Crime Trends, Total Crime, Vancouver & Ottawa, 2008**




Given the initial seasonal results in Tables 4.5 and 4.6, it is unsurprising that Vancouver does not exhibit similar monthly trends to Ottawa. As shown in Figure 4.1, there appears to be a distinct peak in March on the aggregate total crime graph and then crime appears to oscillate at a relatively stable rate for the remainder of the year. Turning to the individual crime types, no particular offence seems to exhibit a definitive peak other than in March (Fig. 4.2). Contrary to the literature and theoretical framework listed above, a summer spike in crime is not necessarily observed. In fact, offences such as theft from vehicle and mischief show a somewhat bi-modal distribution throughout the year. Moreover, trends for commercial break and enter as well as theft of vehicle are even less apparent.

**Figure 4.2. Monthly Crime Trends, Disaggregate Crime Types, Vancouver, 2008.**

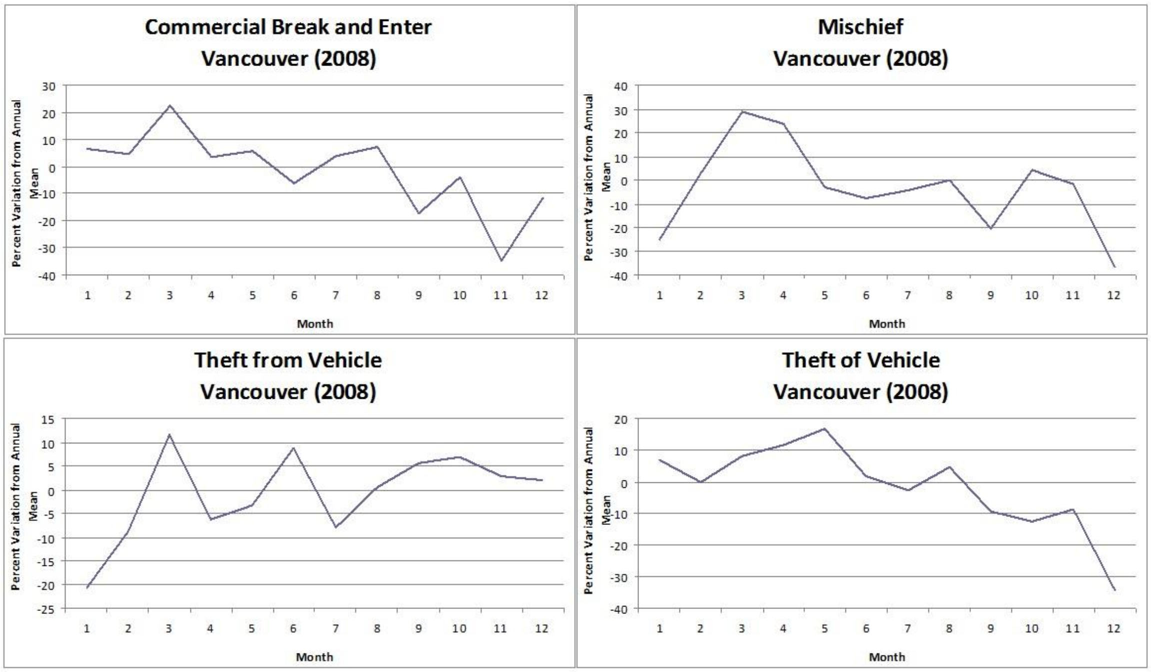
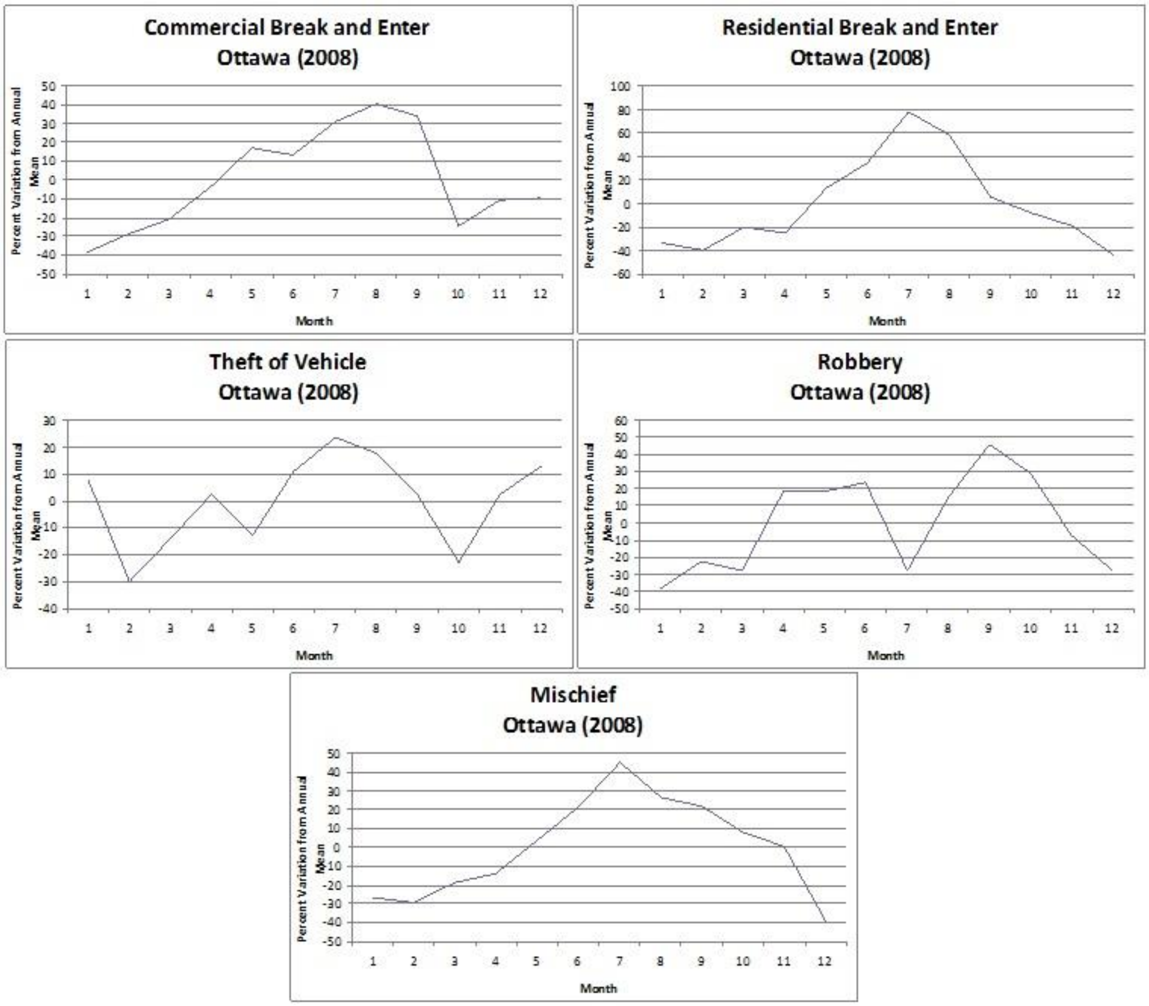


**Figure 4.3. Monthly Crime Trends, Disaggregate Crime Types, Ottawa, 2008**




Because the above results were discussed solely based on visual inspection, further analyses of these seasonal trends were conducted in the attempt to gain additional insights on these phenomena prior to making any inferences. The regression results that incorporated weather, illumination, dummy and trend variables are examined in the following section.

### 4.5.2. Regression Results

The first regression models that were run for this study merely involved each of the available crime types and the month and month squared variables. Seeing as a seasonal/quadratic relationship was anticipated for these data, a standard OLS regression would not provide an accurate reflection of the data because it assumes that a linear relationship exists between the independent and dependent variables. As such, month and month squared variables were computed and incorporated to test/control for the quadratic (inverted U-shaped) distribution that was likely present in the data. Tables 4.7 and 4.8, show the 11 models that were run with the trend variables to test for the presence of crime seasonality using all 14 years of data. Not surprisingly, quadratic relationships were present across all crime types in Ottawa and were statistically significant at the $p < 0.001$ level. Conversely, mischief was the only crime classification that exhibited a significant curvilinear distribution in Vancouver between 2003 and 2013. Nevertheless, these results provide evidence via statistical means to demonstrate whether the trends in aforementioned graphs are statistically significant.

**Table 4.5. Temporal regression results for presence of a seasonal/quadratic relationship for property crime in Vancouver, 2003-2013**

| | Commercial Break & Enter | Mischief | Theft from Vehicle | Theft of Vehicle | Total Crime |
|---|---|---|---|---|---|
| Month | -0.419 | 25.739** | 15.703 | -1.185 | 39.839 |
| Month Squared | -0.027 | -2.016** | -0.917 | -0.076 | -3.036 |
| | | | | | |
| Adjusted $R^2$ | -0.013 | 0.0688 | -0.013 | -0.013 | -0.012 |
| F-statistic | 0.136 | 5.839** | 0.16 | 0.140 | 0.197 |

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; N = 246,342

**Table 4.6. Temporal regression results for presence of a seasonal/quadratic relationship for property crime in Ottawa, 2006-8; Mischief (2007-8)**

| | Commercial Break & Enter | Residential Break & Enter | Robbery | Theft of Vehicle | Total Crime (w/o mischief) | Mischief (2007-8) |
|---|---|---|---|---|---|---|
| Month | 0.580*** | 1.255*** | 0.227*** | 0.686*** | 2.826*** | 6.323*** |
| Month Squared | -0.042*** | -0.094*** | -0.015** | -0.044** | -0.201*** | -0.465*** |
| | | | | | | |
| Adjusted $R^2$ | 0.033 | 0.092 | 0.013 | 0.033 | 0.123 | 0.283 |
| F-statistic | 19.770*** | 56.510*** | 8.233*** | 19.280*** | 77.720*** | 127.800*** |

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; N = 20,108 (total crime w/o mischief); N = 14,024 (mischief)

### 4.5.3. Vancouver, BC

Results from the final OLS regression models for Vancouver can be seen in Table 4.7 (for full models, see Appendix E). Despite the addition of weather, dummy, trend and illumination variables, month and month squared only remain statistically significant for mischief ($\beta$ = 32.637; $\beta$ = -2.452 respectively). Moreover, these models generated much higher Adjusted $R^2$ values and indicate that the inclusion of these variables accounts for between 53 and 89 percent of the variance in the models. The trend variable that was created to represent each of the months over the 11 year time period and number of days in the month were all statistically significant and possessed the same directional relationships. In other words, as time went on between 2003 and 2013, crime decreased and when there were more days in a given month, more crime was committed. These two trends are consistent with previous literature and crime statistics. As previously mentioned, reports from Statistics Canada have shown that crime in Canada and Vancouver in particular has been decreasing since 2003 (see table 3.1). The decrease in crime is unsurprising given much of the work that has been conducted chronicling and examining the well-documented crime drop that has been occurring in North America and Europe (see Blumstein & Wallman, 2006; Farrell, Tilley, Tseloni & Mailley, 2011). Moreover, it is more than expected that crime will occur more frequently in months that contain more days due to the increased time (and, thus, opportunity) that it allows for criminal activity (see also Harries et al., 1984, p.595). Other than those two variables, however, no additional variables possess significant relationships across all crime types. As such, a disaggregate evaluation of each offence classification is warranted.

Commercial break and enter in Vancouver does not maintain a significant relationship with any of the weather, illumination or dummy variables that were entered into the final model (see table 4.7). This is not surprising, however, considering little to no temporal seasonal patterns were apparent in either the graphical representation or the regression model that solely examined the month and month squared variables. Although many of the weather and illumination variables possess quadratic shapes based on their natural occurrence throughout the year, a corresponding relationship with commercial break and enter does not appear to exist.

**Table 4.7. Final Models: Temporal regression results for property crime in Vancouver, 2003-2013**

| | Commercial Break & Enter | Mischief | Theft from Vehicle | Theft of Vehicle | Total Crime |
|---|---|---|---|---|---|
| Month | | 32.637*** | | | |
| Month Squared | | -2.452*** | | | |
| Month Total (Trend) | -1.259*** | -1.280*** | -8.078*** | -4.018*** | -14.510*** |
| # Days in Month | 6.830* | 13.891*** | 111.929*** | 10.499** | 137.693** |
| # weekend days in month | | 6.978* | | | |
| Spring (Dummy) | | | | | |
| Summer (Dummy) | | -24.832* | | | -160.453* |
| Fall (Dummy) | | | | | |
| Maximum Temperature | | | | -6.152*** | |
| Average Temperature | | | | 7.779*** | 31.098*** |
| Maximum Rain | | | | 0.455* | |
| Average Rain | | | 826.159** | | 891.888* |
| Total Rain | | | -26.780** | | -29.011* |
| Maximum Snow | | | | | |
| Average Snow | | | | | |
| Total Snow | | | | | |
| Total Hours of Illumination | | | | | -34.507* |
| # Twilight Hours | | | | | |
| Adjusted $R^2$ | 0.686 | 0.535 | 0.826 | 0.891 | 0.893 |
| F-statistic | 144.000*** | 26.070*** | 156.400*** | 268.800*** | 157.200*** |

* p < 0.05; ** p < 0.01; *** p < 0.001; N = 246,342

Although mischief possessed more variables that are statistically significant in the final model than in the model for commercial break and enter, they are similarly unrelated to any of the weather or illumination variables. Interestingly, table 4.7 shows significant relationships between the dependent variable and month ($\beta = 32.637$; $p < 0.001$) and month squared ($\beta = -2.452$; $p < 0.001$) thus confirming the existence of a quadratic/curvilinear trend. Again, mischief is the only crime type that appears to maintain this relationship in the Vancouver data. It is also exclusively related to the number of weekend days in a month ($\beta = 6.978$; $p < 0.05$). In other words, the addition of a weekend day in a given month leads to an increase in nearly 7 mischief offences. The final significant variable left to discuss is rather puzzling. Although it was expected that the dummy variable created to represent the summer months would be impactful, the negative directionality of the result is surprising ($\beta = -24.832$; $p < 0.05$). This could indicate that instead of having a peak in the frequency of crime during one of the pre-defined summer months (i.e. July, August or September), the highest volumes of crime are occurring earlier in the year before starting on their downward trend.

The results for theft from and theft of vehicle have the potential to provide invaluable insights into the seasonality literature regarding cities with different climates. Once again, the month and month squared variables indicate that there is no quadratic relationship present in the data. Moreover, none of the seasonal dummy variables were able to elicit specific temporal concentrations to a given time of the year. Instead, the weather variables played the most meaningful role in the models. In particular, the rain variables appear to have an incredible impact on thefts of vehicle in Vancouver. More specifically, when the average rainfall increases by one millimeter, the number of thefts from vehicle increase by an astounding 826 offences ($\beta = 826.159$; $p < 0.01$). However, when the total monthly rainfall increases, the number of thefts from vehicle decreases by nearly 27 offences ($\beta = -26.780$; $p < 0.01$). Based on these results it is possible that thefts from vehicle increase with rainfall due potentially to decreased guardianship because fewer people are outside. On the other hand, if there is an overly high amount of rainfall coming down, it will even deter potential offenders from seeking out targets. Conversely, when the maximum rainfall amount rises, thefts of vehicle actually increase, albeit marginally ($\beta = 0.455$; $p < 0.05$). This could indicate that when there is a disproportionately high level of rainfall, offenders opt to steal a vehicle in order to obtain shelter from the rain instead of steal any items from one. Lastly, the model indicates that as the average monthly temperature increased, the data exhibited an increase of nearly 8 thefts of vehicle ($\beta = 7.779$; $p < 0.001$). However, when the maximum temperature for each month increased, the number of offences actually decreased ($\beta = -6.152$; $p < 0.001$). It is possible that warmer temperatures make activities outside of the home more attractive thus increasing the exposure to potential targets. However, when temperatures become too hot, offenders may desist from crime simply because they are not spending as much time outdoors.

These vehicle theft results are rather telling in that they demonstrate the importance of weather variables on crime. Instead of patterning relating to the overall annual routine activities of persons, these results indicate that certain crime types may likely be affected by the weather. As previously discussed, Vancouver is a city that experiences a great deal of rainfall throughout all months of the year and does not experience very distinct climatic changes throughout the year. As such it is very possible to have crime trends (especially property crimes such as vehicle theft) that are not directly related to calendar months/routines of daily life and instead that follow weather patterns.

Finally, the aggregate total crime variable was tested in part to determine the appropriateness of disaggregating crime types in the examination of seasonal crime trends. As anticipated, different results were generated using an aggregate dependent variable as opposed to individual crime classifications (see Table 4.7). The dummy variable for summer revealed a rather substantial decrease in overall crime during the summer months ($\beta = -160.453$; $p < 0.05$). However, this is unsurprising given that the month and month squared variables were not statistically significant indicating that a quadratic relationship is not present in these aggregate data. Similarly, as the number of hours of illumination increases, crime declines overall ($\beta = -34.507$; $p < 0.05$). In spite of this, as the average temperature rises, there appears to be an increase in overall property crime ($\beta = 31.098$; $p < 0.05$). Akin to the theft from vehicle results, total crime increased by nearly 900 offences when average monthly rain levels increased ($\beta = 891.888$; $p < 0.05$) and conversely decreased by almost 30 offences when the total monthly rainfall rose ($\beta = -29.011$; $p < 0.05$). As such, disproportionately high levels of total rain may be acting as somewhat of a deterrent for crime. Nevertheless, results from this aggregate variable should be taken with caution. As shown in table 4.3, thefts from vehicle are consistently the most frequently occurring offence in these data. It is, thus, unsurprising that the total crime trends resemble those of theft of vehicle. This individual crime type could essentially be driving the overall trend thus masking underlying patterns present in the other offences.

### 4.5.4. Ottawa, ON

Akin to the Vancouver data, OLS regression models that exclusively included month and month squared variables can be seen in table 4.6. Given the differences in climate, it is not surprising that crime in Ottawa yielded differing results. Each of the aggregate and disaggregate crime variables generated statistically significant results when tested with the aforementioned predictor variables indicating the existence of quadratic relationships. More specifically, the positive beta values for the month variables and reciprocal negative values for the month squared variable imply that a curvilinear relationship exists. That is, crime levels increase early in the year and subsequently decline over time. The specific seasons in which this occurs will be discussed below.

Final and full OLS regression models were run on the Ottawa data using a nearly identical framework[10] to the Vancouver data and can be seen in table 4.8 and appendix F respectively. Interestingly, the R squared values generated in these models are much lower than for Vancouver despite the inclusion of more independent variables. Moreover, the addition of additional weather, illumination and dummy variables renders the month and month squared relationship insignificant in all models except for mischief and commercial break and enters. These outcomes suggest that the additional variables are accounting for further variation in crime that was initially captured by the month and month squared variables. This implies that with the exception of these two offences, factors other than time and/or calendar months contribute to the seasonal fluctuations of crime in the city.

In the case of commercial break and enter, the dummy variable for summer ($\beta = 0.601$; $p < 0.001$) indicates that such offences are statistically significantly higher on days in the summer months, albeit by a relatively minor amount. This supplements the month ($\beta = 0.389$; $p < 0.05$) and month squared ($\beta = -0.029$; $p < 0.05$) results and thus implies that the summer months are when the peak frequencies of commercial break

[10] Note: As mentioned above, the Ottawa data possessed sufficient information to run analyses on a daily basis. As such, results are representations of daily trends, not monthly trends as per Vancouver.

and enters are occurring. On the other hand, the temperature variables provide further insights into these seasonal trends. The model indicates that as the average temperature rises, the data exhibit a coinciding increase in offences ($\beta = 0.126$; $p$ ¸0.01). Conversely, as the maximum temperature rises, commercial break and enters begin to decrease ($\beta = -0.121$; $p < 0.01$). This could imply that warmer temperatures are more conducive to crime but that exceedingly hot/warm weather could actually deter offenders from breaking and entering businesses. Lastly, as snowfall levels rise the number of offences subsequently decrease somewhat ($\beta = -0.044$; $p < 0.05$). It is possible that the climatic conditions required to elicit snowfall as well as the snow itself also deter individuals from offending. It should be noted, however, that the adjusted $R^2$ shows that the climatic variables only account for 4.8% of the variance in the model. As such, there are likely other factors beyond weather and/or illumination that are affecting the temporal fluctuations commercial break and enter.

The availability and inclusion of residential break and enter data provides an invaluable opportunity to evaluate crime at yet another level of disaggregation. In other words, not only have the data been broken down according to individual crime types, but these data allow for a comparison of two distinct sub-types of break and enter. Given the differences in characteristics that offenders search for in residential break and enters (see Wright, Logie & Decker, 1995; Neel & Taylor, 2000), it is unsurprising that some of the regression results differ from the commercial equivalent. More specifically, the final model (see Table 4.8) generated some additional statistically significant relationships. Also of note is the fact that this model generated a much higher Adjusted $R^2$ value than the commercial equivalent and can thus account for nearly 23 percent of the variance in the model. Moreover, when climatic variables were added to the model, the initial quadratic trend variables were no longer as prominent. Instead, it appears that weather and illumination conditions account for more variation in the model. For instance, as the average temperature increases the number of offences follows suit ($\beta = 0.062$; $p < 0.001$). Conversely, as snowfall amounts rise, residential break and enters decrease ($\beta = -0.051$; $p < 0.05$). Interestingly, the variable that demonstrates the largest magnitude increase in offences is the number of twilight hours ($\beta = 7.630$; $p < 0.001$). Given the fact that warmer temperatures and longer twilight hours in the Northern Hemisphere (i.e. North Solstice) tend to coincide, it is unsurprising that increases in residential break and enters can result. Such climate conditions are not only more conducive to committing the offences but also compel many individuals to engage in outdoor activities thus leaving their property unguarded. Moreover, this rising break and enter trend can also be observed with the statistically significant dummy variables representing summer ($\beta$ = 2.094; $p < 0.01$) and fall ($\beta$ = 2.178; $p < 0.05$).

**Table 4.8. Final Models: Temporal regression results for property crime in Ottawa, 2006-8**

| | Commercial Break & Enter | Residential Break & Enter | Robbery | Theft of Vehicle | Total Crime (w/o mischief) | Mischief (2007-8) |
|---|---|---|---|---|---|---|
| Month | 0.389* | | | | 0.206** | 3.052*** |
| Month Squared | -0.029* | -0.018* | | 0.017*** | | -0.209*** |
| Day of Dataset (Trend) | | -0.003*** | | -0.004*** | -0.07*** | -0.012*** |
| Major Holiday (Dummy) | | | | -1.009* | | |
| Minor Holiday (Dummy) | | | | | | |
| Spring (Dummy) | | | | | | |
| Summer (Dummy) | 0.601** | 2.094** | | 0.785** | 2.281*** | |
| Fall (Dummy) | | 2.178* | | | | |
| Maximum Temperature | -0.121** | | 0.020*** | | | 0.187*** |
| Average Temperature | 0.126** | 0.062*** | | | 0.132*** | |
| Total Rain | | | | | | |
| Total Snow | -0.044* | -0.051* | | -0.052* | -0.142*** | -0.225*** |
| Total Hours of Illumination | | | | 0.198*** | | |
| # Twilight Hours | | 7.630*** | | | 2.510* | |
| Adjusted $R^2$ | 0.048 | 0.230 | 0.023 | 0.154 | 0.278 | 0.373 |
| F-statistic | 10.2*** | 47.47*** | 26.65*** | 40.65*** | 70.87*** | 77.59*** |

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; N = 20,108 (total crime w/o mischief); N = 14,024 (mischief)

When weather, illumination and dummy variables are added to the robbery model, the only variable that remains statistically significant is maximum temperature. More specifically, it indicates that as the maximum daily temperatures rise, a slight increase in robberies follows ($\beta = 0.020$; $p < 0.001$). No other variable provided a significant impact to the final parsimonious model. In addition, the low adjusted $R^2$ value for the model (0.023) indicates that the variables incorporated into the analysis explain very little of the variance in the model. As such, these data indicate that climatic conditions have little to no impact on the occurrence of robberies.

Theft of vehicle was the only crime classification that exhibited any significant change on holidays throughout the year (see Table 4.8). More specifically, the data indicated that major holidays, such as Christmas and Easter, experienced one fewer offence ($\beta = -1.009$; $p < 0.05$). In some cases, this is a rather substantial change because the mean and maximum number of stolen vehicles on a given day in this dataset was 6.46 and 20 respectively. As such, these results appear to coincide with the notion that “even criminals take a holiday” (Cohn & Rotton, 2003, p.351). In other words, offenders may very well be engrossed in holiday activities of their own that reduce their interest to offend. Moreover, the negative relationship between snowfall and thefts of vehicle ($\beta = -0.052$; $p < 0.05$) may also relate to offenders’ routine activities. First, higher snowfall levels may decrease the availability of targets if people stay home on snow days or commute to work via transit thus reducing the number of vehicles in other areas. Second, colder snow conditions may also increase the amount of effort necessary to steal a vehicle. It is thus unsurprising that variables representing warmer summer conditions produced positive relationships in the model. Both the dummy variable representing summer ($\beta = 0.785$; $p < 0.01$) and increasing number of hours of illumination ($\beta = 0.198$; $p < 0.001$) produced significant increases in thefts of vehicle.

As previously mentioned, the total crime variable was created with the specific exclusion of mischief because data were not available for the particular crime type over the entire 2006 to 2008 time period. Once again, the addition of climatic variables was able to account for variation that was initially captured by the quadratic trend variables (see table 4.8). Moreover, this expanded model was able to account for nearly 28 percent of the variance in the model (Adjusted $R^2 = 0.278$). Similar to many of the disaggregate results, variables associated with warmer temperatures and longer days generated increases in property crime. More specifically, summer days generally experience over 2 more offences ($\beta = 2.281$; $p < 0.001$) and as the number of twilight hours increase, property crimes also rise by over 2.5 offences ($\beta = 2.510$; $p < 0.05$). Similarly, rising average temperatures increase the overall frequency of offences ($\beta = 0.132$; $p < 0.001$). And consistent with every other disaggregate crime type other than robbery, increasing snowfall amounts actually decrease crime ($\beta = -0.142$; $p < 0.01$). As such, it seems as though snowfall may have a significant impact in reducing the opportunity and/or motivation to commit a property offence.

Lastly, the inclusion of mischief in Ottawa between April 2007 and December 2008 will be discussed because it can provide valuable insights into the trends for another disaggregate crime type as well as preliminary information for comparison to mischief patterns in Vancouver. It should also be noted that the Adjusted $R^2$ indicates that over 37 percent of the variance in the model can be accounted for using the climate-related variables (see table 4.8). Despite the inclusion of other weather and illumination variables, month ($\beta = 3.052$; $p < 0.01$) and month squared ($\beta = -0.209$; $p < 0.01$) remained statistically significant thus indicating that a quadratic relationship exists. More specifically, the magnitude and direction of these variables implies that crime begins to increase over time and subsequently decrease later in each year. Although it is unsurprising that snowfall decreases the number of mischief offences ($\beta = -0.225$; $p < 0.01$), the maximum temperature variable shows a significant increase in crime ($\beta = 0.187$; $p < 0.01$). The lack of significance for the average temperature variable may instead suggest that more extreme heat may be a stronger predictor of mischief in general.

## 4.6. Discussion

Although a number of studies have been conducted to assess the temporal component of crime seasonality, far fewer works have focused on property crime trends. Moreover, as previously discussed, when property offences were evaluated, the investigators often aggregated the crime types into an aggregate property crime variable. For instance, some studies combined offences such as burglary, larceny and motor vehicle theft together into a sole property crime variable and murder, robbery and assault into their violent crime variable (see Hipp et al., 2004, p.1343). Although this practice was effective in testing the merits of temperature aggression theory, it does not provide the reader with an understanding of individual crime trends. Looking at distinct offences, however, other studies still lacked an ideal level of disaggregation. Many of the aforementioned studies included separate variables such as motor vehicle theft or burglary, but were unable to distinguish between the sub-categories of each offence (see Farrell & Pease, 1994; McDowall et al., 2012). Although this may be attributed to the unavailability of data at the time, this study was able to shed some light on even more specific disaggregate crime patterns. Fortunately, the datasets employed in these analyses contained sufficient information to assess some more distinct crime types separately. For instance, both the commercial and residential break and enter offence variables in Ottawa and the theft of and theft from vehicle data from Vancouver allow some very interesting comparisons. Given the frequently cited offence-specific characteristics sought out by offenders in the search of suitable targets regardless of crime type (see Clarke, 1980; Kennedy, 1990; Wright et al., 1995; Neel & Taylor, 2000; Beauregard, Rebocho & Rossmo, 2010), it is thus unsurprising that different offences yielded distinct seasonal patterns. Moreover, the direct examination of two cities with differing climates also generated some valuable insights into the existence (or lack thereof) of seasonal crime trends.

### 4.6.1. Limitations

Before proceeding to further discussion, it should be noted that no research is conducted without limitations and this study is no exception. First, although these results are certainly informative, they can only provide insights into the various property crime types included in the datasets. As previously mentioned, the total crime variables are simply an aggregate of each of the crime types included in the data. Therefore, no conclusions can be made regarding other crime classifications such as assault, homicide or drug offences. Second, the crime classifications were not explicitly defined in the data and should thus be factored into all interpretations particularly when comparing results from the two cities. Although crime types such as theft of vehicle and/or commercial break and enter are relatively straightforward, a variable such as mischief could be defined differently by each police department.

The above issue also coincides with the concern regarding the accuracy of police data. While discrepancies in reporting practices of different police agencies are a very common occurrence, one must also consider the variation between the individual police officers who file the reports. For instance, if two different officers arrive to the scene of a vehicle that has had its window broken, a variety of equally plausible explanations could be attributed to the resulting state of the vehicle. Depending on whether the offender tried, but failed to steal the car itself, steal something from within the vehicle or simply vandalize it would lead to the designation of a very different crime classification.[11] For an in-depth discussion of the accuracy of police report data, see Sherman et al. (1989).

Lastly, the differing temporal units of analysis should be discussed. Although the analyses incorporated Vancouver crime data over an 11 year period, the data were aggregated to the month of occurrence as opposed to the day. Conversely, the Ottawa Police Department released data containing the specific date of offence (i.e. day) but only for a 3 year period. Despite these discrepancies between cities/data[12], however, comparisons are still warranted, but must be taken with some caution.

### 4.6.2. Addressing the Research Questions/Hypotheses

By comparing the temporal property crime trends in two cities with different climates, it is no surprise that divergent trends emerged. In fact, these results are consistent with past research that had concluded that cities with warmer climates had flatter seasonal crime cycles and that, conversely, seasonality was strongest in colder climate cities (McDowall et al., 2012, p.402; see also Hipp et al. 2004). As such, because Vancouver experiences relatively minor climatic fluctuations throughout the year it was expected that annual variations would likely be limited. Instead, factors such as frequent rainfall, that is famously characteristic of the city, and warmer temperatures appeared to have more of an impact. Given the scarcity of snowfall, it was also predictable to find that snow had no effect on crime in Vancouver.

[11] Example provided by Professor Paul J. Brantingham (via personal communication, 2014).

[12] Note: This is why the beta ($\beta$) values generated in the regression models have such large magnitude differences between both cities.

Conversely, Ottawa's more distinct seasons exhibited readily apparent impacts on crime in the regression models. In fact, with the exception of robbery, each of the property crimes generated multiple significant relationships with many of the climate variables. A prime example would be the consistently significant negative relationships between snowfall and crime across nearly every crime type. Such findings reinforce the results of Hipp et al. (2004) who found "considerable evidence of a seasonal effect for property crime" thus providing support for the explanatory use of routine activities theory as opposed to temperature aggression theory (Hipp et al., 2004, p.1363). Therefore, the hypothesis that posited that seasonality would exist in cities with more distinct weather seasons appears to be substantiated by these data.

