The Potential Influence of Environmental Variables on Spatial and Temporal Crime Patterns in a Small Canadian City: A Case Study in North Bay, Ontario, Using Call-for-Service Data, 2015-2019

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Abstract

The objectives of this study are two-fold, consisting of both aspatial and spatial components. The aspatial portion of the study seeks to determine the influences of weather and calendar variables on crime occurrence, while the spatial component seeks to explore spatial patterns of crime, and to assess the degree of similarity in these patterns across seasons. Both objectives are accomplished using five years of call for service data (2015 – 2019) from a small Northern Ontario city; North Bay.

To accomplish the aspatial objective, a series of eight negative binomial regression models (one each for violent and property crime in each of the four seasons) were used to assess the relationships between crime, weather, and calendar variables. Equality of coefficient z tests, based on the model coefficients, were used to compare results between seasons. Based on the results of the models, relationships between the dependent and independent variables were found to differ significantly from season to season, and between crime types. Moreover, property crime appears to be influenced more by calendar variables than by weather variables, whereas the opposite relationship was observed for violent crime.

For the spatial component of the study, exploratory data analysis was conducted using descriptive statistics and kernel density mapping. Andresen's spatial point pattern test (SPPT) was then used to assess the degree of similarity between the seasonal patterns for each call type at four different spatial scales. While kernel density mapping appears to show different seasonal patterns for some crime types, the SPPT found no evidence of dissimilarity for any call type across the city as a whole. Where a degree of local dissimilarity exists, it is focused in only two areas of the city, one of which is the downtown core.

Preface

This thesis is the original, unpublished, independent work by the author, Ysabel Castle.

Preliminary findings of this study were presented at this conference: Canadian Association of Geographers Ontario Division Annual Meeting, at Guelph, Ontario, October 26, 2019: *Seasonal spatial patterns in police calls for service*.

Findings were also presented at the Nipissing University GIS Day, North Bay, Ontario, November 13, 2019 poster sessions: *Spatial and temporal patterns in police calls for service*.

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Chapter 1: Introduction

1.1 Research Question

Criminal activity is not constant, but displays variation at both fine and coarse scales, temporally and spatially. However, much of this variation occurs at too fine of a timescale to be explained using the traditional variables, such as neighborhood demographics and socioeconomic status, which tend to change slowly over time (Cohn, 1990). The question, then, is whether this fine-scale variation is predictable, and if so, which factors might be able to explain it. A large body of literature now indicates that weather and seasonality may be useful in explaining temporal variation in particular (Cohn, 1990). Less is known about how weather and seasonality impact spatial patterns of crime (Haberman et al., 2018). Additionally, there is some disagreement about the nature of these relationships, with different weather variables influencing crime in different study areas, as well as the degree and direction of their influence (Ranson, 2014; Linning et al., 2017a). Even seasonal variations in crime have been shown to be inconsistent across space and crime types (Cohn and Rotton, 2000; McDowall et al., 2012).

Given these inconsistencies, it is also troublesome that very little research on crime-weather and crime-season relationships has been conducted in small study areas, with the majority focusing on metropolitan-sized urban centers. The aim of this thesis is to address these gaps in our understanding by determining if and how seasonality and weather influence crime patterns, both temporally and spatially, in the city of North Bay, Ontario, Canada. This work draws on both psychological and criminological understandings of crime. The work was conducted in partnership with the North Bay Police Service (NBPS), who have kindly provided several years of calls for service data at no expense. Understanding trends in spatial patterns of crime can provide police departments such as the NBPS with the ability to police proactively

(Gundhus, 2005; Cohen et al., 2007; Herchenrader and Myhill-Jones, 2015), and the NBPS have indicated a particular interest in the crime mapping possibilities inherent in the data.

1.2 Objectives

This study has three major objectives. The first is to integrate police call for service data, which is inherently spatial, with aspatial data pertaining to weather and major calendar events in the city of North Bay. The second is to use these data to analyze potential relationships between the temporal patterns of crimes, aggregated into the categories of violent crime and property crime, and specific weather variables. The third is to understand whether the spatial patterns of specific crimes differ during different seasons of the years, and if so, in what ways.

1.3 Theoretical Background

1.3.1 The Temperature Aggression Theory

A number of theories exist which have the potential to explain relationships between weather or season and crime. One of the oldest is the temperature aggression theory, which has its roots in the work of the statistician Adolph Quetelet. He studied crime in France in the early 1800s, and noted that violent crime peaked during the summer, which he speculated might be linked to "the violence of passions predominating in summer" (Quetelet, 1842, pg. 90). He also explicitly linked an increase in violent crime to hot climates (Quetelet, 1842). In modern times, the temperature aggression theory has been accepted by both psychologists and criminologists, and a large body of experimental evidence exists to show that heat increases discomfort, which can lead to aggression (Cohn, 1990). Although laboratory evidence is not a perfect match for real world conditions (Cohn, 1990), a number of crime-weather studies discuss this theory as a potential link between weather and crime rates (e.g. Brunsdon et al., 2009; Ranson, 2014). However, it is somewhat limited in its utility, as it only applies to studies involving both temperature and aggressive (i.e. violent) crimes, although many other weather variables and crime types may be related.

Further, there is some disagreement about the exact relationship the temperature aggression theory predicts between crime and temperature. The General Affect (GA) or General Aggression Model (GAM) postulates that complex interactions occur between personality and temperature, which will determine how any given person responds to heat (Anderson et al., 1997); studies using this model generally predict a positive linear relationship between temperature and crime (Mares, 2013). Under Baron and Bell's (1976) Negative Affect Escape (NAE) model, on the other hand, a temperature inflection point is assumed to exist, above which people become more likely to seek an escape from the heat than to become aggressive (Mares, 2013). The NAE also predicts that a similar effect will be seen in very cold temperatures (Peng, 2011), and thus predicts a negative quadratic relationship between temperature and violent crime. Interestingly, the NAE provides a means by which temperature aggression theory might influence spatial patterns of crime. For example, if people in some parts of a study area do not have the means to escape heat easily, such as access to air conditioning or swimming pools, it is possible that these areas would see an unusual increase in violent crime during very hot weather as compared to other areas (Ceccato, 2005).

1.3.2 The Routine Activities Theory

Despite the longstanding use of temperature aggression theory to explain crime-weather interactions, recent studies have tended to focus more on the routine activities theory (Haberman et al., 2018; Oliveira et al., 2018). Some have even suggested that this may be the dominant mechanism by which weather influences crime (e.g. Hipp et al., 2004). The routine activities theory was originally developed by Cohen and Felson (1979) to explain how social changes might influence crime rates. According to this theory, the likelihood of crime increases when and where a potential offender, a suitable target, and a lack of guardianship come together in both time and space (Cohen and Felson, 1979; Weir-Smith, 2004). Notably, while an offender must be a person, the other two criteria may not necessarily be so. For example, buildings such as empty houses, may be suitable targets for property crime (de Melo et al., 2018), while CCTV or other technologies may provide guardianship (Reynald, 2019).

The intersection of these circumstances is mediated by peoples' routine activities, which are generally consistent unless disrupted by some external factor (Cohn, 1990; Brunsdon et al., 2009). These routine activities can be divided into two categories. Obligatory describes mandatory activities such as attending work or school, which do not change readily, whereas discretionary activities tend to be associated with leisure time, and thus are more susceptible to change based on outside influences (Breetzke and Cohn, 2012; Quick et al., 2019). Seasonal factors may shape routine activities in the long run, while weather is a short term external influence that might act to disrupt them by changing peoples' willingness to engage in non-essential outdoor activities. Consequently, the routine activities theory has the potential to link both weather and seasonality to crime patterns (Andresen and Malleson, 2013). Given that the routines which form the basis of this theory are themselves spatial, occurring on and shaped by the physical landscape, the routine activities theory can be effective in explaining spatial patterns of crime, as well as their temporal distribution (Haberman et al., 2018).

1.3.2 Other Crime Theories

Cohn (1990) notes that rational choice theory can also be important for studies analyzing crime patterns; this theory states that individuals will choose whether to commit a crime based on a rational analysis of their circumstances. This theory is explicitly spatial (Brunsdon et al., 2009), and although it is rarely referenced in the crime-weather literature, it is not inconceivable that weather could influence offender decision-making regarding crime location and timing.

Also potentially relevant is the crime pattern theory, particularly for those studies focusing on the spatial distribution of crime (Brunsdon et al., 2009). This theory relates to the physical infrastructure of a study area, and how that physical landscape shapes the flows of people through that area, leading to their convergence in time and space (Brantingham and Brantingham, 1993). Given that, in some study areas, the use of certain infrastructure can change on a seasonal basis (Quick et al., 2019), this theory provides a link between seasonality and spatial crime patterns. Logically speaking, it should also link weather and crime patterns, as places like parks should see less use during inclement weather.

Finally, it is worth noting that some attempts have been made to integrate many of the above crime theories, as none are mutually exclusive, and they may operate simultaneously to link crime and weather in any given study area. In particular, Cohn and Rotton (2006) developed the social escape and avoidance theory, which posits that the shape of the relationship between temperature and crime occurrence depends on complex interactions with factors such as the time of day and year, the location of the crime, and the degree of social interaction occurring between the people involved (Breetzke and Cohn, 2012). This notion that crime-temperature relationships vary based on setting and timing is supported by the results of recent analysis (Towers et al., 2018). One implication of the social escape and avoidance theory is that high temperatures might decrease crime by encouraging people to stay home and therefore decrease social interaction; thus, this theory integrates the temperature aggression and routine activities theories (Breetzke and Cohn, 2012). Some authors further extend this concept to apply to other adverse weather (Tompson and Bowers, 2015), making the integration of the two theories even more explicit.

1.4 Review of Literature

1.4.1 General Overview of Weather and Crime Studies

As noted in section 1.3.1, the first study suggesting links between temperature and crime was published in 1842, and described an increase in crimes against persons during the summer, while crimes against property were lowest at this time (Quetelet, 1842). Quetelet's work quite clearly falls into the trap of environmental determinism, and as such is somewhat problematic by modern standards; at one point he states that "[c]limate appears to have some influence, especially on the propensity to crime against persons: this observation is confirmed at least among the races of southern climates" (Quetelet, 1842, pg. 95). Despite this, interest in temperature and other weather variables as a factor underlying crime rates has continued.

In 1990, Cohn published a review of the relevant literature, and found that a series of riots in the United States of America during the 1960s had renewed this interest (Cohn, 1990). She attributes this interest to the fact that variables traditionally used to explain changes in crime rates, particularly demographics, do not change quickly enough to explain the hourly and daily variations of crime that occur. The literature at this time indicated strong links between temperature and many types of crime, generally positive, although results tended to vary somewhat by study area. Further, the shape of the crime-temperature relationships found in many studies did not match what experimental work on temperature and aggression predicted. The relationships between crime and other weather variables, such as sunlight and precipitation, were less consistent, and some weather variables such as wind, pressure, and humidity were very rarely examined. Cohn also identified many methodological issues with sample size and multicolinearity in the literature, and chose not to review literature published before 1950, as these issues made it impossible to rely on the results of earlier studies.

1.4.1.1 Recent Crime-Weather Studies

Cheatwood's study (1995) investigated relationships between homicide, and temperature, humidex, precipitation, and hours of daylight in the city of Baltimore, Maryland. This study used a series of logistic regressions to determine the interactions between these variables and confounding factors such as day of the week and statutory holidays. This inclusion of calendar-based confounding factors in analysis of weather and crime occurs frequently in the literature (see table 1), and is especially important because both weather and these confounding factors vary on a seasonal basis. As such, it is necessary to ascertain if changes in crime rates result from the weather which is common at a certain time of year, or from the calendar events which happen to occur at the same time. Cheatwood's results indicate that only the number of consecutive days with a high humidex is important in predicting homicides. Interestingly, the results also appear to indicate that temporal patterns of homicide in the city of Baltimore vary considerably from those of homicides aggregated at the national scale. This is in line with Hipp et al.'s (2004) findings that crime and temperature do not seem to interact in the same way in all places, with variables such as population density and the degree of seasonality in weather influencing the degree of seasonality observed in crime rates.

Many subsequent studies of crime and weather follow the same pattern as Cheatwood (1995), that is, a regression analysis focused on determining the relationship between weather variables and crime in a study area, often while controlling for calendar variables (see Temporal variables column in table 1). Often the researchers use their results to support one or another of the crime theories, as discussed in section 1.3. One such study is Cohn and Rotton (2000), which used police calls for service in Minneapolis in 1987 and 1988 to study the relationship of weather and property crime, specifically burglary, robbery, and theft. Robbery, which is theft involving violence or the threat of violence, is more usually classified as a violent crime than a property crime. However, Cohn and Rotton include it in their analysis of property crime. They do so because the violence involved in robbery is focused on attaining a goal, and thus is classified as instrumental. This makes it more similar to property crimes than assaults and other violence, which are generally not goal-focused and thus classified as expressive. While Cohn and Rotton found that temperature had a significant positive relationship to all three crime types, the calendar variables appeared to explain a much greater proportion of the variance in crime rates. They note that these results are as expected, based on the routine activities theory.

Ikegaya and Suganami's (2008) study is unique in this review, as it ignores temperature as an explanatory variable, focusing instead on general weather conditions. While they do calculate a discomfort index, which combines temperature and humidity, they do not use this in their analysis, but rather use it as a talking point to discuss the seasonality of weather in their study region of eastern Tokyo. This study also used autopsy reports to determine the number of homicides, which is a novel data source (see table 1). Using poisson regression, they found that homicide and injury resulting in death are greatest on sunny days. They link this result to routine activities theory, in that sunny weather should increase interaction and therefore crime rates relative to cloudy or rainy weather, and also temperature aggression theory, as sunny days may be warmer and therefore increase aggression. However, without an analysis of temperature and crime rates, this latter assertion must remain speculative.

While Peng et al.'s (2011) methodology was typical of the crime-weather literature, their results were somewhat more ambiguous. Their study of burglary and robbery in Beijing from 2004-2005 found that weather variables had no relationship to crime rates, with the exception of sunlight to burglary. While several other studies have found that calendar variables are more important to crime than weather variables, in their studies temperature tended to be the most important weather variable predictor (Cohn and Rotton, 2000; Ceccato, 2005). Peng et al. note that the unique cultural characteristics of Beijing might result in different temporal patterns of crime, which are quite unique in comparison to, for example, the United States. However, they make no attempt to explain how this would change weather crime relationships in their study area.

Tompson and Bowers (2015) studied crime in the Strathclyde region of Scotland from 2002-2011, looking to support two hypotheses. One, the adverse-favorable weather hypothesis, is an extension of the negative affect escape model, in which uncomfortable weather in general may discourage social contact. The other, the discretionary activities hypothesis, appears to be a restatement of the routine activities theory, focusing on how people use their leisure time. They tested these hypotheses using regression models with interaction terms for weather and temporal variables, and found support for both. Notably, the coefficients for interactions between temperature and season indicate that high temperatures during the winter increase robberies, while the coefficients for interactions between temperature and time of day find similar increases when the weather is warm during typical leisure hours. In addition, since peoples' degree of comfort with heat and other weather depends on the climate where they live, they suggest reactions to these variables will likewise vary across space.

In addition to Cheatwood's (1995), a more recent study also examined crime-weather relationships in the city of Baltimore. Using publically available crime data from 2008-2013, Michel et al.'s (2016) findings appear to contradict those of Cheatwood, in that homicide is the only type of violent crime not explained by weather variables. The results of this study are mixed, however; a simple correlation analysis does appear to indicate a positive relationship between homicide and temperature, while subsequent negative binomial regression analysis did not. Despite this inconsistency, and in line with Cohn's (1990) review of the literature, temperature appeared to be the only weather variable associated with the majority of violent crime types. Total precipitation had a negative association with violent and all crime, and snowfall a negative association with all crime, but these relationships disappeared when examining disaggregate crime types. Michel et al. (2016) did not use any of the crime theories previously discussed to explain why these relationships exist, perhaps because the paper is written more from a medical than a criminological perspective.

A recent study of arson in Toronto from 1996-2007 also employed regression techniques to determine the impact of weather on crime (Yiannakoulias and Kielasinska, 2016). The authors used reports from the Ontario Fire Marshall rather than typical sources of crime report data, and included hockey playoffs among their calendar variables. There are strong theoretical reasons to expect links between weather and arson, given that conditions such as precipitation and high winds can affect the ease with which fires can be set. As might be expected, precipitation had a negative relationship to instances of arson, while air temperature and air pressure had positive linear relationships. Temperature also had a negative quadratic relationship, indicating a decrease in cases of arson at very high or very low temperatures. Notably, their inclusion of hockey playoffs in the analysis was beneficial, as they were shown to be significantly linked to arson; this might indicate that, in large cities where major sporting events occur, these should be accounted for in the analysis of crime patterns.

The most recent study considered in this review combines a typical regression methodology with wavelet coherence analysis to study crime in Hampton Roads from 1973-2009 (Wu et al., 2020). The regression analysis from this investigation shows that model fit can be a concern, as the majority of the models produced were poorly fitted. However, the authors still used these models to determine that temperature had significant positive relationship to all crime types except manslaughter and burglary. Precipitation, on the other hand, was never found to be significant. The wavelet analysis indicated that crime and temperature have similar yearly oscillations, indicating that they are related on a seasonal basis. However, the common oscillation for crime and precipitation was decadal, suggesting that if a relationship exists between these two variables, which the regression does not support, then it must operate over a much longer timespan.