The disaggregation of crime types has also proven useful in understanding some of the underlying property crime trends. The most obvious example demonstrating the advantages of individual analyses is robbery in Ottawa. Although the initial month and month squared only models indicated that quadratic relationship existed, the models with climatic variables showed virtually no seasonal pattern and captured very little variance in the model. On the other hand, the aggregate variable for Ottawa indicated that temporal-, illumination- and weather-related influences were all present and that they could account for much of the occurrence of crime. Therefore, had the disaggregation of crime types been omitted from these analyses, the underlying robbery patterns would have been masked within the overall total crime variable. As such, these results provide further support for the situational crime prevention literature and the importance of studying crime-specific trends (see Clarke, 1980; Clarke & Cornish, 1986; Cohen & Felson, 1979).

At yet another level, different climate-related variables demonstrated varying impacts on each crime classification in both cities. There were, however, weather variables that possessed more common impacts on various crime types in Ottawa than Vancouver. More specifically, rainfall variables appeared to be the only ones that mattered for the occurrence of thefts of vehicle, but temperature variables were the only factors that impacted thefts of vehicle. Furthermore, there were no set variables that were consistently significant across all crime types. In Ottawa, however, very different trends emerged. Instead, climatic variables such as total rain and snowfall generated consistent relationships across all crime types incorporated into the models. For example, with the exception of robbery, there was a statistically significant decrease in crime as snowfall levels increased. Simultaneously, increasing rainfall amounts had no significant impact whatsoever on any of the crime types included. Interestingly, other variables such as hours of illumination and temperature provided significant impacts on crime but only with certain types of offences. This provides some support for the third hypothesis that different weather variables will only impact certain crime types. Therefore, these results indicate that not only was the disaggregation of crime types important in order to parse out individual offence patterns, but that these disaggregate patterns can also vary across cities with differing climates. As such, replication of such temporal analyses in different cities would not be redundant to our knowledge of seasonal crime trends.

# Chapter 5.

# The Spatial Component of Crime Seasonality

## 5.1. Literature Review

As previously demonstrated, the research on crime seasonality has concentrated primarily on temporal fluctuations. Far less attention has been paid to the corresponding spatial patterns that exist (Brunsdon et al., 2009, p.906). Given the framework of routine activities theory and the spatio-temporal convergence of offenders and targets, it is clear that inquiry into the accompanying spatial trends is warranted. Of the limited research that exists, however, focus has been placed more prominently on identifying chronic locations at particular times (see Ceccato, 2005; Breetzke & Cohn, 2013). Moreover, most of the analyses examine neighbourhood contexts and their varying seasonal trends (Harries et al., 1984).

At a city-wide level, Quetelet (1842) conducted some of the first seasonal analyses and subsequent mapping of the spatial distribution of crime in France. The data revealed that crimes against persons were disproportionately higher in the south of France, more specifically, Corsica, Languedoc and Provence (Quetelet, 1842, p.40). From these initial findings, he was then able to arrange all cases into three principle classes based on the number of crimes committed in each province. These classes included: (a) provinces with above average crime against persons and property, (b) provinces with below average crime against persons and property, and (c) provinces with below average crime against persons only or property only (Quetelet, 1842, pp.47-8). These results, while relatively preliminary, provided some of the first empirical evidence that crime is not spatially distributed in a uniform manner (see Sherman et al., 1989).

It was not until the 1970s that scholars such as Lewis and Alford (1975) revisited the concepts initiated by Quetelet (1842). Their study focused on incidences of assault over a three year period in largely populated American cities. Their findings indicated that assaults could not be directly attributed to ambient temperatures. At the same time, however, they do not attribute seasonal fluctuations to increased social contact. They make the point that while more southern cities have relatively stable climates, namely that even the cold months are relatively warm and, thus, conducive to outdoor activities, their assault rates still fluctuate (Lewis & Alford, 1975, p.215). Despite these conclusions, it should be noted that routine activities theory had yet to be proposed to account for such discrepancies (see Cohen & Felson, 1979). Namely, that while temperatures may not change drastically, peoples' annual activities still follow seasonal calendars. For instance, even though individuals may be able to engage in outdoor activities such as camping in the winter months, they instead may opt to go in the summer months when children are out of school.

Almost a decade later, Harries et al. (1984) used the findings of Lewis and Alford (1975) to assist in the design of a neighbourhood-level study of seasonality and assault. In their study, the authors hypothesized that because some homogeneity often exists within neighbourhoods, the behaviours exhibited by the individuals within particular areas would be relatively similar. Moreover, they believed that differences in living conditions and/or socio-economic statuses of residents would result in varying coping mechanisms to deal with environmental and social conditions (Harries et al., 1984, p.593). They proposed that four main factors would contribute to the differences in assault rates within the city of Dallas, Texas, namely: (a) increased population density leads to higher levels of crime, (b) assaults are more likely to occur in and around establishments that sell alcohol, (c) calendar effects, such as holidays, evenings and weekends, experience greater levels of assault due to increased social interaction, and (d) neighbourhood contexts play a critical role in the number of assaults that are likely to be observed (Harries et al., 1984, pp. 594-5). After controlling for the aforementioned factors, they found that assaults consistently peaked in the summer months (Harries et al., 1984, p.593). When considering the spatial context across neighbourhoods, however, they discovered that low-status neighbourhoods[13], "showed a more distinct summer peak of assaults than did other neighbourhoods" (Harries et al., 1984, p.601). Moreover, the results revealed strong support for all of the proposed factors except for the alcohol hypothesis. Furthermore, it was found that assaults were even more prevalent in the streets and/or within apartment buildings within the lower status neighbourhoods (Harries et al., 1984, p.599). The authors concluded that their findings provided further support for the consideration of physical and social environments in the understanding of crime patterns (Harries et al., 1984, p.603).

Using a similar framework, Breetzke and Cohn (2012) set out to investigate seasonal fluctuations in assaults in South Africa across neighbourhoods. The authors argued that studying the crime trends of a city located in the southern hemisphere might provide further insights into the temperature-crime literature (Breetzke & Cohn, 2012, p.643). Their analyses confirmed both of their hypotheses, namely that assaults did in fact peak during the summer months and dropped off in the winter (Breetzke & Cohn, 2012, p.650) and that a portion of seasonal differences could be attributed to neighbourhood deprivation. More specifically, neighbourhoods characterized by higher deprivation[14] experienced disproportionately higher levels of assault. However, while the highly deprived neighbourhoods had the highest assault rates in the summer, assault rates were more evenly distributed across all neighbourhood types in the winter months (Breetzke & Cohn, 2012, p.653). The authors argued that such results provided support for the notion that socially deprived persons are "more inclined to commit assault in the summer months" (Breetzke & Cohn, 2012, p.658). On the other hand, such trends may simply be the result of a differential capacity to cope with the heat based on economic status. In other words, more deprived individuals will usually have less access to heat regulating equipment such as air conditioning units (Harries et al., 1984, p.595). Other work, such as Brunsdon et al. (2009), has observed a direct relationship with temperature and the spatial occurrence of crime. Their study in the United Kingdom

[13] Low status neighborhoods were characterized by higher percentages of substandard housing, black residents and lower median household incomes (Harries et al., 1984, p.597).

[14] Deprivation was measured using dimensions that included the percentage of: (a) residents living in informal housing, (b) housing with no flush toilet, (c) households with no water supply, (d) households with no electricity, and (e) households with no refuse removal (Breetzke & Cohn, 2012, p.649).

found that as temperatures rose, crimes began to cluster more prominently outside of the city center (Brunsdon et al., 2009, p.919). Nevertheless, data from cities on different continents have simultaneously demonstrated a lack of uniformity in the spatial occurrence of crime.

In addition to exploring seasonality and weather variables that might affect the occurrence of crime, Ceccato (2005) explored the changing geographic patterns of homicide in São Paulo, Brazil. While a distinct summer peak existed in the temporal dimension, the results of the spatial Kulldorf scan test revealed that homicides tended to cluster in more disadvantaged areas of the city “regardless of the time of the year” (Ceccato, 2005, p.317). Furthermore, she found that homicides tended to cluster towards the south of the city in the summer months whereas they became more prominent in the “eastern, southern and city core” in the winter and spring (Ceccato, 2005, p.317). Not surprisingly, these groupings of homicide locations also coincided with various crime generators such as “commercial areas, places of entertainment and drug related markets that attract economically motivated crime” (Ceccato, 2005, p.317). These results have provided further evidence that crime does not occur randomly in space or time.

Using the same Kulldorf scan test of space-time crime clusters, Uittenbogaard & Ceccato (2012) examined the geographic patterns of violent and property crime in Stockholm, Sweden. This study was particularly useful to the seasonality research in that it employed smaller units of analysis[15] and disaggregated the dependent variable to multiple crime types including: assault, threat, theft, robbery and burglary. Similar to much of the previous literature, violent crimes generated distinct seasonal differences whereas property crimes remained relatively static (Uittenbogaard & Ceccato, 2012, p.153). When assessing all crime types simultaneously, the data revealed that the downtown core of Stockholm constituted a consistent crime hotspot throughout the entire year. This overall prolific pattern was generated by a combination of the spatial patterning of both crime types. More specifically, the city center was host to violent

[15] The authors used the “basomrad”, the Swedish equivalent to population based units of analysis such as census tracts and dissemination areas (Uittenbogaard & Ceccato, 2012, p.151).

crimes in the winter and property crime in the summer. When examining violent crime exclusively, however, the authors found that the offences became more prominent in the suburbs of Stockholm during the summer months (Uittenbogaard & Ceccato, 2012, p.153).

As demonstrated by some of the aforementioned work, research at smaller levels of analysis was beginning to be introduced into the seasonality literature and provided valuable insights. However, much of this work used population based units of analysis such as census tracts. As a contrast, Cohen et al. (2003) instead elected to use 4000 foot[16] square grid cells overlaid on the city of Pittsburgh, Pennsylvania. Furthermore, they were able to obtain nine years worth of data for multiple crime types, namely robbery, larceny, motor vehicle theft, simple assault, aggravated assault, shots fired and drug-related calls for service (Cohen et al., 2003, p.10). Interestingly, the authors employed a principle components analysis to generate factors that lead to crime clustering in various areas within the city. The first of their five factors produced, low human capital[17], demonstrated that grid cells that scored high in this category experienced more crime, particularly for simple assault, robbery and burglary (Cohen et al., 2003, pp.14-25). Factor two, young adults, also spawned higher crime areas for motor vehicle theft, robbery, drug calls and aggravated assault particularly within grid cells that contained colleges and universities. Moreover, the frequency of crime varied with the school calendar. Population density, their third factor, was particularly prominent within the eastern part of the city for larceny, simple assault, shots fired, burglary, drug calls and aggravated assault. They attributed the importance of this variable to routine activities theory and the fact that increased populations lead to greater criminal opportunities (Cohen et al., 2003, pp.15-25). Finally, the grouping of their fourth and fifth factors, retail establishments and convenience stores/drinking places, was also consistent under the routine activities theoretical framework. These locations were more likely to experience motor vehicle theft and larceny (Cohen et al., 2003, p.24). While the

[16] This was estimated to equal roughly 10 city blocks (Cohen et al., 2003, p.10).

[17] Low human capital included variables that scored higher on: “the rental proportion of housing, the dropout rate among youth adults, the unemployment rate, the proportion of households that are female headed, the poverty rate, and the black proportion of the population” (Cohen et al., 2003, p.14).

former experienced “distinct seasonal patterns of behaviour associated with shopping”, the latter saw summer peaks particularly for violent crimes (Cohen et al., 2003, p.16). From these results it is very apparent that different crime types occur at different places and times depending on the environmental makeup of a given area. Given the fact that municipal land is clustered based on land use, it is not surprising that crime is not spatially homogeneous.

More recently, Andresen and Malleson (2013) conducted a spatio-temporal analysis of seasonality in Vancouver, British Columbia in 2001. Their study included data for assault, burglary, robbery, sexual assault, theft, theft from vehicle and theft of vehicle. For comparison purposes, they were also able to assess changes in criminal activity using both census tracts and dissemination areas as their units of analysis. When exploring the data using an aggregate total crime variable, the authors found little to no spatial similarity at both levels of analysis. In other words, the locations of summer-committed crimes were not the same as the places where crime occurred in the fall, winter or spring (Andresen & Malleson, 2013, p.31).

At a disaggregate level, however, Andresen and Malleson (2013) found that some patterns emerged that contradicted the overall trends. Using census tracts, the spatial patterns for assault mirrored the initial aggregate results. When compared at the dissemination area level, however, the spatial similarity increased across the seasons. While the relationships did not reach the authors’ accepted threshold for sufficient similarity, the increases should be noted as they would have otherwise gone unnoticed at the aggregate level. Surprisingly, burglaries at both levels of analysis did not stray from the overall trends. Once again, this indicates that the burglaries committed in the city are not occurring in the same places throughout the year and that a spatial seasonal trend exists. Robbery, on the other hand, displayed entirely different results. At the census tract level, spatial similarity increased from the total crime equivalent, however, when moving to dissemination areas the similarity indices exceed the aforementioned threshold in almost all cases. This implies that robberies “occur in the same places regardless of the season of year” (Andresen & Malleson, 2013, p.31). Results for sexual assault demonstrated similar outcomes as robbery, but were even more spatially concentrated at the smaller level of analysis. Lastly, analyses for theft, theft of and theft from vehicle generated fairly similar findings. The authors' results at both levels of analysis showed relatively low levels of spatial similarity indicating the presence of seasonal fluctuations (Andresen & Malleson, 2013, p.32). In other words, the locations that are host to these theft-related crimes are dependent upon the time of year. Furthermore, such places likely coincide with the seasonal activities of people.

Overall, the authors concluded that the "spatial patterns of crime are predictable" and that much of their results could be accounted for by routine activities theory (Andresen & Malleson, 2013, p.32). As previously discussed in the temporal component chapter, crimes such as sexual assault often produce repeat victimization between victims and offenders who know one another in the same places, such as their homes (Maguire & Brookman, 2009, p.517; Leclerc, Wortley & Smallbone, 2010, p.649; Lussier, Bouchard & Beauregard, 2011, p. 441). As such, it is not surprising that the data generated nearly identical spatial patterns throughout the year. When considering other crimes such as assault, theft and burglary, however, the authors were not surprised to discover spatial dissimilarity across the seasons. As anticipated, they found that "crime [increased] in the downtown shopping area, other shopping/tourist areas, large parks around the city, and the location of Vancouver's summer fair" (Andresen & Malleson, 2013, p.32). While results from this study provide excellent insights into our understanding of the spatial component of crime seasonality, further investigation within this field is certainly warranted. Andresen and Malleson's (2013) results were based only on one-year worth of data and investigation of the stability of these trends was not possible with the available data. Further inquiry using a longitudinal sample would be particularly useful in a similar context. Moreover, analysis at a micro-spatial scale would also offer valuable information to supplement the crime at places literature.

### 5.1.1. Non-Criminal Factors that Impact Annual Differences in Spatial Offending Patterns

It has become increasingly apparent through both the theoretical and empirical literature that crime is influenced not only by motivation but also by opportunity (Clarke, 1980, p.140). As previously discussed, while there are crime-specific factors that influence offending across different crime types, there are also non-criminal phenomena to consider. This is not surprising given the considerable focus that has been given to routine activities theory in the empirical literature. Peoples' habits and activities, both criminal and non-criminal, can alter their likelihood of being the victim or offender in a given situation. This is why routine activities theory was so readily able to explain why crime increased as living conditions improved (Cohen & Felson, 1979, p.588). As household incomes increased in the 1950s and 1960s, people began to engage in more leisure activities outside of the home. These drastic changes in behaviour lead to an increased availability of suitable targets "without invoking changes in criminal motivation" (Andresen, 2010, p.16). In other words, the opportunities for crime became more abundant thus increasing offending.

These non-criminal factors that can impact the prevalence of opportunities can include changes in: the economy, weather trends, major holidays, schooling schedules, sporting events, tourist activity, and even the number of daylight hours (see Cantor & Land, 1985; Cohen & Felson, 1979; Cohn & Rotton, 2003; Carbone-Lopez & Lauritsen, 2013; Breetzke & Cohn, 2013; Barker, Page & Meyer, 2002; Cohn, 1993). A review of such influences on offending can also provide valuable insights into the existence of crime seasonality. Many of these events/activities can be tied to the aforementioned concepts of crime generators and crime attractors (Brantingham & Brantingham, 1995). Often, the simple fact of having large volumes of people converge at a specific place and time can provide sufficient means for successful offending. A prime example of this is the Stanley Cup riots that occurred on June 15th, 2011 in Vancouver, British Columbia. As Schneider & Trottier (2012) describe, in addition to the hockey game being held at Rogers Arena, there were four other large screens that were installed in the downtown core of Vancouver that drew over fifty-five thousand spectators. Following the loss of the home team, spectators began to riot and "set fires, [overturn] cars, [smash] windows, and even [loot] retail establishments" as a result (Schneider & Trottier, 2012, p.58). This event/location could, however, be simultaneously classified as both a crime generator and attractor. Information acquired during and after the riot revealed that a small subset of the population travelled to the so-called "Live Site" with the intent of causing trouble, whereas others joined in on the night's events once they had been initiated (Schneider & Trottier, 2012, p.67). As such, for the former group, the Live Site can be considered a crime attractor in that these individuals travelled to the downtown core with intent and motivation to commit criminal offences. For the latter group, however, the site created a crime generator for less criminally motivated offenders. More specifically, they travelled to the Live Site with the intent of watching and participating in Stanley Cup festivities but later decided to engage in rioting behaviour once instigated by others providing them with sufficient opportunity to act criminally (see Brantingham & Brantingham, 1995).

Other studies have examined the relationship between crime and sporting events and have demonstrated that multiple crime types can be affected differently. For instance, it has been found that domestic violence increases following football games that end in a result contrary to those predicted by “pre-game point spread[s]” (Card & Dahl, 2009, p.32). Other studies have shown, for example, that while crime remained relatively similar to historical trends in Vancouver during a Canucks hockey game, certain neighbourhoods would experience drastic increases in vehicular theft in the hours following a game (Kirk, 2008, p.75). More recently, Breetzke and Cohn (2013) investigated the spatial patterning of crime surrounding the Loftus Versfeld stadium in Tshwane, South Africa relative to soccer and rugby game days. They discovered that, overall, while the volume of crime was higher on games days, the locations in which crimes occurred were not evenly distributed. More specifically, “sporting events [did] not significantly impact crime levels across the city” but they did increase within a half-mile and 1-mile radius from the stadium (Breetzke & Cohn, 2013, pp.405-6). Furthermore, these increases in crime were only observed for overall crime, assault and drunk/disorderly behaviour, but not for burglary (Breetzke & Cohn, 2013, p.406). Differences in offending patterns across different crime types may be linked to the nature of the crimes themselves coupled with the routine activities of people. As theoretically expected, creating an environment where large numbers of people congregate to view a sporting event while simultaneously consuming alcohol is far more conducive to crimes of passion against the person such as assault and drunk/disorderly behaviour than property crimes such as burglary (Cohen & Felson, 1979; Brantingham & Brantingham, 1995). Finally, based on these results, practitioners should be cognizant of the scheduling of such events in attempts to develop the most effective policing strategies (Andresen & Malleson, 2013).

Large-scale sporting events have also been known to increase tourism levels in the host cities and or countries (see Barker, Page & Meyer, 2002). As a result, certain areas experience not only an influx of local residents who travel to and from events, but also tourists who often engage in different routine activities. For instance, Barker et al. (2002) conducted a study on spatial crime patterns in Auckland New Zealand during the America’s Cup Yacht Race and found disparate crime trends for domestic versus overseas guests. The authors found that peoples’ choices in accommodation played an important part in explaining the occurrence of victimization. More specifically, their results revealed that

> Overseas guests were more likely to experience theft from accommodation or person than domestic tourists, reflecting their greater tendency to use commercial accommodation and campervans. The domestic group was more likely to experience crime in public places, particularly theft from vehicles, which reflects the greater self-drive travel among this group (Barker et al., 2002, p.770).

As a result, because outsider tourists are more likely to stay in commercial accommodations than domestic ones who often have friends and relatives that they can stay with, the type of victimization varies accordingly (Barker et al., 2002, p.771). Interestingly, tourist attractions such as large sporting events can act as a hot spot or safe enclave for crime. On one hand, these locations can provide a wealth of opportunity for motivated offenders against suitable tourist targets who are unfamiliar with their environments. On the other hand, increased police and security presence can also deter offenders via capable guardianship of an area (Barker et al., 2002, p.778). The latter effect, however, can generate problems when analyzing crime data. For example, police report data may become artificially inflated due simply to the fact that more police officers were present at a given place (see Andresen & Tong, 2012). In other words, the actual volume of crime may not have increased significantly, but appears to be higher simply because more police officers are present to record it.

Tourism unrelated to sporting events can also impact crime rates on a seasonal basis. Similar trends to the aforementioned studies have been identified. For instance, in Hawaii it was found that tourists were more likely to be the victims of property crime as well as robbery and rape (Chesney-Lind & Lind, 1986, p.173). These increased victimization trends have often been attributed to the routine activities of tourists in that they more often frequent bars, nightclubs, and travel to unfamiliar areas when on vacation (Chesney-Lind & Lind, 1986, p.178). Similarly, de Albuquerque and McElroy (1999) found that while tourists in the Caribbean were more likely to be the victims of property crime or robbery, local residents experienced disproportionately higher rates of violent crime such as murder and aggravated assault (de Albuquerque & McElroy, 1999, p.976). Furthermore, the authors believed that the seasonal fluctuations were further influenced by economic factors such as unemployment that led to changes in the volume of persons travelling on vacation (de Albuquerque & McElroy, 1999, p.978).

The more recent crime seasonality literature that has emerged continues to provide empirical support for routine activities theory and the notion that people's movements through time and space lead to predictable offending patterns (Andresen & Malleson, 2013). Moreover, these movements occur at very specific times and places. As discussed above, daily changes such as the occurrence of a government holiday can drastically impact crime patterns (Cohn & Rotton, 2003). Other studies have also looked at temporal crime trends at very fine levels of analysis, namely the hourly level (see Ceccato, 2005; Cohn & Rotton, 2000; Cohn & Rotton, 1997). Despite these findings, no studies have simultaneously explored seasonal spatial patterns at a micro-spatial scale. As previously discussed, the vast majority of research in this area has been conducted using neighbourhoods (see Harries et al., 1984; Breetzke & Cohn, 2012), overlaid grid cells (Cohen et al., 2003), space-time clusters (Ceccato, 2005; Uittenbogaard & Ceccato, 2012), census tracts and dissemination areas (Andresen & Malleson, 2013). None of these studies can thus attest to the spatial patterns of discrete places. Inquiry into such spatial trends has the potential to contribute to the literature.

### 5.1.2. The Importance of Employing Analyses at a Micro-Spatial Scale

Given the information presented in previous sections it has become increasingly apparent that different crime types can exhibit drastically different temporal and spatial trends. Furthermore, routine activities theory demands such spatial and temporal trends to converge at a very precise level in order for a crime to occur (Cohen & Felson, 1979).

From this, a focus on analysis at a micro-spatial scale should be considered and many empirical studies have proven the value of such levels of analysis. Based on the principles of routine activities theory, Sherman et al. (1989) set out to analyze crime at a micro-level, namely street segments within a city. Much of the work prior to their study focused on crime within neighbourhoods and relied on data drawn at the corresponding level (Sherman et al., 1989, p.28). This in turn, identified problem areas within various cities and aided police in their deployment of resources to more problematic areas. Based on the fact that crime is not randomly distributed (Sherman et al., 1989, p.29), however, Sherman et al (1989) hypothesized that distinct crime patterns would emerge at a finer level of analysis. Their study of Minneapolis, Minnesota ended up confirming that crime is not randomly distributed and instead occurs in very concentrated areas (Sherman et al., 1989, p.28). Moreover, their analysis found that just over half of all crimes reported to the police in their data occurred in only 3.3% of street blocks in the city (Sherman et al., 1989, p.37). The authors subsequently coined the term “crime at place” that spawned a wealth of studies concentrating on the advantages of employing a micro-spatial scale of analysis (Sherman et al., 1989, p.44; see Weisburd et al., 2004; Weisburd, Morris & Groff, 2009a; Weisburd, Bruinsma & Bernasco, 2009b; Andresen & Malleson, 2011; Bernasco & Block, 2011; Braga, Hureau & Papachristos, 2011; Andresen & Linning, 2012; Curman et al., 2014).

Replication has continued to corroborate these results. In a longitudinal study of crime in Seattle, Weisburd et al. (2004) not only revisited Sherman et al.’s (1989) approach to assessing crime concentrations at a micro-spatial scale, but they also looked at the stability of those concentrations. First, they found that half of the crime in the city occurs in 4-5 percent of the street blocks and that all crime took place between 48-53 percent of the street segments (Weisburd et al., 2004, p.294). Once again, it was shown that crime was driven by a disproportionately small subset of street blocks within the city. However, the authors furthered their analysis by examining how crime at these specific areas changed over time. Their trajectory analyses revealed that overall the majority of all trajectories generated remained relatively stable over the 14 year period (Weisburd et al., 2004, p.294). When examining the trajectories more closely, however, the authors found that those with low intercepts remained consistently low throughout the study period. This was also the characteristic of the majority of trajectories generated

(Weisburd et al., 2004, p.300). Conversely, of the few trajectories that possessed high intercepts, they remained some of the highest throughout the observations (Weisburd et al., 2004, p.302). Only three of their eighteen trajectories represented around two percent of their street segments, but produced the largest magnitude changes in crime thus consequently impacting the overall trends (Weisburd et al., 2004, p.302). Lastly, the authors conclude that the decreasing trajectories “appear to account for the crime drop observed in Seattle during the study period” (Weisburd et al., 2004, p.303). In other words, similar to the lack of random occurrence shown by Sherman et al. (1989), the overall crime drop within the city can be accounted for by a small subset of street segments within the city as opposed to a more broad city-wide trend (Weisburd et al., 2004, p.284).

Interestingly, a replication of the above study by Curman et al. (2014) using data from Vancouver, British Columbia revealed similar results. The authors found that over a 16 year period, around 40% of street segments experienced no crime whatsoever. Moreover, even though their Vancouver data generated trajectories with characteristics similar to Weisburd et al.’s (2004) in Seattle, they found that the overall decline in crime could not be as strongly attributed to the so-called ‘chronic’ street segments. In other words, while the crime drop in Weisburd et al.’s (2004) study was largely driven by the smaller sub-set of problem street blocks in the city, Curman et al.’s (2014) data suggest that a more ubiquitous decrease in crime over the 16 year period occurred across the entire city of Vancouver (Curman et al., 2014).

Weisburd et al. (2009) also replicated the Seattle study using data on juvenile offenders that spawned similar results. Unsurprisingly, their analyses revealed that juvenile crime was strongly spatially concentrated. In fact, less than one percent of street segments were host to half of the criminal incidents in Seattle and all crime could be attributed to only 3-5 percent of street blocks over a 14 year period (Weisburd et al., 2009, p.451). Once again, their trajectory analysis found relatively stable crime trends within the data and only a small number of street segments exhibit high crime (Weisburd et al., 2009, p.454). Moreover, the authors were able to confirm the strong clustering of juvenile crime within the city, namely in the downtown core, due most likely to the relatively concentrated routine activities of these youths (Weisburd et al., 2009, p.457).

While the aforementioned Seattle articles focused on aggregate total crime variables, others have also applied these micro-spatial principles to specific crime types. In a 29-year longitudinal study in Boston, Braga et al. (2011) examined robberies and their stability over time. Unsurprisingly they found that only 12 percent of street segments “experienced only one robbery incident between 1980 and 2008”, and that half of the robberies in Boston occurred in only 8.1 percent of street blocks during that same time period (Braga et al. 2011, p.16). Moreover, they found that street blocks that experienced disproportionately higher crime remained the highest, more chronic locations over time (Braga et al., 2011, p.21). This led the authors to additionally explore the characteristics of street segments in Boston via growth curve regression to determine which factors contribute to their increased criminality. Most notably, they found support for the disaggregation of robbery types. More specifically, different street block characteristics rendered certain areas more prone to delinquency depending on the type of robbery being examined. For instance, while street robberies were more prevalent near intersections, they were far less likely in areas located near major thoroughfares. Conversely, commercial robberies were more likely to occur on street segments than intersections (Braga et al., 2011, p.21).

Andresen and Malleson (2011) were one of the first to explore multiple crime types individually in Vancouver, British Columbia at three levels of analysis, namely census tracts, dissemination areas and street segments. Similar to the aforementioned articles, they found that depending on the crime type, half of all crime could be accounted for by 1-8 percent of street segments. Moreover, half of all street blocks in the city experienced none of the crime types and that these figures remained relatively stable throughout the years of data examined[18] (Andresen & Malleson, 2011, p.65). The authors then took their analysis one step further and employed a spatial point pattern test to assess the degree of spatial similarity of criminal events at all three levels of analysis. Their results demonstrate that as one moves to a finer spatial scale, crime patterns occur in increasingly similar places (Andresen & Malleson, 2011, p.71). In addition, a replication of these tests using data from Ottawa, Ontario also revealed even stronger spatial similarity across crime types (Andresen & Linning, 2012, p.278). This

[18] Years examined: 1991, 1996 and 2001 (see Andresen & Malleson, 2010, p.61).

provides further support for Sherman et al.'s (1989) assertions that safe areas exist within problematic neighbourhoods. Moreover, these underlying patterns would have gone unnoticed if the data were analyzed using the conventionally employed census tracts as the unit of analysis (Andresen & Linning, 2012, p.279).

These findings are important for criminological research because they are able to show that the majority of crime occurs in a small number of chronic locations. If these data were analyzed at a larger level, such as the neighbourhood, it may have appeared that the entire neighbourhood possessed a great deal of crime when in fact only a very small subset of locations was driving the area's crime rate (Sherman et al., 1989). This provides further support for the importance of disaggregation as well as the importance of analyzing crime at a micro-spatial scale.

## 5.2. Spatial Hypotheses

In examining the spatial aspect of crime seasonality, a distinct set of hypotheses emerges that are unlike those generated for any corresponding temporal analyses. Given the aforementioned literature and proposed research questions the following hypotheses were developed:

(1) All property offences will occur at a very small number of street segments in each city.

(2) Given the nature of annual human movement patterns, micro-spatial property crime patterns will vary in different seasons.

(3) Seasonal variation in micro-spatial property crime trends will be more prominent in cities with more distinct weather seasons.

(4) Different crime types should be examined individually because each offence type will exhibit different spatial patterns.

## 5.3. Data

The same data from Vancouver (2003-2013) and Ottawa (2006-2008) that were used in the temporal chapter were employed in the spatial analyses that follow. The Vancouver data contained the month of occurrence and addresses anonymized to the 100-block. In other words, the last two digits of each listed address were removed prior to their posting in the database. As such, a random number generator was used in Microsoft Excel to input the placeholders for geocoding[19] in ArcMap v.10.2. Matches for a given observation were permitted provided the address fell within the appropriate street block or intersection. Frequency and geocoding percentage tables for the Vancouver data can be found in appendix G. For the Ottawa data, information regarding the date, time, and address anonymized to the 100-block were included. Once again, a random number generator was used in Microsoft Excel and subsequently spliced into the anonymized address. All observations were geocoded to the corresponding street block or intersection in Ottawa using ArcMap v.10.2. The frequency and geocoded statistics tables for these Ottawa data can be found in appendix H. Overall, geocoding hit rate percentages ranged from 96.3 – 97.1 percent in Vancouver to 93.5 – 98.2 percent in Ottawa and, thus, exceed Ratcliffe's (2004a) recommended minimum acceptable hit rate of 85 percent (Ratcliffe, 2004a, p.69). Moreover, street segments (or 100-block) were chosen as the unit of analysis in order to capture the spatial patterns present at a micro-spatial scale. For the purposes of this study, street segments consist of the distance between two consecutive intersections and include all addresses located on either side of the street block (Andresen & Malleson, 2011, pp.62-3).

## 5.4. Methods

For analysis of the spatial patterns of various crime types, the computerized spatial point pattern test originally developed by Andresen (2009) was employed. The test was designed to "measure the degree of similarity between two spatial point patterns" (Andresen, 2009, p.333; see also Andresen & Malleson, 2011). In order to more efficiently implement the test, a computer program was later developed by Andresen and Malleson (2011) that carries out the following steps:

> 1. Nominate a base data set [e.g., commercial break and enter, winter] and count, for each area, the number of points that fall within it.

[19] Example: If 25 were randomly generated, 1XX Main street in the original data was replaced with 125 Main street.

2. From the test data set [e.g., commercial break and enter, summer], randomly sample 85 percent of the points, with replacement. As with the previous step, count the number of points within each area using the sample. This is effectively a bootstrap created by sampling from the test data set.

3. Repeat (2) a number of times (100 is used here).

4. For each area in the test data set, calculate the percentage of crime that has occurred in the area. Use these percentages to generate a 95 percent nonparametric confidence interval by removing the top and bottom 2.5 percent of all counts (5 from the top and 5 from the bottom in this case). The minimum and maximum of the remaining percentages represent the confidence interval. It should be noted that the effect of the sampling procedure will be to reduce the number of observations in the test data set but, using percentages rather than the absolute counts, comparisons between data sets can be made even if the total number of observations are different.

5. Calculate the percentage of points within each area for the base data set and compare this to the confidence interval generated from the test data set. If the base percentage falls within the confidence interval, then the two data sets exhibit a similar proportion of points in the given area. Otherwise they are significantly different.

The output of the test is comprised of two parts. First, a global parameter that ranges from 0 (no similarity) to 1 (perfect similarity): the index of similarity, S, is calculated as:

$$S = \frac{\sum_{i=1}^{n} s_i}{n}$$

where $s_i$ is equal to one if two crimes are similar in spatial unit i and zero otherwise, and n is the total number of spatial units. Therefore, the S-Index simply represents the percentage of spatial units that have a similar spatial pattern for both data sets, ranging from zero to one. Second, the test can be used to generate mappable output that shows where statistically significant change has occurred; that is, which [street segments and intersections] have undergone a statistically significant change (Andresen & Malleson, 2011, p.64).

For the purposes of this study, an S-index value of 0.8 is considered sufficient to assume that the spatial patterns of two variables are similar enough to be substitutable (see Andresen & Malleson, 2013, p.28). Finally, for this test the seasons were defined as the following: Winter (January – March); Spring (April – June); Summer (July –

September); Fall (October – December).[20] As such, individual shape files for each of the seasons within each city, year and crime type were created in order to import them into the spatial point pattern test software.

## 5.5. Results

Akin to the temporal chapter, for ease of legibility only the results for the 2008 data in both cities will be shown in the following sections. Once again, these data were chosen because they contain the most information, namely a full year of mischief data in Ottawa. Additional results can be found in appendices I through N for reference. The next sections will discuss the findings generated from the spatial analyses on these Vancouver and Ottawa data. First, the replication of Sherman et al.'s (1989) original work regarding the spatial concentration of crime within street segments will be presented. Second, the spatial point pattern test results will be shown. Lastly, notable mappable outputs of crime types that revealed statistically significant changes at the street segment level will be discussed.

### 5.5.1. Micro-Spatial Crime Concentrations

As previously discussed, Sherman et al. (1989) found that half of all crime reported to the police in their Minneapolis, MN data occurred in only 3.3% of street segments (Sherman et al., 1989, p.37). Subsequent replications of these analyses have yielded similar results. In fact, other studies found that half of crime in their datasets occurred in only 4-5% and 1-8% of street segments respectively depending on the crime type being assessed (Weisburd et al., 2004, p. 294; Andresen & Malleson, 2011, p.65). These same calculations were replicated in this study to provide context for the degree of (dis)similarity present within these Vancouver and Ottawa data. Furthermore, analyses were also supplemented by the inclusion of offences that occurred at intersections. As such, calculations of these spatial concentrations were conducted

[20] Note: Shapefiles were created and tested with different month groupings so that the fall season file would begin with September in order to coincide with the beginning of the academic school year. Results were not qualitatively different from those generated using the listed seasons.

using both street segments and intersections for comparison and contextual purposes. This allows us to compare results to the aforementioned studies as well as explore an additional aspect of offending patterns relevant to the crime at place literature.

**Table 5.1. Crime Concentrations within Street Segments, Vancouver, 2008**

| | (a) Percentage of Street Segments Accounting for 50% of Crime | (b) Percentage of Street Segments & Intersections Accounting for 50% of Crime | (c) Percentage of Street Segments that Have Any Crime | (d) Percentage of Street Segments & Intersections that Have Any Crime | (e) Percentage of Street Segments with Crime that Account for 50% of Crime |
|---|---|---|---|---|---|
| Commercial B&E | 1.88 | 1.19 | 8.80 | 5.60 | 21.32 |
| Mischief | 4.42 | 2.81 | 22.86 | 14.54 | 19.31 |
| Theft from Vehicle | 4.67 | 2.97 | 14.60 | 9.29 | 31.99 |
| Theft of Vehicle | 2.62 | 1.66 | 29.33 | 18.65 | 8.92 |
| Total (Aggregate) | 4.50 | 2.86 | 44.42 | 28.25 | 10.13 |

**Table 5.2. Crime Concentrations within Street Segments, Ottawa, 2008**

| | (a) Percentage of Street Segments Accounting for 50% of Crime | (b) Percentage of Street Segments & Intersections Accounting for 50% of Crime | (c) Percentage of Street Segments that Have Any Crime | (d) Percentage of Street Segments & Intersections that Have Any Crime | (e) Percentage of Street Segments with Crime that Account for 50% of Crime |
|---|---|---|---|---|---|
| Commercial B&E | 0.63 | 0.42 | 2.13 | 1.41 | 29.57 |
| Residential B&E | 1.26 | 0.84 | 3.34 | 2.21 | 37.86 |
| Robbery | 0.46 | 0.30 | 1.22 | 0.80 | 37.64 |
| Theft of Vehicle | 1.07 | 0.71 | 3.09 | 2.04 | 34.76 |
| Total (w/o mischief) | 2.01 | 1.33 | 8.01 | 5.29 | 25.12 |
| Mischief | 2.38 | 1.57 | 9.24 | 6.10 | 25.79 |
| Total (w/mischief) | 3.01 | 1.99 | 14.04 | 9.28 | 21.43 |

Columns (a) and (b) of tables 5.1 and 5.2 show the micro-spatial crime concentration percentages in Vancouver and Ottawa. Not surprisingly, the numbers generated from these calculations are very similar to the findings of the previous studies. Similar to previous findings, column (a) indicates that half of all property offences in the data occur in less than 5% of street segments in both cities. At an individual level, these concentrations can be as low as 1.88% of street segments when looking solely at commercial break and enters to 4.67% of street blocks in the case of thefts of vehicle in Vancouver. In Ottawa, however, many of these offences are even more spatially concentrated. For instance, while half of all commercial break and enters and robberies occur in 0.63% and 0.46% of street segments respectively, half of the total (aggregate) crimes that includes all mischief offences can be accounted for in as little as 3.01% of street blocks in the city. These results are very comparable to the aforementioned studies and thus provide further credence to the notion that crime does not occur randomly in space (Sherman et al., 1989).

Similarly, column (b) provides some additional insight into these trends by also considering the intersections in each city. Given the fact that intersections have been omitted from all known crime and place studies to date (see Weisburd et al., 2004; Weisburd et al., 2009, Andresen & Malleson, 2011; Curman et al., 2014) but that crime does occur at these locations, their inclusion into the analyses is beneficial. Although it is unsurprising that these percentages decreased because the number of spatial units considered increased, it should be noted that the data employed in all analyses also include offences that took place at intersections. In other words, past research had only assessed the number of crimes that took place on street blocks and their subsequent prevalence across street segments within a city. This meant that offences that occurred at intersections were actually omitted from all analyses (again, see Weisburd et al., 2004; Weisburd et al., 2009, Andresen & Malleson, 2011; Curman et al., 2014). As such, column (b) actually provides a more accurate representation of the spatial concentrations within each city that will relate directly to the subsequent spatial point pattern tests (discussed below).

Given these added features, the resulting percentages in column (b) are quite telling. The Vancouver calculations revealed that half of all offences occurred in only 1.19 to 2.86% of street segments and intersections in the city depending on the crime classification being assessed. Once again, the same calculations generated even smaller values in Ottawa. More specifically, half of all crime could be attributed to between 0.30 and 1.99% of street segments and intersections in the city. These results show and incredible degree of crime concentration across many types of property offences.

Moving to columns (c) & (d) in tables 5.1 and 5.2, it is apparent that even the assessment of all offences contained within the datasets exhibit strong spatial consolidation. In Vancouver, for example, all property crime in 2008 was captured in nearly 45% of street segments and just over 28% of street segments and intersections. Of particular interest is the degree of spatial concentration amongst commercial break and enter offences. All of these crimes can be attributed to 8.8% of street segments or 5.6% of street segments and intersections depending on which relationship is chosen to evaluate. Despite this high degree of spatial concentration, these values are relatively large in comparison to those in Ottawa. For instance, the aforementioned commercial break and enter percentages are actually larger than the total (aggregate) crime equivalent in Ottawa when mischief is not considered (8.01% and 5.29% respectively). This is a rather astounding finding and indicates that as many as four property crime offences combined occur in the same percentage of street segments in the city regardless of whether intersections are considered. Moreover, when mischief is included in the calculations, the total (aggregate) crime results in Ottawa are still more spatially concentrated than the disaggregate theft of vehicle offences in Vancouver (14.04% and 9.28% in Ottawa vs. 14.60% and 9.29% in Vancouver). For context, a series of kernel density estimation maps (see Appendix K & L) were also generated for each of these crime types as a means to show the more prominent levels of “crime intensity” in Vancouver and Ottawa (Ratcliffe, 2004b, p.8). Not surprisingly, regardless of crime type chosen, the locations with the highest crime density are located in the downtown areas of both cities.

Lastly, column (e) is a replication of a calculation that was first introduced by Andresen and Malleson (2011) to demonstrate whether spatial concentrations within concentrations exist in the data. This calculation simply consisted of taking only the street segments that experience any crime in that year and determining what percentage of those street segments accounted for 50% of the offence that occurred. Notably, in Vancouver the result for thefts from vehicle was 8.92%. This means that of the places that experienced thefts from vehicle, a small subset of those places experienced disproportionately higher levels of victimization. In other words, there are hotspots within hotspots when this disaggregate crime type is considered. However, this value happens to be the smallest of all generated for that crime type over the 11 year period contained in the data (see Appendix I). Although this may be a particularly exceptional result in comparison, the values produced for thefts of vehicle are still relatively low indicating there are hotspots within hotspots. All other offences exhibit relatively strong concentrations within concentrations, but just not to the same degree. More specifically, the other crime types generated values between 10.13% and 31.99%.

Despite the overall Vancouver findings, the equivalent calculations in Ottawa produced very different results (see column (e)). Surprisingly, the values ranged between 21.43% and 37.86% depending on the crime type being assessed. This indicates that of the locations that contained any crime during the year, half of all offences occur in places that are far more spread out spatially than in Vancouver. As such, there may be hotspots within hotspots in Ottawa, but they are not as prominent as in Vancouver. It should also be noted that this is a relatively consistent finding in Ottawa during other years of study (see Appendix J). This is rather surprising given the extreme degree of spatial similarity of offence locations exhibited in the first four columns of these tables. Nevertheless, they provide a great deal of insight into the underlying disaggregate spatial patterns in the city.

Lastly, the utility of producing such calculations at a disaggregate level should be discussed. Although the total (aggregate) crime classifications generated values indicating strong spatial concentrations in both cities, evaluations of the individual crime types were equally, if not more informative. The degree of spatial similarity within each of the cities was rather pronounced, particularly with offences such as commercial break and enter and robbery. Had these classifications not been assessed separately, their distinct patterns would have been masked within the overall aggregate crime variable. Moreover, it is always more advantageous to have as much information as possible and it is always possible to aggregate crime trends afterwards whereas the opposite is not always possible. This crime-specific information could be of great use to practitioners and policy makers when assessing crime trends and measures that could be implemented to reduce crime.

### 5.5.2. Spatial Point Pattern Tests

Results for the seasonal spatial point patterns tests for 2008 in both Vancouver and Ottawa can be seen in tables 5.3 through 5.15. Recall, that the test generates a universal index value where "a value of 1 represents identical spatial patterns and a value of 0 represents completely different spatial patterns" (Andresen & Malleson, 2011, p.67). Moreover, an index value of 0.8 or greater is sufficient to assume two point patterns are similar enough to be substitutable (see Andresen & Malleson, 2013).

### 5.5.3. Annual Crime Trends

Without considering seasonal trends, tables 5.3 and 5.4 show each of the annual aggregate crime types and the degree of spatial similarity they possess compared to other classifications. With the exception of three total crime[21] comparisons in Vancouver, all s-index values generated were 0.8 or greater demonstrating a strong similarity in spatial patterns. Moreover, two of the index values for Vancouver and all of the index values produced for Ottawa were 0.9 or greater. This indicates that property crime trends, particularly in Ottawa, are nearly identical regardless of the crime type examined. Interestingly, with the exception of commercial break and enter and total crime in Vancouver, exceedingly similar index values were produced in both cities regardless of the year selected for analysis (see appendix M). Once again, all Ottawa results from 2006-2008 yielded outputs that exceeded 0.9 implying nearly identical spatial patterns of property crime. Similarly, the Vancouver data became increasingly similar when moving from the comparisons of total crime to the individual crime types.

[21] For the purposes of these analyses, total crime is simply an aggregate measure of all crime types included in the Vancouver and Ottawa datasets respectively.

**Table 5.3. Indices of Similarity, 2008, Vancouver, Aggregate Crime, Street Segments & Intersections (w/7m buffer)**

| | Comm BnE | Mischief | TFV | TOV |
|---|---|---|---|---|
| Total Crime | 0.717 | 0.790 | 0.823 | 0.760 |
| Comm BnE | | 0.917 | 0.810 | 0.941 |
| Mischief | | | 0.826 | 0.866 |
| TFV | | | | 0.829 |

**Table 5.4. Indices of Similarity, 2008, Ottawa, Aggregate Crime, Street Segments & Intersections (w/7m buffer)**

| | Comm BnE | Res BnE | Mischief | TOV | Robbery |
|---|---|---|---|---|---|
| Total Crime | 0.957 | 0.965 | 0.947 | 0.962 | 0.952 |
| Comm BnE | | 0.983 | 0.974 | 0.984 | 0.986 |
| Res BnE | | | 0.966 | 0.977 | 0.977 |
| Mischief | | | | 0.940 | 0.938 |
| TOV | | | | | 0.980 |

### 5.5.4. Aggregate Seasonal Crime Trends

Looking at crime seasonality solely using an all-inclusive total (aggregate) crime variable, tables 5.5 and 5.6 show once again that spatial crime patterns in both cities are relatively similar. For instance, in Vancouver, when all offences are separated into distinct seasons but compared to the annual aggregate, s-index values of at least 0.776 or greater are produced. Although these do not quite meet the 0.8 threshold, they are still relatively high. When all offences are compared between seasons, however, all index values generated are well over this threshold and range between 0.868 and 0.875 throughout. On the other hand, s-index values of well over 0.9 are produced for the same relationships in Ottawa regardless of whether you are assessing the annual aggregate or each individual season. Interestingly, the lowest level of the s-index is 0.984 indicating nearly identical spatial patterns overall in the city. Although these results are even more pronounced in Ottawa, it is apparent that the spatial crime patterns in both cities are extremely similar. In fact, the majority of the results suggest that the point patterns are similar enough to be substitutable and in most cases an aggregate seasonal measure of crime could have sufficed in revealing the spatial trends present.

**Table 5.5. Indices of Similarity, 2008, Vancouver, Total Crime, Street Segments & Intersections (w/7m buffer)**

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.780 | 0.779 | 0.782 | 0.776 |
| Spring | | 0.869 | 0.868 | 0.870 |
| Summer | | | 0.871 | 0.875 |
| Fall | | | | 0.870 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

**Table 5.6. Indices of Similarity, 2008, Ottawa, Total Crime, Street Segments & Intersections (w/7m buffer)**

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.961 | 0.964 | 0.959 | 0.956 |
| Spring | | 0.982 | 0.982 | 0.983 |
| Summer | | | 0.979 | 0.979 |
| Fall | | | | 0.985 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

### 5.5.5. Disaggregate Seasonal Crime Trends

Given much of the past crime at place research that has demonstrated the utility of analyzing crime at a disaggregate level, the spatial point pattern test was also used to examine each of the individual property crime types. Tables 5.7 through 5.15 provide the resulting outputs generated for Vancouver and Ottawa respectively.[22] Such analyses allow for an assessment of whether, for example, robberies in the summer occur at the same physical locations as robberies in the winter. Interestingly, no matter which crime type or city is selected for assessment, all s-index values exceeded the aforementioned 0.8 threshold of sufficient similarity. In fact, the lowest value generated in 2008 was for theft from vehicle in Vancouver when the offences in the winter were compared to the all year aggregate (s-index = 0.847). Given that this crime type had the highest frequency of

[22] Seasons: Winter (Jan – March); Spring (April – June); Summer (July – Sept); Fall (Oct – Dec)

occurrence of any other classification (N = 11,411), it is unsurprising that it generated the lowest output. However, it is quite remarkable that its corresponding spatial point patterns are so similar. Nevertheless, all possible seasonal property crime combinations produced markedly comparable results and suggested that there are little or no spatial seasonality trends present in both cities.

**Table 5.7. Indices of Similarity, 2008, Vancouver, Commercial Break and Enter, Street Segments & Intersections (w/7m buffer)**

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.960 | 0.960 | 0.956 | 0.961 |
| Spring | | 0.979 | 0.982 | 0.978 |
| Summer | | | 0.982 | 0.979 |
| Fall | | | | 0.980 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

**Table 5.8. Indices of Similarity, 2008, Vancouver, Mischief, Street Segments & Intersections (w/7m buffer)**

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.891 | 0.888 | 0.887 | 0.889 |
| Spring | | 0.948 | 0.952 | 0.946 |
| Summer | | | 0.953 | 0.950 |
| Fall | | | | 0.950 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

**Table 5.9. Indices of Similarity, 2008, Vancouver, Theft from Vehicle, Street Segments & Intersections (w/7m buffer)**

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.857 | 0.853 | 0.860 | 0.847 |
| Spring | | 0.922 | 0.920 | 0.924 |
| Summer | | | 0.919 | 0.927 |
| Fall | | | | 0.919 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

**Table 5.10. Indices of Similarity, 2008, Vancouver, Theft of Vehicle, Street Segments & Intersections (w/7m buffer)**

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.932 | 0.930 | 0.927 | 0.930 |
| Spring | | 0.971 | 0.973 | 0.970 |
| Summer | | | 0.976 | 0.973 |
| Fall | | | | 0.973 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

**Table 5.11. Indices of Similarity, 2008, Ottawa, Commercial Break and Enter, Street Segments & Intersections (w/7m buffer)**

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.989 | 0.990 | 0.989 | 0.988 |
| Spring | | 0.995 | 0.996 | 0.996 |
| Summer | | | 0.995 | 0.995 |
| Fall | | | | 0.996 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

**Table 5.12. Indices of Similarity, 2008, Ottawa, Residential Break and Enter, Street Segments & Intersections (w/7m buffer)**

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.984 | 0.986 | 0.982 | 0.981 |
| Spring | | 0.993 | 0.993 | 0.993 |
| Summer | | | 0.991 | 0.991 |
| Fall | | | | 0.995 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

**Table 5.13. Indices of Similarity, 2008, Ottawa, Mischief, Street Segments & Intersections (w/7m buffer)**

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.953 | 0.958 | 0.952 | 0.948 |
| Spring | | 0.978 | 0.980 | 0.980 |
| Summer | | | 0.975 | 0.975 |
| Fall | | | | 0.982 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

**Table 5.14. Indices of Similarity, 2008, Ottawa, Robbery, Street Segments & Intersections (w/7m buffer)**

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.994 | 0.994 | 0.994 | 0.993 |
| Spring | | 0.997 | 0.997 | 0.997 |
| Summer | | | 0.997 | 0.997 |
| Fall | | | | 0.998 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

**Table 5.15. Indices of Similarity, 2008, Ottawa, Theft of Vehicle, Street Segments & Intersections (w/7m buffer)**

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.985 | 0.986 | 0.985 | 0.984 |
| Spring | | 0.994 | 0.994 | 0.995 |
| Summer | | | 0.993 | 0.993 |
| Fall | | | | 0.994 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

### 5.5.6. Mappable Outputs from the Spatial Point Pattern Tests

Fortunately, the spatial point pattern test software is also able to generate shape files that can be imported back into ESRI's ArcMap software for visual analysis. These files contain the street segments that generated statistically significant increases and decreases from the base data that were inputted into the tests. Several of examples of such outputs have been published in recent studies (see Andresen & Malleson, 2011; Andresen & Linning, 2012; Andresen & Malleson, 2013). However, it should be noted that outputs from analyses conducted using larger scales of analysis, such as dissemination areas and/or census tracts, are easier to interpret. The evaluation of these street segment-based outputs can be particularly challenging because there are so many units of analysis present.

In the case of these data, however, the consistently high spatial similarity present within the data meant that very few street segments experienced any significant change throughout the year. As a result, outputs for selected crime types were able to show any distinct seasonal variability. For instance, figures 5.1 through 5.3 demonstrate that the thefts of vehicle in both Vancouver and Ottawa are only significantly higher in some seasons at a very small number of street blocks and intersections in the cities. Moreover, the majority of these changes occur in the downtown areas, particularly in Ottawa. As such, the initial index values coupled with the accompanying mappable outputs indicate that although seasonal variations in crime are not overly prominent in either city, there are still some micro-spatial seasonal movements throughout the year.

**Figure 5.1. Mappable Outputs from the Spatial Point Pattern Test, Seasonal Increases from Annual Aggregate, Theft of Vehicle, Ottawa, 2008**

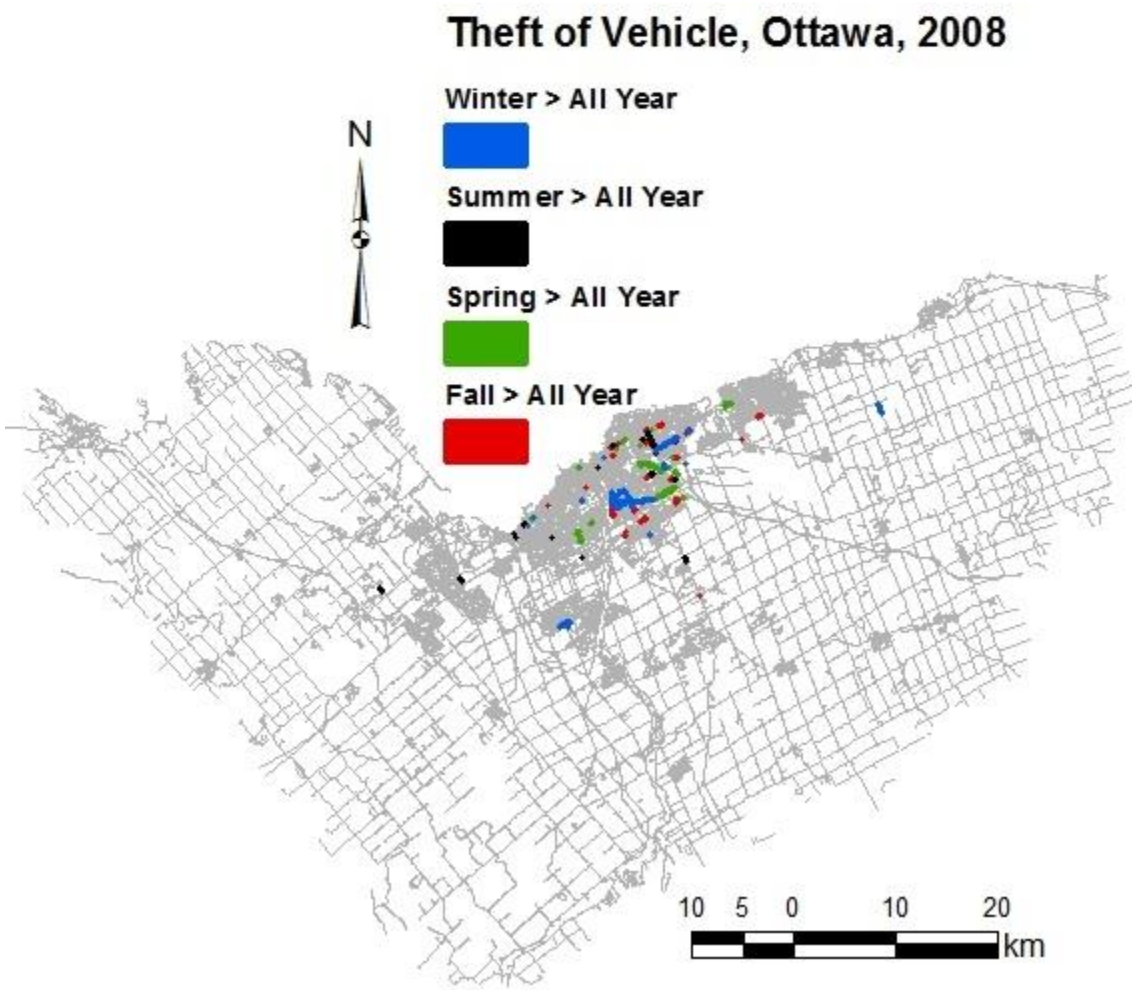


**Figure 5.2. Mappable Outputs from the Spatial Point Pattern Test, Seasonal Increase from Annual Aggregate, Theft of Vehicle, Ottawa (Downtown Area), 2008**

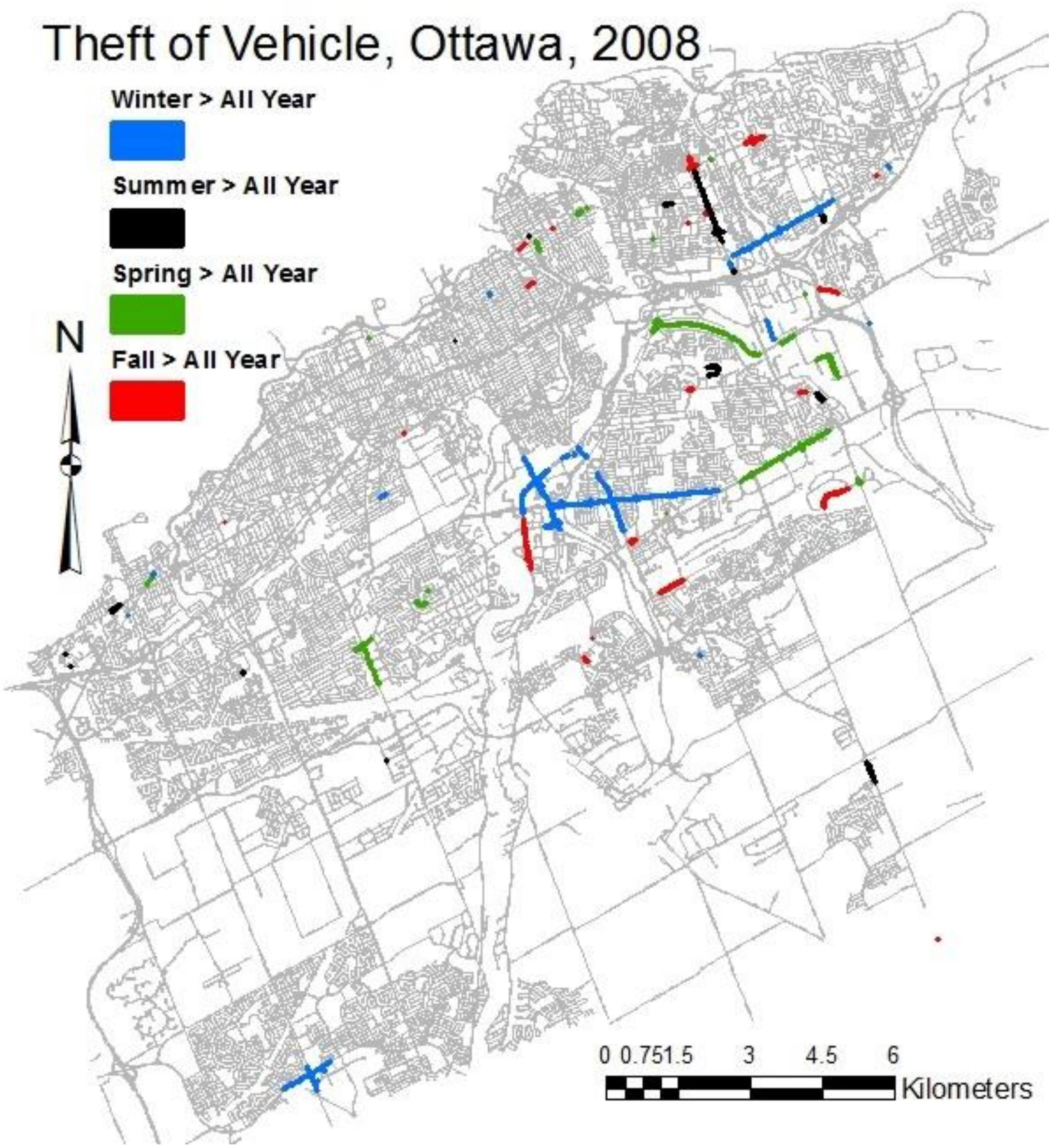


**Figure 5.3. Mappable Outputs from Spatial Point Pattern Test, Seasonal Increases from Annual Aggregate, Theft of Vehicle, Vancouver, 2008**

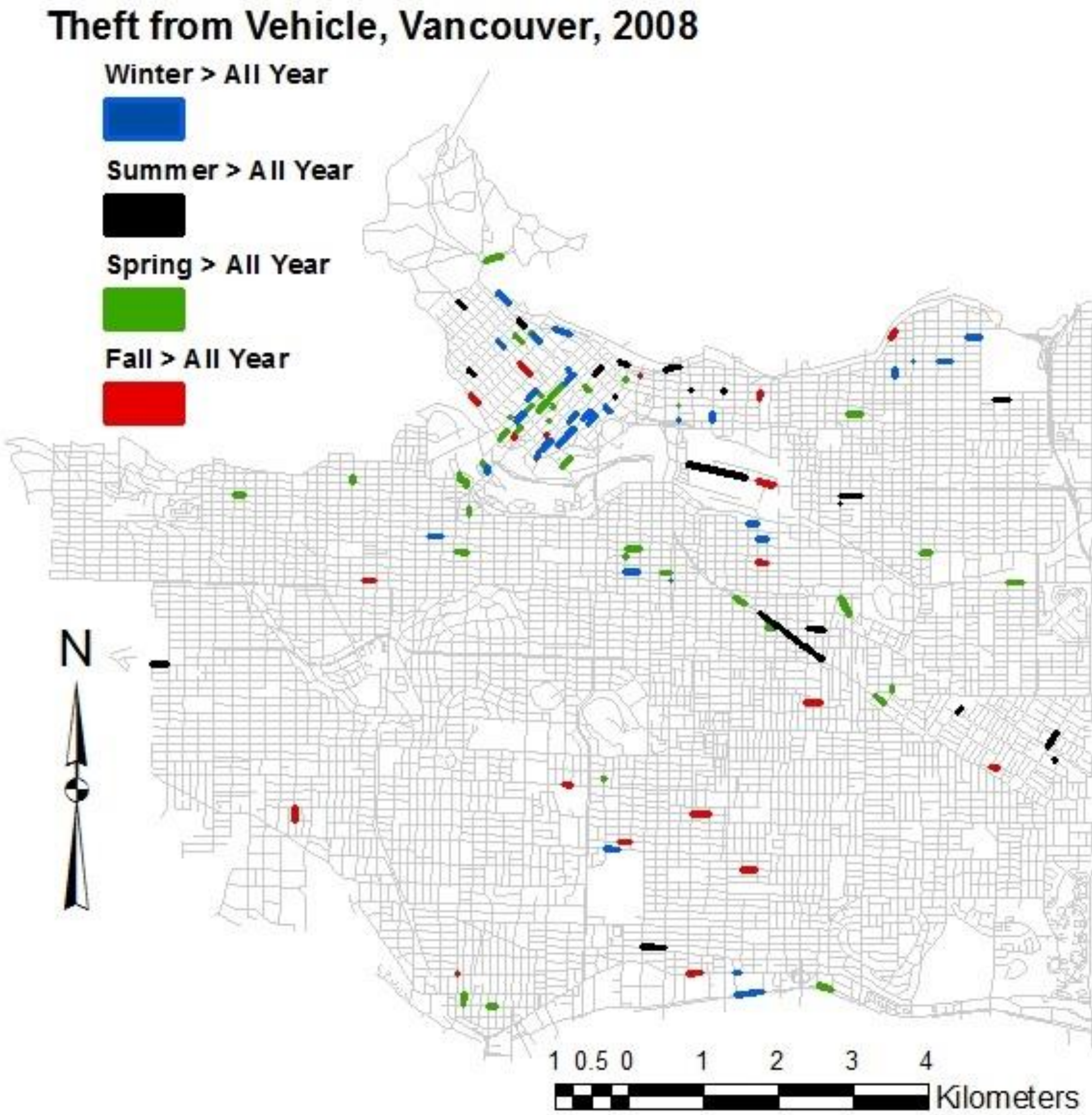



Figure 5.2 provides a closer look at Ottawa's downtown area and demonstrates how few street segments experience spatial patterns that are significantly distinct from the annual aggregate trends. Neighborhoods where these seasonal variations of thefts of vehicle exist include the Byward Market area, industrial park, Vanier area (i.e. French Ottawa), Billings bridge/Confederation heights and Barrhaven. Some of these areas,

such as Byward Market, tend to attract large volumes of people due to the entertainment activities and businesses located within the area.[23] Their resulting seasonal differences in offending patterns are thus consistent with the ideas concerning crime generators and attractors posited by Brantingham and Brantingham (1995). The output for thefts of vehicle in Vancouver also shows some consistency with theoretical expectations. Some of the most notable changes seen in Figure 5.3 relate to a spring increase in Stanley Park along the seawall, a rise in the summer adjacent to the Pacific National Exhibition (PNE) and a winter surge near Vancouver's sports stadiums, namely Rogers Arena, BC Place and the Pacific Coliseum.[24] Although these mappable outputs are consistent with theoretical expectations, it should be remembered that they only represent changes present within a very small portion of the data. The indices of similarity generated from the spatial point pattern tests indicate that the spatial patterns of the offences are overwhelmingly similar and in some cases are nearly identical (see tables 5.3 through 5.15).