1.4.1.2 Crime-Weather Studies for a Specific Purpose

While the aforementioned studies are typical of the aspatial crime-weather literature, a number of other studies exist which do not use the traditional techniques of analysis. Specifically, their research questions require different methodologies, or the inclusion of non-standard variables. Rotton and Cohn's (2004) unique contribution is that they examined the interaction of assault and weather variables in environments both with and without climate control. The study area for this research was Dallas, and thus climate control implies cooling rather than heating. The authors thus postulate that climate control can function as a form of escape from the heat, and should influence crime rates under both the negative affect escape model and the routine activities theory. Their results support the negative affect escape model, as temperature has a positive linear relationship to assault in climate controlled environments but a cubic relationship outside of these settings. This implies that, above a certain temperature, people are more likely to seek to escape high temperatures rather than become aggressive; air conditioned environments may prevent people from reaching this escape point. Unsurprisingly, they also found that crime was more seasonal outside of climate controlled environments.

Towers et al.'s (2018) study is likewise unusual, as the technique selected was intended to be useful for predicting crime rates. As such, it involved validation of the results using a subset of the data, which is notably absent from much of the crime-weather literature, and controls for both autocorrelation and long term trends in the data. Further, the method employed was intended for use in predicting crime at a relatively short time scale, while the other predictive papers in this review (Mares, 2013; Ranson, 2014) focused on determining the likely impact of climate change on crime rates. The study by Towers et al. (2018) used publically available crime data from Chicago between 2001 and 2014 to construct a series of harmonic linear regression models, one for each season and crime type; they also separated indoor and outdoor crimes into separate models where possible. During this process, they found that weather variables are more important for modelling some crime types than others, based on model fit before and after adding these variables. They also found that the effect of weather variables can change based on season within any given crime type. For example, assault, theft, battery, and damage all had a negative relationship to precipitation, but only at some times of year. Only battery showed consistent relationships with weather variables across seasons, with temperature always having a positive relationship and wind speed always having a negative relationship. However, temperature had relationships to the most crime types during the most seasons. A further important finding was that outdoor crimes appear to be more seasonal than indoor crimes. Although the climate of Chicago is quite different to Dallas, this is similar to Rotton and Cohn's (2004) finding that season is more related to crime outside of climate controlled environments. Though neither study is explicitly spatial, both results would seem to indicate that place is important to determining crime relationships with weather, even at the micro scale.

As previously mentioned, the crime-weather literature contains several studies on the potential impact of climate change on crime rates. While climate change is not the focus of this thesis, these papers necessarily draw some relevant conclusions on crime-weather relationships. For example, Mares (2013) used 1990-2009 crime report data from St. Louis in their study, and found that temperature anomalies were related to an increase in all crime types except homicide, rape, and motor vehicle theft, while the expected temperature in any given month has a positive relationship with all crime types. Moreover, expected precipitation had a negative relationship with robbery, burglary, motor vehicle theft, and aggregate crime, but precipitation anomalies appeared to have no impact. This contradicts the results from another study which suggest precipitation impacts crime more in cities which are not used to it (Linning et al., 2017a). However, Mares notes that the monthly time scale may obscure the true relationships of precipitation and crime. Another study of crime and climate change did not focus on temperature anomalies, but rather on the number of days in a month that the author considered warm, normal, or cool (Ranson, 2014). Using this approach with data from across the USA, from 1980 to 2009, Ranson concluded that the number of warm days in a month has a much stronger relationship to monthly rates of violent crimes than monthly rates of property crimes. Both of these studies, however, indicate a positive relationship between crime and weather.

1.4.2 Studies of Crime and Seasonality

Many of the studies discussed so far have considered the effects of season on crime-weather relationships. However, a subset of the literature makes crime seasonality a focus of its analysis. This is particularly common in spatial studies, which will be discussed later in section 1.4.3, but does also occur in the aspatial literature (table 1). As previously noted, the first study to link crime and temperature (Quetelet, 1842), did so on the basis of seasonality. However, it is important to note that, while the literature tends to discuss temperature differences between seasons as a driver of crime seasonality, temperature and season of the year should not be used as proxies for one another (Haberman et al., 2018). This is because, as previously mentioned, calendar variables are often as influential of crime rates as weather variables, and generally occur at consistent times of the year. Either, then, might contribute to crime seasonality (McDowall et al., 2012).

One study which considers crime seasonality in the more academic sense of the term is Hipp et al. (2004). This study was not based on seasonality in the sense of the usual quarterly division of the year, but rather in the sense that it examined the repetitive patterns evident in crime rates, year after year. Specifically, they compared crime seasonality to weather seasonality in communities across the USA, from 1990-1992, as a test of both the temperature aggression and routine activities theories. Using the latent curve model, the authors compared the mean temperature for each city, the standard deviation of temperature in that city, and the interaction of the two to both violent and property crime. They found that the greatest increases in property crime are coincident with the moderately warm summer temperatures that occur in cities with an overall cool climate. They interpret this as support for the routine activities theory, as the temperature aggression theory would predict that the greatest crime rates occur in the hottest weather, during summer in hot-climate cities.

Based on Quetelet's (1842) initial research, as well as the more recent temperature aggression theory, one might expect that peaks in crime would occur during the same seasons of the year in all study areas. This should be especially true of violent crime. However, this does not appear to be the case; the timing of crime peaks in fact varies both by study area, and by the specific type of crime under consideration (McDowall et al., 2012). McDowall et al.'s 2012 study attempted to determine, for the USA as a whole, when crime peaks occur, in the hopes that such results would be more generalizable than for research conducted in a single city. They used a lengthy time series of crime data, from 1977 to 2000, and included all cities in the USA with a population greater than 200,000. The results of their time series decomposition analysis indicated that, with the exception of robbery, all crime types had summer peaks, and winter troughs. These authors also found that monthly temperature variations were unable to completely explain this seasonal variation, and that the effects of season and temperature on crime were not constant across all the cities in their study. A further study, using a longer time series and focused only on homicide and assault, confirmed the seasonal patterns from the earlier research; both crimes had roughly similar seasonal patterns, with peaks in July, though the degree of seasonality in each differed (McDowall and Curtis, 2015). However, from the results it appeared that these seasonal patterns were broadly similar across all the cities, and that temperature did in fact appear to explain the seasonality evident in assaults (McDowall and Curtis, 2015).

A pair of Canadian studies further confirmed that the timing of crime peaks can vary between cities. Linning et al. (2017a) studied seasonal crime rates in eight British Columbia communities, and found that even within this single province, the timing of crime peaks was inconsistent. These authors also considered weather variables, and found that their effects also varied by city. Precipitation in particular seemed to have a negative relationship with crime in cities that were not used to these weather conditions, unlike those where they were more frequent. Linning et al. (2017b) obtained similar results in a study comparing crime in Vancouver and Ottawa. Although they compared two different study periods, 2006 to 2008 for Ottawa and 2003 to 2013 for Vancouver, using two different types of regression analysis, they concluded that Ottawa had a greater degree of crime seasonality than did Vancouver. They link this to the greater degree of seasonality in Ottawa's climate. As with the previous study, the effect of the weather variables on crime was also found to be different in each city; temperature had a relationship to more crime types in Ottawa than in Vancouver. However, these authors also found that when temperature was added to their model, the season and month coefficients became insignificant. This may indicate that, contrary to McDowall et al.'s (2012) results, temperature does explain crime seasonality, at least in Ottawa.

In study areas where the seasons differ from those frequently discussed in the literature, seasonal crime patterns obviously differed. For example, in Afon and Badiora's (2018) study of crime in Ibadan, Nigeria, the year was divided into wet, dry, and moderate seasons, rather than seasons based on temperature, which is more common in the literature. Their study, which was based on crime perception, found that residents felt break-ins and assaults were most common in the dry season, while robberies were more common in the wet season. While Yan's (2004) study of property crime in Hong Kong does use the descriptors of summer and winter for the seasons, these were described based primarily on precipitation patterns (rainy vs. dry). Further, Yan noted that summer crime peaks were not expected, as widespread use of air conditioning and uncomfortable rain and heat outdoors encourage people to stay at home during this time of year. The results mostly bear this out; although pickpocketing has a weak summer peak, neither theft nor burglary were found to be seasonal, and shop theft peaked in winter, which Yan attributed to the ease with which stolen items can be hidden in heavier winter clothing.

Table 1 Recent aspatial studies of interactions among crime, weather, and seasonality. Weather variables with a significant relationship to crime are bolded.

Study	Dates	Study Area	Crime Data Source	Crime Types	Includes Seasonality?	Weather Variables	Temporal Variables	Method	Temporal Resolution
Afon and Badiora, 2018	Unspecified	Ibadan, Nigeria	Crime perception surveys	Assault, burglary, robbery	Yes	None	None	ANOVA, multiple linear regression	Season
Cohn and Rotton 2000	1987-1988	Minneapolis, Minnesota	Calls for service	Burglary, robbery, theft	No	**Temp**, precip, cloud, wind, humidity	Period length, day of week, month, first day of month, presence/absence of light, school breaks, holidays, local festivals	Hierarchical regression	6 hour
Hipp et al. 2004	1990-1992	USA	Crime reports	All	No	**Temp**	None	Latent curve model	Bi-monthly
Ikegaya and Suganami 2008	1998-2002	Tokyo, Japan	Autopsy reports	Homicide	No	Precip, cloud, **sun**	None	Poisson regression	Daily
Linning et al. 2017a	2000-2006	British Columbia cities: Burnaby, Nanaimo, Kamloops, Cranbrook, Prince George, Terrace, Fort St. John, Fort Nelson	Crime reports	Assault, robbery, motor vehicle theft, break and enter	Yes	**Temp**, precip	Daylight hours, month, month squared, month of dataset	Poisson and negative binomial regression	Monthly
Linning et al. 2017b	2003-2013 and 2006-2008	Vancouver, British Columbia and Ottawa, Ontario	Calls for service	Property crime, burglary, theft, robbery	Yes	**Temp, precip, sun**	Month, month length, weekend days per month, day of year, day of dataset, holidays	Ordinary least squares regression, negative binomial regression	Daily, monthly
Mares 2013	1990-2009	St. Louis, Missouri	Crime reports	Homicide, rapes, robbery, burglary, larceny, auto theft, property, violent, all	No	**Temp, precip, temp anomalies,** precip anomalies	Days per month	Time series analysis	Monthly
McDowall and Curtis 2015	1960-2004	USA	Crime reports	Homicide, assault	Yes	**Temp**	None	Time series decomposition	Monthly

McDowall et al. 2012	1977-2000	USA	Crime reports	Homicide, rapes, robbery, aggravated assault, burglary, larceny, auto theft	Yes	Temp	Number of each day of week per month	Time series decomposition	Monthly
Michel et al. 2016	2008-2013	Baltimore, Maryland	Crime reports, hospital admissions	All, violent crime, gun crime, homicide	No	**Temp**, precip	Month, weekend, day of week	Multivariate regression	Daily
Peng et al. 2011	2004-2005	Beijing, China	Calls for service	Property crime	Yes	Temp, wind, **sun**	Holidays, school breaks, weekends	ANOVA, ordinary least squares regression	Hourly, aggregate to daily for regression
Ranson 2014	1960-2009	USA	Crime reports	Murder, manslaughter, rape, aggravated assault, simple assault, robbery, burglary, larceny, vehicle theft	No	**Temp, precip**	None	Poisson regression	Monthly
Rotton and Cohn 2004	1994-1996	Dallas, Texas	Calls for service	Assault	Yes	**Temp**, humidity, wind	Time of day, day of week, season, holidays	MANOVA	6 hour
Tompson and Bowers 2015	2002-2011	Strathclyde Region, United Kingdom	Unspecified	Robbery	Yes	**Temp, wind, humidity, rain**, fog, snow	Weekend, time of day, bank holidays	Negative binomial regression	6 hour
Towers et al. 2018	2001-2014	Chicago, Illinois	Crime reports	All, assault, battery, burglary, narcotics, robbery, theft	No	**Temp, precip, wind**, humidity, pressure	Holidays, day of year, day of week, paydays	Harmonic regression	Five periods per day

Wu et al. 2020	1973-2009	Hampton Roads, Virginia	Crime reports	All, violent crime, property crime, Murder, manslaughter, rape, aggravated assault, simple assault, robbery, burglary, larceny, vehicle theft	No	**Temp, precip**	None	Ordinary least squares regression, wavelet analysis	Monthly
Yan 2004	1991-2000	Hong Kong	Crime reports	Theft, shop theft, snatching and pickpocketing	Yes	None	None	ANOVA, regression	Monthly
Yiannakoulias and Kielasinska 2016	1996-2007	Toronto, Ontario	Fire Marshall incident reports	Arson	No	**Temp, precip**, wind, **pressure**	Weekend, holidays, school breaks, halloween, Leafs playoffs, year, day-night, period length	Poisson regression	Day vs. night based on sunset-sunrise

1.4.3 Spatial Studies of Crime

Many authors have specifically commented that the number of spatial crime-weather and crime-season studies is, in comparison to those which are nonspatial, relatively small (Andresen and Malleson, 2013; Haberman et al., 2018). Fortunately, the gap is narrowing. In addition, if one includes investigations into the changing relationship between crime and neighborhood characteristics, such as land use or socioeconomic status, under different weather conditions, the number of studies increases. This category of studies does not study explicit differences in spatial pattern. However, the neighborhood characteristics they examine are generally treated as fixed in place. Thus, if the relationship between these variables and crime changes under different weather or seasonal conditions, the spatial pattern of crime should also change. For this reason, they can be considered as studies of implicit changes in spatial pattern (table 2).

1.4.3.1 Studies of Explicit Differences in Crime Patterns

There are seven key studies which study explicit differences in spatial patterns of crime. The only one which considers true weather variables rather than seasonality is Brunsdon et al.'s (2009) investigation into spatial patterns of crime under different weather conditions in an unspecified city in the United Kingdom. The authors used statistical analysis, in order to determine whether crime patterns were statistically different in different weather conditions, and density mapping, to visualize these patterns. They found that disorder shifted away from the city center during hot and/or humid weather.

Several studies of seasonal spatial crime patterns have used Andresen's spatial point pattern test (SPPT), to first, identify areas where the proportion of crimes changes between seasons, and second, to calculate from this information a global similarity index. However, it should be noted that all four of the studies discussed here used an older version of the SPPT, which recent work has found to inflate the level of dissimilarity between patterns (Wheeler et al., 2018). As such, the results from these particular studies should be interpreted with caution. The earliest of these studies used this test to study crime in the city of Vancouver in 2001 at two spatial scales (Andresen and Malleson, 2013). At the coarser of these resolutions, burglary and robbery did not show differences in pattern between the seasons, though all other crime types did. At the finer resolution, all crime types displayed different spatial patterns in different seasons. Notably, even crimes which did not appear to display seasonal peaks in intensity, did appear to have different spatial patterns between the seasons. The authors mapped the output of the SPPT and found that in summer, areas of the city with beaches, parks, and shopping centers displayed an increase in crime.

Several of the more recent studies of crime patterns using the SPPT use much finer units of spatial analysis. One considers multiple crime types at the micro-scale of street segments in both Ottawa and Vancouver, from 2001-2013 and 2006-2008 respectively (Linning, 2015). The results of this study appeared to contradict the above finding; the pattern of most crime types was not different between seasons for either city as a whole, with the exception of aggregate crime in Vancouver. Those street segments which did exhibit seasonal differences in crime tended to be located downtown. Another study investigated property crime patterns on a large university campus and in the surrounding community, using 25 m grid cells (Hurst, 2020). This analysis found that, within the university, crime patterns did not differ between seasons, but that they did once the surrounding neighborhoods were included. However, this study considers crime only in one small area of a city where routine activities might be expected to differ significantly from the city as a whole. Consequently, the results may not be generalizable to other study areas. Further, the authors did not discuss where within their study area these spatial difference in crime patterns occurred.

From the somewhat conflicting results of the three studies discussed previously, it appears that the SPPT may be susceptible to questions of scale. This is not unexpected; the modifiable areal unit problem (MAUP) is a known issue in any spatial analysis where data are aggregated into larger analysis units (Ratcliffe and McCullagh, 1999). However, another study investigated differences in seasonal homicide and robbery patterns in Santa Catarina, Brazil from 2011 to 2017, used street segments as their aggregation units, and found a very high degree of dissimilarity between these patterns (Valente, 2019). They also included an analysis conducted at the coarser scale of the "human development unit", a type of census aggregation polygon, and found a higher degree of similarity at this scale. Given the aforementioned results, it is very unexpected that the coarser aggregation units should result in a higher degree of similarity. However, similarly to Andresen and Malleson (2013), Valente (2019) notes that robberies are more common in coastal areas during the summer.