## 5.6. Discussion

Although a great deal of literature has explored the seasonal variations of criminal offending, inquiry into its spatial component is severely lacking (see Brunsdon et al. 2009). Moreover, of the few studies that explore any spatial patterns, none have employed a micro-spatial unit of analysis (see Andresen & Malleson, 2013). Finally, none of the crime at place literature that examines micro-spatial crime trends has incorporated both street segments and intersections into any analyses (see Weisburd et al., 2004; Andresen & Malleson, 2011; Curman et al., 2014). As such, this study provides a wealth of insight into these largely unexplored phenomena. Furthermore, these offending patterns were examined in two cities with varying climates over many years thus allowing for an even better understanding of what is truly taking place.

[23] Thank you to my colleague Katherine Brine for her assistance in identifying and characterizing many of these neighborhoods/locations in Ottawa.

[24] Thank you to professor Paul Brantingham for his assistance/discussion of the theft of vehicle patterns that were present within the Vancouver data.

### 5.6.1. Limitations

Before these findings are discussed in more detail, however, a review of the study's limitations should be considered. Just as these data possessed limitations in the temporal analyses outlined in the previous chapter, they also contain some impediments when assessed at the spatial level. First, the data themselves characterized by both the information contained within and its accuracy must be reviewed. Only property crimes were included in the study, thus no claims regarding the spatial patterns of violent crime can be made. As such, the total crime variable used in these analyses was merely an aggregate representation of all crime types included in the data. In other words, this variable was created to test the utility of aggregate versus disaggregate analyses and was not intended to represent any other crime classifications. Next, although the crime types appear relatively straightforward, no official definitions for each classification were included with the data. Although this may not be a major issue when drawing comparisons across crime types within a city, it could be problematic when contrasting trends between cities.

The above also leads to the third limitation: accuracy. These findings are also bound by the accuracy of the data via police reporting. As Sherman et al. (1989) discuss in their extensive review of the limitations present in police report data, it cannot always be assumed that the correct addresses were inputted into the reports (see Sherman et al., 1989, pp.34-35). For instance, discrepancies in listing the appropriate address for a city park may vary depending on the officer who responded to the call for service. Despite this, however, the use of data at the 100-block level as opposed to the address level should resolve such potential analytic accuracy issues while still allowing for analysis at a micro-spatial scale.

Another matter worth noting is the availability of longitudinal data. It has been argued by different scholars that sufficient crime data over multiple years is required in order to make a more reliable assessment of seasonal trends (see Carbone-Lopez & Lauritsen, 2013; McDowall et al., 2012; Block 1983, 1984). Although this is not a concern for the Vancouver data, it certainly places limitations on the conclusions that can be made in Ottawa. Despite this, having crime data over a 3 year period can still provide valuable insights into the seasonal variations of offending. However, it should be noted that Carbone-Lopez and Lauritsen's (2013) specific criticism appeared to be reserved for studies that only utilized data from one year. Although this is not the case in this study, more grandiose conclusions regarding definitive seasonal patterns over a long period of time cannot be made.

Lastly, some could argue that the high level of spatial concentration and/or similarity exhibited in these analyses are largely "an artifact of the data and/or method" due to the micro-spatial scale of analysis and high prevalence of crime-free places (Andresen & Malleson, 2011, p.69). In other words, because there are so many street blocks that experienced no crime (i.e. high frequency of zero values) the high degree of spatial similarity could be artificially inflated/skewed. There are, however, a number of studies that have run the spatial point pattern test using a sensitivity technique in order to address this concern (see Andresen & Malleson, 2011, Andresen & Linning, 2012). It has been accomplished by simply omitting all crime-free street segments from the analyses. By removing these locations, the authors then only retested the remaining nonzero street segments. The results of both studies generated s-index values that had qualitatively no change (see Andresen & Malleson, 2011, p.71; Andresen & Linning, 2012, pp.278-9). It should be noted, however, that the retention of all crime-free street segments is arguably just as important to our understanding of these crime patterns. In fact, the lack of crime at these 'safe' places is telling information in itself and their inclusion in the analyses provides an overall comprehension of offence variation. Analyses of only nonzero street segments would instead provide insights solely into the spatial patterns of places with crime. As such, the aforementioned spatial point pattern tests without sensitivity changes can still be considered an accurate representation of the data.

### 5.6.2. Addressing the Research Questions/Hypotheses

Given much of the past research conducted in the crime at place literature it is not surprising that the results of this study revealed strong similarity of spatial patterns and high degrees of spatial concentration within each city. In fact, no matter which city and/or year is selected for assessment, all property crime in the data were captured by less than 37% of street segments and intersections in Vancouver (see Appendix I; this value was highest in 2004) and 10% in Ottawa. Moreover, in some cases, certain individual crime types exhibited concentrations within concentrations, particularly in Vancouver. Such findings confirm the first hypothesis that property crime is highly spatially concentrated at a micro-spatial scale within both cities.

The more unexpected results arose from the outputs of the spatial point pattern tests. Although it was initially hypothesized that the spatial patterns of property crime would vary with the seasons and be more prominent in cities with more distinct weather seasons, the results suggest otherwise. Instead, it appears that the individual crime types are occurring in the same places and that these locations remain the sole target sites of offenders no matter what time of year.

These unanticipated results could be explained for a number of reasons. First, by forming hypotheses based on routine activities theory it was assumed that the seasonal spatial crime patterns would vary because peoples' routine activities change throughout the year. This implies that the places where both the offender and victim(s) would likely converge are not static throughout the year because the involved persons engage in varying activities during different seasons. However, these data only contained the locations of property crimes and thus could not examine any associated crimes against the person that occurred during that same time. As such, the theoretical underpinnings of target selection should have been given more attention during the formulation of hypotheses.

Target selection for property crimes is environmentally dependent and can often be different from crimes against persons, such as sexual assault or robbery (Beauregard et al., 2010; Canter & Larkin, 1993; Jacobs, 2010). In fact, some research has found that offenders select property crime targets based primarily on "proximity, yield and accessibility" (Hough, 1987, p.355; see also Kennedy, 1990). Moreover, direct comparisons of the target selection process conducted by property versus violent offenders have also revealed very distinct patterns. As Beauregard et al. (2010) note:

> Contrarily to burglars, sex offenders need to adapt their target selection patterns for two reasons: (1) their targets may be mobile, and (2) they need to be controlled (Rossmo, 2000). However, when a target is static,

> the target selection of sex offenders resembles that of burglars (Beauregard et al., 2010, p.146).

This clearly indicates that offenders will adapt their criminal behaviours to the situational-dependent circumstances they face. As such, the inherent static nature of property crime targets will result in very different spatial patterns of crime than in the case of crimes against the person. It is thus unsurprising that the spatial point pattern test results of this study indicate little to no difference in the locations of where these property offences occur. Even if motivated offenders are moving through different locations during other times of the year, they may likely choose only to offend at places with specific environmental characteristics that are conducive to crime.

Second, the creation and reinforcement of crime templates as per the geometric theory of crime (see Brantingham & Brantingham, 1981) may be very prominent in the target selection practices of property offenders. For instance, past research has found that "burglaries clustered within 1-2 months and up to 300-400 metres of a prior burglary" (Bowers & Johnson, 2005, p.67). This indicates that desirable targets act as crime attractors (see Brantingham & Brantingham, 1995) and are enticing enough to compel offenders to overcome any time and/or distance needed to successfully carryout their crimes. The results from this study reinforce this fact and suggest that even though offenders may be frequenting different areas in a city depending on the time of year, they continually return to the same locations to commit their crimes. Moreover, given the results of the temporal chapter, it appears that even the increased frequency of criminal activity does not compel offenders to stray from the locations of these desirable targets. As such, hypotheses (2) and (3) are refuted by the data and instead suggest that targets for property crime at these discrete and prolific locations may be so attractive to offenders that they may even compel them to commit crimes outside of their quotidian activities. It should be noted, however, that these hypotheses may have been more appropriate for the analysis of violent crime types.

Despite the logic used here in attempts to explain why these results occurred, it is even more surprising that the fourth and final hypothesis has also been refuted by the data. Although discussions of the target selection literature provide seemingly plausible explanations for the concentration of spatial patterns for crimes such as commercial and residential burglary, the analogous results for other crime types are very interesting. As previously mentioned, burglary cases involve static targets that cannot move through time and space like a person. However, targets such as motor vehicles are fully mobile and the locations that they are found will be largely dependent upon the routine activities of people and such routines, as described in the literature review, do, in fact, change throughout the year. Given the high degree of spatial similarity in the thefts from and of motor vehicles in the data, it is likely that overall offending patterns are largely driven by crime attractors.

Barclay, Buckley, Brantingham, Brantingham and Whinn-Yates (1996) have argued that problematic crime attracting locations can include park-and-ride commuter vehicle parking lots that encourage travel into downtown urban areas via public transit. This, in turn, creates large “concentrations of parked, unattended cars at most hours of the day and night” and provides ample opportunity to motivated offenders (Barclay et al., 1996, p.134). As such, although the vehicles themselves are mobile, the locations where they are often parked and left remain static throughout the day and arguably throughout the entire year as well. Moreover, crime attracting and generating places such as shopping malls also provide static spatial locations that are rife with often unguarded vehicle theft opportunity (see Hollinger and Dabney, 1999). Establishments such as these usually experience relatively consistent flows of people throughout the year regardless of season. Therefore, more telling fluctuations in some crime types are likely more apparent in analyses that estimate the spatial clustering of data at certain times during the day. Aoristic analysis has been developed to test such spatio-temporal relationships by determining the “temporal…signatures [of crime hotspots]” and could be used in such contexts (Ratcliffe, 2010, p.15; see also Ratcliffe 2002; Ratcliffe, 2000; Ratcliffe & McCullagh, 1998).

Overall, the spatial findings of this study suggest that crime did not need to be disaggregated in the study of seasonal property crime patterns. This is somewhat surprising given the results and recommendations of Andresen and Malleson (2013) who studied seasonal variations in crime at the census tract and dissemination area levels and found sufficient differences in spatial patterns to suggest that the disaggregation of crime types was warranted and that micro-spatial analyses would not likely be as essential for our understanding of seasonality. As shown here, this is clearly not the case; the micro-place has been shown to be highly relevant for understanding spatial crime. Based solely on this study's findings, however, once again, the availability and inclusion of violent crime types would likely provide very different results. Therefore, these results are not inclusive enough to suggest the complete aggregation of crime types going forward. Additional research using more extensive crime types is needed.

# Chapter 6.

# Conclusions

This thesis has explored both the temporal and spatial aspects of property crime seasonality in two cities with differing climates. Temporally, the overall results suggest that cities with more distinct seasons experience fluctuations in the frequency of crime throughout the year. Spatially, however, the findings indicate that property offences are highly concentrated in cities and occur at the same prolific locations regardless of time. These discoveries can provide a number of practical implications to the academic literature, theory and policy.

Although a great deal of research has been conducted in the area of crime seasonality, with the exception of assault, little consensus exists regarding the universally accepted trends for individual crime types (Uittenbogaard & Ceccato, 2012, p.150; McDowall et al., 2012, p.407). Using routine activities theory has proven very effective in our understanding of these temporal patterns, but the accompanying results suggest that the seasonal variations of crime differ across cities and/or countries simply because the routine activities of people in these cities and/or countries are different. Such discrepancies can be attributed to an abundance of factors including differing climates, living conditions and socio-economic statuses of residents, global location, the economy, weather trends, major holidays, schooling schedules, sporting events, tourist activity, and even the number of daylight hours (see McDowall et al., 2012; Hipp et al., 2004; Lewis & Alford, 1975; Harries et al., 1984; Breetzke & Cohn, 2012; Cantor & Land, 1985; Cohen & Felson, 1979; Cohn & Rotton, 2003; Carbone-Lopez & Lauritsen, 2013; Breetzke & Cohn, 2013; Barker, Page & Meyer, 2002; Cohn, 1993). As such, this indicates that there are no universal seasonal variations in crime. Instead, each city has its own unique characteristics that shape and influence the movements and behaviours of people. It is therefore imperative that research continues in this field using data from new and unstudied areas in order to obtain a greater understanding of these annual rhythms.

The above indicates that our study of seasonal variation is not complete and the findings of this study are a prime example why further replication is warranted. For instance, regardless of the limitation that these data only contained property crime offences, both the temporal and spatial analyses produced very different results regarding the appropriateness of disaggregation. In this case, the former showed its utility and the latter rendered it unnecessary for our understanding of the phenomenon. Moreover, other studies have demonstrated the importance of disaggregating crime data and that it is always possible to aggregate data for analysis afterwards (see Maxfield, Rengert, Groff & Eck, 2011; Andresen & Malleson, 2011, 2013; Andresen & Linning, 2012). Nevertheless, the disaggregation of data is still considered imperative and strongly recommended for any subsequent studies in this area.

Lastly, although the use of routine activities theory was invaluable to the design of this thesis, some of the unexpected results suggest increased consideration for an additional perspective, namely target selection. The results from this thesis indicate a need to consider whether the target of the crime type in question is static or mobile and how this could impact the spatial patterns of offending. Although the notion of crime generators and crime attractors (Brantingham & Brantingham, 1995) was initially considered here, the prevalence of the latter appears to have had a much greater impact than initially anticipated. As previously discussed regarding the increased prevalence of offending around crime generators such as sports stadiums and tourist attractions, it was thought that crime would be provoked due to the increased convergence of targets and/or opportunities (see Breetzke & Cohn, 2013; Kirk, 2008; Barker et al., 2002; Chesney-Lind & Lind, 1986). Instead, it appears as though property crimes occur in the same places within cities regardless of their annual climate and/or the time of year.

Future research on these trends is still warranted and any similar replications should strongly consider some of the aforementioned methodological choices. Given the relatively understudied nature of spatial seasonal patterns, further inquiry that employs a micro-spatial scale of analysis would be invaluable to the field. Although this study has employed this level of analysis, the data only represent two Canadian cities over a relatively small period of time. The disaggregation of crime types at both the temporal and spatial levels would also provide a better understanding of the individual crime trends that are present without risking the masking of underlying crime patterns. The use of longitudinal data, particularly of daily intervals, over many years in multiple cities would also be beneficial to the literature. Although the Vancouver data used in this analysis were ideal for the study of a trend over time, data containing which day each offence occurred as opposed to simply which month would have strengthened the study. Lastly, the analysis of data that contain an even greater variety of criminal offences would be even more valuable. Moreover, the examination of data from multiple jurisdictions, ideally recorded by the same provincial and/or federal police agency, would also be invaluable to the seasonality literature. Database technologies such as the Crime Analysis System – Pacific Region (CASPR) developed by the Institute for Canadian Urban Research Studies (ICURS) have been created for such purposes and should be capitalized on (see Ghaseminejad & Brantingham, 2010). As previously discussed, it is very likely that data that included other crime types, such as violent crimes that involved mobile targets (i.e. people), will generate very different spatial results in the study of crime seasonality. Access to and use of such data would provide invaluable insights into the true seasonal variations of crime.

It has been suggested that the use of other temporal statistical methods such as autoregressive integrated moving averages (ARIMA) and/or the Box-Jenkins method, seasonal adjustments and spectral analyses could also provide valuable insights into seasonal crime patterns (see Block, 1983; Rotton & Frey, 1985; Brantingham and Brantingham, 1984; McPheters and Stronge, 1974). The latter, spectral analysis, could have particular advantages given its ability to decompose crime trends into "a set of [uncorrelated] cyclic series [in order to identify] the periodicity or seasonality in the data" (Brantingham and Brantingham, 1984, p.117). In an empirical criminological context, this method has allowed researchers to "measure the relative importance of each frequency band in terms of its contribution to the variance of the entire series" (McPheters & Stronge, 1974, p.330). Despite such potential, the use of this method in the crime seasonality literature has gone largely unexplored (for exceptions see McPheters &

Stronge, 1974, 1973). As such, future studies should consider use of this method and its utility in determining the temporal variations of crime.

Overall, this study has provided some important information that could be readily applied to practical crime prevention initiatives. By demonstrating that the temporal patterns of property crime can vary depending on the climate of a city and the routine activities of its people but that the spatial concentrations and patterns remain the same regardless of these factors, more effective crime prevention strategies can be implemented. In fact, this knowledge can also inform policy makers on when to implement such strategies as well as when to measure them in order to test their effectiveness (see Andresen & Malleson, 2013; see also Block, 1983). Moreover, the fact that the spatial patterns remained relatively consistent throughout the year indicates that targeted crime prevention strategies could be extremely effective if the chronic crime locations are targeted appropriately. Therefore, if used properly, the results of this study could generate very promising and practical insights that could have a drastic impact on the reduction of property crime overall.

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# Appendix A.

# Seasonal Frequency Tables for Vancouver Data (2003-2013)

Frequencies of crime types, by season, counts and percentages, Vancouver, 2003.

| | Winter | | Spring | | Summer | | Fall | | Total |
|---|---|---|---|---|---|---|---|---|---|
| Commercial B&E | 865 | (26.6) | 880 | (27.1) | 715 | (22.0) | 790 | (24.3) | 3250 |
| Mischief | 1622 | (25.2) | 1785 | (27.8) | 1543 | (24.0) | 1479 | (23.0) | 6429 |
| Theft from Vehicle | 3654 | (21.4) | 4880 | (28.6) | 4314 | (25.3) | 4197 | (24.6) | 17045 |
| Theft of Vehicle | 1737 | (27.4) | 1572 | (24.8) | 1423 | (22.5) | 1605 | (25.3) | 6337 |
| All Crimes | 7878 | (23.8) | 9117 | (27.6) | 7995 | (24.2) | 8071 | (24.4) | 33061 |

Note: Percentages are in parentheses; rounded to the nearest tenth and thus may not add evenly to 100.
Seasons: Winter (Jan – March); Spring (April – June); Summer (July – Sept); Fall (Oct – Dec)

Frequencies of crime types, by season, counts and percentages, Vancouver, 2004.

| | Winter | | Spring | | Summer | | Fall | | Total |
|---|---|---|---|---|---|---|---|---|---|
| Commercial B&E | 760 | (22.9) | 818 | (24.6) | 886 | (26.7) | 856 | (25.8) | 3320 |
| Mischief | 1295 | (22.8) | 1466 | (25.8) | 1510 | (26.6) | 1412 | (24.8) | 5683 |
| Theft from Vehicle | 3916 | (22.1) | 4266 | (24.1) | 4779 | (27.0) | 4761 | (26.9) | 17722 |
| Theft of Vehicle | 1547 | (25.5) | 1424 | (23.4) | 1577 | (26.0) | 1525 | (25.1) | 6073 |
| All Crimes | 7518 | (22.9) | 7974 | (24.3) | 8752 | (26.7) | 8554 | (26.1) | 32798 |

Note: Percentages are in parentheses; rounded to the nearest tenth and thus may not add evenly to 100.
Seasons: Winter (Jan – March); Spring (April – June); Summer (July – Sept); Fall (Oct – Dec)

Frequencies of crime types, by season, counts and percentages, Vancouver, 2005.

| | Winter | | Spring | | Summer | | Fall | | Total |
|---|---|---|---|---|---|---|---|---|---|
| Commercial B&E | 619 | (23.0) | 592 | (22.0) | 701 | (26.0) | 782 | (29.0) | 2694 |
| Mischief | 1201 | (23.5) | 1352 | (26.5) | 1246 | (24.4) | 1309 | (25.6) | 5108 |
| Theft from Vehicle | 4125 | (25.3) | 4450 | (27.3) | 3982 | (24.4) | 3750 | (23.0) | 16307 |
| Theft of Vehicle | 1398 | (27.8) | 1263 | (25.1) | 1276 | (25.3) | 1098 | (21.8) | 5035 |
| All Crimes | 7343 | (25.2) | 7657 | (26.3) | 7205 | (24.7) | 6939 | (23.8) | 29144 |

Note: Percentages are in parentheses; rounded to the nearest tenth and thus may not add evenly to 100.
Seasons: Winter (Jan – March); Spring (April – June); Summer (July – Sept); Fall (Oct – Dec)

Frequencies of crime types, by season, counts and percentages, Vancouver, 2006.

| | Winter | | Spring | | Summer | | Fall | | Total |
|---|---|---|---|---|---|---|---|---|---|
| Commercial B&E | 735 | (25.4) | 741 | (25.6) | 667 | (23.1) | 746 | (25.8) | 2889 |
| Mischief | 1322 | (24.8) | 1290 | (24.2) | 1453 | (27.2) | 1268 | (23.8) | 5333 |
| Theft from Vehicle | 3954 | (26.8) | 3421 | (23.2) | 3607 | (24.5) | 3752 | (25.5) | 14734 |
| Theft of Vehicle | 1016 | (27.5) | 873 | (23.7) | 929 | (25.2) | 871 | (23.6) | 3689 |
| All Crimes | 7027 | (26.4) | 6325 | (23.7) | 6656 | (25.0) | 6637 | (24.9) | 26645 |

Note: Percentages are in parentheses; rounded to the nearest tenth and thus may not add evenly to 100.
Seasons: Winter (Jan – March); Spring (April – June); Summer (July – Sept); Fall (Oct – Dec)

Frequencies of crime types, by season, counts and percentages, Vancouver, 2007.

| | Winter | | Spring | | Summer | | Fall | | Total |
|---|---|---|---|---|---|---|---|---|---|
| Commercial B&E | 696 | (27.8) | 609 | (24.4) | 682 | (27.3) | 514 | (20.1) | 2501 |
| Mischief | 1093 | (22.0) | 1327 | (26.7) | 1304 | (26.2) | 1245 | (25.1) | 4969 |
| Theft from Vehicle | 3339 | (27.2) | 3058 | (24.9) | 3132 | (25.5) | 2760 | (22.5) | 12289 |
| Theft of Vehicle | 772 | (23.2) | 788 | (23.7) | 948 | (28.5) | 822 | (24.7) | 3330 |
| All Crimes | 5900 | (25.6) | 5782 | (25.0) | 6066 | (26.3) | 5341 | (23.1) | 23089 |

Note: Percentages are in parentheses; rounded to the nearest tenth and thus may not add evenly to 100.
Seasons: Winter (Jan – March); Spring (April – June); Summer (July – Sept); Fall (Oct – Dec)

Frequencies of crime types, by season, counts and percentages, Vancouver, 2008.

| | Winter | | Spring | | Summer | | Fall | | Total |
|---|---|---|---|---|---|---|---|---|---|
| Commercial B&E | 647 | (28.3) | 578 | (25.3) | 565 | (24.7) | 494 | (21.6) | 2284 |
| Mischief | 1484 | (26.9) | 1476 | (26.8) | 1280 | (23.2) | 1267 | (23.0) | 5507 |
| Theft from Vehicle | 2737 | (24.0) | 2859 | (25.1) | 2846 | (24.9) | 2969 | (26.0) | 11411 |
| Theft of Vehicle | 636 | (26.3) | 675 | (27.9) | 591 | (24.5) | 514 | (21.3) | 2416 |
| All Crimes | 5504 | (25.5) | 5588 | (25.8) | 5282 | (24.4) | 5244 | (24.2) | 21618 |

Note: Percentages are in parentheses; rounded to the nearest tenth and thus may not add evenly to 100.
Seasons: Winter (Jan – March); Spring (April – June); Summer (July – Sept); Fall (Oct – Dec)

Frequencies of crime types, by season, counts and percentages, Vancouver, 2009.

| | Winter | | Spring | | Summer | | Fall | | Total |
|---|---|---|---|---|---|---|---|---|---|
| Commercial B&E | 494 | (26.0) | 498 | (26.2) | 455 | (23.9) | 456 | (24.0) | 1903 |
| Mischief | 1078 | (23.9) | 1196 | (26.5) | 1163 | (25.8) | 1069 | (23.7) | 4506 |
| Theft from Vehicle | 2737 | (27.2) | 2372 | (23.6) | 2611 | (26.0) | 2332 | (23.2) | 10052 |
| Theft of Vehicle | 496 | (26.3) | 452 | (24.0) | 449 | (23.8) | 489 | (25.9) | 1886 |
| All Crimes | 4805 | (26.2) | 4518 | (24.6) | 4678 | (25.5) | 4346 | (23.7) | 18347 |

Note: Percentages are in parentheses; rounded to the nearest tenth and thus may not add evenly to 100.
Seasons: Winter (Jan – March); Spring (April – June); Summer (July – Sept); Fall (Oct – Dec)

Frequencies of crime types, by season, counts and percentages, Vancouver, 2010.

| | Winter | | Spring | | Summer | | Fall | | Total |
|---|---|---|---|---|---|---|---|---|---|
| Commercial B&E | 396 | (23.8) | 414 | (24.9) | 450 | (27.0) | 405 | (24.3) | 1665 |
| Mischief | 1078 | (23.9) | 1191 | (26.4) | 1130 | (25.0) | 1116 | (24.7) | 4515 |
| Theft from Vehicle | 2064 | (23.9) | 1947 | (22.6) | 2308 | (26.8) | 2302 | (26.7) | 8621 |
| Theft of Vehicle | 370 | (25.2) | 343 | (23.4) | 387 | (26.4) | 367 | (25.0) | 1467 |
| All Crimes | 3908 | (24.0) | 3895 | (23.9) | 4275 | (26.3) | 4190 | (25.8) | 16268 |

Note: Percentages are in parentheses; rounded to the nearest tenth and thus may not add evenly to 100.
Seasons: Winter (Jan – March); Spring (April – June); Summer (July – Sept); Fall (Oct – Dec)

Frequencies of crime types, by season, counts and percentages, Vancouver, 2011.

| | Winter | | Spring | | Summer | | Fall | | Total |
|---|---|---|---|---|---|---|---|---|---|
| Commercial B&E | 428 | (25.6) | 432 | (25.9) | 471 | (28.2) | 340 | (20.3) | 1671 |
| Mischief | 1048 | (22.0) | 1440 | (30.3) | 1151 | (24.4) | 1114 | (23.4) | 4753 |
| Theft from Vehicle | 1896 | (25.6) | 1613 | (21.8) | 2118 | (28.6) | 1789 | (24.1) | 7416 |
| Theft of Vehicle | 283 | (25.7) | 276 | (25.1) | 288 | (26.2) | 253 | (23.0) | 1100 |
| All Crimes | 3655 | (24.5) | 3761 | (25.2) | 4028 | (27.0) | 3496 | (23.4) | 14940 |

Note: Percentages are in parentheses; rounded to the nearest tenth and thus may not add evenly to 100.
Seasons: Winter (Jan – March); Spring (April – June); Summer (July – Sept); Fall (Oct – Dec)

Frequencies of crime types, by season, counts and percentages, Vancouver, 2012.

| | Winter | | Spring | | Summer | | Fall | | Total |
|---|---|---|---|---|---|---|---|---|---|
| Commercial B&E | 444 | (26.10) | 429 | (25.2) | 345 | (20.3) | 482 | (28.40) | 1700 |
| Mischief | 1019 | (23.90) | 1074 | (25.2) | 1121 | (26.3) | 1051 | (24.60) | 4265 |
| Theft from Vehicle | 2076 | (25.50) | 1991 | (24.5) | 1976 | (24.3) | 2094 | (25.70) | 8137 |
| Theft of Vehicle | 254 | (22.00) | 294 | (25.5) | 330 | (28.6) | 274 | (23.80) | 1152 |
| All Crimes | 3793 | (24.90) | 3788 | (24.8) | 3772 | (24.7) | 3901 | (25.60) | 15254 |

Note: Percentages are in parentheses; rounded to the nearest tenth and thus may not add evenly to 100.
Seasons: Winter (Jan – March); Spring (April – June); Summer (July – Sept); Fall (Oct – Dec)

Frequencies of crime types, by season, counts and percentages, Vancouver, 2013.

| | Winter | | Spring | | Summer | | Fall | | Total |
|---|---|---|---|---|---|---|---|---|---|
| Commercial B&E | 491 | (27.6) | 445 | (25.0) | 375 | (21.1) | 467 | (26.2) | 1778 |
| Mischief | 1004 | (24.0) | 1059 | (71.7) | 1074 | (25.7) | 1041 | (24.9) | 4178 |
| Theft from Vehicle | 1647 | (19.7) | 2143 | (25.7) | 2029 | (24.3) | 2525 | (30.3) | 8344 |
| Theft of Vehicle | 288 | (27.9) | 275 | (26.6) | 239 | (23.2) | 230 | (22.3) | 1032 |
| All Crimes | 3430 | (23.4) | 3922 | (25.6) | 3717 | (24.2) | 4263 | (27.8) | 15332 |

Note: Percentages are in parentheses; rounded to the nearest tenth and thus may not add evenly to 100.
Seasons: Winter (Jan – March); Spring (April – June); Summer (July – Sept); Fall (Oct – Dec)

# Appendix B.

## Seasonal Frequency Tables for Ottawa Data (2006-2008)

Frequencies of crime types, by season, counts and percentages, Ottawa, 2006.

| | Winter | | Spring | | Summer | | Fall | | Total |
|---|---|---|---|---|---|---|---|---|---|
| Commercial B&E | 346 | (23.0) | 369 | (24.5) | 413 | (27.4) | 378 | (25.1) | 1506 |
| Residential B&E | 582 | (22.0) | 731 | (27.7) | 718 | (27.2) | 610 | (23.1) | 2641 |
| Robbery | 161 | (20.6) | 200 | (25.5) | 206 | (26.3) | 216 | (27.6) | 783 |
| Theft of Vehicle | 562 | (19.5) | 710 | (24.6) | 856 | (29.7) | 755 | (26.2) | 2883 |
| Total Crime | 1651 | (21.1) | 2010 | (25.7) | 2193 | (28.1) | 1959 | (25.1) | 7813 |

Note: Percentages are in parentheses; rounded to the nearest tenth and thus may not add evenly to 100.
Seasons: Winter (Jan – March); Spring (April – June); Summer (July – Sept); Fall (Oct – Dec)

Frequencies of crime types, by season, counts and percentages, Ottawa, 2007.

| | Winter | | Spring | | Summer | | Fall | | Total |
|---|---|---|---|---|---|---|---|---|---|
| Commercial B&E | 324 | (23.4) | 363 | (26.3) | 395 | (28.6) | 300 | (21.7) | 1382 |
| Residential B&E | 450 | (21.9) | 523 | (25.4) | 667 | (32.4) | 416 | (20.2) | 2056 |
| Robbery | 153 | (23.2) | 169 | (25.6) | 185 | (28.1) | 152 | (23.1) | 659 |
| Theft of Vehicle | 531 | (22.9) | 593 | (25.6) | 651 | (28.1) | 539 | (23.3) | 2314 |
| Total Crime | 1458 | (22.7) | 1648 | (25.7) | 1898 | (29.6) | 1407 | (21.9) | 6411 |

Note: Percentages are in parentheses; rounded to the nearest tenth and thus may not add evenly to 100.
Seasons: Winter (Jan – March); Spring (April – June); Summer (July – Sept); Fall (Oct – Dec)

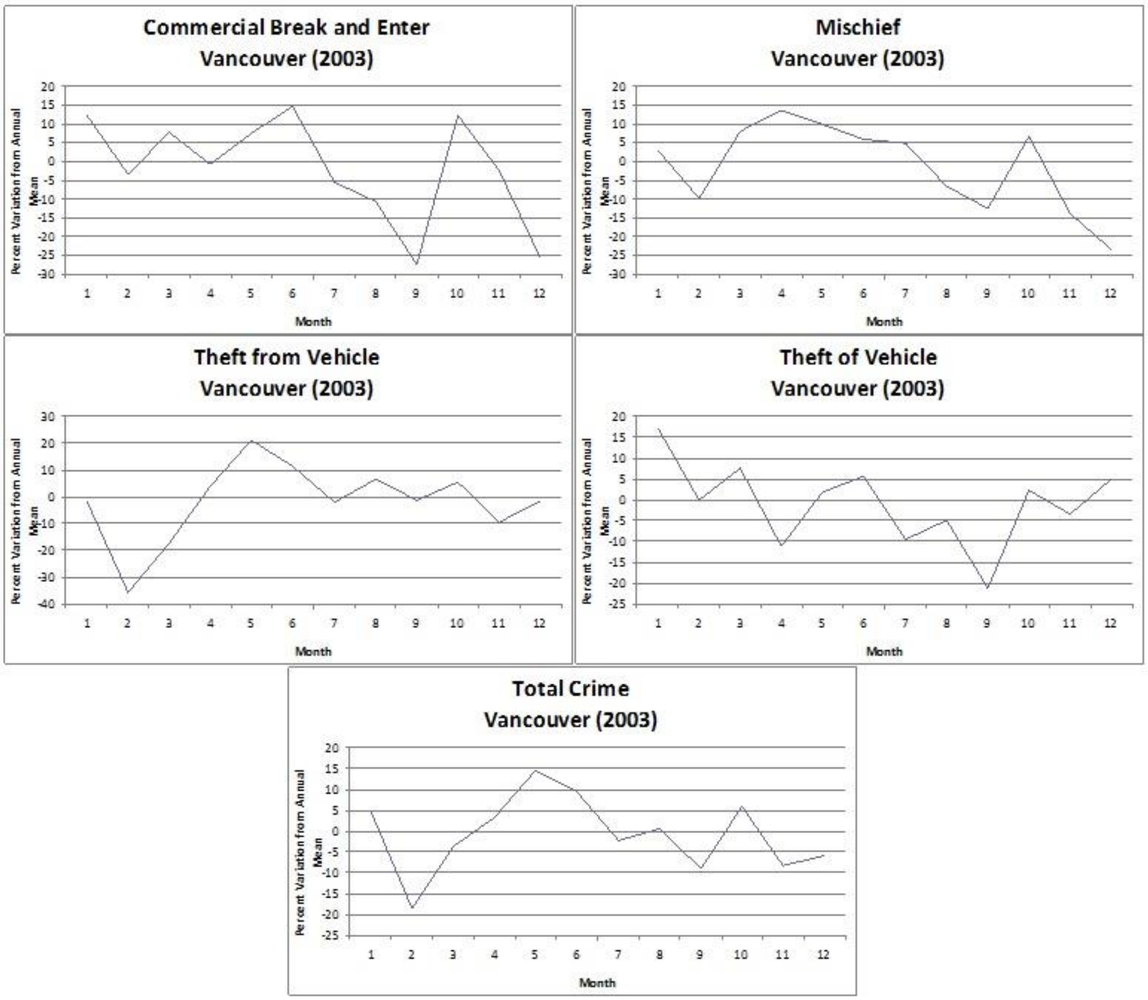
Frequencies of crime types, by season, counts and percentages, Ottawa, 2008.

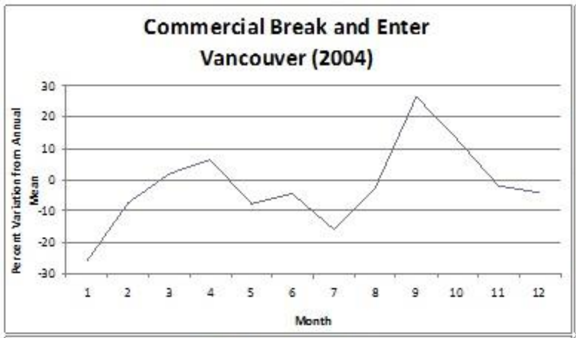
| | Winter | | Spring | | Summer | | Fall | | Total |
|---|---|---|---|---|---|---|---|---|---|
| Commercial B&E | 272 | (19.5) | 385 | (27.6) | 426 | (30.5) | 312 | (22.4) | 1395 |
| Residential B&E | 359 | (18.8) | 494 | (25.8) | 629 | (32.9) | 431 | (22.5) | 1913 |
| Robbery | 133 | (19.1) | 181 | (25.9) | 224 | (32.1) | 160 | (22.9) | 698 |
| Theft of Vehicle | 390 | (20.7) | 497 | (26.4) | 596 | (31.6) | 401 | (21.3) | 1884 |
| Total Crime (w/o mischief) | 1154 | (19.6) | 1557 | (26.4) | 1875 | (31.8) | 1304 | (22.1) | 5890 |
| Mischief | 1215 | (18.2) | 1754 | (26.2) | 2227 | (33.3) | 1490 | (22.3) | 6686 |
| Total Crime (w/mischief) | 2369 | (18.8) | 3311 | (26.3) | 4102 | (32.6) | 2794 | (22.2) | 12576 |

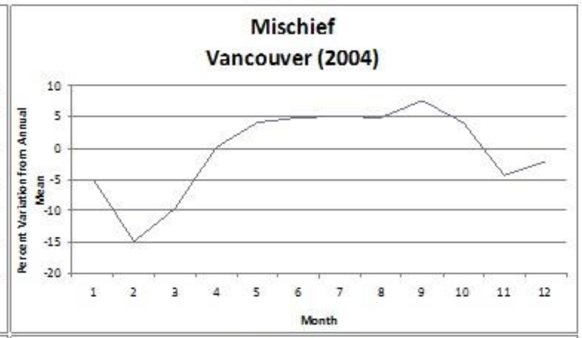
Note: Percentages are in parentheses; rounded to the nearest tenth and thus may not add evenly to 100.
Seasons: Winter (Jan – March); Spring (April – June); Summer (July – Sept); Fall (Oct – Dec)

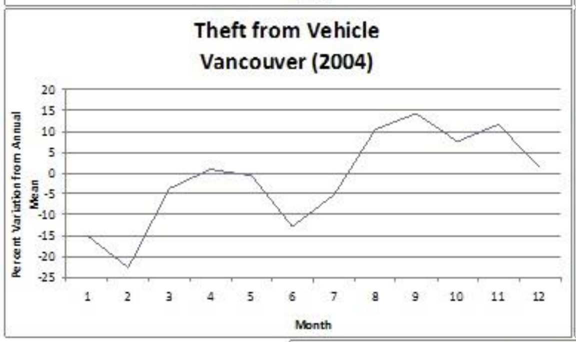
# Appendix C.

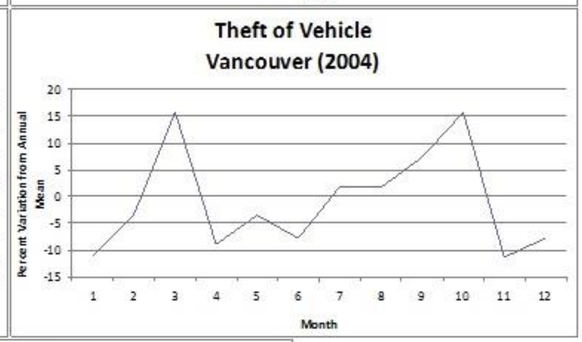
# Temporal Graphs, Vancouver (2003-2013)

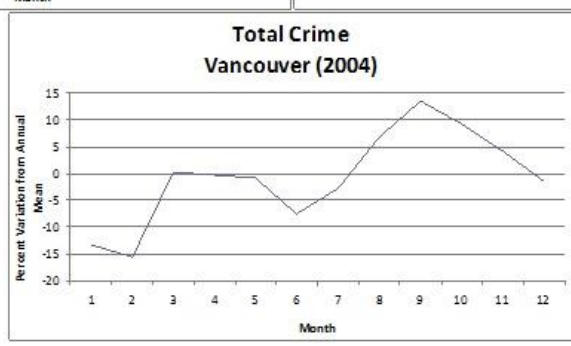


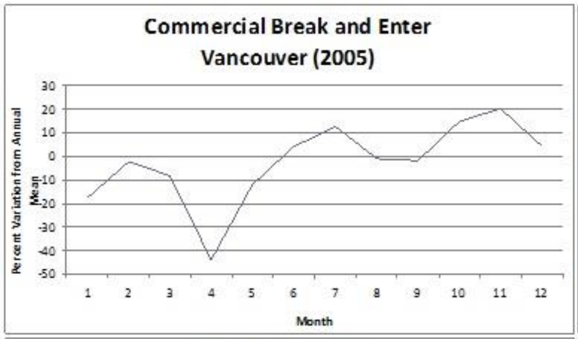

Commercial Break and Enter
Vancouver (2004)
30
20
10
0
-10
-20
-30
Percent Variation from Annual Mean
1 2 3 4 5 6 7 8 9 10 11 12
Month

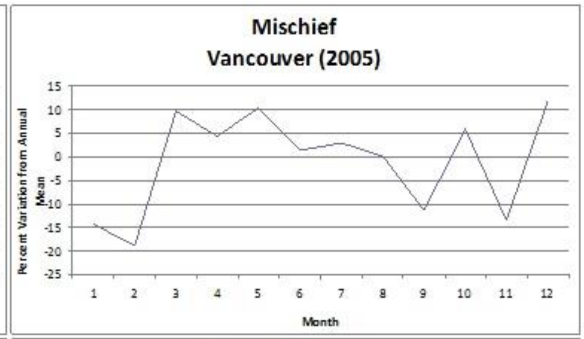

Mischief
Vancouver (2004)
10
5
0
-5
-10
-15
-20
Percent Variation from Annual Mean
1 2 3 4 5 6 7 8 9 10 11 12
Month

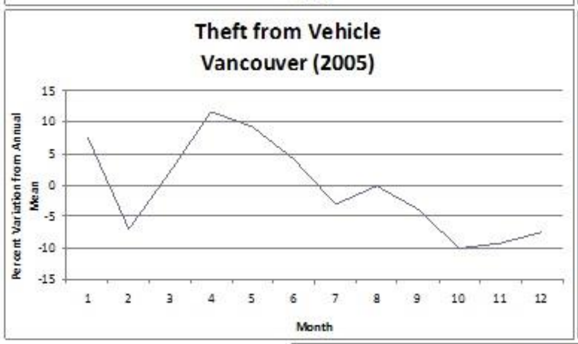

Theft from Vehicle
Vancouver (2004)
20
15
10
5
0
-5
-10
-15
-20
-25
Percent Variation from Annual Mean
1 2 3 4 5 6 7 8 9 10 11 12
Month

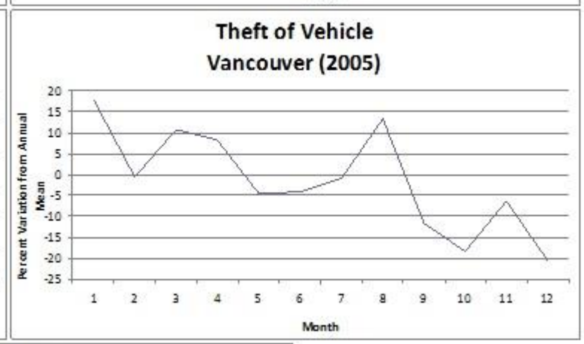

Theft of Vehicle
Vancouver (2004)
20
15
10
5
0
-5
-10
-15
Percent Variation from Annual Mean
1 2 3 4 5 6 7 8 9 10 11 12
Month

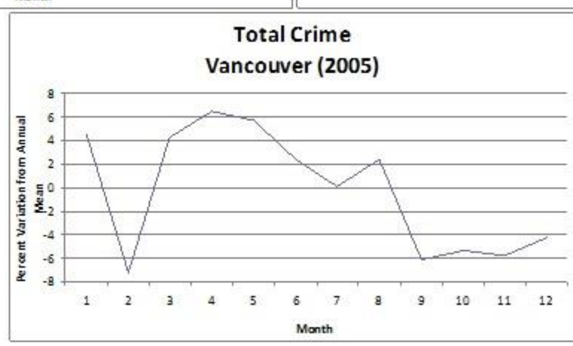

Total Crime
Vancouver (2004)
15
10
5
0
-5
-10
-15
-20
Percent Variation from Annual Mean
1 2 3 4 5 6 7 8 9 10 11 12
Month


Commercial Break and Enter
Vancouver (2005)
Percent Variation from Annual Mean
30
20
10
0
-10
-20
-30
-40
-50
1 2 3 4 5 6 7 8 9 10 11 12
Month


Mischief
Vancouver (2005)
Percent Variation from Annual Mean
15
10
5
0
-5
-10
-15
-20
-25
1 2 3 4 5 6 7 8 9 10 11 12
Month


Theft from Vehicle
Vancouver (2005)
Percent Variation from Annual Mean
15
10
5
0
-5
-10
-15
1 2 3 4 5 6 7 8 9 10 11 12
Month


Theft of Vehicle
Vancouver (2005)
Percent Variation from Annual Mean
20
15
10
5
0
-5
-10
-15
-20
-25
1 2 3 4 5 6 7 8 9 10 11 12
Month


Total Crime
Vancouver (2005)
Percent Variation from Annual Mean
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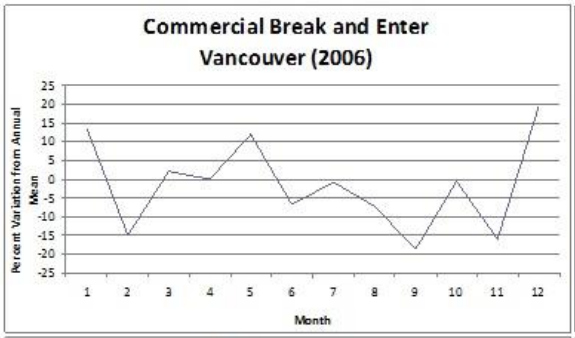
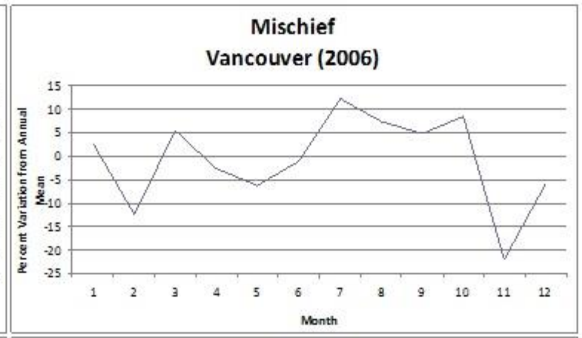
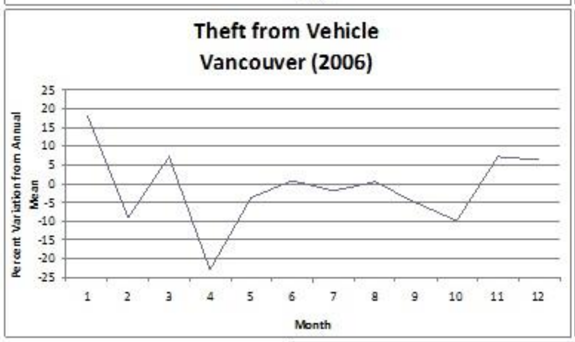
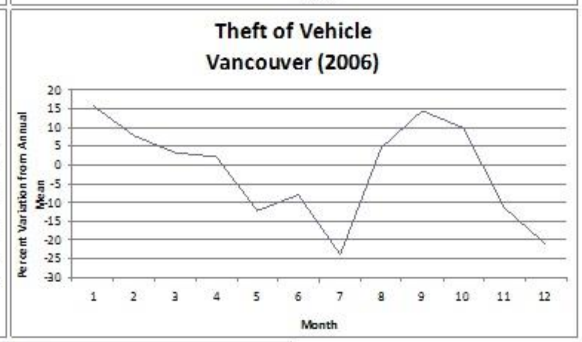
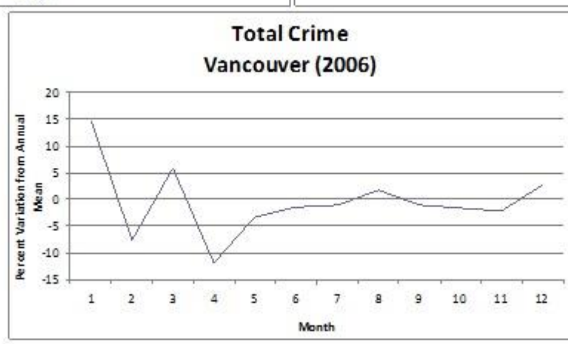
6
4
2
0
-2
-4
-6
-8
1 2 3 4 5 6 7 8 9 10 11 12
Month

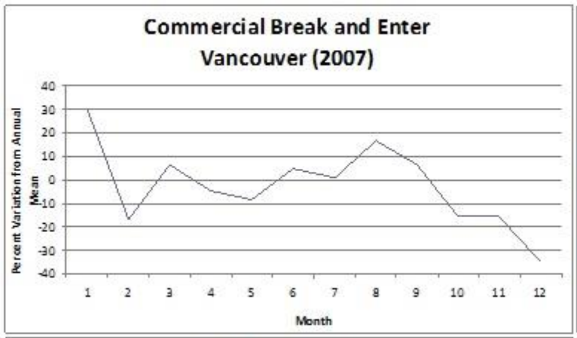

Commercial Break and Enter
Vancouver (2006)
Percent Variation from Annual Mean
Month
25 20 15 10 5 0 -5 -10 -15 -20 -25
1 2 3 4 5 6 7 8 9 10 11 12

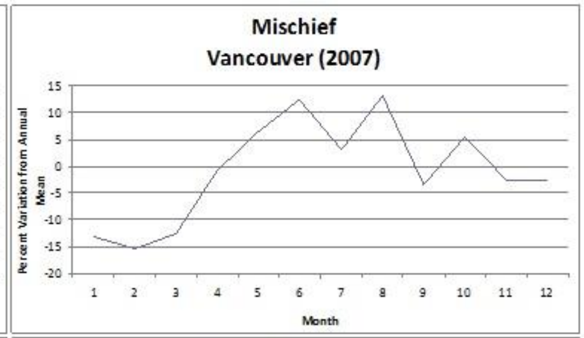

Mischief
Vancouver (2006)
Percent Variation from Annual Mean
Month
15 10 5 0 -5 -10 -15 -20 -25
1 2 3 4 5 6 7 8 9 10 11 12

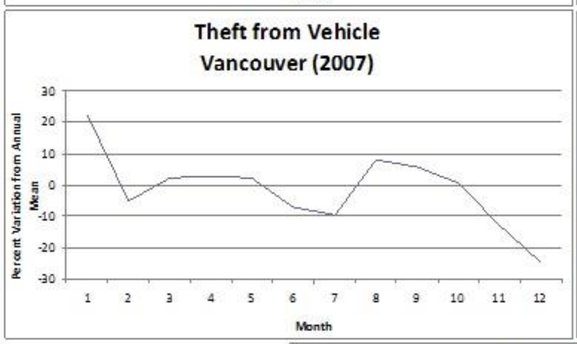

Theft from Vehicle
Vancouver (2006)
Percent Variation from Annual Mean
Month
25 20 15 10 5 0 -5 -10 -15 -20 -25
1 2 3 4 5 6 7 8 9 10 11 12

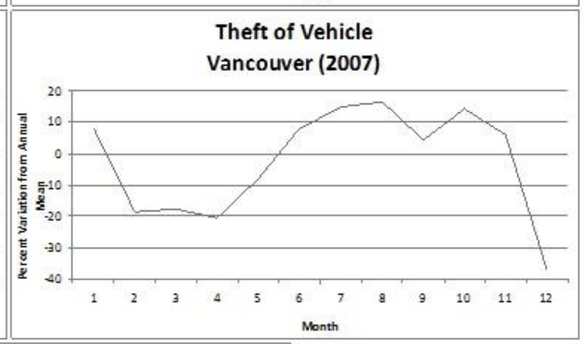

Theft of Vehicle
Vancouver (2006)
Percent Variation from Annual Mean
Month
20 15 10 5 0 -5 -10 -15 -20 -25 -30
1 2 3 4 5 6 7 8 9 10 11 12

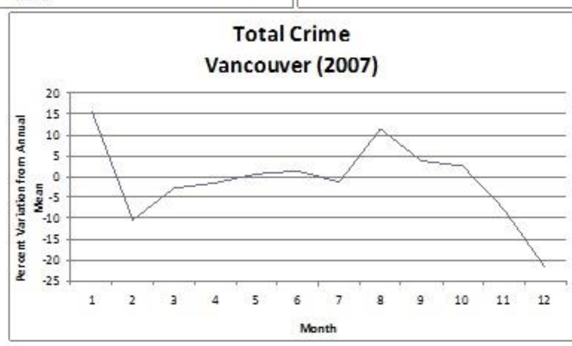

Total Crime
Vancouver (2006)
Percent Variation from Annual Mean
Month
20 15 10 5 0 -5 -10 -15
1 2 3 4 5 6 7 8 9 10 11 12

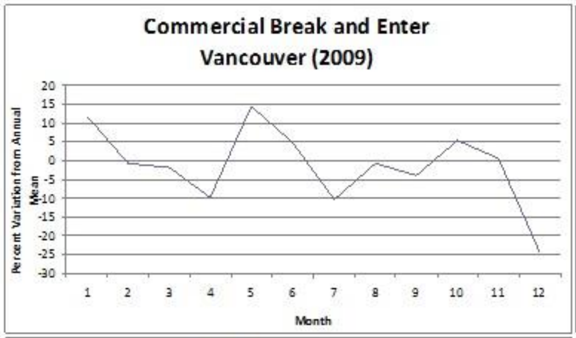

Commercial Break and Enter
Vancouver (2007)
40
30
20
10
0
-10
-20
-30
-40
Percent Variation from Annual Mean
1 2 3 4 5 6 7 8 9 10 11 12
Month

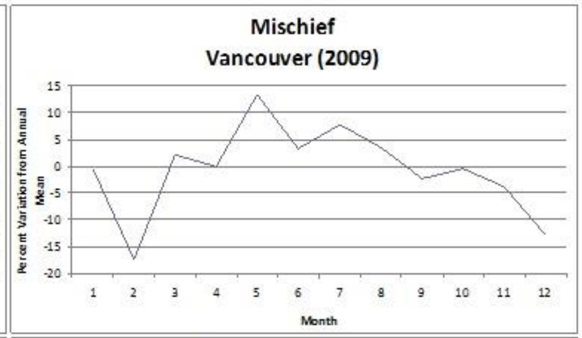

Mischief
Vancouver (2007)
15
10
5
0
-5
-10
-15
-20
Percent Variation from Annual Mean
1 2 3 4 5 6 7 8 9 10 11 12
Month

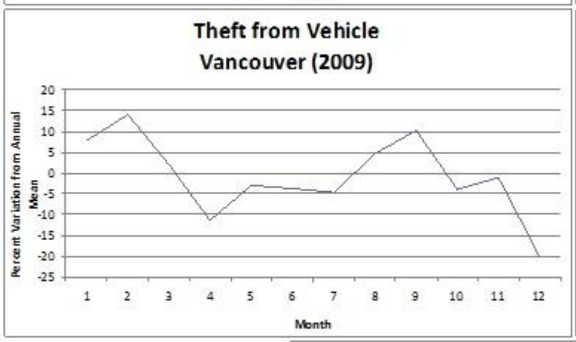

Theft from Vehicle
Vancouver (2007)
30
20
10
0
-10
-20
-30
Percent Variation from Annual Mean
1 2 3 4 5 6 7 8 9 10 11 12
Month

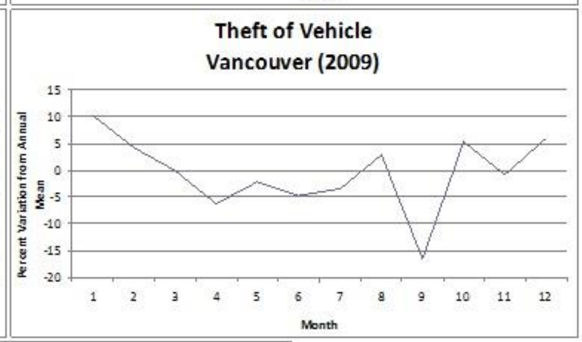

Theft of Vehicle
Vancouver (2007)
20
10
0
-10
-20
-30
-40
Percent Variation from Annual Mean
1 2 3 4 5 6 7 8 9 10 11 12
Month

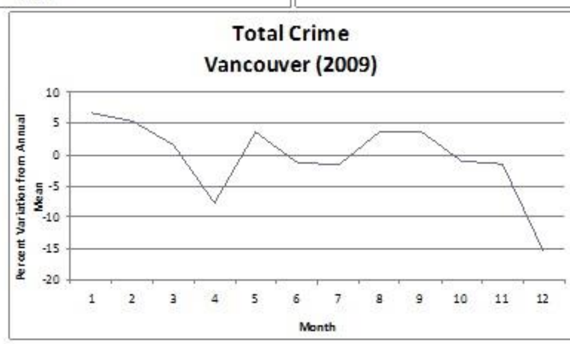

Total Crime
Vancouver (2007)
20
15
10
5
0
-5
-10
-15
-20
-25
Percent Variation from Annual Mean
1 2 3 4 5 6 7 8 9 10 11 12
Month

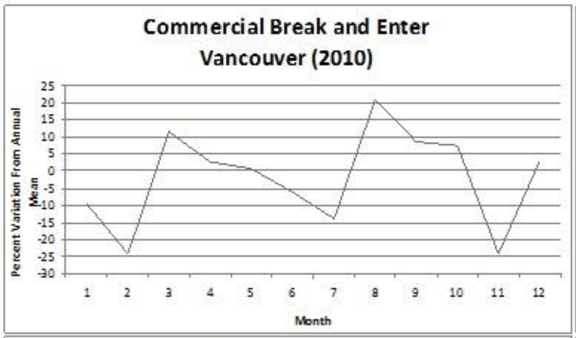

Commercial Break and Enter
Vancouver (2009)
Percent Variation from Annual Mean
Month

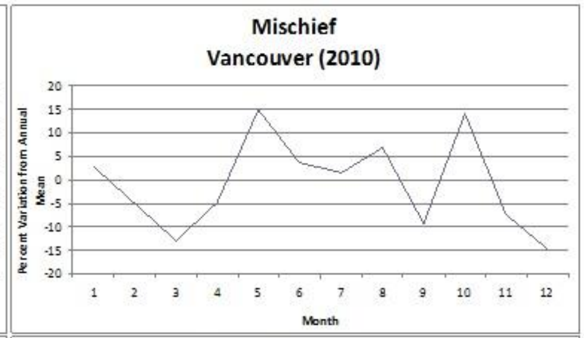

Mischief
Vancouver (2009)
Percent Variation from Annual Mean
Month

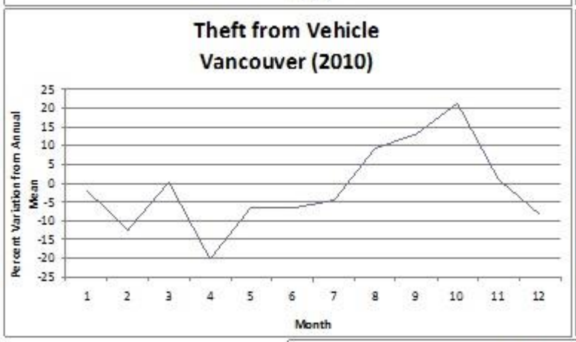

Theft from Vehicle
Vancouver (2009)
Percent Variation from Annual Mean
Month

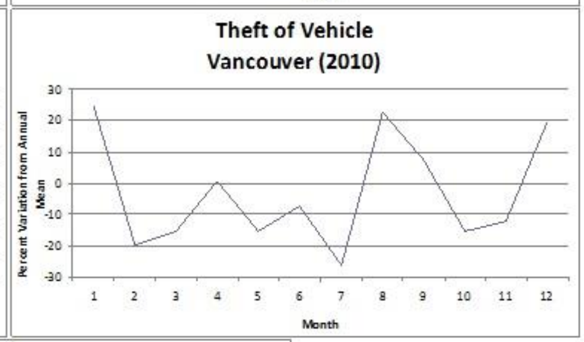

Theft of Vehicle
Vancouver (2009)
Percent Variation from Annual Mean
Month

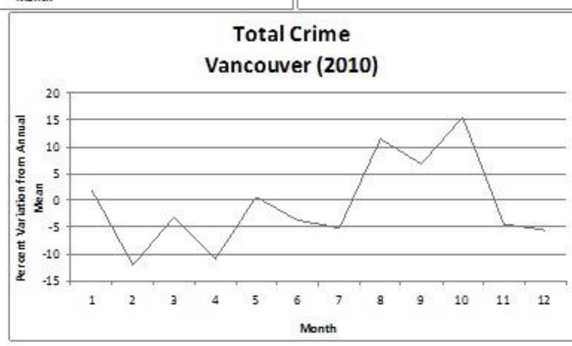

Total Crime
Vancouver (2009)
Percent Variation from Annual Mean
Month

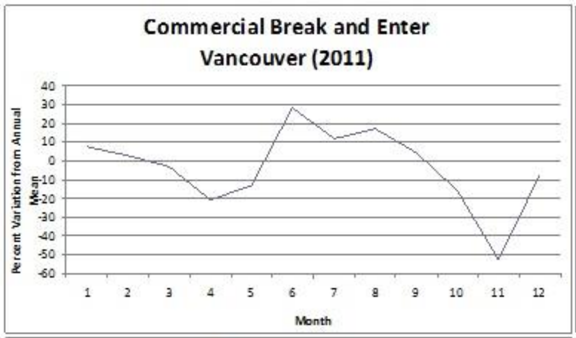

Commercial Break and Enter
Vancouver (2010)
Percent Variation From Annual Mean
25 20 15 10 5 0 -5 -10 -15 -20 -25 -30
1 2 3 4 5 6 7 8 9 10 11 12
Month

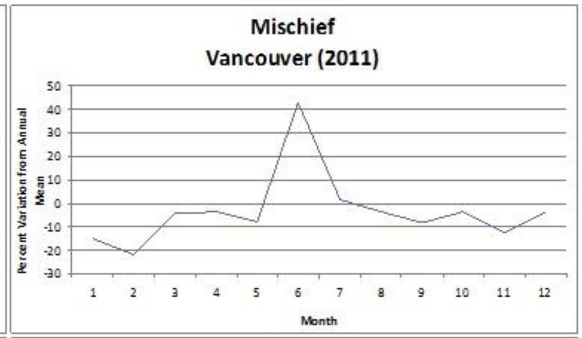

Mischief
Vancouver (2010)
Percent Variation from Annual Mean
20 15 10 5 0 -5 -10 -15 -20
1 2 3 4 5 6 7 8 9 10 11 12
Month