Another approach within the category of studies of explicit difference in spatial patterns is to use Kulldorff's scan test to locate spatio-temporal clusters of crime. There are two such studies, both focused on crime in Brazil. While these clusters are not inherently seasonal, the authors of both papers discuss them in terms of the seasons during which they occur. Ceccato (2005) investigated homicides in Sao Paulo, and in fact analyzed their relationship to weather variables as well as their spatial locations. The weather portion of the analysis found that temperature, cloud cover, and RH were all significant in separate models, but that calendar variables appeared to be more important in explaining crime occurrence. The spatial portion of the analysis found that, while the main cluster of homicides remained in the same place year round, secondary clusters appeared in wealthier areas of the city during times of year when people were more likely to have leisure time and take vacations. De Melo et al. (2018) conducted a similar study in the nearby city of Campinas, but examined a wider range of crime types. Their temporal analysis did not find much evidence of seasonal crime spikes, with the exception of homicide and rape. The Kulldorff's scan test, however, found discrete spatio-temporal clusters for many crime types, and in some cases the temporal components of these clusters were not related to the timing of crime spikes indicated in the regression analysis. Together with Andresen and Malleson's (2013) results, this could indicate that clustering in time, as indicated by crime peaks, and clustering in space, are not necessarily related phenomena. In other words, just because crime in a study area is most common at a certain time of the year, it does not imply that a spatial cluster of said crime will exist at that time of year.

1.4.3.2 Studies of Implicit Differences in Crime Patterns

As previously discussed some papers study the changing relationship between crime and place-specific neighborhood variables, which can be considered studies of implicit differences in spatial pattern. For example, several studies have considered land use and the presence of potentially criminogenic places as a neighborhood characteristic. Haberman et al. (2018) used a series of seasonal regression models to investigate the impact of such places on robberies in Philadelphia from 2009-2011. They found that very few criminogenic places had different relationships to crime in different seasons; in fact, only high schools and higher educational institutions did so in a significant manner. High schools were associated with an increase of crime in autumn as compared to all other seasons, while higher education institutions were associated with a decrease in winter as compared to fall. A similar study by Quick et al. (2019) in the Regional Municipality of Waterloo looked at land use rather than criminogenic places, although these two categories overlap somewhat. Quick et al. found that parks were more strongly associated with crime during the spring and summer, whereas bars and restaurants were more strongly associated with crime in autumn and winter. In a similar vein, Szkola et al. (2019) used risk terrain modelling to understand how the impact of criminogenic places on gun crime changed from month to month in Baltimore. Their findings indicated that, while certain criminogenic places did appear to have a different influence from month to month, there were no consistent patterns in these differences, and thus they could not be described as seasonal. The effect of season on the relationship of crime to criminogenic places, then, appears to vary between studies.

Other studies have focused on the relationships between crime and socioeconomic variables. Sorg and Taylor (2011) studied the distribution of outdoor robberies in Philadelphia from 2007 to 2009. Temperature had a positive relationship to robbery in all of their models, but they noted that this relationship varied over space, being strongest in the city center and the edges of the city. Further, they found that seasonal changes in the rate of robberies were highest in neighborhoods with a higher socioeconomic status. A similar study of assaults in Tshwane (South Africa) from 2001 to 2006 found that neighborhoods with a higher degree of deprivation experienced a greater proportion of the city's assaults during the summer, while in winter assaults were distributed more evenly (Breetzke and Cohn, 2012). Moreover, assault was found to be seasonal in time as well as space, with the city as a whole experiencing more assaults during the summer, with the exception of indecent assaults. It is worth noting that the seasons for this study are the reverse of the majority in the literature, as South Africa is in the southern hemisphere. However, this does not appear to change the association of violent crimes with the warmest times of year.

Table 2 Recent spatial studies of interactions amongst crime, weather, and seasonality. Environmental variables with a relationship to spatial crime patterns are bolded.

Study	Dates	Type	Study Area	Crime Data Source	Crime Types	Includes Seasonality?	Weather Variables	Temporal Variables	Method	Mapping	Temporal Resolution
Andresen and Malleson 2013	Unspecified	Explicit	Vancouver, British Columbia	Calls for service	All, assault, burglary, robbery, sexual assault, theft	Yes	None	None	Spatial point pattern test	Polygons	Seasonal
Breetzke and Cohn 2012	2001-2006	Implicit	Tshwane, South Africa	Crime reports	Assault	Yes	None	None	ANOVA, correlation analysis	None	Monthly
Brunsdon et al. 2009	Unspecified	Explicit	Unspecified	Calls for service	Public disorder	No	**Temp**, precip, wind, **humidity**	None	Probability density analysis	Density surface	Hourly
Ceccato 2005	2001-2002	Explicit	Sao Paulo, Brazil	Crime reports	Homicide	Yes	Temp, cloud, humidity, wind, pressure, visibility	Weekends, paydays, holidays, day-night, month	Ordinary least squares regression, Kulldorff's scan test	Polygons	8 hour, daily, weekly
de Melo et al. 2017	2010-2013	Explicit	Campinas, Brazil	Crime reports	Robbery, rape, homicide, burglary, theft	Yes	None	Summer vacation, winter vacation, pay day, end of month, holiday, weekend	Count regression, Kulldorff's scan test	Polygons	Seasonal, monthly, daily, hourly
Haberman et al. 2018	2009-2011	Implicit	Philadelphia, Pennsylvania	Crime reports	Robbery	Yes	None	None	Negative binomial regression	None	Seasonal
Hurst 2020	2015-2017	Explicit	University of Arkansas Little Rock	Crime reports	Property crime (break and enter, burglary, fraud, larceny, motor vehicle theft, robbery, vandalism)	Yes	None	None	Spatial point pattern test	Grid cells	Seasonal

Linning 2015	2003-2013 and 2006-2008	Explicit	Vancouver, British Columbia and Ottawa, Ontario	Calls for service	Property crime, break and enter, theft from vehicle, theft of vehicle, mischief, robbery	Yes	None	None	Spatial point pattern test	Street segments	Seasonal
Quick et al. 2019	2011-2014	Implicit	Waterloo, Ontario	Crime reports	Property crime	Yes	None	None	Hierarchical poisson regression	Polygons	Seasonal
Sorg and Taylor 2011	2007-2009	Implicit	Philadelphia, Pennsylvania	Unspecified	Street Robbery	No	Temp	Days per month	Poisson regression	Polygons	Monthly
Szkola 2019	2013-2014	Implicit	Baltimore, Maryland	Unspecified	Firearms crime	Yes	None	None	Risk terrain modelling	None	Monthly
Valente 2019	2007-2011	Explicit	Santa Catarina, Brazil	Crime reports	Homicide, robbery	Yes	None	None	Spatial point pattern test	Street segments, polygons	Seasonal, monthly

1.4.4 Summary Points

A number of common themes are evident from this review of the literature. First, weather and seasonal variables do appear to influence the spatial and temporal patterns of crime. However, it is important not to conflate the two, as seasonality combines weather with culturally-based calendar variables. Further, several studies note that these calendar variables may actually be more important than weather variables for determining the temporal patterns of crime, though this assertion has yet to be made regarding spatial crime patterns. Second, the exact relationships between crime and weather variables or season appears to be study-area specific, and may vary based on the climatic conditions, socioeconomic factors, timing of local holidays and vacations, and even the land-uses present in the study area; it is therefore difficult to generalize these findings. This may be problematic as the vast majority of studies are conducted in large cities, and thus there is no reference point for weather-crime or season-crime relationships in other kinds of urban centers. The two exceptions to this are Hurst's (2020) study of crime on a university campus, and Linning et al.'s (2017a) comparison of crime seasonality in eight British Columbia cities, some of which are relatively small. The former study, however, takes place within a much larger city, while the latter does not contrast the results of the smaller cities specifically against the larger.

Also evident in the review of the literature was a reliance on some commonly employed techniques. First, the majority of aspatial studies employ some form of regression analysis (see table 1). The methodologies of the spatial studies are less consistent, but the Kulldorff's scan test and the SPPT appear to be the most popular (see table 2). Second, and related to this point, studies of spatial crime patterns tend to examine these patterns during different seasons rather than under different weather conditions. This appears to be a result of the available spatial methodologies. In the case of the Kulldorff's scan test, this technique is explicitly designed to work with date as a z variable, thus excluding the possibility of weather-based study designs. The SPPT, on the other hand, is based on pairwise comparisons of crime patterns. While it would be possible for each of these patterns to be generated under different weather conditions, in practice this would require that the weather conditions be arbitrarily aggregated into classes, and then would likely require a large number of tests to compare all possible pairs of patterns. While studies using regression analysis to investigate changing relationships between crime and place-based variables are not subject to these limitations, the general pattern of spatial studies being seasonal rather than weather-based nevertheless persists.

1.5 Study Area

North Bay is a small city, with a land area of 327.43 km^2 and a population of 50,396, located in northeastern Ontario. As shown in figure 1, only a small area of the city's landbase is developed, with the majority being forested, and inaccessible by road. The city's location on the poorly drained, acidic soils of the Canadian shield makes it mostly unsuitable for agriculture, and there is very little farmland in the area. Given this large and largely unoccupied land base, the city's overall population density is low. The greatest densities occur in the census tracts around the downtown core (figure 2), which correspond to the city's oldest residential areas. The downtown core itself was formerly a major shopping district, but, like in many other northern Ontario cities, has been declining and now contains a number of abandoned buildings, and has become the focus of concerns about crime and addiction issues (see for example Turl, 2019; Taschner, 2020; Campaigne, 2021). However, the downtown still hosts civic buildings including city hall, the public library, and the museum, and is directly adjacent to the waterfront, which is a popular recreational area. The city is also home to Nipissing University, Canadore College, a regional hospital with both medical and mental health wards, and Canadian Forces Base (CFB) North Bay, a NORAD communication hub. The city is well connected to provincial and national transportation networks; it maintains the Jack Garland Airport (YYB), is traversed by several long distance railways, and sits at the intersection of the Trans-Canada Highway, which links it to Ottawa and Sudbury, and Highway 11, which connects it to Toronto and many smaller communities to the north and south.

Perhaps unsurprisingly, given the state of the downtown core, the population of the city as a whole is decreasing; the population of 50,396 in 2016 represents a decrease of approximately 2,000 since the preceding census in 2011 (Statistics Canada, 2017). Additionally, incomes in North Bay are lower than in most of the province. The 2016 median income was $32,036, with 17.4% of residents being considered low income earners; this is three percentage points above the provincial average (Statistics Canada, 2017). The median age of North Bay residents in 2016 was 43.5, 2.2 years older than for the province as a whole (Statistics Canada, 2017).

The climate of the city is typical of northern Ontario, being strongly seasonal, with hot, dry summers and snowy winters. The hottest month is July, with a long term average temperature of 18.9°C, while the coldest is January, with an average temperature of -12.3°C (Environment and Climate Change Canada, 2019). The city receives an average of 803 mm of rain per year, and an average of 297 cm of snow, which falls mainly between November and April and persists on the ground for much of the winter (Environment and Climate Change Canada, 2019). During the winter months, the lakes in and around the city freeze, becoming popular ice-fishing destinations, while in summer, they tend to attract boaters and beach-goers.

A number of police forces operate in and around North Bay. The city is served mainly by its own municipal police force, the North Bay Police Service (NBPS), which was established in 1882. The Ontario Provincial Police also have a detachment within the city boundaries, CFB North Bay maintains its own military police detachment, and the adjacent Nipissing First Nation is served by the Anishinabek Police Services.

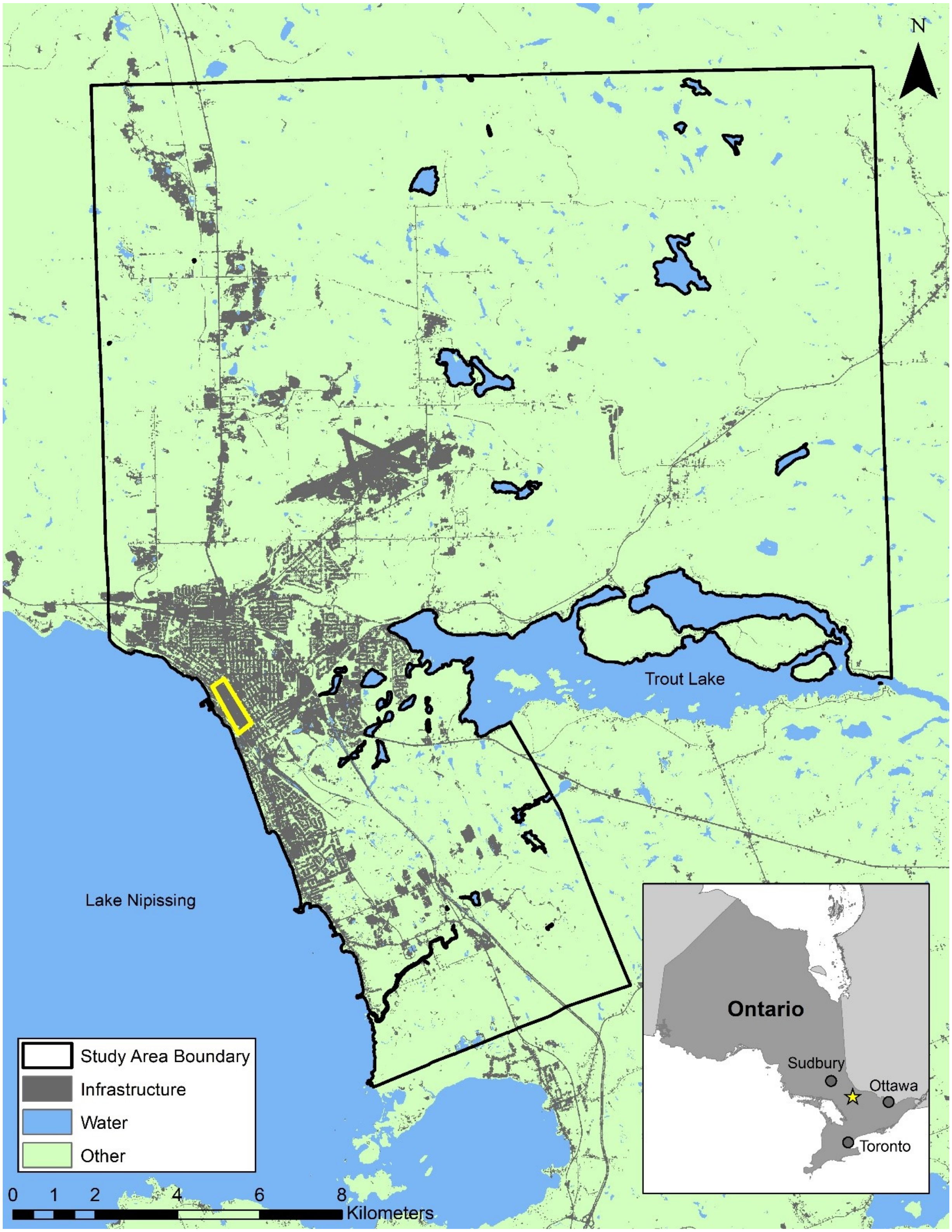

Fig. 1 Land cover in the city of North Bay, classified from Sentinel 2 imagery captured in June 2018. The location of the downtown core is highlighted in yellow.

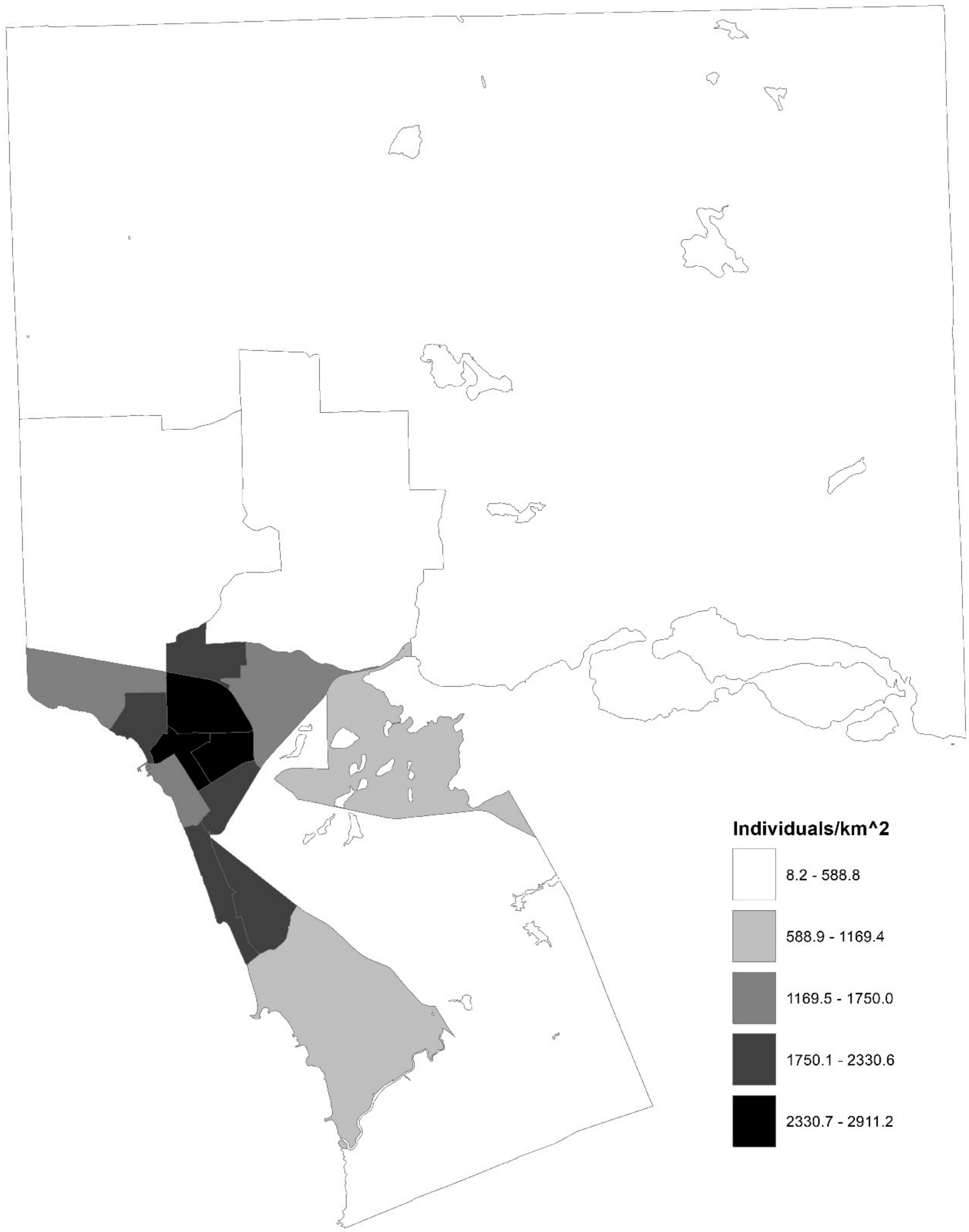

Fig. 2 Population density in the city of North Bay, 2016. With data from Statistics Canada.