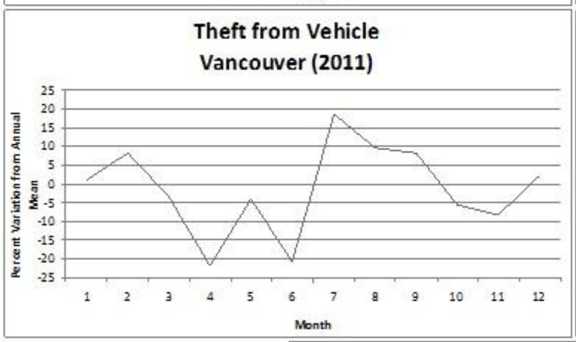

Theft from Vehicle
Vancouver (2010)
Percent Variation from Annual Mean
25 20 15 10 5 0 -5 -10 -15 -20 -25
1 2 3 4 5 6 7 8 9 10 11 12
Month

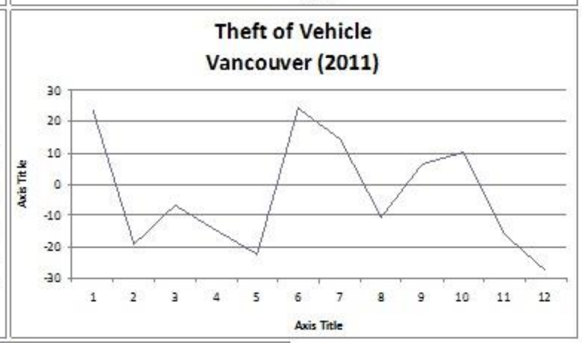

Theft of Vehicle
Vancouver (2010)
Percent Variation from Annual Mean
30 20 10 0 -10 -20 -30
1 2 3 4 5 6 7 8 9 10 11 12
Month

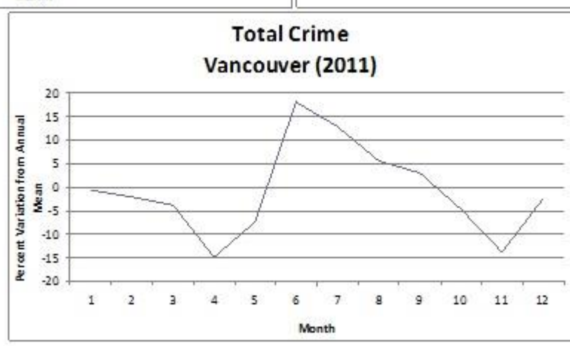

Total Crime
Vancouver (2010)
Percent Variation from Annual Mean
20 15 10 5 0 -5 -10 -15
1 2 3 4 5 6 7 8 9 10 11 12
Month

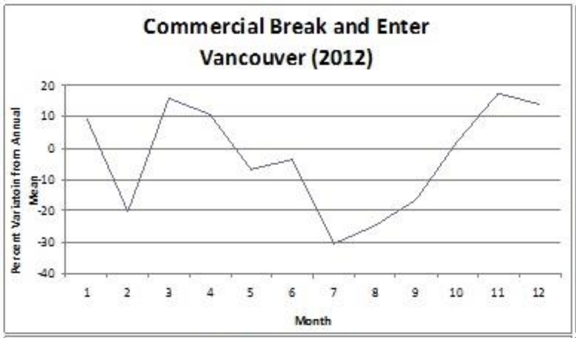

Commercial Break and Enter
Vancouver (2011)
Percent Variation from Annual Mean
40
30
20
10
0
-10
-20
-30
-40
-50
-60
1 2 3 4 5 6 7 8 9 10 11 12
Month

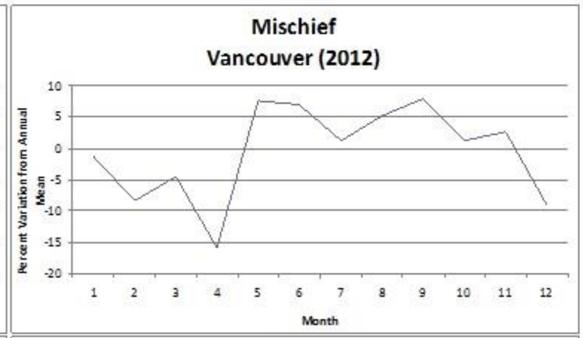

Mischief
Vancouver (2011)
Percent Variation from Annual Mean
50
40
30
20
10
0
-10
-20
-30
1 2 3 4 5 6 7 8 9 10 11 12
Month

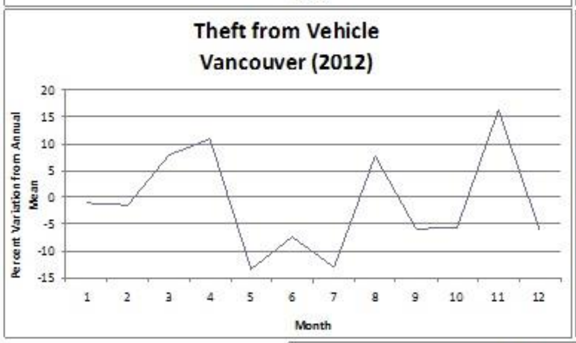

Theft from Vehicle
Vancouver (2011)
Percent Variation from Annual Mean
25
20
15
10
5
0
-5
-10
-15
-20
-25
1 2 3 4 5 6 7 8 9 10 11 12
Month

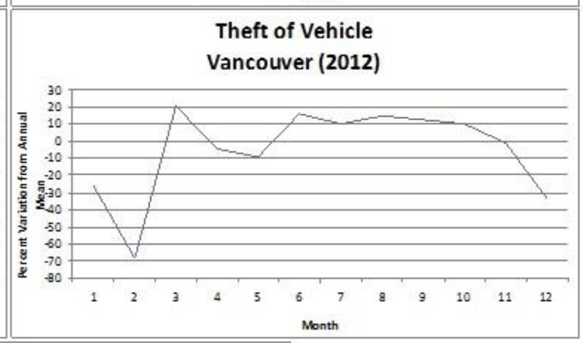

Theft of Vehicle
Vancouver (2011)
Axis Title
30
20
10
0
-10
-20
-30
1 2 3 4 5 6 7 8 9 10 11 12
Axis Title

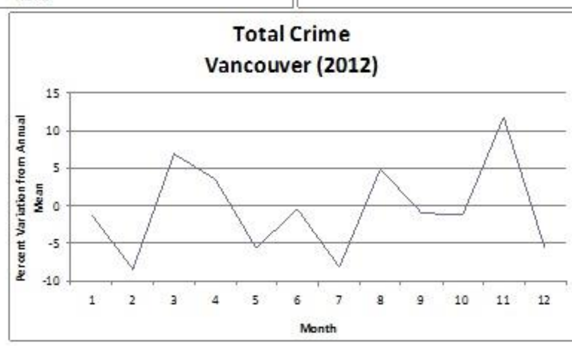

Total Crime
Vancouver (2011)
Percent Variation from Annual Mean
20
15
10
5
0
-5
-10
-15
-20
1 2 3 4 5 6 7 8 9 10 11 12
Month

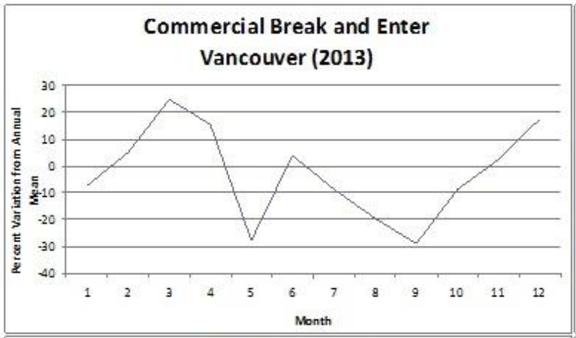

Commercial Break and Enter
Vancouver (2012)
Percent Variatoin from Annual Mean
20 10 0 -10 -20 -30 -40
1 2 3 4 5 6 7 8 9 10 11 12
Month

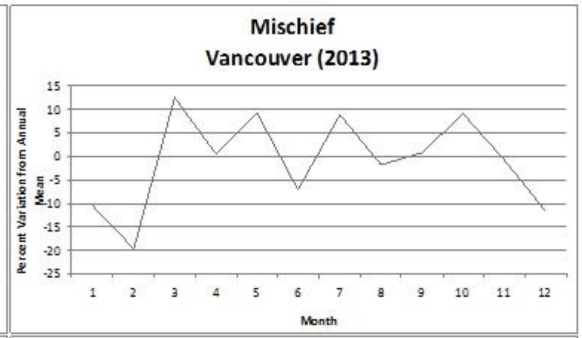

Mischief
Vancouver (2012)
Percent Variation from Annual Mean
10 5 0 -5 -10 -15 -20
1 2 3 4 5 6 7 8 9 10 11 12
Month

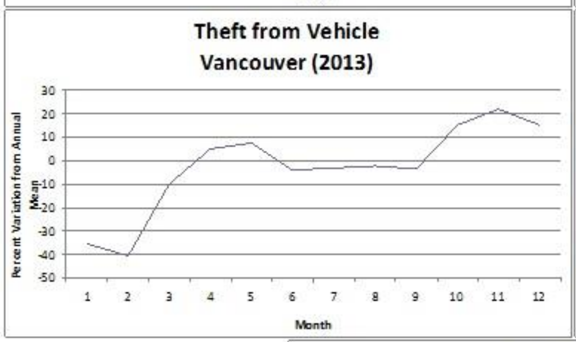

Theft from Vehicle
Vancouver (2012)
Percent Variation from Annual Mean
20 15 10 5 0 -5 -10 -15
1 2 3 4 5 6 7 8 9 10 11 12
Month

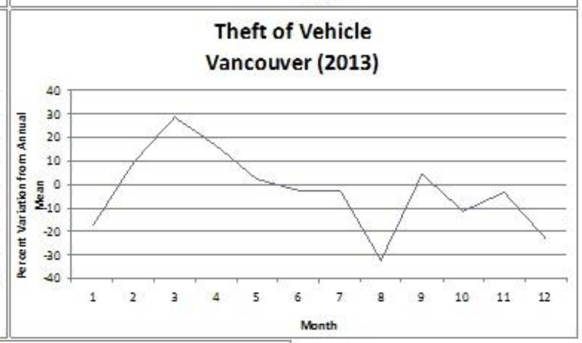

Theft of Vehicle
Vancouver (2012)
Percent Variation from Annual Mean
30 20 10 0 -10 -20 -30 -40 -50 -60 -70 -80
1 2 3 4 5 6 7 8 9 10 11 12
Month

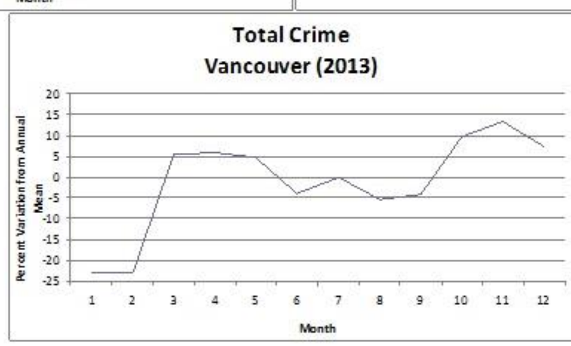

Total Crime
Vancouver (2012)
Percent Variation from Annual Mean
15 10 5 0 -5 -10
1 2 3 4 5 6 7 8 9 10 11 12
Month


Commercial Break and Enter
Vancouver (2013)
Percent Variation from Annual Mean
30
20
10
0
-10
-20
-30
-40
1 2 3 4 5 6 7 8 9 10 11 12
Month


Mischief
Vancouver (2013)
Percent Variation from Annual Mean
15
10
5
0
-5
-10
-15
-20
-25
1 2 3 4 5 6 7 8 9 10 11 12
Month

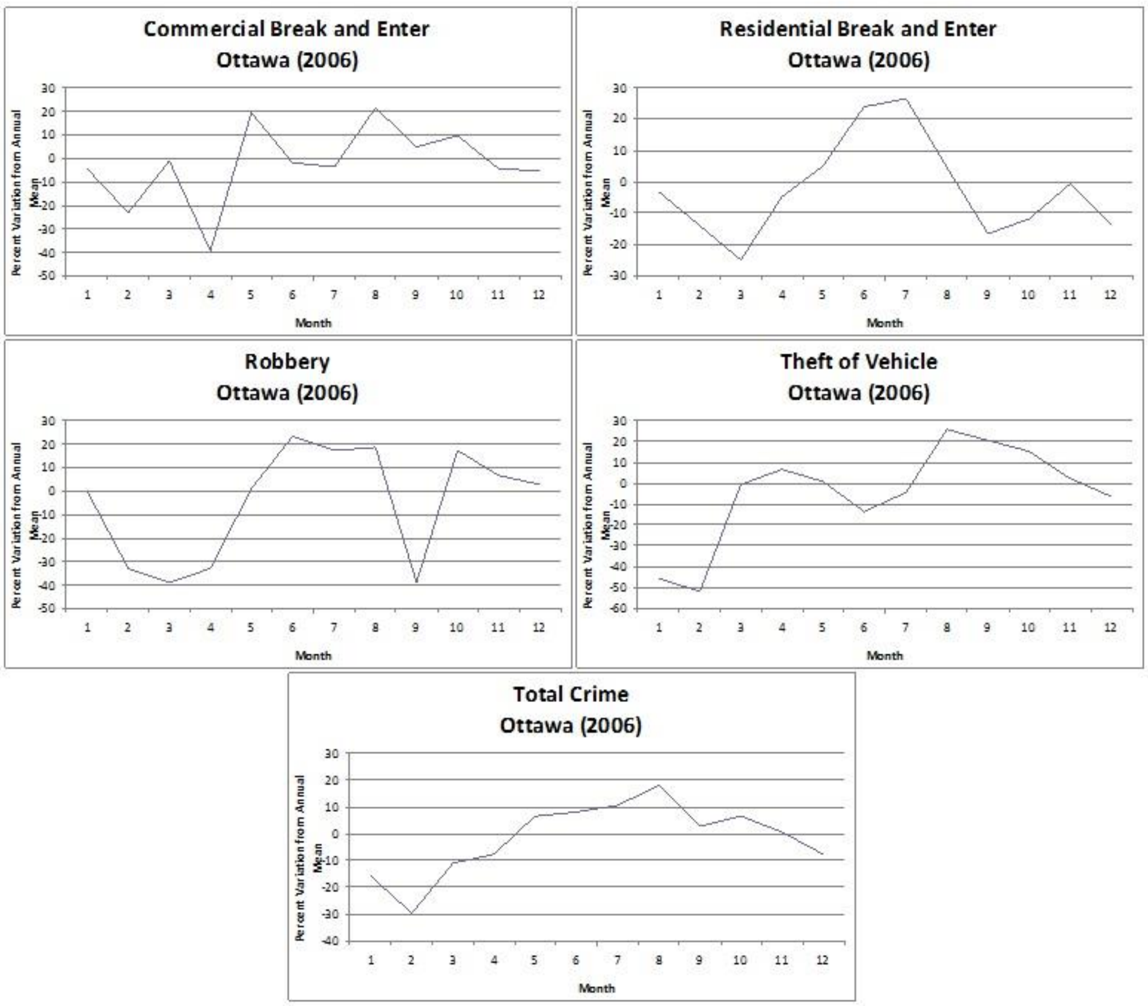

Theft from Vehicle
Vancouver (2013)
Percent Variation from Annual Mean
30
20
10
0
-10
-20
-30
-40
-50
1 2 3 4 5 6 7 8 9 10 11 12
Month

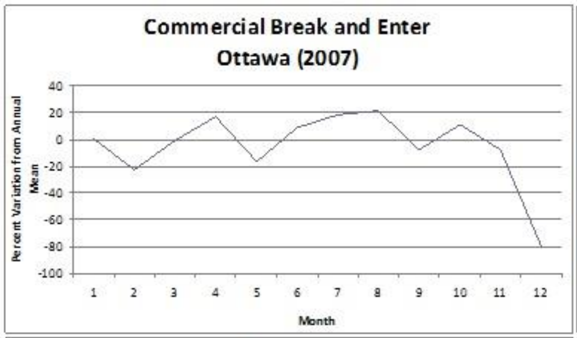

Theft of Vehicle
Vancouver (2013)
Percent Variation from Annual Mean
40
30
20
10
0
-10
-20
-30
-40
1 2 3 4 5 6 7 8 9 10 11 12
Month

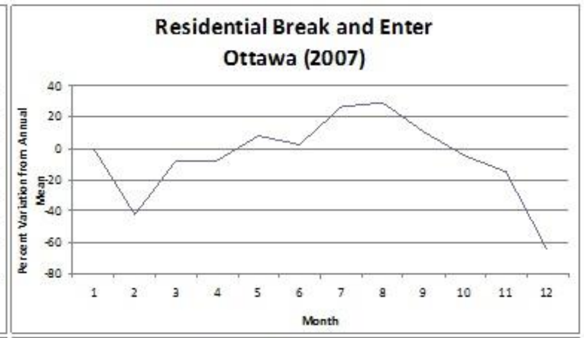

Total Crime
Vancouver (2013)
Percent Variation from Annual Mean
20
15
10
5
0
-5
-10
-15
-20
-25
1 2 3 4 5 6 7 8 9 10 11 12
Month

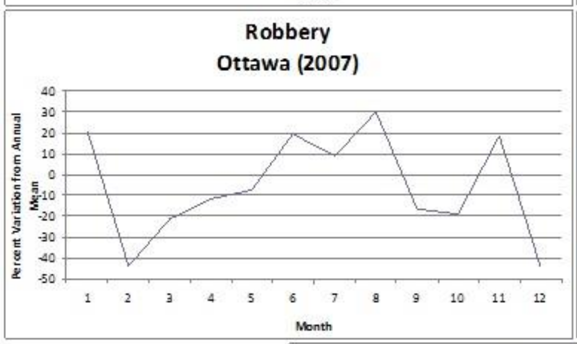
# Appendix D.

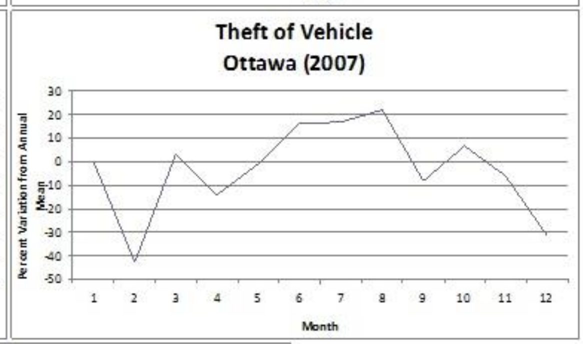
# Temporal Graphs, Ottawa (2006-2007)

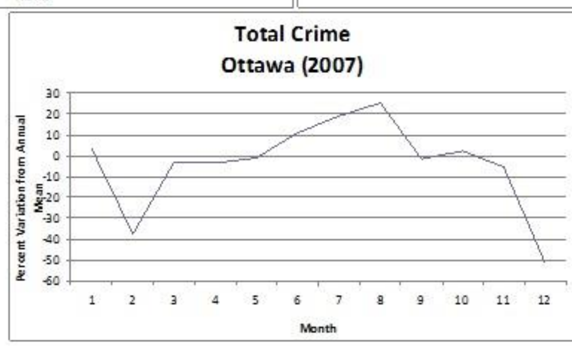



Commercial Break and Enter
Ottawa (2007)
Percent Variation from Annual Mean
Month


Residential Break and Enter
Ottawa (2007)
Percent Variation from Annual Mean
Month


Robbery
Ottawa (2007)
Percent Variation from Annual Mean
Month


Theft of Vehicle
Ottawa (2007)
Percent Variation from Annual Mean
Month


Total Crime
Ottawa (2007)
Percent Variation from Annual Mean
Month

# Appendix E.

# Full OLS Regression Models, Vancouver (2003-2013)

Full Models: Temporal regression results for property crime in Vancouver, 2003-2013

| | Commercial Break & Enter | Mischief | Theft from Vehicle | Theft of Vehicle | Total Crime |
|---|---|---|---|---|---|
| Month | -10.392 | 32.974 | 20.172 | -27.460 | 15.295 |
| Month Squared | 1.074 | -2.441 | -0.490 | 2.295 | 0.437 |
| Month Total (Trend) | -1.261*** | -1.272*** | -7.935*** | -4.046*** | -14.514*** |
| # Days in Month | 13.797* | 17.779 | 103.409*** | 32.206* | 167.191 |
| # weekend days in month | 2.014 | 7.358 | -3.6994 | -2.0931 | 3.579 |
| | | | | | |
| Spring (Dummy) | -19.732 | 0.666 | 43.105 | -12.438 | 11.600 |
| Summer (Dummy) | -46.019* | -44.788 | -124.649 | -70.508 | -285.965** |
| Fall (Dummy) | -34.202 | -7.949 | -141.162 | -32.175 | -215.488* |
| | | | | | |
| Maximum Temperature | -1.883 | -5.321 | 4.340 | -4.854* | -7.718 |
| Average Temperature | 3.953 | 7.165 | 16.368 | 14.349*** | 41.835** |
| Maximum Rain | 0.629 | 0.460 | 1.138 | 0.732 | 2.958 |
| Average Rain | 54.108 | -8.427 | 655.533** | 188.156 | 889.370* |
| Total Rain | -1.857 | 0.070 | -21.395** | -6.340 | -29.522* |
| Maximum Snow | 0.623 | 0.056 | -3.866 | -0.563 | -3.750 |
| Average Snow | 357.584 | 149.991 | 4558.366 | 747.315 | 5813.255 |
| Total Snow | -12.168 | -5.532 | -145.612 | -24.646 | -187.958 |
| | | | | | |
| Total Hours of Illumination | 3.725 | -3.986 | -41.200 | -4.083 | -45.544 |
| # Twilight Hours | -40.717 | 10.227 | -75.418 | -79.433 | -185.341 |
| | | | | | |
| Adjusted $R^2$ | 0.672 | 0.524 | 0.828 | 0.891 | 0.890 |
| F-statistic | 15.910*** | 9.005*** | 35.910*** | 60.390*** | 60.130*** |

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; N = 246,342

# Appendix F.

# Full OLS Regression Models, Ottawa (2006-2008)

Full Models: Temporal regression results for property crime in Ottawa, 2006-8

| | Commercial Break & Enter | Residential Break & Enter | Robbery | Theft of Vehicle | Total Crime (w/o mischief) | Mischief (2007-8) |
|---|---|---|---|---|---|---|
| Month | 0.711 | 0.262 | 0.226 | -0.634 | 0.643 | 1.696 |
| Month Squared | -0.052 | -0.034 | -0.018 | 0.061 | -0.050 | -0.167 |
| Day of Dataset (Trend) | 0.000 | -0.003*** | 0.000 | -0.004*** | -0.007*** | -0.012*** |
| Major Holiday (Dummy) | 0.723 | -0.251 | -0.385 | -1.039* | -0.904 | 0.295 |
| Minor Holiday (Dummy) | 0.348 | 0.060 | -0.286 | -1.184 | -1.006 | -0.006 |
| Spring (Dummy) | 0.284 | -0.504 | 0.197 | 0.103 | 0.032 | 3.253 |
| Summer (Dummy) | 0.748 | 1.460 | 0.093 | 0.976 | 3.236* | 4.821 |
| Fall (Dummy) | -0.282 | 1.615 | 0.217 | 0.746 | 2.343 | 8.079* |
| Maximum Temperature | -0.110** | -0.070 | 0.032 | 0.000 | -0.134 | 0.144 |
| Average Temperature | 0.109* | 0.130* | -0.006 | 0.011 | 0.228** | 0.069 |
| Total Rain | 0.004 | -0.015 | -0.003 | 0.026 | 0.015 | -0.058 |
| Total Snow | -0.045* | -0.056* | 0.001 | -0.040 | -0.142*** | -0.192*** |
| Total Hours of Illumination | -0.166 | 0.024 | -0.150 | 0.415 | 0.141 | 0.207 |
| # Twilight Hours | 1.431 | 7.780** | 1.148 | -3.357 | 6.677 | -6.742 |
| Adjusted $R^2$ | 0.047 | 0.228 | 0.022 | 0.155 | 0.2785 | 0.375 |
| F-statistic | 4.81*** | 23.97*** | 2.74** | 15.27*** | 31.06*** | 28.6*** |

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; N = 20,108 (total crime w/o mischief); N = 14,024 (mischief)

# Appendix G.

# Counts and Percentages of Geocoded Data, Vancouver (2003-2013)

Counts and percentages of geocoded data, Vancouver, 2003.

| | Raw Data | | Geocoded Data | | Percent Geocoded |
|---|---|---|---|---|---|
| | Count | Percentage | Count | Percentage | Percentage |
| Commercial Break & Enter | 3250 | 9.8 | 3181 | 9.9 | 97.9 |
| Mischief | 6429 | 19.4 | 6270 | 19.5 | 97.5 |
| Theft from Vehicle | 17045 | 51.6 | 16459 | 51.3 | 96.5 |
| Theft of Vehicle | 6337 | 19.2 | 6172 | 19.2 | 97.4 |
| Total Crime (Aggregate) | 33061 | 100.0 | 32082 | 100.0 | 97.0 |

Counts and percentages of geocoded data, Vancouver, 2004.

| | Raw Data | | Geocoded Data | | Percent Geocoded |
|---|---|---|---|---|---|
| | Count | Percentage | Count | Percentage | Percentage |
| Commercial Break & Enter | 3320 | 10.1 | 3259 | 10.3 | 98.2 |
| Mischief | 5683 | 17.3 | 5510 | 17.4 | 97.0 |
| Theft from Vehicle | 17722 | 54.0 | 17042 | 53.7 | 96.2 |
| Theft of Vehicle | 6073 | 18.5 | 5943 | 18.7 | 97.9 |
| Total Crime (Aggregate) | 32798 | 100.0 | 31754 | 100.0 | 96.8 |

Counts and percentages of geocoded data, Vancouver, 2005.

| | Raw Data | | Geocoded Data | | Percent Geocoded |
|---|---|---|---|---|---|
| | Count | Percentage | Count | Percentage | Percentage |
| Commercial Break & Enter | 2694 | 9.2 | 2623 | 9.3 | 97.4 |
| Mischief | 5108 | 17.5 | 4968 | 17.7 | 97.2 |
| Theft from Vehicle | 16307 | 56.0 | 15641 | 55.6 | 95.9 |
| Theft of Vehicle | 5035 | 17.3 | 4886 | 17.4 | 97.0 |
| Total Crime (Aggregate) | 29144 | 100.0 | 28118 | 100.0 | 96.5 |

Counts and percentages of geocoded data, Vancouver, 2006.

| | Raw Data | | Geocoded Data | | Percent Geocoded |
|---|---|---|---|---|---|
| | Count | Percentage | Count | Percentage | Percentage |
| Commercial Break & Enter | 2889 | 10.8 | 2828 | 10.9 | 97.9 |
| Mischief | 5333 | 20.0 | 5199 | 20.1 | 97.5 |
| Theft from Vehicle | 14734 | 55.3 | 14227 | 55.0 | 96.6 |
| Theft of Vehicle | 3689 | 13.8 | 3606 | 13.9 | 97.8 |
| Total Crime (Aggregate) | 26645 | 100.0 | 25860 | 100.0 | 97.1 |

Counts and percentages of geocoded data, Vancouver, 2007.

| | Raw Data | | Geocoded Data | | Percent Geocoded |
|---|---|---|---|---|---|
| | Count | Percentage | Count | Percentage | Percentage |
| Commercial Break & Enter | 2501 | 10.8 | 2430 | 10.9 | 97.1 |
| Mischief | 4969 | 21.5 | 4825 | 21.6 | 97.1 |
| Theft from Vehicle | 12289 | 53.2 | 11857 | 53.1 | 96.5 |
| Theft of Vehicle | 3330 | 14.4 | 3220 | 14.4 | 96.7 |
| Total Crime (Aggregate) | 23089 | 100.0 | 22332 | 100.0 | 96.7 |

Counts and percentages of geocoded data, Vancouver, 2008.

| | Raw Data | | Geocoded Data | | Percent Geocoded |
|---|---|---|---|---|---|
| | Count | Percentage | Count | Percentage | Percentage |
| Commercial Break & Enter | 2284 | 10.6 | 2216 | 10.6 | 97.0 |
| Mischief | 5507 | 25.5 | 5345 | 25.7 | 97.1 |
| Theft from Vehicle | 11411 | 52.8 | 10924 | 52.5 | 95.7 |
| Theft of Vehicle | 2416 | 11.2 | 2331 | 11.2 | 96.4 |
| Total Crime (Aggregate) | 21618 | 100.0 | 20816 | 100.0 | 96.3 |

Counts and percentages of geocoded data, Vancouver, 2009.

| | Raw Data | | Geocoded Data | | Percent Geocoded |
|---|---|---|---|---|---|
| | Count | Percentage | Count | Percentage | Percentage |
| Commercial Break & Enter | 1903 | 10.4 | 1830 | 10.4 | 96.2 |
| Mischief | 4506 | 24.6 | 4380 | 24.8 | 97.2 |
| Theft from Vehicle | 10052 | 54.8 | 9626 | 54.5 | 95.8 |
| Theft of Vehicle | 1886 | 10.3 | 1844 | 10.4 | 97.7 |
| Total Crime (Aggregate) | 18347 | 100.0 | 17680 | 100.0 | 96.4 |

Counts and percentages of geocoded data, Vancouver, 2010.

| | Raw Data | | Geocoded Data | | Percent Geocoded |
|---|---|---|---|---|---|
| | Count | Percentage | Count | Percentage | Percentage |
| Commercial Break & Enter | 1665 | 10.2 | 1625 | 10.3 | 97.6 |
| Mischief | 4515 | 27.8 | 4376 | 27.8 | 96.9 |
| Theft from Vehicle | 8621 | 53.0 | 8307 | 52.8 | 96.4 |
| Theft of Vehicle | 1467 | 9.0 | 1421 | 9.0 | 96.9 |
| Total Crime (Aggregate) | 16268 | 100.0 | 15729 | 100.0 | 96.7 |

Counts and percentages of geocoded data, Vancouver, 2011.

| | Raw Data | | Geocoded Data | | Percent Geocoded |
|---|---|---|---|---|---|
| | Count | Percentage | Count | Percentage | Percentage |
| Commercial Break & Enter | 1671 | 11.2 | 1608 | 11.2 | 96.2 |
| Mischief | 4753 | 31.8 | 4596 | 31.9 | 96.7 |
| Theft from Vehicle | 7416 | 49.6 | 7132 | 49.6 | 96.2 |
| Theft of Vehicle | 1100 | 7.4 | 1054 | 7.3 | 95.7 |
| Total Crime (Aggregate) | 14940 | 100.0 | 14390 | 100.0 | 96.3 |

Counts and percentages of geocoded data, Vancouver, 2012.

| | Raw Data | | Geocoded Data | | Percent Geocoded |
|---|---|---|---|---|---|
| | Count | Percentage | Count | Percentage | Percentage |
| Commercial Break & Enter | 1700 | 11.1 | 1648 | 11.3 | 96.9 |
| Mischief | 4265 | 28.0 | 4124 | 28.3 | 96.7 |
| Theft from Vehicle | 8137 | 53.3 | 7714 | 52.9 | 94.8 |
| Theft of Vehicle | 1152 | 7.6 | 1099 | 7.5 | 95.6 |
| Total Crime (Aggregate) | 15254 | 100.0 | 14585 | 100.0 | 96.3 |

Counts and percentages of geocoded data, Vancouver, 2013.

| | Raw Data | | Geocoded Data | | Percent Geocoded |
|---|---|---|---|---|---|
| | Count | Percentage | Count | Percentage | Percentage |
| Commercial Break & Enter | 1778 | 11.6 | 1727 | 11.7 | 97.1 |
| Mischief | 4178 | 27.3 | 4057 | 27.4 | 97.1 |
| Theft from Vehicle | 8344 | 54.4 | 8000 | 54.1 | 95.9 |
| Theft of Vehicle | 1032 | 6.7 | 1000 | 6.8 | 96.9 |
| Total Crime (Aggregate) | 15332 | 100.0 | 14784 | 100.0 | 96.4 |