1.6 Methodological Overview

This section describes the data and methodologies used in this research in more detail than was possible in chapters 2 or 3, which are formatted as articles for publication in a peer-reviewed journal, and thus must tend towards brevity rather than detailed explanations of all phases of analysis. In particular, sections 1.6.2 and 1.6.3, data processing and exploratory spatial data analysis respectively, are not discussed in chapters 2 and 3. The overall design of the research workflow is summarized in figure 3.

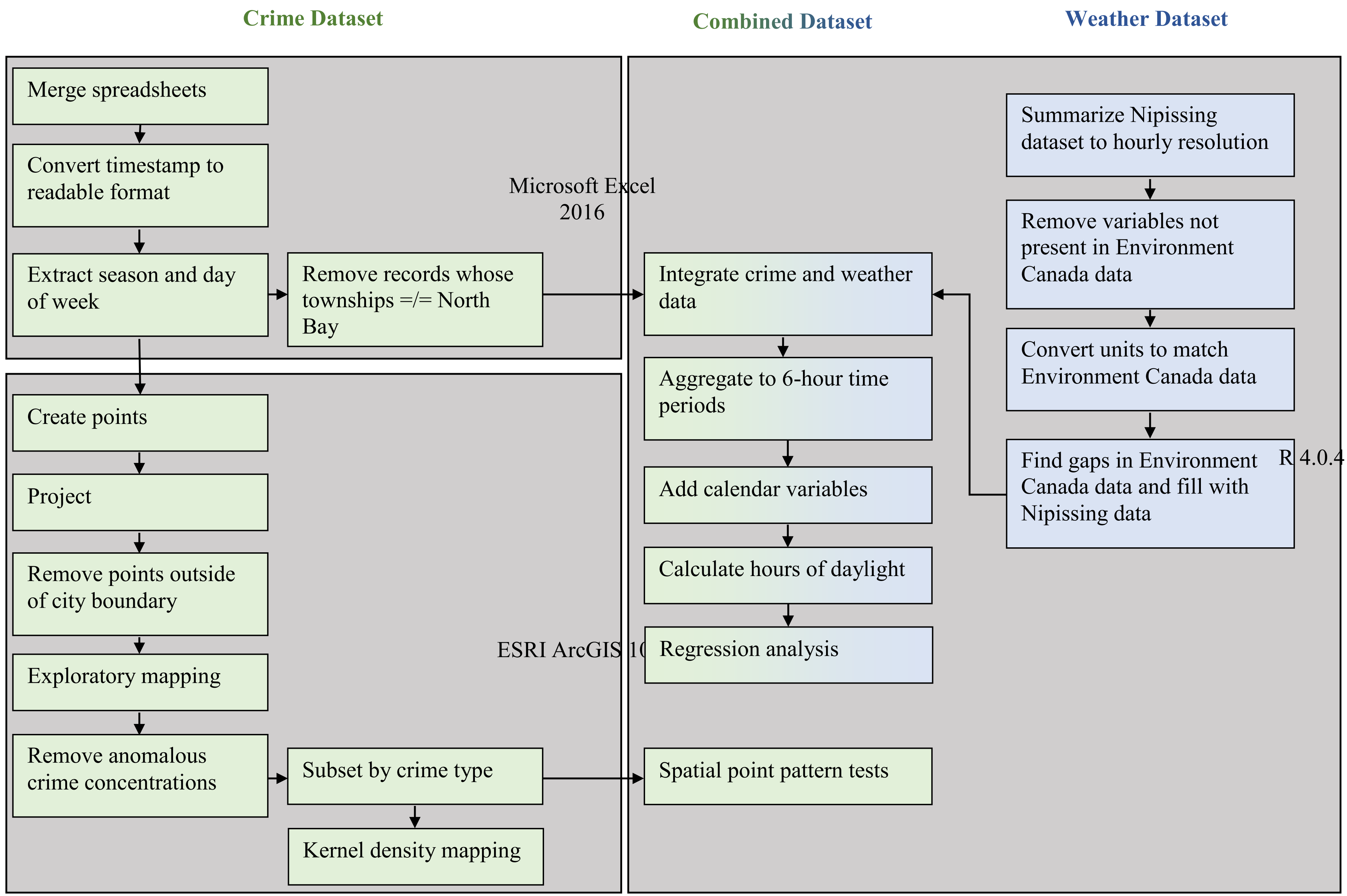

Fig. 3 Data processing and analysis workflow

1.6.1 Data Acquisition

1.6.1.1 Calls for Service Records

Calls for service data for the period 2015-2019 were obtained from the North Bay Police Service (NBPS), following a written agreement between the Chief of Police, Mr. Scott Todd, and the Vice President Academic and Research, Dr. Arja Vainio-Mattila. These data represent all calls for police service, including those made directly to the police and those passed along by 911 operators, as well as interactions initiated by the police themselves, such as traffic stops. Calls are recorded by a Computer Aided Dispatch (CAD) system. This calls dataset is stored as a series of spreadsheets, one per year of data, as illustrated in figure 4. For all calls, the spreadsheets record a unique identifying number, a call type in both full and abbreviated form, a timestamp, and the location in decimal degrees. Some calls also include a further call type, where the responding officer found this to differ from the situation reported by the caller, and some include address data such as the street and the municipality where the call occurred. The raw data consist of a total of 156,179 records.

1	AG_ID	NUM_1	TYP_ENG	TYCOD	SITFND	CDTS	ESTNUM	EFEANME	EFEATYPE	EMUN	LAT	LONG
2	NTHBAY	NB12345	THEFT	THEFT		20191229114559	123	STREET	AVE	NTH	46.123456	-79.442619
3	NTHBAY	NB12346	THEFT	THEFT		20191229114560		ROAD	PL	NTH	46.123457	-79.44262
4	NTHBAY	NB12347	AMBULANCE ASSISTANCE	AMBULANCEASSIST		20191229114561				NTH	46.123458	-79.442621
5	NTHBAY	NB12348	EXECUTE WARRANTS	WARRANTS		20191229114562				NTH	46.123459	-79.442622
6	NTHBAY	NB12349	COMPLAINT	TRAFFIC		20191229114563				NTH	46.12346	-79.442623
7	NTHBAY	NB12350	EXECUTE WARRANTS	WARRANTS		20191229114564				NTH	46.123461	-79.442624
8	NTHBAY	NB12351	MISCHIEF	MISCH		20191229114565				NTH	46.123462	-79.442625
9	NTHBAY	NB12352	MENTAL HEALTH ACT	MENTAL		20191229114566				NTH	46.123463	-79.442626
10	NTHBAY	NB12353	ROUTINE TRAFFIC STOP	TS	TRAFENF	20191229114567		94		NTH	46.123464	-79.442627
11	NTHBAY	NB12354	LANDLORD TENANT PROBLEM	LANDLORD		20191229114568				NTH	46.123465	-79.442628
12	NTHBAY	NB12355	NOISE COMPLAINT	NOISE		20191229114569	231	CRESCENT	ST	NTH	46.123466	-79.442629
13	NTHBAY	NB12356	ALARM	ALARM		20191229114570				NTH	46.123467	-79.44263
14	NTHBAY	NB12357	ESCORT	ESCORT		20191229114571				NTH	46.123468	-79.442631

Fig. 4 A sample spreadsheet, using dummy data, showing the format of the calls for service dataset as provided by the NBPS

There are some errors present in the CAD dataset, related to the location of calls, in addition to the missing address information. Preliminary exploration of the data revealed that there are two anomalous concentrations of calls, the first located at police headquarters, and the second located in roughly the center of the city. Together, these anomalies represent 13,083 calls, or 8.4% of the entire dataset. Consultation with the NBPS suggested that neither location represents an actual crime hotspot, and further investigation showed that all calls at each location were precisely coincident in space, which is unlikely to occur in reality. As such, the location of these calls, though not their other attributes, was assumed to be erroneous. Consequently, they were removed from the dataset used for spatial analysis, but not from the dataset used for regression analysis.

In addition to these actual errors, the nature of calls for service datasets means they cannot be used uncritically as proxies for crime data. First, the North Bay dataset contains numerous calls which may not represent actual crimes. These range from those which certainly do not represent crimes, such as notifications of death, to more ambiguous situations such as the very broad category “911 call”. Second, calls for service can include duplicate calls about the same incident if it is reported by more than one person (Brower and Carroll, 2007). Third, calls represent only those incidents of which the police are aware, and as such can over or underrepresent actual incidence rates in a way that varies both by call type and by location across the study area (Buil-Gil et al., 2021). While it is possible to compensate for the first issue by analyzing only those call types which are unambiguously crime-related, such as assault and theft calls, it is not possible to avoid the latter two problems with the data available. Despite this, use of calls for service as a proxy for crime data is well attested in the literature (Cohn, 1990), and can have advantages such as the temporal specificity of the data (Brunsdon et al., 2009) and the inclusion of locational information (Andresen and Malleson, 2013). Further, in the case of North Bay, data availability was a primary consideration, as crime data from Statistics Canada are only available for Census Metropolitan Areas.

1.6.1.2 Weather Records

Weather data from North Bay are available from two sources. The first is the Environment Canada weather station located at the Jack Garland Airport, which records hourly. The variables recorded by this station are weather type, humidex (°C), precipitation amount (mm), pressure (kPa), relative humidity (%), temperature (°C), dew point temperature (°C), visibility (km), wind chill (°C), wind direction (10°), and wind speed (km/h). This dataset is freely available online, and was downloaded using the R package 'weathercan'. The second source of North Bay weather data is a weather station maintained by Nipissing University, located on campus. This station records pressure (mbar), rainfall (mm), air temperature (°C), soil temperature (°C), dew point temperature (°C), photosynthetically active radiation (uE), solar radiation (uE), relative humidity (%), wetness (%), soil water content (m^3/m^3), wind speed (m/s), gust speed (m/s), and wind direction (°), at a temporal resolution of 5 minutes. This dataset is not publically available, and was provided by Dr. April James.

1.6.1.3 Defining the Seasons

Unlike crime and weather data, seasonality is date based, and can thus be calculated based on the date of any given call for service. However, there are varying definitions of seasonality. The question of when the seasons begin seems like a relatively simple one, but recent literature on the seasonality of crime has been divided on this topic, as shown in table 3. Many authors choose not to specify what definition of the seasons they use in their studies, while among those that do specify, the chosen definition varies widely. The most popular definitions are meteorological and monthly. For temperate regions of the world, in which the majority of the literature is based, the meteorological seasons divide the year into four portions of three months each, based on the mean temperature in those months, so that the summer season consists of the warmest three months, and winter the coldest. In the United States, the warmest months are June, July, and August, while the coldest are December, January, and February (Trenberth, 1983). This definition is also adopted by the Canadian government (Environment and Climate Change Canada, 2016). Authors using this definition of the seasons tend to justify their decision based on its usage in previous studies (Haberman et al., 2018; Cohn and Rotton, 2000). The monthly definition treats each month as its own "season", and tends to be used in studies that are looking for patterns of crime that repeat yearly, sometimes without describing these patterns in terms of the traditional four seasons. The use of monthly seasons is sometimes justified in terms of providing increased temporal resolution for analysis (Szkola et al., 2019; McDowall et al., 2012).

Table 3 Summary of recent approaches to defining the seasons in crime literature

Study	Study Area	Definition	Justification
Afon and Badiora, 2018	Ibadan, Nigeria	Local; dry and wet seasons	None
Andresen and Malleson, 2013	Vancouver, BC	Astronomical	None
Breetzke and Cohn, 2012	Tshwane, South Africa	Meteorological	Temperature matters, so meteorological is better than astronomical
Brunsdon et al., 2009	Unspecified UK city	Half year	None
Ceccato, 2005	Sao Paulo, Brazil	Undefined	None
Ceccato, 2014	Stockholm, Sweden	Undefined	None

Cohn and Rotton, 2000	Minneapolis, MN	Meteorological	Follows previous research
De Melo, 2018	Campinas, Brazil	Undefined	None
Haberman et al., 2018	Philadelphia, PA	Meteorological	Follows previous research
Hipp et al., 2014	USA	Bimonthly	None
Hurst, 2020	Little Rock, AR	Astronomical	Follows previous research
Ikegaya and Suganami, 2008	Eastern Tokyo	Meteorological	None
Linning et al., 2017a	British Columbia	Undefined	None
Linning et al., 2017b	Vancouver, Ottawa	Modified meteorological, seasons starting a month later than typical	None
Linning, 2015	Vancouver, BC Ottawa, ON	Modified meteorological, seasons starting a month later than typical	None
McDowall and Curtis, 2015	USA	Monthly	None
McDowall et al., 2012	USA	Monthly	Allows more detailed analysis than quarterly division
Michel et al., 2015	Baltimore, MD	Monthly	None
Peng et al., 2011	Beijing	Undefined	None
Quick et al., 2019	Waterloo, ON	Astronomical	None
Ranson, 2014	USA	Monthly	None

Rotton and Cohn, 2004	Dallas, TX	Modified meteorological, seasons starting a month later than typical	Previous research suggests quarterly division adequately explains monthly variation
Szkola et al., 2019	Baltimore, MD	Monthly	Allows more detailed analysis than quarterly division
Towers et al., 2018	Chicago, IL	Meteorological	None
Valente, 2019	Santa Caterina, Brazil	Undefined	None
Yan, 2004	Hong Kong	Local; four unequal seasons	Distinct weather patterns

In contrast to this justification, Cohn and Rotton decided that, based on previous studies, a quarterly division of the year adequately captured monthly variation in crime (Cohn and Rotton, 2004). In their study of crime in Dallas, Texas, they divided the year such that winter included the months of January, February, and March, while summer ran from July through September. This approach was also taken in several comparisons between crime patterns in Vancouver, British Columbia, and Ottawa, Ontario (Linning et al., 2017b; Linning, 2015). However, none of these studies mention why the seasons were defined in this way, rather than using the more typical meteorological seasons. Equally popular as this quarterly division is the astronomical definition of the seasons, in which summer starts on the summer solstice of any given year, and winter on the winter solstice. One author justified this definition based on its use in previous studies (Hurst, 2020). However, temperature change tends to lag behind insolation (Trenberth, 1983), and as such the astronomical definition may not be appropriate in studies where temperature, rather than hours of daylight or other variables more directly linked to insolation, is expected to cause variation.

In addition to these most common ways of defining the seasons, many other approaches are possible. For example, in local applications, a more local definition of the seasons may be particularly appropriate (Trenberth, 1984). As an extension of this, the seasons do not start at the same time the world over, and many places do not divide the year into the same four seasons as used in places such as the United States. Examples of this include a study of crime in Hong Kong, which found it necessary to define four seasons of different lengths based on distinctive local patterns of temperature and precipitation (Yan, 2004), and a study of crime in Nigeria, which broke the year down into the wet and dry seasons, as precipitation in the study area is far more variable through the year than temperature (Afon and Badiora, 2018).

Clearly, the existing crime literature provides many options for how to delineate the seasons, and little definitive guidance. In order to make a more informed choice between definitions, a closer examination of annual patterns occurring in North Bay's weather, specifically its temperature, was conducted. Temperature was chosen as the variable in this analysis because it mediates many other phenomena which could be used to define the seasons, such as the form of precipitation and the timing of the spring freshet. The daily temperature data for this analysis were downloaded from Environment Canada's North Bay weather station, for 1939 – 2012, the longest period for which data were available in a single dataset. These data were used to determine a mean temperature for each day of the year, creating the time series illustrated in figure 5.

Two forms of analysis were conducted using this data. First, in an attempt to replicate Trenberth's methodology (1983), a rolling average of temperatures occurring within a 92-day period was constructed. This period represents a quarter of a year. The goal of this analysis was to determine when the warmest and coldest quarters of the year in North Bay occur, at a finer resolution than is possible using the monthly data that defines the meteorological seasons. The greatest difference in quarterly average temperatures was found when the warm quarter, or summer, began on June 7th and the cold quarter, or winter, began on December 8th (see table 5). In accordance with Trenberth's (1983) findings for mid latitudes in North America, this suggests that if seasons must be of equal length, and are best defined by temperature, then the meteorological rather than astronomical seasons best represent reality.

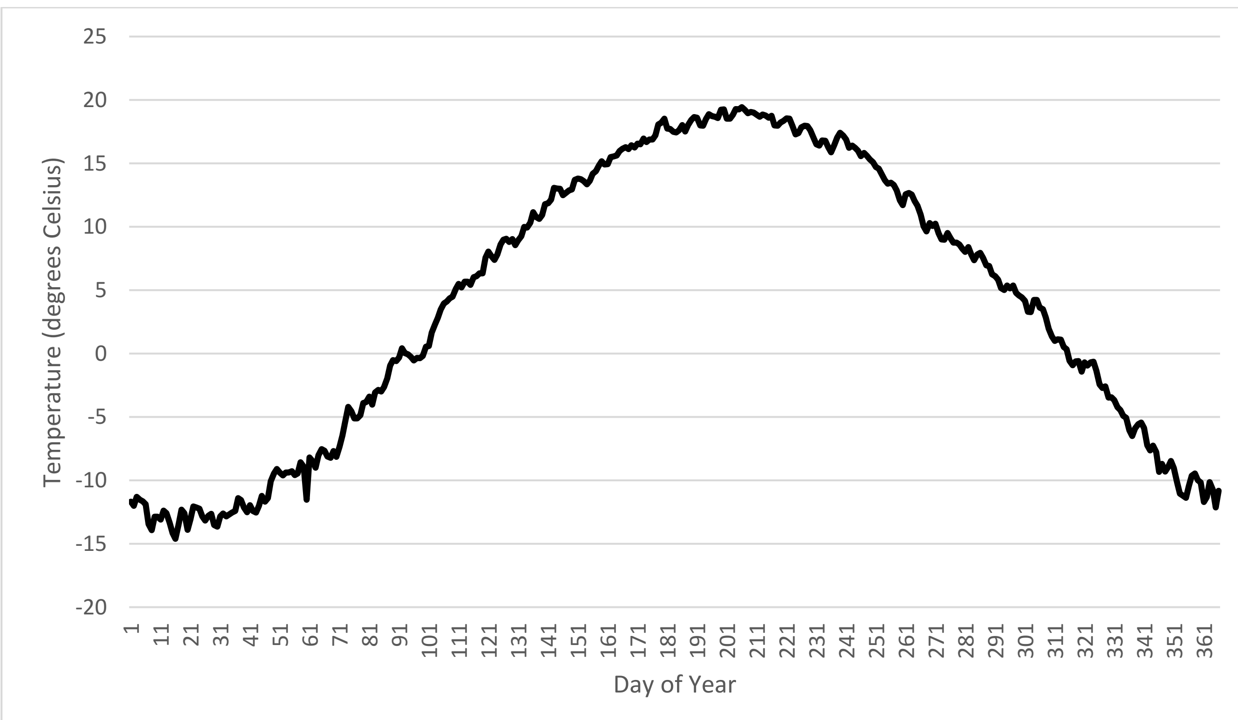

Fig. 5 Mean daily temperatures in North Bay, 1939-2012

Table 5 Season start dates defined by greatest difference in average quarterly temperature

Season	Start date from rolling averages	Difference from Astronomical start date (days)	Difference from Meteorological start date (days)
Spring	March 7th	13	6
Summer	June 7th	14	6
Fall	September 7th	15	6
Winter	December 8th	13	7

In addition to this rolling average methodology, change point estimation analysis was conducted on the time series, in order to determine four segments within the data at which the mean temperature became most significantly different than for the previous segment; these segments could thus be assumed to represent seasons. As the temperature data is not normally distributed, a finding confirmed by the Kolmogorov-Smirnov normality test, and it was necessary to obtain exactly four segments, this analysis was conducted using the Segment Neighbours method and the Cumulative Sum test statistic from the R package ‘changepoint’ (Killick and Eckley, 2014). The results of the change point estimation suggest that summer should begin on May 19th, and winter on November 26th. In contrast to the rolling average methodology, the seasons produced by this method are of slightly unequal length (see table 6).

Table 6 Season start dates defined by change point estimation

Season	Start date from changepoint estimation	Length	Difference from Astronomical start date (days)	Difference from Meteorological start date (days)
Spring	March 12th	91	8	11
Summer	May 19th	95	32	12
Fall	September 20th	92	1	20
Winter	November 26th	88	25	4

All analysis having been conducted, the question remains; which definition of the seasons is most appropriate in North Bay? The time series graph of mean temperatures (figure 5), as well as the rolling average and change point estimation, suggest that seasons in North Bay match quite neatly with the traditional four seasons, being distinctly hot in the summer and cold in the winter. As such, creating a truly local definition of the seasons seems unnecessary. In addition, this study seeks to understand whether season specifically, rather than month of the year, may have an impact on crime patterns, so a monthly definition of seasonality is inappropriate, despite the benefit of increased temporal resolution. This leaves a choice between the astronomical and meteorological definitions of the seasons. The seasons defined by both the rolling average and the changepoint estimation are closest to the meteorological seasons. As a result of this better fit, the more frequent usage of the meteorological definition in recent crime literature, and in accordance with Trenberth’s recommendation (1983), this study adopts the meteorological definition of the seasons.

1.6.2 Data Processing

1.6.2.1 Calls for Service Database Management

All calls for service were combined into a single spreadsheet, for ease of processing and analysis. Then, since the timestamps in the original dataset were not in a format that Microsoft Excel or R could recognize, Excel formulas were used to extract each component of the date and time, and recombine these into a usable format. Additionally, Excel formulas were used to determine the day of week and the season during which each call occurred. In order to produce the final dataset used for statistical analysis of crime rates in relation to weather, all records whose township was not recorded as North Bay were excluded from this spreadsheet.

Further data processing was both possible and necessary prior to spatial analysis of the data. This was conducted prior to removing the records from townships other than North Bay. First, the combined spreadsheet was imported into ESRI ArcMap 10.7, using the decimal degree coordinates to create a point feature representing each call. This newly spatial dataset was projected into the coordinate system NAD 1983 UTM 17 N. Then, a data layer representing North Bay's city boundary was created, based on census tract boundaries available from Statistics Canada, and projected into the same coordinate system. Any areas of water were removed from this boundary, and it was then used to clip the call points, removing any which fell outside the city. Following this, mapping was conducted as described in section 1.6.3, and revealed the two anomalous crime concentrations previously discussed. The points at these locations were deleted to create the final spatial dataset used in analysis.

1.6.2.2 Weather Data Processing

Both the Environment Canada and the Nipissing datasets contained numerous gaps. In order to create the most complete record of weather conditions possible, the decision was made to combine these two datasets. This approach is not without its potential problems, largely relating to the possibility that the values recorded by the two stations could differ in some way, either due to differences in the instruments, or due to different weather occurring at each station. Regarding this latter point, the two stations are located only 5.3 km apart, and both are on top of the escarpment which bisects the city. This distance is much smaller than the distance between either weather station and the southern extremes of the city, so if we are willing to accept that the weather occurring at either station can adequately represent the weather at the other end of the city, we must also accept that the weather occurring at the two stations should, for the most part, be the same. Further, and touching on the point of differences in instrumentation, visual examinations of the datasets did not reveal any noticeable differences in values. While a statistical test of the differences in mean for each variable between the stations would have been preferable, the different timings of the gaps in each dataset meant that the means could differ significantly without actually indicating an actual difference in the variables being recorded at any given time.

To combine the datasets, the variables in the Nipissing data were first summarized to create hourly values. The mean was calculated for most variables, with two exceptions. The first was rain amount, where a sum would create a value more consistent with the Environment Canada data, which records the total amount of precipitation per hour, not the mean of precipitation over that hour. The second was wind direction, which is a circular variable, meaning that a value of 360^{o} is closer to a value of 1^{o} than it is to a value of 180^{o}. As such, taking the mean of 360^{o} and 1^{o}, both of which represent a northerly wind, would result in a value indicating a southerly wind. For this reason, the mode was deemed to be a more appropriate statistic for summarizing this variable. Next, any columns not held in common between the two datasets were deleted from the Nipissing spreadsheet. This resulted in a variable list of precipitation, barometric pressure, relative humidity, air temperature, dew point temperature, wind direction, and wind speed. Those columns in the Nipissing data which had different units than the Environment Canada data were converted to match using Excel formulas. Finally, differences of more than an hour between consecutive rows of the Environment Canada data were identified using an R script, and were manually filled with the appropriate data from the Nipissing spreadsheet.

1.6.2.3 Combining the Calls for Service and Weather Datasets

Once both the weather dataset and the aspatial calls for service dataset were processed satisfactorily, they were combined in R 4.0.4. First, the calls were classified as either violent or property related, and aggregated into hourly counts for every hour of the study period. Following this, the mean count for each category was calculated, and it became apparent that they were too low for many goodness-of-fit tests for count-based regression to be used. As such, the decision was made to further aggregate the calls into 6-hour time periods. Following this, calendar dates of interest were added to the datasets using a lookup function, and the number of hours of daylight occurring during each 6-hour aggregation period were calculated based on sunrise and sunset times from the 'StreamMetabolism' package. Finally, the weather data were joined to the call counts using a rolling join. The script used for these procedures is available in appendix 1.

1.6.3 Exploratory Spatial Data Analysis

Upon receipt of the dataset but following basic data processing, exploratory spatial data analysis (ESDA) was conducted to gain a basic understanding of spatial patterns of crime in the city. Initially, the call points were subsetted based on seasons of the year, and then again into selected call types. The call types chosen for initial analysis were alarms, assaults, break and enters, domestic disputes, narcotics incidents, robberies, thefts, shoplifting, and motor vehicle thefts. As an appropriate definition for seasonality had not been decided at this time, July and August were arbitrarily chosen to represent summer, while January and February were chosen to represent winter. Each crime type was mapped for the year as a whole, and for each of these stand-in seasons. This process was automated using a python script due to the repetitive nature of the work. Each dataset was mapped in four different ways – by joining the points to dissemination areas and dissemination blocks using the Spatial Join tool, by joining them to road segments using a custom Python script, and by using Kernel Density Estimation (KDE) to produce heat maps. All scripts described in this section are available in appendix 2.

In addition to the basic mapping described above, spatial analysis was conducted using the Optimized Hotspot tool in ESRI ArcMap 10.7. As the resulting maps were intended to be exploratory in nature, and not necessarily to be statistically reliable, this technique was chosen based on convenience rather than a review of crime mapping literature. Based on a local version of the Getis-Ord GI* statistic, Optimized Hotspot analysis produces maps of statistically significant clusters of high (hotspot) or low (coldspot) values in the study area. It should be noted that all ESDA described in this section was conducted in 2019, before the NBPS provided that year's call for service data, and so only encompasses the time period 2015 to 2018.

Initial examination of the street segment maps revealed the anomalies described in section 1.6.2.1. These are visible in figure 6. Further mapping showed that calls for police service as a whole are mostly concentrated in the downtown core and immediately surrounding areas, although unusually discrete concentrations of calls are visible at Northgate Mall and the jail (figure 7). These concentrations do not appear to be anomalous, as they occur in locations that would be expected to generate large volumes of calls, in the case of Northgate because of the large numbers of visitors it receives, and in the case of the provincial jail due to calls for assistance from the staff as well as police visits for other reasons such as escorting inmates to other locations. The only call type which appears to depart substantially from the general pattern and to concentrate outside of the downtown core is shoplifting, which is very highly concentrated at Northgate mall.

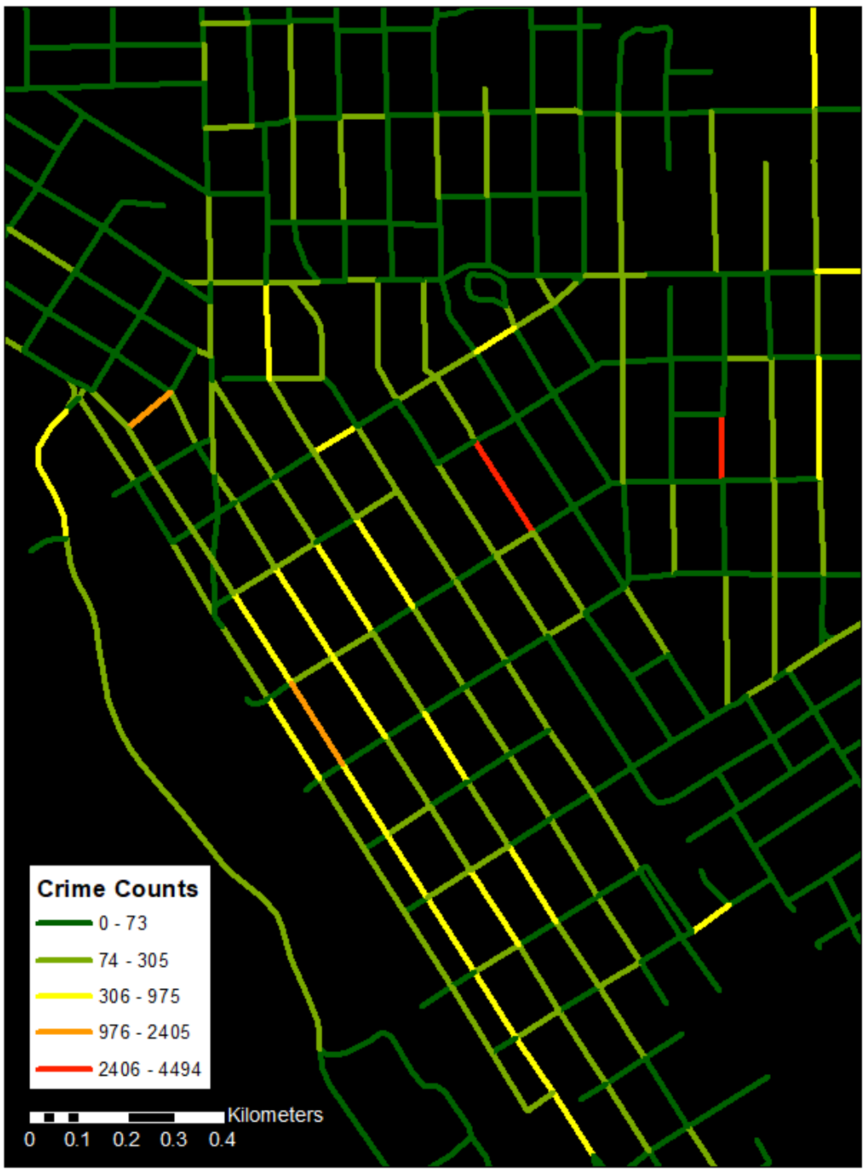

Fig. 6 All calls for police service in downtown North Bay, 2015-2018. Both red street segments represent anomalous concentrations of calls.

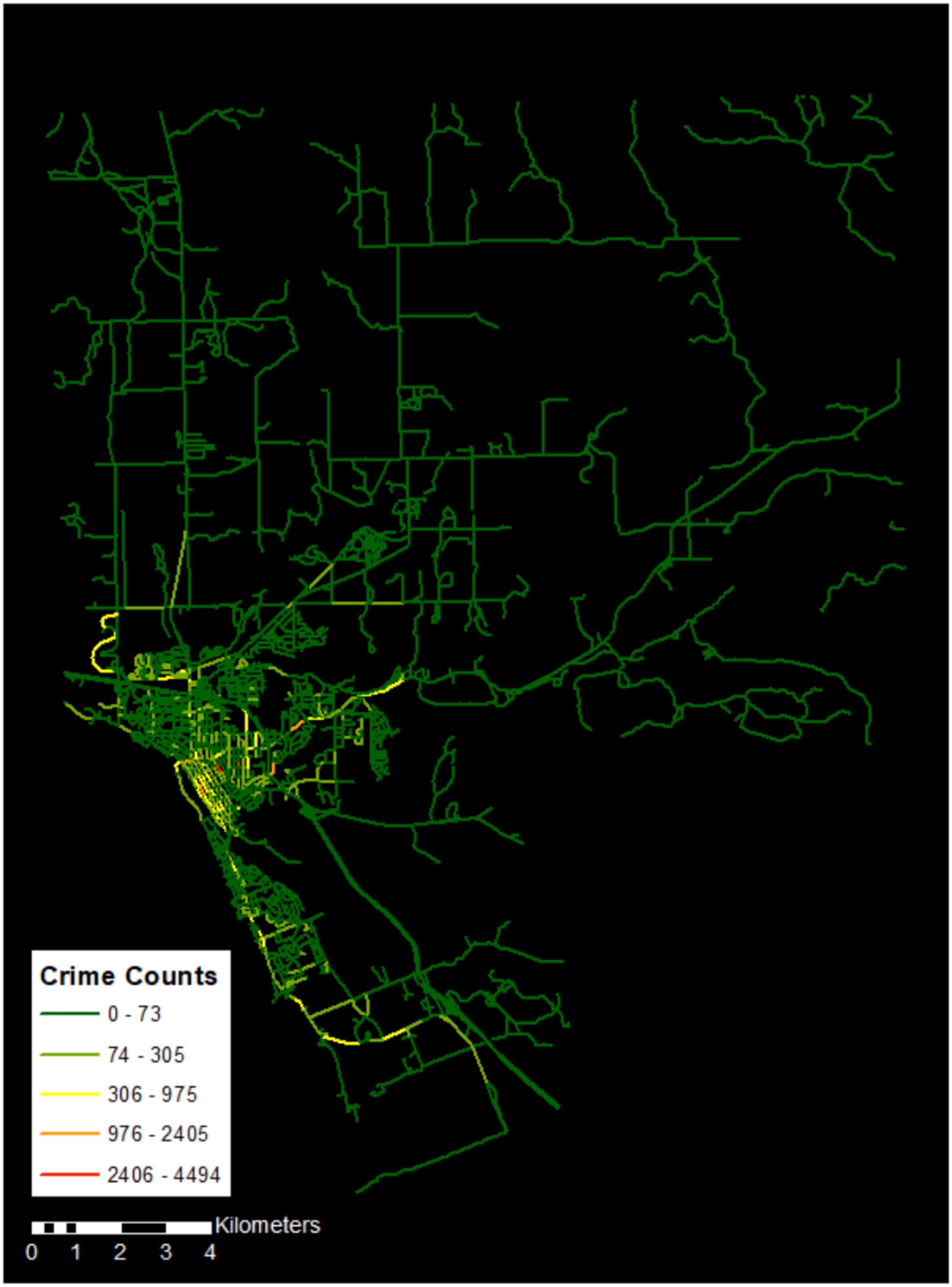

Fig. 7 All calls for police service in North Bay, 2015-2018.