# Appendix H.

## Counts and Percentages of Geocoded Data, Ottawa (2006-2008)

Counts and percentages of geocoded data, Ottawa, 2006.

| | Raw Data | | Geocoded Data | | Percent Geocoded |
|---|---|---|---|---|---|
| | Count | Percentage | Count | Percentage | Percentage |
| Commercial Break & Enter | 1506 | 19.3 | 1466 | 19.1 | 97.3 |
| Residential Break & Enter | 2641 | 33.8 | 2618 | 34.1 | 99.1 |
| Robbery | 783 | 10.0 | 759 | 9.9 | 96.9 |
| Theft of Vehicle | 2883 | 36.9 | 2830 | 36.9 | 98.2 |
| Total Crime (Aggregate) | 7813 | 100.0 | 7673 | 100.0 | 98.2 |

Counts and percentages of geocoded data, Ottawa, 2007.

| | Raw Data | | Geocoded Data | | Percent Geocoded |
|---|---|---|---|---|---|
| | Count | Percentage | Count | Percentage | Percentage |
| Commercial Break & Enter | 1382 | 21.6 | 1341 | 21.4 | 97.0 |
| Residential Break & Enter | 2056 | 32.1 | 2030 | 32.4 | 98.7 |
| Robbery | 659 | 10.3 | 644 | 10.3 | 97.7 |
| Theft of Vehicle | 2314 | 36.1 | 2253 | 35.9 | 97.4 |
| Total Crime (Aggregate) | 6411 | 100.0 | 6268 | 100.0 | 97.8 |

Counts and percentages of geocoded data, Ottawa, 2008.

| | Raw Data | | Geocoded Data | | Percent Geocoded |
|---|---|---|---|---|---|
| | Count | Percentage | Count | Percentage | Percentage |
| Commercial Break & Enter | 1395 | 23.7 | 1297 | 23.6 | 93.0 |
| Residential Break & Enter | 1913 | 32.5 | 1793 | 32.7 | 93.7 |
| Robbery | 698 | 11.9 | 657 | 12.0 | 94.1 |
| Theft of Vehicle | 1884 | 32.0 | 1742 | 31.7 | 92.5 |
| Total Crime (without mischief) | 5890 | 100.0 | 5489 | 100.0 | 93.2 |
| Mischief | 6686 | 53.2 | 6270 | 53.3 | 93.8 |
| Total Crime (with mischief) | 12576 | 100.0 | 11759 | 100.0 | 93.5 |

# Appendix I.

# Crime Concentration Tables, Vancouver (2003-2013)

Crime Concentrations within Street Segments & Intersections, Vancouver, 2003

| | (a) Percentage of Street Segments Accounting for 50% of Crime | (b) Percentage of Street Segments & Intersections Accounting for 50% of Crime | (c) Percentage of Street Segments that Have Any Crime | (d) Percentage of Street Segments & Intersections that Have Any Crime | (e) Percentage of Street Segments with Crime that Account for 50% of Crime |
|---|---|---|---|---|---|
| Commercial B&E | 1.88 | 1.20 | 10.09 | 6.41 | 18.68 |
| Mischief | 5.25 | 3.34 | 26.13 | 16.62 | 20.10 |
| Theft from Vehicle | 6.72 | 4.27 | 28.08 | 17.86 | 23.92 |
| Theft of Vehicle | 3.93 | 2.50 | 39.11 | 24.87 | 10.05 |
| Total (Aggregate) | 5.90 | 3.75 | 54.68 | 34.77 | 10.79 |

Crime Concentrations within Street Segments & Intersections, Vancouver, 2004

| | (a) Percentage of Street Segments Accounting for 50% of Crime | (b) Percentage of Street Segments & Intersections Accounting for 50% of Crime | (c) Percentage of Street Segments that Have Any Crime | (d) Percentage of Street Segments & Intersections that Have Any Crime | (e) Percentage of Street Segments with Crime that Account for 50% of Crime |
|---|---|---|---|---|---|
| Commercial B&E | 1.94 | 1.23 | 10.72 | 6.81 | 18.06 |
| Mischief | 5.48 | 3.49 | 24.99 | 15.89 | 21.94 |
| Theft from Vehicle | 7.80 | 4.96 | 29.52 | 18.77 | 26.42 |
| Theft of Vehicle | 4.88 | 3.10 | 42.53 | 27.05 | 11.47 |
| Total (Aggregate) | 6.83 | 4.34 | 57.52 | 36.58 | 11.87 |

Crime Concentrations within Street Segments & Intersections, Vancouver, 2005

| | (a) Percentage of Street Segments Accounting for 50% of Crime | (b) Percentage of Street Segments & Intersections Accounting for 50% of Crime | (c) Percentage of Street Segments that Have Any Crime | (d) Percentage of Street Segments & Intersections that Have Any Crime | (e) Percentage of Street Segments with Crime that Account for 50% of Crime |
|---|---|---|---|---|---|
| Commercial B&E | 2.05 | 1.31 | 10.07 | 6.40 | 20.41 |
| Mischief | 5.30 | 3.37 | 23.09 | 14.69 | 22.96 |
| Theft from Vehicle | 7.49 | 4.77 | 26.72 | 16.99 | 28.05 |
| Theft of Vehicle | 4.99 | 3.17 | 41.23 | 26.22 | 12.10 |
| Total (Aggregate) | 7.01 | 4.46 | 55.68 | 35.41 | 12.59 |

Crime Concentrations within Street Segments & Intersections, Vancouver, 2006

| | (a) Percentage of Street Segments Accounting for 50% of Crime | (b) Percentage of Street Segments & Intersections Accounting for 50% of Crime | (c) Percentage of Street Segments that Have Any Crime | (d) Percentage of Street Segments & Intersections that Have Any Crime | (e) Percentage of Street Segments with Crime that Account for 50% of Crime |
|---|---|---|---|---|---|
| Commercial B&E | 1.99 | 1.26 | 10.14 | 6.45 | 19.60 |
| Mischief | 5.06 | 3.22 | 23.60 | 15.01 | 21.46 |
| Theft from Vehicle | 5.64 | 3.59 | 20.55 | 13.07 | 27.47 |
| Theft of Vehicle | 3.94 | 2.50 | 36.56 | 23.25 | 10.77 |
| Total (Aggregate) | 5.78 | 3.68 | 50.82 | 32.32 | 11.37 |

Crime Concentrations within Street Segments & Intersections, Vancouver, 2007

| | (a) Percentage of Street Segments Accounting for 50% of Crime | (b) Percentage of Street Segments & Intersections Accounting for 50% of Crime | (c) Percentage of Street Segments that Have Any Crime | (d) Percentage of Street Segments & Intersections that Have Any Crime | (e) Percentage of Street Segments with Crime that Account for 50% of Crime |
|---|---|---|---|---|---|
| Commercial B&E | 1.78 | 1.13 | 9.11 | 5.80 | 19.55 |
| Mischief | 4.33 | 2.75 | 21.13 | 13.44 | 20.49 |
| Theft from Vehicle | 3.30 | 2.10 | 32.57 | 20.71 | 10.13 |
| Theft of Vehicle | 5.35 | 3.40 | 19.07 | 12.13 | 28.03 |
| Total (Aggregate) | 5.06 | 3.21 | 47.40 | 30.14 | 10.67 |

Crime Concentrations within Street Segments & Intersections, Vancouver, 2008

| | (a) Percentage of Street Segments Accounting for 50% of Crime | (b) Percentage of Street Segments & Intersections Accounting for 50% of Crime | (c) Percentage of Street Segments that Have Any Crime | (d) Percentage of Street Segments & Intersections that Have Any Crime | (e) Percentage of Street Segments with Crime that Account for 50% of Crime |
|---|---|---|---|---|---|
| Commercial B&E | 1.88 | 1.19 | 8.80 | 5.60 | 21.32 |
| Mischief | 4.42 | 2.81 | 22.86 | 14.54 | 19.31 |
| Theft from Vehicle | 4.67 | 2.97 | 14.60 | 9.29 | 31.99 |
| Theft of Vehicle | 2.62 | 1.66 | 29.33 | 18.65 | 8.92 |
| Total (Aggregate) | 4.50 | 2.86 | 44.42 | 28.25 | 10.13 |

Crime Concentrations within Street Segments & Intersections, Vancouver, 2009

| | (a) Percentage of Street Segments Accounting for 50% of Crime | (b) Percentage of Street Segments & Intersections Accounting for 50% of Crime | (c) Percentage of Street Segments that Have Any Crime | (d) Percentage of Street Segments & Intersections that Have Any Crime | (e) Percentage of Street Segments with Crime that Account for 50% of Crime |
|---|---|---|---|---|---|
| Commercial B&E | 1.70 | 1.08 | 7.90 | 5.03 | 21.47 |
| Mischief | 4.91 | 3.12 | 21.08 | 13.41 | 23.29 |
| Theft from Vehicle | 5.00 | 3.18 | 12.86 | 8.18 | 38.90 |
| Theft of Vehicle | 3.52 | 2.24 | 29.65 | 18.86 | 11.87 |
| Total (Aggregate) | 5.30 | 3.37 | 43.80 | 27.86 | 12.11 |

Crime Concentrations within Street Segments & Intersections, Vancouver, 2010

| | (a) Percentage of Street Segments Accounting for 50% of Crime | (b) Percentage of Street Segments & Intersections Accounting for 50% of Crime | (c) Percentage of Street Segments that Have Any Crime | (d) Percentage of Street Segments & Intersections that Have Any Crime | (e) Percentage of Street Segments with Crime that Account for 50% of Crime |
|---|---|---|---|---|---|
| Commercial B&E | 1.59 | 1.01 | 7.07 | 4.49 | 22.44 |
| Mischief | 4.22 | 2.68 | 19.99 | 12.71 | 21.11 |
| Theft from Vehicle | 4.09 | 2.60 | 10.14 | 6.45 | 40.34 |
| Theft of Vehicle | 4.91 | 3.12 | 30.66 | 19.50 | 16.01 |
| Total (Aggregate) | 6.05 | 3.85 | 43.35 | 27.57 | 13.96 |

Crime Concentrations within Street Segments & Intersections, Vancouver, 2011

| | (a) Percentage of Street Segments Accounting for 50% of Crime | (b) Percentage of Street Segments & Intersections Accounting for 50% of Crime | (c) Percentage of Street Segments that Have Any Crime | (d) Percentage of Street Segments & Intersections that Have Any Crime | (e) Percentage of Street Segments with Crime that Account for 50% of Crime |
|---|---|---|---|---|---|
| Commercial B&E | 1.44 | 0.92 | 7.07 | 4.49 | 20.39 |
| Mischief | 3.86 | 2.46 | 20.33 | 12.93 | 18.99 |
| Theft from Vehicle | 3.33 | 2.12 | 7.83 | 4.98 | 42.59 |
| Theft of Vehicle | 5.05 | 3.21 | 28.45 | 18.09 | 17.74 |
| Total (Aggregate) | 5.89 | 3.75 | 41.49 | 26.39 | 14.20 |

Crime Concentrations within Street Segments & Intersections, Vancouver, 2012

| | (a) Percentage of Street Segments Accounting for 50% of Crime | (b) Percentage of Street Segments & Intersections Accounting for 50% of Crime | (c) Percentage of Street Segments that Have Any Crime | (d) Percentage of Street Segments & Intersections that Have Any Crime | (e) Percentage of Street Segments with Crime that Account for 50% of Crime |
|---|---|---|---|---|---|
| Commercial B&E | 1.82 | 1.16 | 7.70 | 4.90 | 23.70 |
| Mischief | 4.10 | 2.61 | 19.33 | 12.29 | 21.22 |
| Theft from Vehicle | 3.38 | 2.15 | 8.06 | 5.13 | 41.97 |
| Theft of Vehicle | 5.00 | 3.18 | 29.90 | 19.01 | 16.74 |
| Total (Aggregate) | 6.04 | 3.84 | 41.67 | 26.50 | 14.48 |

Crime Concentrations within Street Segments & Intersections, Vancouver, 2013

| | (a) Percentage of Street Segments Accounting for 50% of Crime | (b) Percentage of Street Segments & Intersections Accounting for 50% of Crime | (c) Percentage of Street Segments that Have Any Crime | (d) Percentage of Street Segments & Intersections that Have Any Crime | (e) Percentage of Street Segments with Crime that Account for 50% of Crime |
|---|---|---|---|---|---|
| Commercial B&E | 1.90 | 1.21 | 8.19 | 5.21 | 23.20 |
| Mischief | 3.79 | 2.41 | 18.48 | 11.75 | 20.53 |
| Theft from Vehicle | 2.89 | 1.84 | 7.15 | 4.55 | 40.41 |
| Theft of Vehicle | 4.60 | 2.93 | 29.97 | 19.06 | 15.36 |
| Total (Aggregate) | 5.66 | 3.60 | 41.26 | 26.24 | 13.72 |

# Appendix J.

# Crime Concentration Tables, Ottawa (2006-2008)

Crime Concentrations within Street Segments & Intersections, Ottawa, 2006

| | (a) Percentage of Street Segments Accounting for 50% of Crime | (b) Percentage of Street Segments & Intersections Accounting for 50% of Crime | (c) Percentage of Street Segments that Have Any Crime | (d) Percentage of Street Segments & Intersections that Have Any Crime | (e) Percentage of Street Segments with Crime that Account for 50% of Crime |
|---|---|---|---|---|---|
| Commercial B&E | 0.77 | 0.51 | 2.46 | 1.63 | 31.11 |
| Residential B&E | 1.65 | 1.09 | 4.68 | 3.09 | 35.26 |
| Robbery | 0.52 | 0.34 | 1.40 | 0.92 | 37.25 |
| Theft of Vehicle | 1.24 | 0.82 | 4.52 | 2.99 | 27.51 |
| Total (Aggregate) | 2.50 | 1.65 | 10.36 | 6.85 | 24.09 |

Crime Concentrations within Street Segments & Intersections, Ottawa, 2007

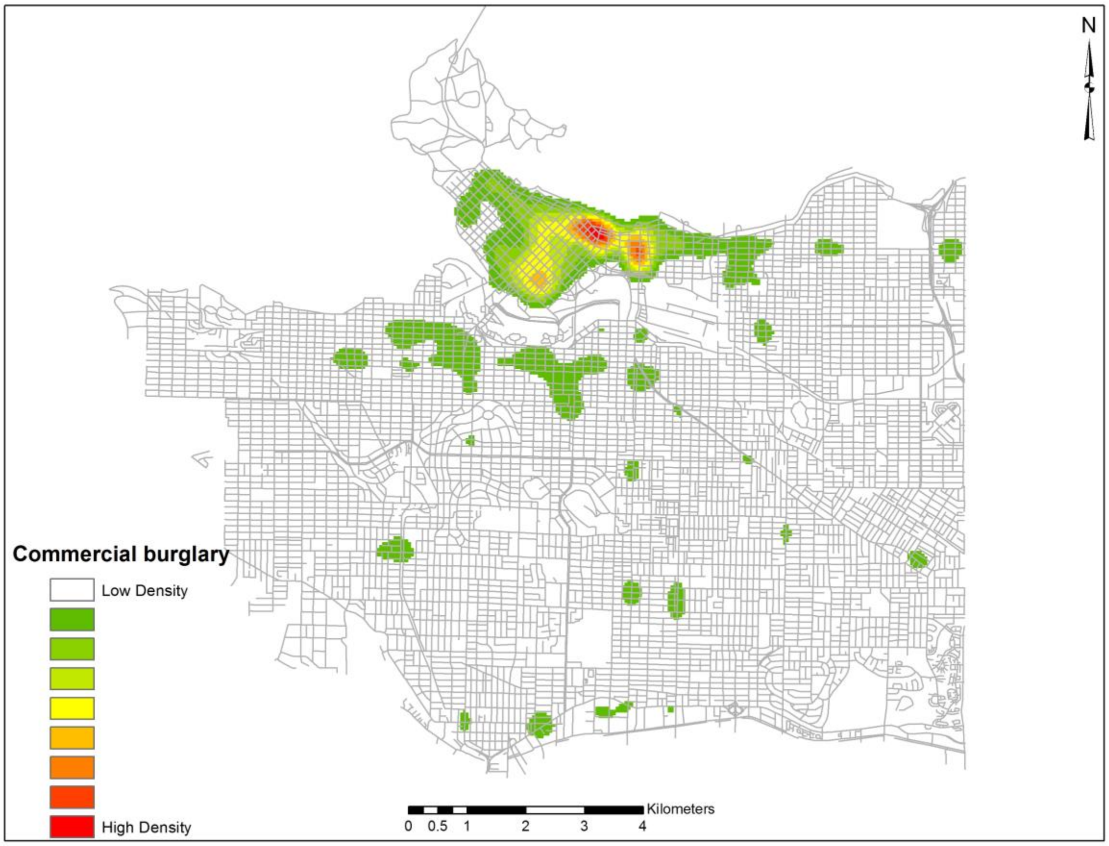
| | (a) Percentage of Street Segments Accounting for 50% of Crime | (b) Percentage of Street Segments & Intersections Accounting for 50% of Crime | (c) Percentage of Street Segments that Have Any Crime | (d) Percentage of Street Segments & Intersections that Have Any Crime | (e) Percentage of Street Segments with Crime that Account for 50% of Crime |
|---|---|---|---|---|---|
| Commercial B&E | 0.67 | 0.44 | 2.22 | 5.98 | 30.14 |
| Residential B&E | 1.46 | 0.97 | 3.81 | 1.47 | 38.37 |
| Robbery | 0.48 | 0.32 | 1.22 | 2.52 | 39.13 |
| Theft of Vehicle | 1.27 | 0.84 | 3.87 | 0.08 | 32.70 |
| Total (Aggregate) | 2.30 | 1.52 | 9.04 | 2.56 | 25.40 |

Crime Concentrations within Street Segments & Intersections, Ottawa, 2008

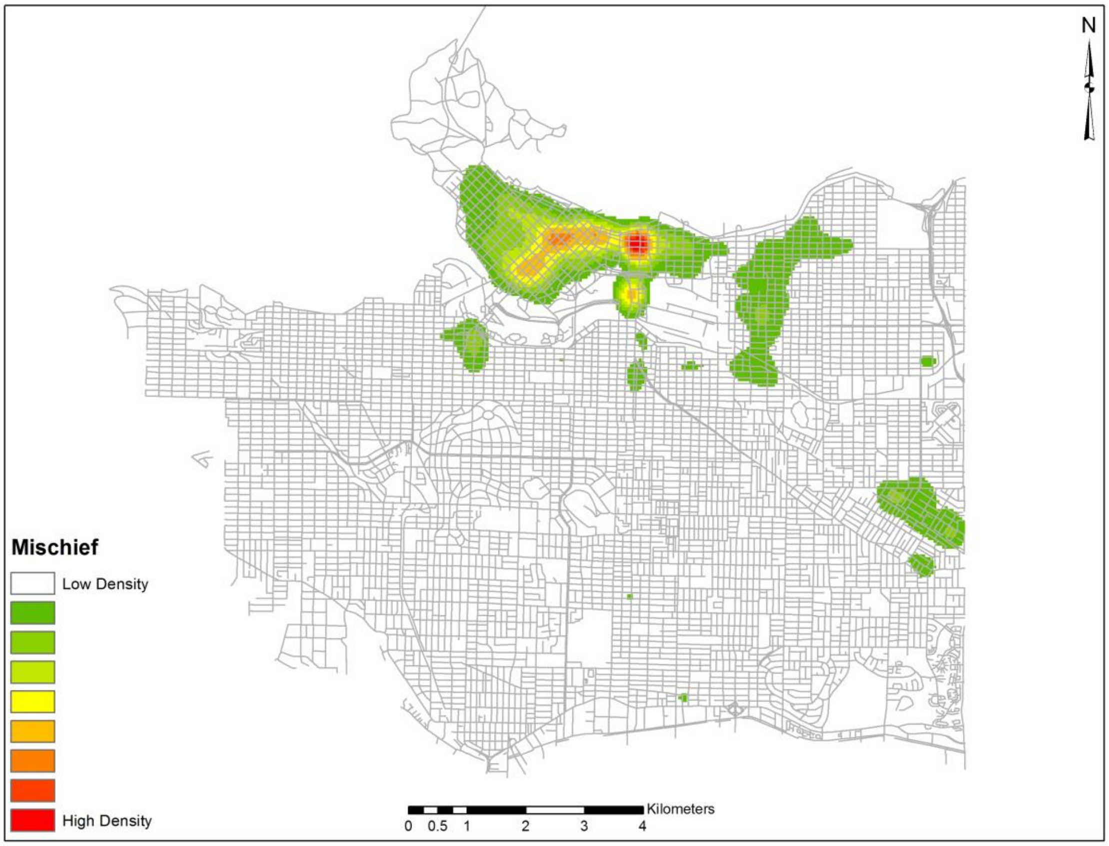
| | (a) Percentage of Street Segments Accounting for 50% of Crime | (b) Percentage of Street Segments & Intersections Accounting for 50% of Crime | (c) Percentage of Street Segments that Have Any Crime | (d) Percentage of Street Segments & Intersections that Have Any Crime | (e) Percentage of Street Segments with Crime that Account for 50% of Crime |
|---|---|---|---|---|---|
| Commercial B&E | 0.63 | 0.42 | 2.13 | 1.41 | 29.57 |
| Residential B&E | 1.26 | 0.84 | 3.34 | 2.21 | 37.86 |
| Robbery | 0.46 | 0.30 | 1.22 | 0.80 | 37.64 |
| Theft of Vehicle | 1.07 | 0.71 | 3.09 | 2.04 | 34.76 |
| Total (w/o mischief) | 2.01 | 1.33 | 8.01 | 5.29 | 25.12 |
| Mischief | 2.38 | 1.57 | 9.24 | 6.10 | 25.79 |
| Total (w/mischief) | 3.01 | 1.99 | 14.04 | 9.28 | 21.43 |