While the NBPS prefer the street segment maps, where call counts are low their fine spatial resolution tends to obscure the overall patterns inherent in the data, making comparison difficult. As such, initial comparisons of seasonal patterns of crime were conducted using the density and hotspot maps. This visual comparison did appear to show differences in seasonal patterns of some call types. The most dramatic differences appeared in narcotics calls (figure 8) and motor vehicle theft calls (figure 9). The narcotics calls are illustrated using hotspot maps, and the motor vehicle thefts using density maps, to demonstrate their different appearances. The exploratory maps produced during this phase of the research (with the exception of fine scale domestic violence maps, which are excluded to protect the privacy of the victims) are presented in appendix 3 for the interested reader, but the maps produced during final analysis, presented in chapter 3, were created with more methodological rigor and will likely be sufficient for most audiences.

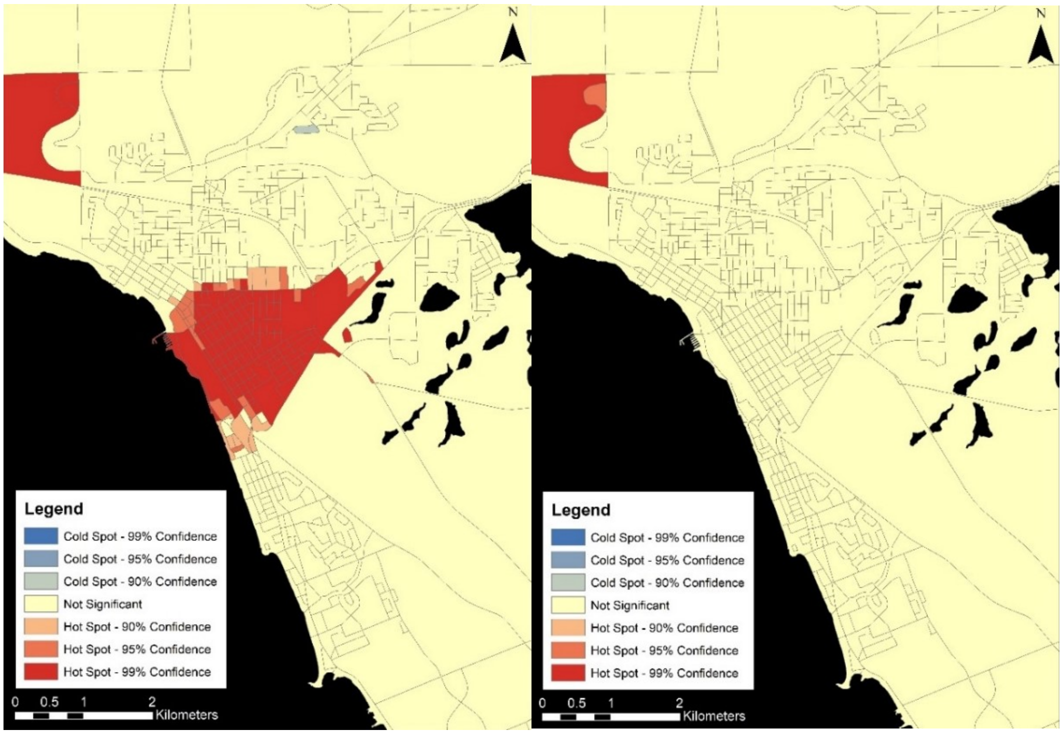

Fig. 8 Hotspot analysis of narcotics calls in the city of North Bay, 2015-2018, at the dissemination block scale. Left: July and August, right: January and February.

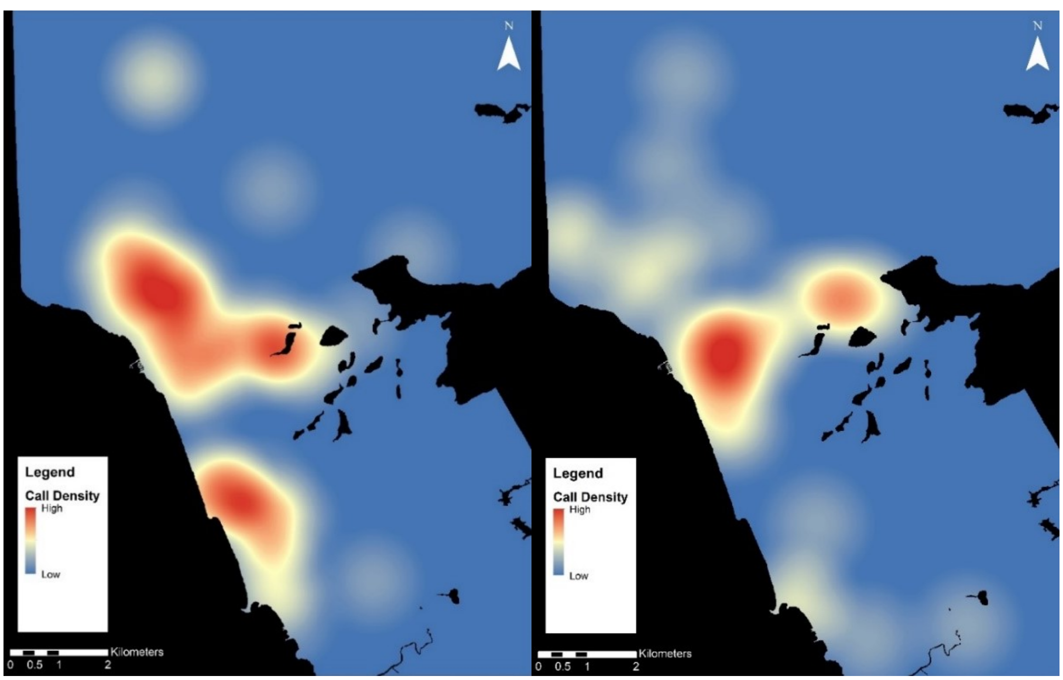

Fig. 9 Density analysis of motor vehicle theft calls in the city of North Bay, 2015-2018. Left: July and August, right: January and February.

1.6.4 Analysis Techniques for Crime-Weather and Crime-Season Relationships

This subsection provides a brief theoretical background on the statistical analyses utilized in this study. For more detail on the actual implementation, please consult the manuscripts in chapters 2 and 3.

1.6.4.1 Count-Based Regression for Analysis of Crime-Weather Relationships

Given that one of the objectives of this study is to understand how environmental variables, specifically weather and season, influence crime rates in the city of North Bay, regression analysis was chosen as a suitable technique. Of the eighteen aspatial studies considered in the literature review, thirteen used some version of regression analysis (see table 1). Further, some spatial studies also relied on regression analysis, some for their spatial components and others for complementary aspatial analysis. Among these regression models, the count-based poisson and negative binomial regression models were particularly common. These models are used where the outcome variable is a count of some kind; in the case of this study, the number of calls for police service occurring during a certain time period. Ordinary least squares regression is not always appropriate for count data, because the error of such data tends not to be normally distributed, instead following a poisson or negative binomial distribution (Coxe et al., 2009). The poisson distribution is a special case of the negative binomial that only occurs when the mean and variance of the data are equal; the negative binomial distribution itself does not have this limitation, and is modelled by including an extra parameter to account for the variance (Piegorsch, 1990). Both poisson and negative binomial regression are generalized linear models and thus rely on maximum likelihood for estimation of model parameters (Fox and Weisberg, 2011). As such, the fit statistics traditionally used in OLS regression do not apply to these models (Coxe et al., 2009).

1.6.4.2 Application of the Spatial Point Pattern Test for Comparison of Seasonal Spatial Crime Patterns

Methodologies for spatial analysis of crime-weather or crime-season relationships vary more widely than aspatial methodologies (see table 2), and the most appropriate methodology depends heavily on the precise nature of the research question. Since this study seeks to determine whether patterns of crime differ between seasons, Andresen's spatial point pattern test (SPPT) would appear to be the most appropriate technique. While there are numerous methods for comparing similarity in spatial patterns, most are based in ecology, medical sciences, or remote sensing, and many have restrictions regarding underlying assumptions, appropriate sample size, and the conclusions it is possible to draw from their results (Long and Robertson, 2017). As the SPPT was initially published using crime data (Andresen, 2009), and has successfully been used in a number of crime studies beyond those listed in table 2 (e.g. Andresen and Linning, 2012; Andresen and Malleson, 2014; Vandeviver and Steenbeek, 2019) it should be appropriate for this study. Further, the test is available as a package in R and so does not need to be coded from scratch. This R package has been updated to address the most recent concerns and methodological innovations surrounding the use of the SPPT (Wheeler et al., 2018; Steenbeek and Wheeler, 2020).

In brief, the SPPT aggregates points into polygons, and then uses a Fisher's exact test to determine whether each polygon contains a greater proportion of the study area's points in one pattern than the other (Steenbeek and Wheeler, 2020). This level of the output is mappable, and can reveal where in a study area differences in pattern are occurring, which is an improvement over several older measures of spatial similarity (Long and Robertson, 2017). Then, the test determines what percentage of the aggregation polygons in the study area are different from one another, in order to decide whether the two patterns as a whole are different or similar (Steenbeek and Wheeler, 2020).

Chapter 2: Weather and Crime in a Small Northern City

2.1 Abstract

2.1.1 Objectives

To determine the influence of weather and calendar variables on crime occurrence, both violent and property related, in a small city located in northern Ontario, Canada.

2.1.2 Methods

Using five years of police call for service data (2015 – 2019), a negative binomial regression model approach was used to assess the relationships between crime, weather, and calendar variables. Based on the four seasons (spring, summer, fall, winter) and the crime types (violent, property), a total of 8 models were constructed. Equality of coefficient z tests, based on the model coefficients, were used to compare results between seasons.

2.1.3 Results

Based on the results of the models, relationships between the dependent and independent variables were found to differ significantly from season to season, and between crime types. Moreover, property crime appears to be influenced more by calendar variables than by weather variables, whereas the opposite relationship was observed for violent crime. Crime in the city of North Bay has increased in every season between 2015 and 2019, with the exception of violence during the summer.

2.1.4 Conclusions

Although many of the relationships found in this study are in line with the results of others and can be explained using current crime-weather theories, other relationships appear unusual and may be related to the size, location, and structure of the city.

2.1.5 Keywords

Crime, weather, calendar variables, seasonality, small city

2.2 Introduction

The notion that the amount of crime which occurs in a city might be related to weather conditions is not novel. Research has been conducted on this topic since at least the 1800s, and a plethora of further research has been produced since the 1960s (Cohn, 1990; Andresen and Malleson, 2013). Of particular concern was the inability to explain fine scale variability in crime rates over time using traditional variables such as demographic factors. Consequently, a large body of literature now exists to suggest that changes in weather may explain this variability (Cohn, 1990).

Several theories have been advanced to explain how weather might influence crime rates. Perhaps the oldest is the temperature aggression theory, which is frequently classified as a psychological theory of crime. According to this theory, as temperature increases people become more uncomfortable and thus more prone to lash out with acts of aggression (Cohn, 1990; Brunsdon et al., 2009). The utility of this theory is limited, however, as it only applies to those crimes involving an act of aggression, and is limited solely to the impact of temperature, though a range of other weather variables may in fact be linked to crime (Brunsdon et al., 2009). Further, there is some disagreement about the precise nature of the relationship between crime and temperature as predicted by this theory. For example, some researchers posit that there may be a threshold temperature above which people are more likely to simply try and escape the heat rather than lash out; this is termed the negative affect escape model (Rotton and Cohn, 2004). Another psychological theory of crime that may explain links between weather and crime rates is the rational choice theory, which acknowledges that offenders choose when and whether to commit a crime based on a logical assessment of their circumstances (Cohn, 1990). Although the rational choice theory is less frequently linked to weather than the temperature aggression theory, it is not inconceivable that weather could influence offender decision-making regarding the timing of criminal activity.

More recent studies on weather and crime have tended to focus on environmental theories of crime, particularly the routine activities theory (Haberman et al., 2008; Oliveira et al., 2018). This theory focusses on the conditions necessary for crime to occur; that is, the convergence in time and space of a potential offender, a suitable target, and a lack of capable guardianship (Weir-Smith, 2004). This convergence of circumstances depends on the habits and movements of people; their routine activities, which tend to be consistent unless some external factor intervenes to change them (Cohn, 1990; Brunsdon et al., 2009). Weather has the potential to be one such external factor, and thus routine activities theory provides an explanation for how weather might influence crime patterns (Linning et al., 2017a). However, determining empirically the degree to which each of these theories links crime and weather is a difficult, if not impossible, task (Ranson, 2004). Accordingly, this investigation does not attempt to determine which theories link weather and crime in North Bay, but considers all of them in the interpretation of the results.

Cohn (1990) reviewed the literature on crime and weather published from 1950 to 1990 and concluded that there is a strong positive correlation between crime and temperature, but that the evidence is weaker for other weather variables. This relationship between temperature and crime can extend to temperature-based indices; for example, the discomfort index, which combines temperature and humidity, has been shown to have a positive association with homicides in Baltimore (Cheatwood, 1995). The majority of studies conducted since then generally agree with these findings; temperature almost always has a positive relationship to crime, while the results for other weather variables such as precipitation and humidity are less consistent. For example, a more recent study of violent crime in Baltimore showed a link between high temperatures and some types of violent crime, while the association with other weather variables was less frequently significant (Michel et al., 2016). In their study of violent crime in Tokyo, Ikegaya and Suganami (2008) likewise found no relationship between precipitation and violence resulting in death.

Cohn (1990) also found that the relationships between weather variables and certain categories of crime can differ from the relationship between those same variables and crime as a whole. Suitable targets and even potential offenders for different crime types will not necessarily be the same (Johnson and Summers, 2015), and as such Cohn's finding relates well to routine activities theory. Since then, several studies have found further support for differing relationships between weather variables and certain crime types. Towers et al. (2018), for example, found a relationship between precipitation and wind speed and various types of violent crime in Chicago, but not for property crimes. In a study of property crime in Minneapolis, similar results were found (Cohn and Rotton, 2000). Specifically, temperature was linked to all the crime types studied, but cloud cover and wind speed were only related to thefts, and not to burglaries or robberies.

Linning et al. (2017b) found that not only can crime-weather relationships vary based on crime type, but that they can also differ between similarly sized cities in the same country. Specifically, they found temperature to be a significant predictor of most crime in Ottawa but not in Vancouver, and suggest that Ottawa's more distinctly seasonal weather may account for this difference. Hipp et al. (2004) also showed that crime appears to interact differently with weather in different locations, and that factors such as population density and the degree of seasonality present in a place's weather can mediate these relationships. The weather typical to a region may also play a role, as large amounts of precipitation have been shown to decrease crime more notably where such weather does not often occur (Linning et al., 2017a). It is also important to consider that seasonal patterns of crime are not always consistent from place to place, with crime peaks often occurring at different times of year (McDowall et al., 2012); apparently, then, the relationship of crime to season can also be location dependent.

Seasonality combines a number of factors that might be expected to influence the rate and location of crime incidents (McDowall et al., 2012). For example, environmental variables such as temperature and precipitation can display distinct seasonal trends, reoccurring in a consistent cycle, while cultural and calendar variables such as holidays and school breaks by their nature tend to occur at the same time each year. Given that crime is also seasonal in nature, it is suggested that both weather and calendar variables may be linked to its seasonal patterns (Cohn & Rotton, 2000). Some researchers control for calendar variables, as Yiannakoulias and Kielasinska (2016) did with official holidays and hockey playoffs, in order to ensure they did not act as confounding factors in their analysis of weather and arson in Toronto. Others include season itself as a variable. Ceccato (2005) found evidence for seasonality in homicides in Sao Paulo, but also found that cultural and temporal variables played a larger role in crime patterns than did weather variables. In contrast, Linning et al. (2017b) found in their investigation of Canadian cities, that for most crime types, weather variables played a greater role in explaining crime than did calendar variables.

A notable absence in the literature are studies of weather or seasonality and crime for non-metropolitan sized cities. If place does in fact matter with regards to relationships between crime and weather, then the unique demographics and population densities of such urban centers may provide novel information lacking in mainstream studies. Consequently, to address this gap in the literature, the purpose of this investigation is to analyze the influence of season, weather and calendar variables on the occurrence of both property and violent crime in a small northern Ontario city (population approximately 50,000) with distinct seasonality.

2.3 Data and Methods

2.3.1 Study Area

North Bay is a small city with a land area of 327.43 km^2, located in northern Ontario, Canada. The population as of the 2016 census was 50,396, giving an overall population density of 153.9/km^2. However, the population density is very unevenly distributed across the city, as large areas of the city are forested and only sparsely populated (figure 1). These include many of the outlying census tracts, where population density can be as low as 8.3 people/km^2. In contrast, some of the census tracts in the city's downtown core have population densities exceeding 2000 people/km^2 (figure 2). The population is currently in decline, with a recorded decrease of roughly 2000 people between the 2011 and the 2016 national censuses. The median income as of the 2016 census was $32,036 CAD ($24,196 USD), and 17.4% of residents are considered low income earners, which is three percentage points higher than the provincial average. Despite the decreasing population, a perceived increase in crime is currently of major concern to the community at large (BayToday Staff, 2019; Pickrell, 2020; Campaigne, 2021). The city has its own municipal police force, the North Bay Police Service (NBPS), which is responsible for most law enforcement within the city's boundaries, and also in the adjacent town of Callander.

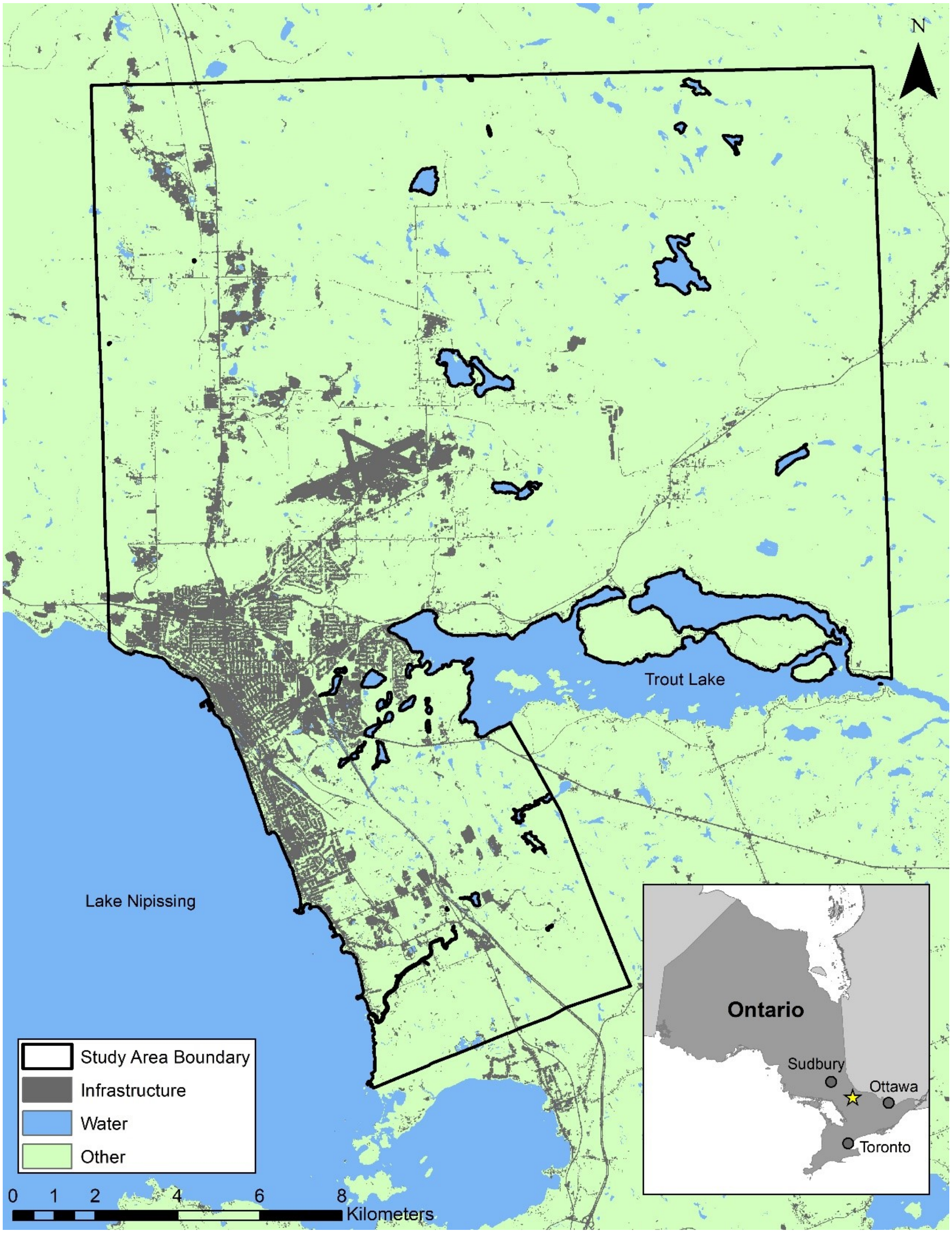

Fig. 1 Land cover map of the city of North Bay, classified from Sentinel 2 imagery captured in June 2018.

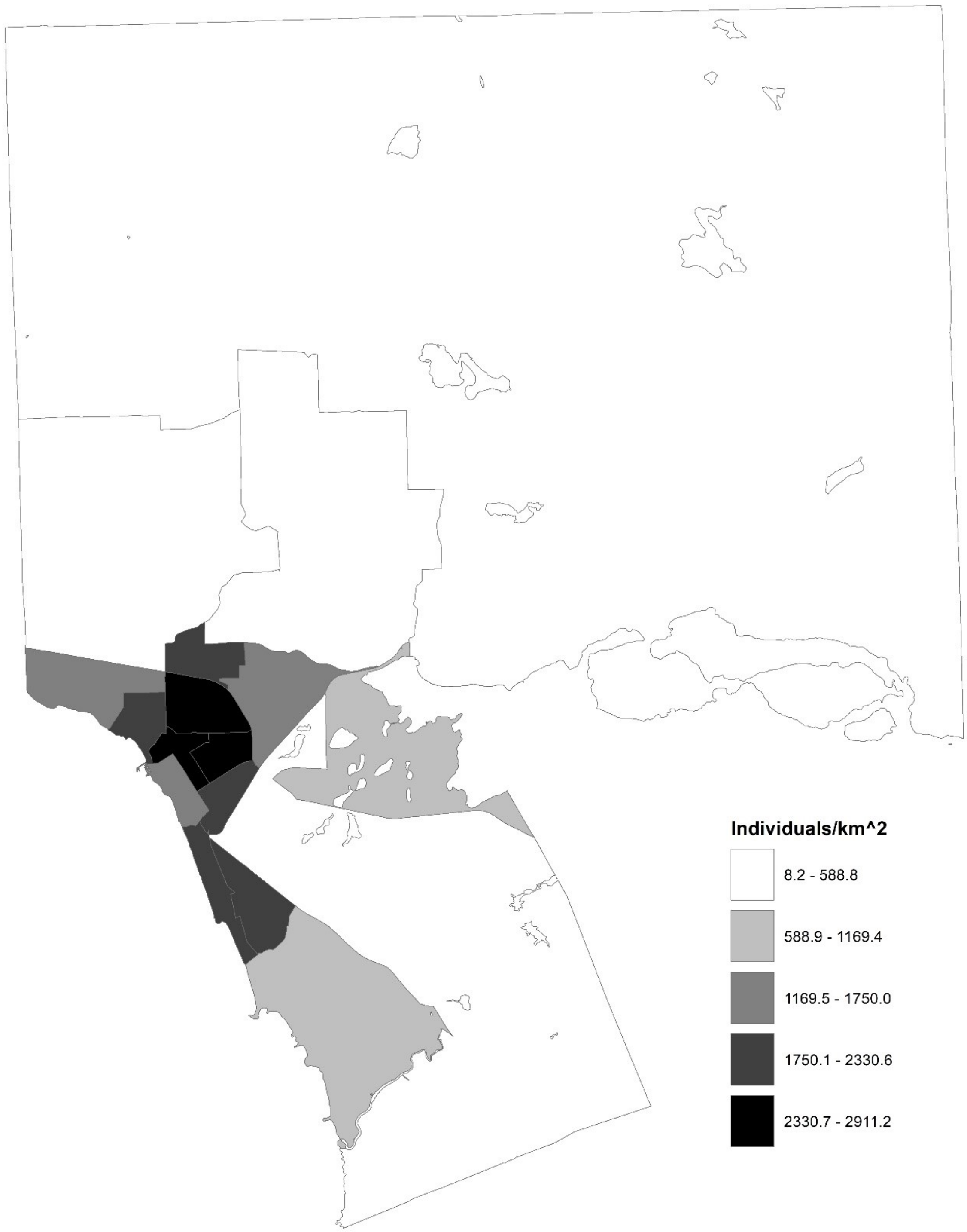

Fig. 2 Population density in the city of North Bay, 2016, based on census tracts. With data from Statistics Canada.

As a northern Ontario city, North Bay's weather is notably seasonal. Summers are hot and relatively dry, with maximum temperatures sometimes exceeding 30ºC. Winters are cold, with temperatures generally below freezing, and occasionally falling below -30ºC. As transitional seasons, spring and autumn are both more variable and more moderate in their temperatures. Precipitation occurs year round, as either rain or snow depending on the temperature. Snow cover is persistent during the colder months.

2.3.2 Dependent Variable: Crimes

We use a database of calls for police serviced provided by the North Bay Police Service (NBPS). This dataset consists of all requests for police service in North Bay from 2015 – 2019, both those made to the national emergency phone number and those made directly to police, as well interactions initiated by the police, such as traffic stops. As such, much of the dataset consists of non-crime incidents, including wellness checks, and incidents that may or may not be related to a crime, such as 911 calls. Each record in the dataset includes the date, time, and location of the incident. It also includes a code specifying the type of incident as reported by the caller, and the actual incident type where the responding officer found this to differ from the initial call. Calls for service data is prone to some issues not found in crime report data; in addition to containing call types which are likely not crime related, it can include duplicate calls if multiple people reported the same incident (Brower and Carroll, 2007). However, the temporal specificity of calls for service data makes it ideal for studies of phenomena occurring on a short time scale (Brunsdon et al., 2009), and unlike crime report data, it has the advantage of being available for our study area.

Due to low incident counts for many call types, we chose to aggregate the five years of data into two broad categories, violent crime and property crime, rather than analyzing individual call types. Specifically, calls regarding arson, break and enters, possession of stolen property, theft, theft of motor vehicle, and shoplifting were classified as property crimes, totaling 10,478 incidents, as summarized by season in table 1. Alternatively, those incidents reported as abductions, assaults, sexual assaults, child abuse, domestic disputes, elder abuse, family disputes, neighbor disputes, robberies, and threats were classified as violent, totaling 10,643 incidents. Summary statistics for violent crimes, broken down by season, are provided in table 2. Notably, property crime occurrences are more variable than violent crime occurrences, with wider ranges and greater differences in mean.

Table 1 Summary statistics for property crimes per 6-hour period, by season, 2015-2019

	Spring	Summer	Autumn	Winter
Mean	1.3	1.8	1.5	1.1
Standard Deviation	1.5	1.8	1.7	1.4
Range	0, 10	0, 20	0, 13	0, 10
Total	2,459	3,237	2,819	1,955

Table 2 Summary statistics for violent crimes per 6-hour period, by season, 2015-2019

	Spring	Summer	Autumn	Winter
Mean	1.4	1.5	1.5	1.3
Standard Deviation	1.4	1.4	1.3	1.3
Range	0, 8	0, 9	0, 7	0, 11
Total	2,514	2,766	2,643	2,297

2.3.3 Independent Variables: Weather and Calendar Events

The weather data used in this study come from two different sources. The first is a weather station maintained by Environment Canada, located at North Bay's Jack Garland Airport (YYB). This station records hourly. The second is a weather station maintained by Nipissing University, located on the campus, approximately 5.3 km from the airport. This station records every 5 minutes. The datasets from both weather stations included numerous gaps; to create as complete a record as possible of weather during the study period, the data from Nipissing University was averaged to create hourly values, and used to fill the gaps in the Environment Canada dataset.

Weather variables analyzed in this study are temperature (ºC), relative humidity (%), and precipitation. While both weather stations record an actual amount of precipitation, measured in mm, neither records whether the precipitation being measured is rain or snow. As such, we converted precipitation to a dichotomous variable, simply indicating whether any precipitation occurred during that six-hour period (N = 7304). This is because we expect that the same amounts of rain and snow would have very different impacts on the city. Further, Yiannakoulias and Kielasinka (2016) took the same approach to precipitation in their analysis of weather and arson, in their case because precipitation measurements are so highly skewed, which is also true of our dataset. In addition to the variables from the weather station datasets, we include daylight hours as a weather variable, because unlike the other calendar variables discussed below, it is not based on cultural events. The hours of daylight occurring in each time period were calculated based on sunrise and sunset times.

Because weather in North Bay is so strongly seasonal, and we expect that the effect of variables such as temperature may vary between the seasons, we analyzed these variables separately for each seasons of the year. We define the seasons as spring: March to May, summer: June to August, autumn: September to November, and winter: December to February. This is sometimes described as the meteorological definition of seasonality, and groups the months into seasons on the basis of similar temperatures (Trenberth, 1983). Similar groupings of months into seasons are well attested in the crime literature (e.g. Breetzke and Cohn, 2012; Towers et al., 2018), and the Government of Canada also defines the seasons in this way (Environment and Climate Change Canada, 2016). It is also possible to use individual months to describe seasonality, but a quarterly division of the year adequately explains monthly variation (Rotton and Cohn, 2004), so we choose to adopt such a division to keep the number of models more manageable. Summary statistics for the continuous weather variables during each season are presented in table 3, while a count of days with precipitation in each season is included in table 4.

Table 3 Summary statistics for continuous weather variables analyzed in this study, 2015-2019

		Spring	Summer	Autumn	Winter
Air Temperature (ºC)	Mean	2.5	17.9	6.8	-9.8
	Standard Deviation	9.3	4.6	8.7	8.3
	Range	-25.1, 29.5	2.9, 30.9	-22.0, 28.5	-34.2, 13.2
Relative Humidity (%)	Mean	73.5	69.7	83.4	84.6
	Standard Deviation	17.4	20.9	13.4	10.3
	Range	24.3, 100	16.0, 100	26.7, 100	34.3, 100
Hours of Daylight	Mean	3.3	3.1	2.7	2.3
	Standard Deviation	2.7	2.8	2.7	2.4
	Range	6, 0	6, 0	6, 0	6, 0

In addition to weather and the seasons, we include variables to account for calendar-based factors that we expect to have an impact on crime occurrences. These are statutory holidays, weekends, and major school breaks. We also include a sequence variable, to capture the effect of potential linear trends in crime. The number of time periods falling into each of these categories varies by season, and is listed in table 4.

Table 4 Number of 6-hour periods (N = 7304) during which each discrete weather or cultural variable is present, 2015-2019

	Spring	Summer	Autumn	Winter
Precipitation	342	306	420	350
Statutory Holiday	40	40	40	80
School Break	100	1,272	88	240
Weekend	524	524	520	513

2.3.4 Analytic Strategy

We constructed a series of regression models to understand the impact of weather and calendar variables on crime in our study area. Since our outcome variable is a count of crimes, and a large degree of overdispersion is present in our dataset, we utilized negative binomial regression (Fox and Weisberg, 2011). Several common goodness of fit statistics for count based regression models do not perform well when mean values are low (Wood, 2002; Pawitan, 2013; Ye et al., 2013), so to achieve a balance between acceptable mean values and temporal specificity, we aggregated our weather and crime data to six-hour time periods (00:00 – 05:59, 06:00 – 11:59, 12:00 – 17:59, and 18:00 – 23:59). In addition to the weather data, for each time period we calculated the hours of daylight that occur during it, and assigned a value to indicate the season of the year, and whether the time period falls during a statutory holiday, a major school break, or a weekend. We also assigned a sequence variable, with the earliest time period having a value of 1, and the latest a value of 7304.

We conducted a separate analysis for each season of the year, and each category of crime. Within each analysis, we took a hierarchical approach to model selection; constructing a series of increasingly complex models, before selecting only the most relevant variables to build our final model. The first model contains only the weather variables. The second contains only the calendar variables. The next combines the weather and calendar variables. The fourth, full, model includes all previous variables, with the addition of interaction terms for air temperature and all other variables, precipitation and all calendar variables, and sequence and all weather variables. This model also includes quadratic terms where the residual plots indicate these may be warranted; these are fitted using orthogonal polynomials to avoid any potential issues with collinearity. The final model is created based on this largest iteration, and contains all weather and calendar variables, any quadratic terms which are significant at the 0.05 level in the full model, and any interaction terms that are significant at the 0.01 level in the full model. While several fit statistics were examined, we chose to compare the Aikake Information Criterion (AIC) for each model to ensure it was better than the previous model in the sequence.

Following the regressions analysis, we used a series of z tests to compare any significant regression coefficients between the seasons. These tests allow us to say whether the coefficient in question is significantly greater in one season than in another. Following Paternoster et al. (1998), the equation for this test is:

$$Z = \frac{\beta_1 - \beta_2}{\sqrt{SE\beta_1{}^2 - SE\beta_2{}^2}}$$

2.4 Results

2.4.1 Fit Statistics

The Aikake Information Criterion (AIC) for our models are presented in table 5. The AIC should only be used to compare models based on the same data (Kurosawa et al., 2020); within such a set of models, a lower AIC indicates the best ratio of likelihood to number of variables. For all four seasons and both crime types, the AIC finds the final model to perform best.