# Appendix K.

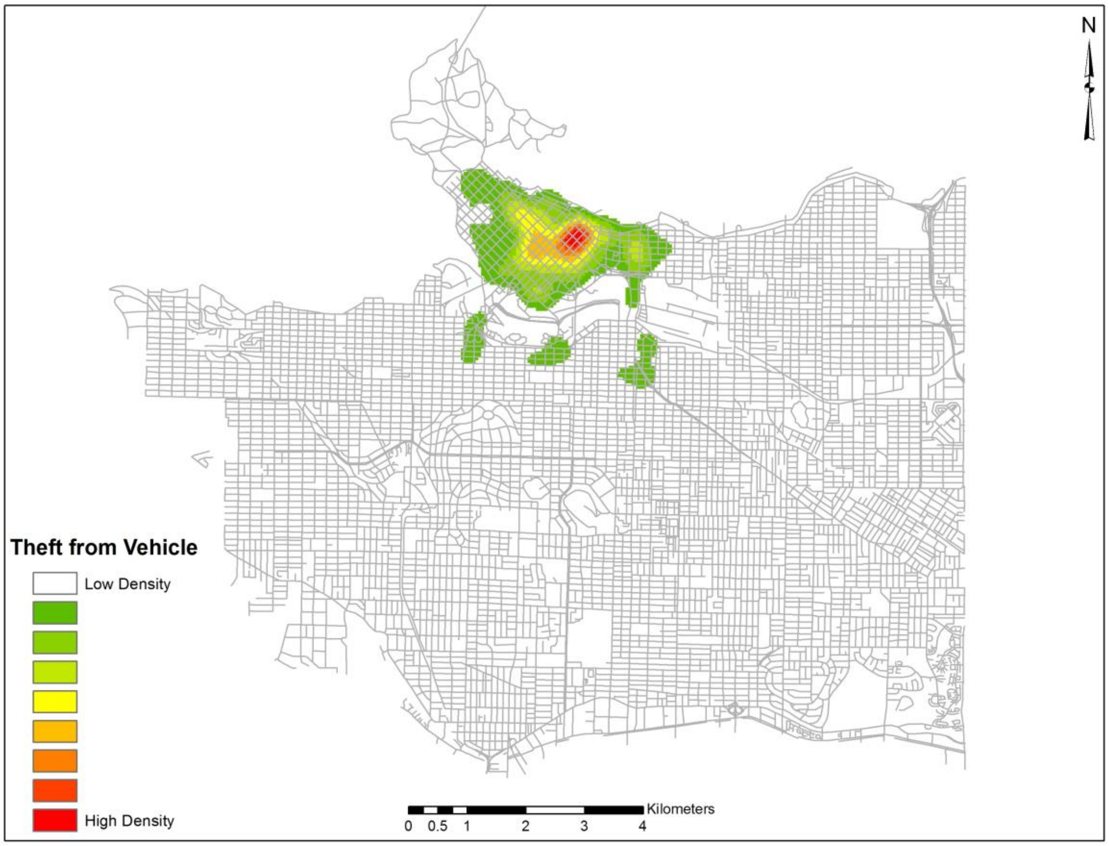
# Kernel Density Maps, Vancouver, 2008



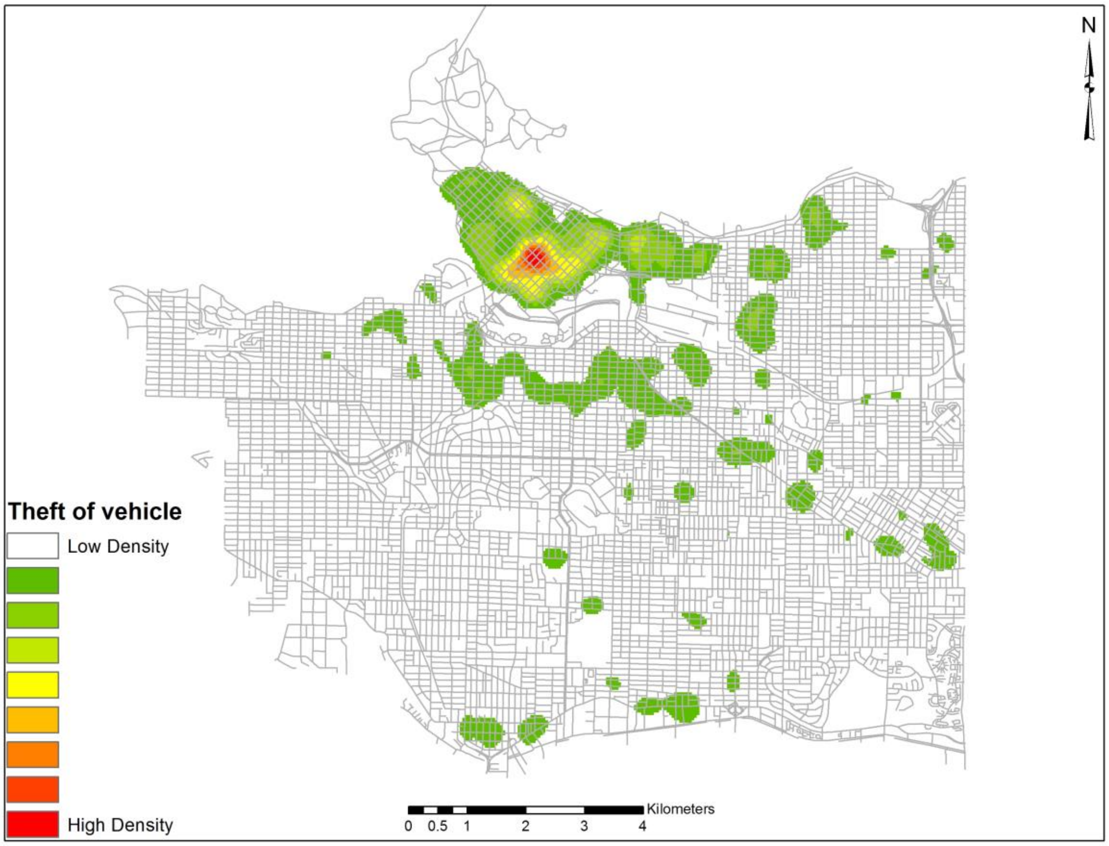

**Kernel Density Estimation Map, Commercial Burglary, Vancouver, 2008**




**Kernel Density Estimation Map, Mischief, Vancouver, 2008**



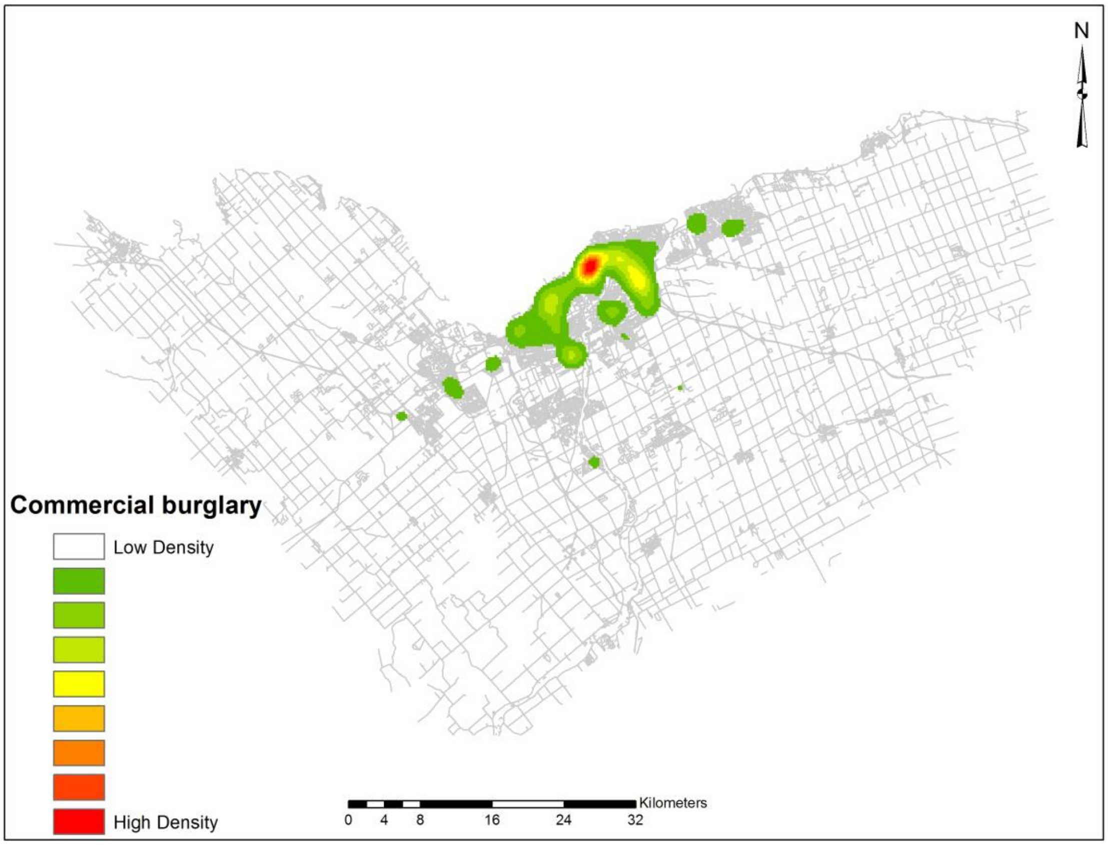

**Kernel Density Estimation Map, Theft from Vehicle, Vancouver, 2008**



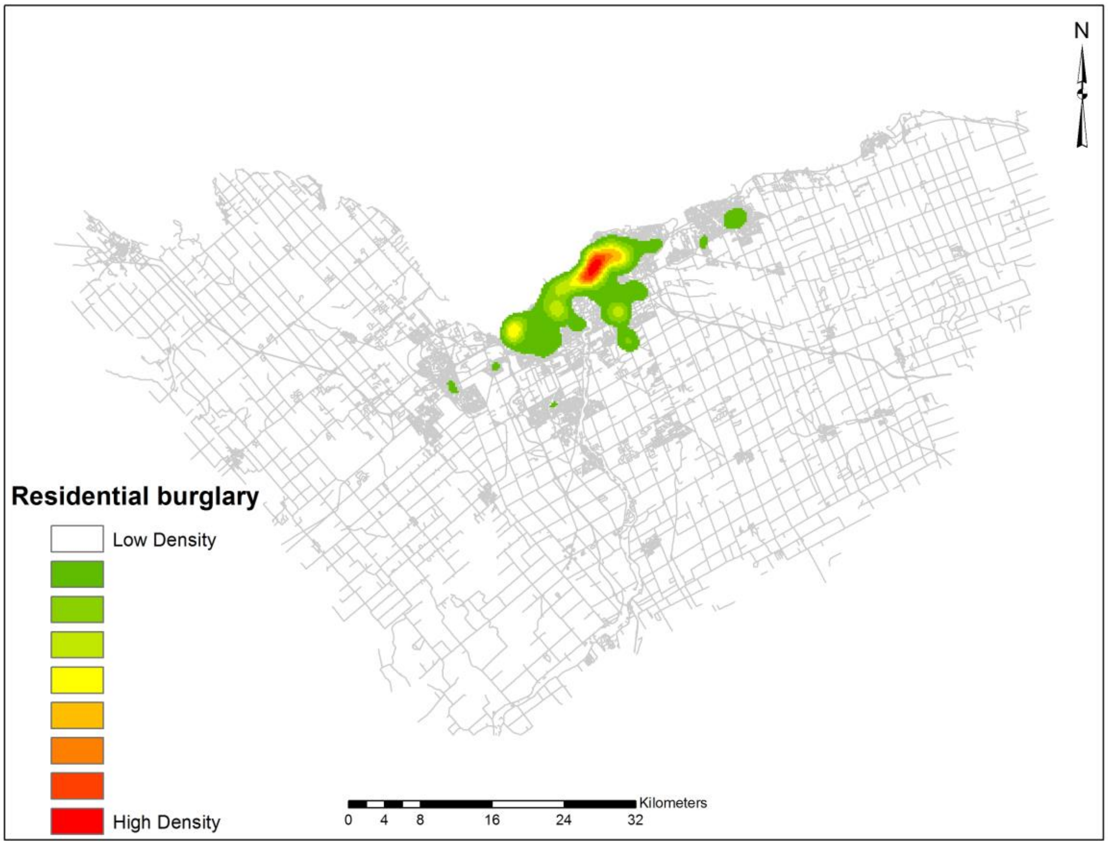

**Kernel Density Estimation Map, Theft of Vehicle, Vancouver, 2008**

# Appendix L.

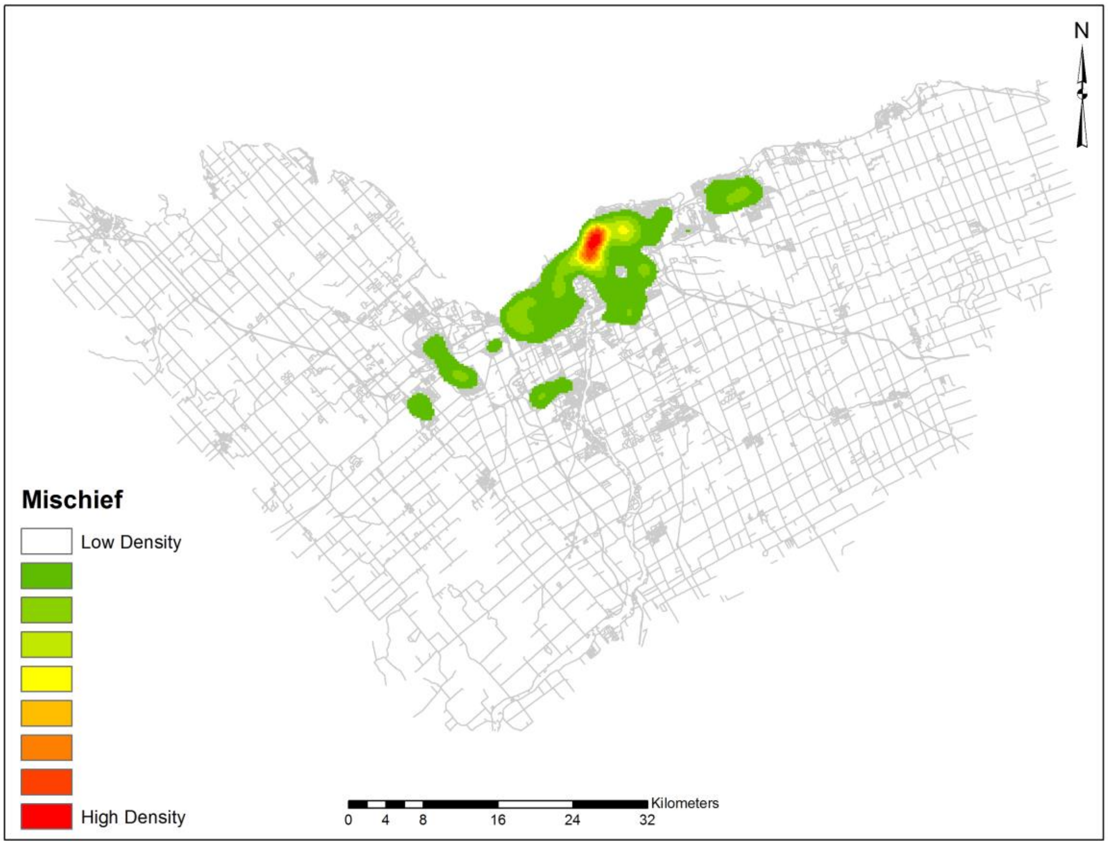
## Kernel Density Maps, Ottawa (2008)



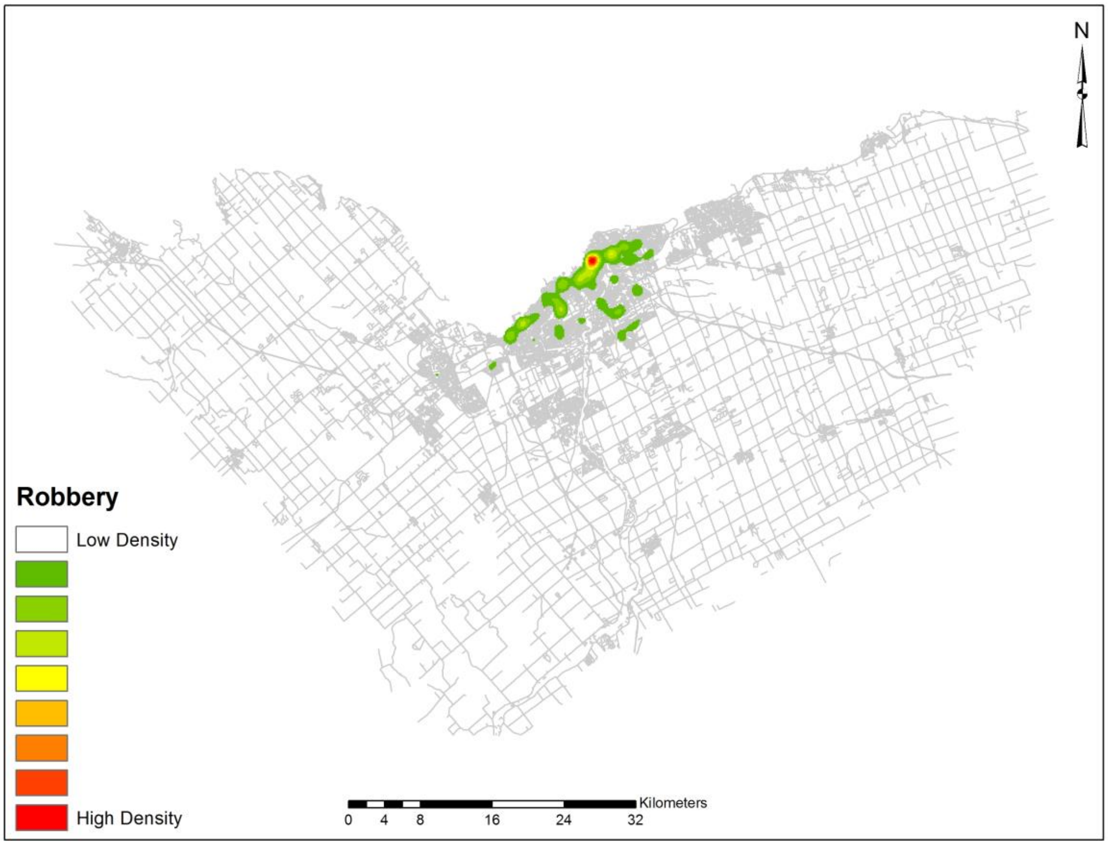

**Kernel Density Estimation Map, Commercial Burglary, Ottawa, 2008**



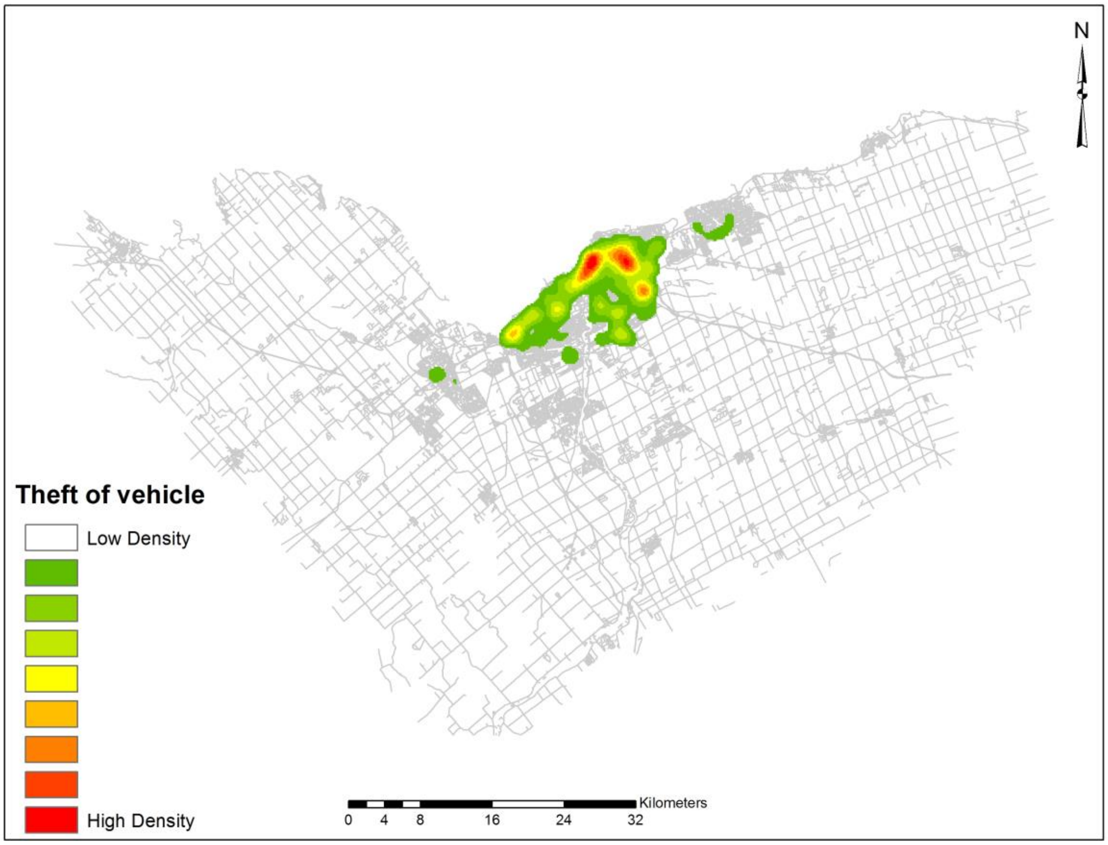

**Kernel Density Estimation Map, Residential Burglary, Ottawa, 2008**




**Kernel Density Estimation Map, Mischief, Ottawa, 2008**




**Kernel Density Estimation Map, Robbery, Ottawa, 2008**




**Kernel Density Estimation Map, Theft of Vehicle, Ottawa, 2008**

# Appendix M.

# Spatial Point Pattern Test Results, Indices of Similarity, Vancouver (2003-2013)

Indices of Similarity, 2003, Vancouver, Aggregate Crime, Street Segments & Intersections (w/7m buffer)

| | Comm BnE | Mischief | TFV | TOV |
|---|---|---|---|---|
| Total Crime | 0.640 | 0.726 | 0.784 | 0.729 |
| Comm BnE | | 0.904 | 0.742 | 0.894 |
| Mischief | | | 0.780 | 0.836 |
| TFV | | | | 0.776 |

Indices of Similarity, 2003, Vancouver, Total Crime, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.746 | 0.733 | 0.734 | 0.730 |
| Spring | | 0.820 | 0.829 | 0.820 |
| Summer | | | 0.831 | 0.832 |
| Fall | | | | 0.827 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2003, Vancouver, Commercial Break and Enter, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.953 | 0.951 | 0.952 | 0.952 |
| Spring | | 0.972 | 0.974 | 0.972 |
| Summer | | | 0.975 | 0.971 |
| Fall | | | | 0.974 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2003, Vancouver, Mischief, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.881 | 0.875 | 0.869 | 0.874 |
| Spring | | 0.936 | 0.938 | 0.935 |
| Summer | | | 0.947 | 0.940 |
| Fall | | | | 0.944 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2003, Vancouver, Theft from Vehicle, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.819 | 0.809 | 0.811 | 0.804 |
| Spring | | 0.889 | 0.893 | 0.888 |
| Summer | | | 0.894 | 0.900 |
| Fall | | | | 0.893 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2003, Vancouver, Theft of Vehicle, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.870 | 0.865 | 0.870 | 0.872 |
| Spring | | 0.938 | 0.937 | 0.937 |
| Summer | | | 0.937 | 0.935 |
| Fall | | | | 0.937 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2004, Vancouver, Aggregate Crime, Street Segments & Intersections (w/7m buffer)

| | Comm BnE | Mischief | TFV | TOV |
|---|---|---|---|---|
| Total Crime | 0.625 | 0.701 | 0.783 | 0.719 |
| Comm BnE | | 0.905 | 0.725 | 0.892 |
| Mischief | | | 0.757 | 0.843 |
| TFV | | | | 0.763 |

Indices of Similarity, 2004, Vancouver, Total Crime, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.718 | 0.724 | 0.732 | 0.716 |
| Spring | | 0.826 | 0.805 | 0.828 |
| Summer | | | 0.807 | 0.822 |
| Fall | | | | 0.810 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2004, Vancouver, Commercial Break and Enter, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.949 | 0.950 | 0.952 | 0.948 |
| Spring | | 0.974 | 0.971 | 0.973 |
| Summer | | | 0.972 | 0.971 |
| Fall | | | | 0.971 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2004, Vancouver, Mischief, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.883 | 0.884 | 0.881 | 0.876 |
| Spring | | 0.945 | 0.944 | 0.943 |
| Summer | | | 0.946 | 0.943 |
| Fall | | | | 0.944 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2004, Vancouver, Theft from Vehicle, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.790 | 0.795 | 0.806 | 0.791 |
| Spring | | 0.892 | 0.871 | 0.895 |
| Summer | | | 0.873 | 0.888 |
| Fall | | | | 0.873 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2004, Vancouver, Theft of Vehicle, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.859 | 0.862 | 0.863 | 0.862 |
| Spring | | 0.938 | 0.935 | 0.940 |
| Summer | | | 0.935 | 0.936 |
| Fall | | | | 0.936 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2005, Vancouver, Aggregate Crime, Street Segments (w/7m buffer)

| | Comm BnE | Mischief | TFV | TOV |
|---|---|---|---|---|
| Total Crime | 0.638 | 0.706 | 0.798 | 0.725 |
| Comm BnE | | 0.913 | 0.735 | 0.905 |
| Mischief | | | 0.760 | 0.854 |
| TFV | | | | 0.770 |

Indices of Similarity, 2005, Vancouver, Total Crime, Street Segments (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.728 | 0.731 | 0.730 | 0.726 |
| Spring | | 0.828 | 0.830 | 0.826 |
| Summer | | | 0.834 | 0.829 |
| Fall | | | | 0.828 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2005, Vancouver, Commercial Break and Enter, Street Segments (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.952 | 0.954 | 0.955 | 0.950 |
| Spring | | 0.975 | 0.973 | 0.977 |
| Summer | | | 0.974 | 0.975 |
| Fall | | | | 0.973 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2005, Vancouver, Mischief, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.891 | 0.888 | 0.892 | 0.885 |
| Spring | | 0.948 | 0.948 | 0.947 |
| Summer | | | 0.946 | 0.950 |
| Fall | | | | 0.946 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2005, Vancouver, Theft from Vehicle, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.805 | 0.798 | 0.802 | 0.798 |
| Spring | | 0.887 | 0.890 | 0.883 |
| Summer | | | 0.892 | 0.893 |
| Fall | | | | 0.890 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2005, Vancouver, Theft of Vehicle, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.872 | 0.874 | 0.867 | 0.877 |
| Spring | | 0.946 | 0.951 | 0.946 |
| Summer | | | 0.951 | 0.943 |
| Fall | | | | 0.946 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2006, Vancouver, Aggregate Crime, Street Segments & Intersections (w/7m buffer)

| | Comm BnE | Mischief | TFV | TOV |
|---|---|---|---|---|
| Total Crime | 0.668 | 0.743 | 0.809 | 0.734 |
| Comm BnE | | 0.914 | 0.760 | 0.918 |
| Mischief | | | 0.788 | 0.859 |
| TFV | | | | 0.791 |

Indices of Similarity, 2006, Vancouver, Total Crime, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.745 | 0.746 | 0.748 | 0.756 |
| Spring | | 0.852 | 0.848 | 0.847 |
| Summer | | | 0.850 | 0.850 |
| Fall | | | | 0.848 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2006, Vancouver, Commercial Break and Enter, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.951 | 0.951 | 0.953 | 0.953 |
| Spring | | 0.976 | 0.974 | 0.975 |
| Summer | | | 0.974 | 0.976 |
| Fall | | | | 0.975 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2006, Vancouver, Mischief, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.887 | 0.889 | 0.883 | 0.885 |
| Spring | | 0.947 | 0.952 | 0.946 |
| Summer | | | 0.950 | 0.944 |
| Fall | | | | 0.951 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2006, Vancouver, Theft from Vehicle, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.819 | 0.817 | 0.821 | 0.827 |
| Spring | | 0.908 | 0.902 | 0.906 |
| Summer | | | 0.904 | 0.905 |
| Fall | | | | 0.900 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2006, Vancouver, Theft of Vehicle, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.900 | 0.902 | 0.900 | 0.904 |
| Spring | | 0.962 | 0.961 | 0.957 |
| Summer | | | 0.961 | 0.958 |
| Fall | | | | 0.958 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2007, Vancouver, Aggregate Crime, Street Segments & Intersections (w/7m buffer)

| | Comm BnE | Mischief | TFV | TOV |
|---|---|---|---|---|
| Total Crime | 0.695 | 0.760 | 0.818 | 0.755 |
| Comm BnE | | 0.923 | 0.789 | 0.927 |
| Mischief | | | 0.803 | 0.870 |
| TFV | | | | 0.812 |

Indices of Similarity, 2007, Vancouver, Total Crime, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.767 | 0.775 | 0.759 | 0.765 |
| Spring | | 0.861 | 0.870 | 0.865 |
| Summer | | | 0.870 | 0.855 |
| Fall | | | | 0.871 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2007, Vancouver, Commercial Break and Enter, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.956 | 0.958 | 0.956 | 0.959 |
| Spring | | 0.979 | 0.978 | 0.979 |
| Summer | | | 0.979 | 0.976 |
| Fall | | | | 0.978 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2007, Vancouver, Mischief, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.901 | 0.901 | 0.897 | 0.893 |
| Spring | | 0.951 | 0.955 | 0.959 |
| Summer | | | 0.954 | 0.950 |
| Fall | | | | 0.953 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2007, Vancouver, Theft from Vehicle, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.839 | 0.845 | 0.834 | 0.841 |
| Spring | | 0.928 | 0.925 | 0.919 |
| Summer | | | 0.924 | 0.909 |
| Fall | | | | 0.915 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2007, Vancouver, Theft of Vehicle, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.908 | 0.912 | 0.907 | 0.907 |
| Spring | | 0.960 | 0.965 | 0.964 |
| Summer | | | 0.965 | 0.964 |
| Fall | | | | 0.964 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2009, Vancouver, Aggregate Crime, Street Segments & Intersections (w/7m buffer)

| | Comm BnE | Mischief | TFV | TOV |
|---|---|---|---|---|
| Total Crime | 0.723 | 0.789 | 0.739 | 0.760 |
| Comm BnE | | 0.924 | 0.812 | 0.948 |
| Mischief | | | 0.824 | 0.874 |
| TFV | | | | 0.827 |

Indices of Similarity, 2009, Vancouver, Total Crime, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.784 | 0.788 | 0.782 | 0.782 |
| Spring | | 0.879 | 0.878 | 0.878 |
| Summer | | | 0.881 | 0.874 |
| Fall | | | | 0.880 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2009, Vancouver, Commercial Break and Enter, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.961 | 0.963 | 0.962 | 0.963 |
| Spring | | 0.983 | 0.982 | 0.983 |
| Summer | | | 0.983 | 0.982 |
| Fall | | | | 0.982 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2009, Vancouver, Mischief, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.900 | 0.901 | 0.896 | 0.895 |
| Spring | | 0.854 | 0.856 | 0.952 |
| Summer | | | 0.956 | 0.952 |
| Fall | | | | 0.956 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2009, Vancouver, Theft from Vehicle, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.852 | 0.859 | 0.854 | 0.853 |
| Spring | | 0.932 | 0.927 | 0.930 |
| Summer | | | 0.927 | 0.924 |
| Fall | | | | 0.926 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2009, Vancouver, Theft of Vehicle, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.937 | 0.937 | 0.938 | 0.939 |
| Spring | | 0.978 | 0.977 | 0.978 |
| Summer | | | 0.977 | 0.978 |
| Fall | | | | 0.976 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2010, Vancouver, Aggregate Crime, Street Segments & Intersections (w/7m buffer)

| | Comm BnE | Mischief | TFV | TOV |
|---|---|---|---|---|
| Total Crime | 0.721 | 0.793 | 0.850 | 0.750 |
| Comm BnE | | 0.933 | 0.802 | 0.953 |
| Mischief | | | 0.820 | 0.879 |
| TFV | | | | 0.816 |

Indices of Similarity, 2010, Vancouver, Total Crime, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.786 | 0.792 | 0.787 | 0.781 |
| Spring | | 0.886 | 0.882 | 0.887 |
| Summer | | | 0.883 | 0.877 |
| Fall | | | | 0.882 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2010, Vancouver, Commercial Break and Enter, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.967 | 0.967 | 0.968 | 0.967 |
| Spring | | 0.984 | 0.984 | 0.984 |
| Summer | | | 0.984 | 0.984 |
| Fall | | | | 0.983 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2010, Vancouver, Mischief, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.905 | 0.905 | 0.901 | 0.902 |
| Spring | | 0.955 | 0.958 | 0.955 |
| Summer | | | 0.959 | 0.954 |
| Fall | | | | 0.959 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2010, Vancouver, Theft from Vehicle, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.846 | 0.855 | 0.853 | 0.846 |
| Spring | | 0.928 | 0.923 | 0.932 |
| Summer | | | 0.925 | 0.924 |
| Fall | | | | 0.924 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2010, Vancouver, Theft of Vehicle, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.950 | 0.952 | 0.951 | 0.952 |
| Spring | | 0.983 | 0.982 | 0.984 |
| Summer | | | 0.952 | 0.982 |
| Fall | | | | 0.982 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2011, Vancouver, Aggregate Crime, Street Segments & Intersections (w/7m buffer)

| | Comm BnE | Mischief | TFV | TOV |
|---|---|---|---|---|
| Total Crime | 0.740 | 0.809 | 0.852 | 0.754 |
| Comm BnE | | 0.931 | 0.818 | 0.954 |
| Mischief | | | 0.923 | 0.875 |
| TFV | | | | 0.826 |

Indices of Similarity, 2011, Vancouver, Total Crime, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.795 | 0.801 | 0.797 | 0.793 |
| Spring | | 0.894 | 0.900 | 0.894 |
| Summer | | | 0.889 | 0.884 |
| Fall | | | | 0.888 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2011, Vancouver, Commercial Break and Enter, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.966 | 0.967 | 0.965 | 0.967 |
| Spring | | 0.984 | 0.984 | 0.985 |
| Summer | | | 0.985 | 0.985 |
| Fall | | | | 0.985 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2011, Vancouver, Mischief, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.903 | 0.900 | 0.900 | 0.897 |
| Spring | | 0.951 | 0.953 | 0.952 |
| Summer | | | 0.958 | 0.955 |
| Fall | | | | 0.957 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2011, Vancouver, Theft from Vehicle, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.855 | 0.868 | 0.863 | 0.859 |
| Spring | | 0.837 | 0.933 | 0.937 |
| Summer | | | 0.931 | 0.927 |
| Fall | | | | 0.931 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2011, Vancouver, Theft of Vehicle, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.962 | 0.963 | 0.962 | 0.963 |
| Spring | | 0.987 | 0.987 | 0.987 |
| Summer | | | 0.987 | 0.986 |
| Fall | | | | 0.987 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2012, Vancouver, Aggregate Crime, Street Segments & Intersections (w/7m buffer)

| | Comm BnE | Mischief | TFV | TOV |
|---|---|---|---|---|
| Total Crime | 0.739 | 0.801 | 0.857 | 0.751 |
| Comm BnE | | 0.931 | 0.811 | 0.950 |
| Mischief | | | 0.825 | 0.882 |
| TFV | | | | 0.818 |

Indices of Similarity, 2012, Vancouver, Total Crime, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.797 | 0.798 | 0.791 | 0.788 |
| Spring | | 0.888 | 0.889 | 0.889 |
| Summer | | | 0.892 | 0.883 |
| Fall | | | | 0.889 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2012, Vancouver, Commercial Break and Enter, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.964 | 0.961 | 0.964 | 0.963 |
| Spring | | 0.983 | 0.981 | 0.983 |
| Summer | | | 0.982 | 0.984 |
| Fall | | | | 0.981 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2012, Vancouver, Mischief, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.908 | 0.909 | 0.905 | 0.902 |
| Spring | | 0.958 | 0.960 | 0.957 |
| Summer | | | 0.960 | 0.955 |
| Fall | | | | 0.959 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2012, Vancouver, Theft from Vehicle, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.855 | 0.854 | 0.852 | 0.853 |
| Spring | | 0.932 | 0.930 | 0.932 |
| Summer | | | 0.932 | 0.931 |
| Fall | | | | 0.932 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2012, Vancouver, Theft of Vehicle, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.961 | 0.963 | 0.961 | 0.960 |
| Spring | | 0.956 | 0.986 | 0.956 |
| Summer | | | 0.956 | 0.984 |
| Fall | | | | 0.957 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2013, Vancouver, Aggregate Crime, Street Segments & Intersections (w/7m buffer)

| | Comm BnE | Mischief | TFV | TOV |
|---|---|---|---|---|
| Total Crime | 0.745 | 0.798 | 0.860 | 0.748 |
| Comm BnE | | 0.930 | 0.811 | 0.949 |
| Mischief | | | 0.822 | 0.886 |
| TFV | | | | 0.814 |

Indices of Similarity, 2013, Vancouver, Total Crime, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.801 | 0.793 | 0.802 | 0.789 |
| Spring | | 0.866 | 0.881 | 0.885 |
| Summer | | | 0.885 | 0.895 |
| Fall | | | | 0.882 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2013, Vancouver, Commercial Break and Enter, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.961 | 0.958 | 0.962 | 0.961 |
| Spring | | 0.982 | 0.981 | 0.981 |
| Summer | | | 0.982 | 0.984 |
| Fall | | | | 0.981 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2013, Vancouver, Mischief, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.911 | 0.912 | 0.909 | 0.909 |
| Spring | | 0.958 | 0.960 | 0.959 |
| Summer | | | 0.963 | 0.959 |
| Fall | | | | 0.920 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2013, Vancouver, Theft from Vehicle, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.858 | 0.851 | 0.863 | 0.844 |
| Spring | | 0.929 | 0.921 | 0.928 |
| Summer | | | 0.922 | 0.935 |
| Fall | | | | 0.920 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2013, Vancouver, Theft of Vehicle, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.967 | 0.964 | 0.965 | 0.966 |
| Spring | | 0.987 | 0.989 | 0.986 |
| Summer | | | 0.989 | 0.987 |
| Fall | | | | 0.987 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

# Appendix N.

# Spatial Point Pattern Test Results, Indices of Similarity, Ottawa (2006-2007)

Indices of Similarity, 2006, Ottawa, Aggregate Crime, Street Segments & Intersections (w/7m buffer)

| | Comm BnE | Res BnE | Robbery | TOV |
|---|---|---|---|---|
| Total Crime | 0.941 | 0.955 | 0.936 | 0.954 |
| Comm BnE | | 0.979 | 0.984 | 0.980 |
| Res BnE | | | 0.969 | 0.966 |
| Robbery | | | | 0.986 |

Indices of Similarity, 2006, Ottawa, Total Crime, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.948 | 0.952 | 0.949 | 0.946 |
| Spring | | 0.978 | 0.978 | 0.978 |
| Summer | | | 0.974 | 0.975 |
| Fall | | | | 0.977 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2006, Ottawa, Commercial Break and Enter, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.988 | 0.988 | 0.988 | 0.988 |
| Spring | | 0.995 | 0.995 | 0.995 |
| Summer | | | 0.995 | 0.995 |
| Fall | | | | 0.995 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2006, Ottawa, Residential Break and Enter, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.976 | 0.978 | 0.976 | 0.976 |
| Spring | | 0.991 | 0.991 | 0.991 |
| Summer | | | 0.989 | 0.989 |
| Fall | | | | 0.992 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2006, Ottawa, Robbery, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.993 | 0.994 | 0.994 | 0.993 |
| Spring | | 0.997 | 0.998 | 0.998 |
| Summer | | | 0.997 | 0.997 |
| Fall | | | | 0.997 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2006, Ottawa, Theft of Vehicle, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.978 | 0.979 | 0.979 | 0.976 |
| Spring | | 0.991 | 0.991 | 0.991 |
| Summer | | | 0.990 | 0.990 |
| Fall | | | | 0.990 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2007, Ottawa, Aggregate Crime, Street Segments & Intersections (w/7m buffer)

| | Comm BnE | Res BnE | Robbery | TOV |
|---|---|---|---|---|
| Total Crime | 0.950 | 0.961 | 0.946 | 0.960 |
| Comm BnE | | 0.983 | 0.986 | 0.983 |
| Res BnE | | | 0.975 | 0.974 |
| Robbery | | | | 0.989 |

Indices of Similarity, 2007, Ottawa, Total Crime, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.957 | 0.960 | 0.955 | 0.954 |
| Spring | | 0.981 | 0.981 | 0.981 |
| Summer | | | 0.978 | 0.977 |
| Fall | | | | 0.983 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2007, Ottawa, Commercial Break and Enter, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.989 | 0.990 | 0.989 | 0.989 |
| Spring | | 0.995 | 0.995 | 0.996 |
| Summer | | | 0.995 | 0.996 |
| Fall | | | | 0.996 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2007, Ottawa, Residential Break and Enter, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.981 | 0.983 | 0.980 | 0.980 |
| Spring | | 0.992 | 0.993 | 0.993 |
| Summer | | | 0.991 | 0.991 |
| Fall | | | | 0.994 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2007, Ottawa, Robbery, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.994 | 0.994 | 0.994 | 0.994 |
| Spring | | 0.998 | 0.998 | 0.998 |
| Summer | | | 0.997 | 0.997 |
| Fall | | | | 0.998 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)

Indices of Similarity, 2007, Ottawa, Theft of Vehicle, Street Segments & Intersections (w/7m buffer)

| | Spring | Summer | Fall | Winter |
|---|---|---|---|---|
| All Year | 0.982 | 0.983 | 0.981 | 0.980 |
| Spring | | 0.993 | 0.992 | 0.993 |
| Summer | | | 0.991 | 0.991 |
| Fall | | | | 0.993 |

Seasons: Winter (Jan - March); Spring (April - June); Summer (July - Sept); Fall (Oct - Dec)