Table 5 AIC values calculated for seasonal models of both violent and property crime, 2015-2019

		Weather Variables	Calendar Variables	Weather and Calendar Variables	Final Model Including Interaction Terms
Property	Spring	5293.2	5736.4	5147.0	5058.8
	Summer	6061.3	6477.5	5933.3	5744.6
	Autumn	5532.8	6115.7	5428.2	5418.6
	Winter	4858.2	5120.0	4784.0	4774.8
Violent	Spring	5658.6	5724.4	5616.6	5558.6
	Summer	5845.9	5951.3	5791.0	5600.8
	Autumn	5658.9	5761.6	5642.5	5631.2
	Winter	5351.0	5404.6	5343.6	5294.1

2.4.2 Property Crime

The results of the final models for property crime are presented in table 6. For property crime, precipitation is never significant. Temperature is significant and positive in all seasons except summer, and RH negative and quadratic only in winter and autumn, while hours of daylight are significant in all seasons. The effect of the calendar variables is more varied. Statutory holidays and weekends have a negative association with property crime in all seasons, while school breaks show no relationship. The sequence variable always has a positive association with property crime.

Table 6 Final models for property crime in North Bay, 2015-2019

	Spring		Summer		Autumn		Winter	
(Intercept)	-0.7514	***	-0.1276		-2.1940	***	-3.7416	***
Temperature	0.0353	***	0.0018		0.0090	***	0.0207	***
Precipitation	0.0183		-0.0926		-0.0074		0.0360	
RH	-0.0011		0.0007		0.1280	***	0.0430	**
RH^2					-0.0008	***	-0.0003	***
Daylight Hours	-0.6656	***	-0.9770	***	0.2077	***	0.2281	***
Daylight Hours^2	0.1431	***	0.1854	***				
Stat Holiday	-0.7669	**	-0.2966	*	-0.7071	***	-0.5433	**
School Holiday	0.1421		-0.0551		0.0064		-0.0503	
Weekend	-0.2013	***	-0.3381	***	-0.2592	***	-0.2311	***
Sequence	0.0001	***	0.0001	***	0.0001	***	0.0001	***
Temperature x Daylight Hours	-0.0046	*						
Temperature x RH					0.0008	*		
Temperature x Stat Holiday	0.0451	***						

*p < .05 **p < .01 ***p < .001

The results of the comparisons of the seasonal regression coefficients for property crime are presented in table 7. Only the coefficients from spring are different to those from the other seasons. In regards to temperature, the coefficients for spring are significantly greater than those in autumn and winter, and the sequence variable for spring is different to those of all other seasons. While the sequence coefficients appear to be equal because of the rounding applied to table 6, the spring sequence coefficient is in fact greater than any of the others, indicating a larger positive relationship. In addition, the relationships between property crime and daylight hours, and property crime and weekends, are greater in spring than summer.

Table 7 Z scores for comparisons of significant coefficients from final property crime models

	Spring Summer	Spring Autumn	Spring Winter	Summer Autumn	Summer Winter	Autumn Winter
Temperature		4.51 ***	2.25 *			-2.46
Precipitation						
RH						-1.46
Daylight Hours	2.24 *	-8.38	-8.17	-13.36	-13.09	1.28
Statutory Holiday	-1.60	-0.73	-0.08	1.06	1.93	0.80
School Break						
Weekend	1.97 *	0.42	0.73	-1.58	-1.02	0.37
Sequence	2.53 **	1.99 *	2.59 **	-0.46	0.38	0.77

*p < .05 **p < .01 ***p < .001

2.4.3 Violent Crime

Model results for violent crime are presented in table 8. Unlike for property crime, temperature has a significant relationship to violent crime in all seasons except summer, and precipitation becomes significant in summer and autumn. Either relative humidity or its quadratic term is also significant in every season except summer for violent crime. The calendar variables, however, seem to matter less for violent crime; none are significant except for school breaks and weekends during the summer. The sequence variable is significant and positive in all seasons except summer. However, there is a significant positive interaction between temperature and sequence for summer violent crime.

Table 8 Final models for violent crime in North Bay, 2015-2019

	Spring		Summer		Autumn		Winter	
(Intercept)	-0.3532		0.3584		-0.8901		-3.0207	*
Temperature	0.0089	***	0.0068		0.0075	**	-0.1023	**
Temperature^2							-0.0010	**
Precipitation	0.0973		0.1392	*	0.1677	**	-0.0719	
RH	0.0139		0.0058		0.0379	**	0.0711	*
RH^2	-0.0001	*	-0.0001		-0.0003	***	-0.0004	*
Daylight Hours	-0.5949	***	-0.9803	***	0.0439	***	-0.3186	***
Daylight Hours^2	0.1069	***	0.1595	***			0.0756	***
Stat Holiday	-0.0321		-0.0471		0.0233		-0.1445	
School Break	0.1460		-0.2079	***	-0.0765		0.0636	
Weekend	0.0192		0.5832	***	-0.0029		-0.0262	
Sequence	0.0001	***	-0.0001		0.0001	***	4.39E-05	***
Temperature x RH							0.0012	**
Temperature x Weekend			-0.0365	***				
Temperature x Sequence			7.05E-06	***				
*p < .05 **p < .01 ***p < .001								

For violent crime, the results of the coefficient comparisons are shown in table 9. There are fewer differences in coefficients for violent than for property crime, and they occur less consistently between seasons. The variables for which significant differences exist are the same for both property and violent crime; these being temperature, daylight hours, weekends, and the sequence variable. The coefficient for temperature in winter is less than spring or autumn. As with property crime, the violent crime coefficient for daylight hours is greater in spring than summer. The weekend coefficient is greater in summer than winter, however, and the sequence variable coefficient is only greater in spring than winter.

Table 9 Z scores for comparisons of significant coefficients from final violent crime models

	Spring Summer	Spring Autumn	Spring Winter	Summer Autumn	Summer Winter	Autumn Winter
Temperature		0.38	3.27 **			3.22 *
Precipitation				-0.34		
RH	-1.50	-1.54	-1.85	-0.04	-1.03	-1.01
Daylight Hours	3.19 **	-7.05	-2.60	-12.64	-6.72	6.35
Statutory Holiday						
School Break						
Weekend						
Sequence		1.56	2.14 *			0.61

*p < .05 **p < .01 ***p < .001

2.5 Conclusion and Discussion

2.5.1 Property crime

Temperature has a positive linear relationship to property crime in both spring and winter, and the tests of equality indicate that this is stronger in spring. Routine activities theory provides an explanation for the positive linear relationship with temperature; people are more likely to be outside during warmer, more favorable weather, and thus are more likely to come into contact with one another (Cohn and Rotton, 2000). In the case of property crime, this also increases the likelihood that they leave their homes unsupervised, decreasing guardianship and increasing the suitability of those homes as a target.

Relative humidity has a relationship to property crime in both autumn and winter. In both cases it appears to become quadratic and negative, indicating an increase in crime at moderate humidity levels, and a decrease with very low or very high humidity. As with the results for temperature, this relationship is supported by previous research (Towers et al., 2018). However, the relationship is curious, as there is no immediately apparent theoretical reason for it to exist. By itself, humidity has no particular reason to impact human behavior. In combination with high temperatures it should increase discomfort (Cheatwood, 1995; Rotton and Cohn, 2004), which could cause a decrease in all crimes according to routine activities theory, as people are less likely to go out in inclement weather. This predicted decrease should also hold true if we accept that high humidity is often associated with precipitation (Rotton and Cohn, 2004). However, if this was the case we would expect to see a significant interaction term for humidity and temperature, particularly in summer, or for humidity and precipitation at any time of year. A humidity temperature interaction does exist in autumn for property crime, but as autumn temperatures tend to be fairly low, humidity should not be contributing to temperature-based discomfort in this season.

Hours of daylight have a relationship to property crime in all seasons. In spring and summer, it is quadratic and positive, indicating an increase in crimes during periods with the most or least light, and fewer crimes during periods with moderate light hours. In autumn and winter, the relationship is linear and positive, suggesting that most property crimes are occurring in those time periods with the most daylight. While Linning et al. (2017b) found a relationship between hours of illumination and mischief crimes in Ottawa, this relationship was negative and linear, and spanned the entire year rather than being confined to a single season. In North Bay at least, it seems that property crimes are simply more likely to occur, or at least to be reported, during daylight hours in certain seasons. This question of reporting date versus date of occurrence is relevant for other calendar variables in this study. For violent crime, the relationship with daylight hours is similar, except that it is quadratic in all seasons except autumn. Notably, even where the signs of the linear coefficients have different signs, the equality of coefficient tests do not find them to differ significantly. We also note that some caution is warranted in interpreting these trends, as hours of daylight vary across each season, so these relationships have potential to capture trends in crime occurring based on date within the season. For example, it is possible that more property crimes occur early in the winter, when there are coincidentally more hours of daylight; this would produce the appearance of a positive linear relationship, whether or not hours of daylight actually mediate these crime rates.

The relationship between statutory holidays and property crime is always negative, and the magnitude of this relationship does not differ significantly between seasons. This is in agreement with previous findings from Chicago, where many holidays decreased crime rates

(Towers et al., 2018). It is also consistent with results from Brazil (de Melo et al., 2018). Under a routine activities paradigm, this might suggest that people are leaving their homes less, making their homes less ideal targets and also bringing them into contact with fewer other people (Cohn and Rotton, 2000). However, this negative relationship may indicate a reporting bias, as discussed in the case of daylight hours. For example, if property crimes in commercial buildings were only discovered and reported after the holiday when staff returned to work, property crime would appear to be less common on holidays than regular days.

The sequence variable has a significant and positive relationship to property crime in all seasons, and the equality of coefficient tests show that it is greatest in spring. This indicates that property crime rates have been increasing throughout the study period, though not to the same degree in all seasons.

2.5.2 Violent crime

For violent crime, the relationship with temperature is positive in spring and autumn, but in winter it becomes negative and quadratic. Given the change in sign, it is unsurprisingly significantly different in winter than spring and autumn. As with property crime, routine activities theory explains the positive linear relationship between violent crime and temperature as a function of people leaving their homes during good weather, and being more likely to meet (Michel et al., 2016). However, unlike for property crime, temperature aggression theory is also applicable, as under this paradigm we would expect aggression to increase with temperature and lead to an increase in violent crime (Cohn, 1990).

That violent crime is more consistently sensitive than property crime to temperature is in line with previous research; however, this relationship should theoretically be quadratic in all seasons, given that people are less likely to go outside and interact in extremely cold or extremely hot weather (Rotton and Cohn, 2004; Towers et al., 2018). Despite theoretical predictions of quadratic relationships between weather and temperature, previous research at a large scale has found that violent crime has a more linear relationship to temperature than property crime (Ranson, 2014). Further, the use of separate models for each season in our study may explain this difference; extremely cold or extremely hot temperatures are less likely to both occur during the course of a single season than in the course of an entire year.

Unlike property crime, violent crime does have some association with precipitation. In summer and autumn, the occurrence of precipitation during a time period is associated with an increase in the amount of violent crime that occurs. This result is not in line with previous research (Michel et al, 2016; Towers et al., 2018), and is also contrary to what routine activities theory would predict; precipitation should make people less inclined to go outside and interact, and thus lead to a decrease in crime. However, our data does not include information on whether a crime is committed inside or outside; it is possible that the increase comes from incidents that are more likely to occur in the home or another building, such as domestic violence.

As with property crime, violent crime displays negative quadratic relationships to relative humidity in autumn and winter. Also as with property crime, this result is somewhat unexpected, both under routine activities theory and temperature aggression theory. Relative humidity ought to increase discomfort in association with high temperatures, decreasing crime according to routine activities theory or increasing it according to temperature aggression theory. However, the only interaction between temperature and relative humidity for violent crime is in winter, when temperatures rarely become hot enough for humidity to worsen heat-based discomfort. That relative humidity should influence crime occurrences on its own without the mediating influence of another variable, and that the relationship should be quadratic in nature, is difficult to explain using these theories.

In general, the calendar variables seem to be less important for violent crime than for property crime. This is in line with Ceccato's (2005) findings from Brazil. Statutory holidays have no relationship to violent crime in any season, and school breaks and weekends are only significant during the summer. During this time, school breaks are associated with a decrease in violent crime, while weekends are associated with an increase. The finding of an increase in violent crime on weekends matches previous research (Michel et al., 2016), and could be explained by routine activities theory, especially if people are more likely to be outside and engaging in leisure activities that bring them into contact with others on the weekend. Notably, there is also an interaction between temperature and weekends for violent crime; on summer weekends, increased temperatures appear to be associated with a decrease in violent crime. This is not necessarily the relationship we would expect, as both major crime theories considered in this study suggest that temperature should increase aggression and therefore violence. However, it is possible that some people choose to leave the city on hot summer weekends, decreasing the opportunity for violence. Given that there are more violent crime incidents on weekends, possibly due to an increased likelihood of offenders and victims meeting, we might then expect a similar effect from school breaks, particularly given that many youths are no longer occupied during the day and the pool of potential offenders increases (Cohn and Rotton, 2000). However, no such effect occurs in our study area, and school breaks are in fact associated with a decrease in violent crime during the summer.

As with property crime, the sequence variable has a positive relationship to violent crime; the only season in which this does not hold true is summer. In this case, we note that a significant positive interaction exists between temperature and the sequence variable. Overall, this suggests that the rate of violent crime has been increasing in North Bay throughout the study period, and that in summer, temperature is becoming more important to the rate of crime occurrence. We take this, in combination with the positive relationship between property crime and the sequence variable in all seasons, as an indication that North Bay is not experiencing the same crime drop that has been observed in North America as a whole (Farrell et al., 2014).

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Chapter 3: Identifying Seasonal Spatial Patterns of Crime in a Small Northern City

3.1 Abstract

3.1.1 Objectives

To explore spatial patterns of crime in a small northern city, and assess the degree of similarity in these patterns across seasons.

3.1.2 Methods

Calls for police service frequently associated with crime, including theft, theft of motor vehicle, shoplifting, break and enter, threats, family dispute, neighbor dispute, domestic dispute, assault, and sexual assault, were acquired for a five year time span (2015 – 2019) for the city of North Bay, Ontario, Canada (population 50,396). Exploratory data analysis was conducted using descriptive statistics and a kernel density mapping technique. Andresen's spatial point pattern test (SPPT) was then used to assess the degree of similarity between the seasonal patterns (spring, summer, autumn, winter) for each call type at four different spatial scales (dissemination block, dissemination area, census tract, neighborhood).

3.1.3 Results

Exploratory data analysis of crime concentration at street segments showed that break and enter and theft are more dispersed throughout the city, whereas shoplifting and sexual assault are more concentrated. While kernel density mapping appears to show different seasonal patterns for some crime types, the SPPT found no evidence of dissimilarity for any call type at the global scale. Where a degree of local dissimilarity exists, it is focused in only two areas of the city, one of which is the downtown core.

3.1.4 Conclusions

For the various crime types examined, preliminary analysis and kernel density mapping of the data showed seasonal patterns consistent with routine activities theory. However, application of the SPPT at four spatial scales found no global dissimilarity in seasonal patterns, which may indicate limited applicability in small study areas.

3.1.5 Key Words

crime mapping, seasonality, small city, spatial point pattern test, kernel density mapping

3.2 Introduction

Links between weather and the degree of criminal activity that occurs have long been of interest to researchers and policy makers alike (Cohn, 1990; Linning, 2015). Additionally, some authors have also studied the influence of seasonality on the rate and location of crime occurrence by integrating weather data with potential confounding factors that also vary on a seasonal basis (e.g. Linning et al., 2017; de Melo et al., 2018). These include cultural variables such as holidays and sporting events which tend to recur at the same time each year (Yiannakoulias & Kielasinka, 2016). Both weather and cultural variables, then, might be expected to contribute to crime’s similarly seasonal nature (Cohn & Rotton, 2000; McDowall et al., 2012).

There are currently a number of theories which try to explain various relationships often observed between crime, weather, and other seasonal variables. Among the earliest is the temperature aggression theory, which posits that heat makes people uncomfortable, and thus more likely to commit acts of aggression (Cohn, 1990; Brunsdon et al., 2009; Ranson, 2014). However, this theory is limited, as it only relates to crimes involving aggression, and only considers temperature, while a wide range of weather variables may influence crime (Brunsdon et al., 2009; Linning, 2015). Moreover, there is increasing evidence to suggest that temperature aggression theory is not an adequate explanation for the temporal distribution of violent crime (Hipp et al., 2004).

More recently, environmental theories of crime have gained considerable acceptance. Among the most popular is the routine activities theory. According to this theory, crime is most likely to occur where a potential offender, a suitable target, and a lack of guardianship occur at the same time and place (Cohen and Felson, 1979). However, a suitable target does not have to be a person; it could alternatively be a location, such as an unoccupied house, which represents an ideal target for burglars (de Melo et al., 2018). According to this theory, the times and places in which these circumstances intersect are determined by people's routine activities, which tend to be consistent in the absence of some external disruption (Cohn, 1990; Brunsdon et al., 2009). School holidays represent one such external factor, as they temporarily change the routine activities of both children and their parents or guardians. Weather is another such external disruption; for example, inclement weather conditions can change peoples' willingness to engage in various non-essential outdoor activities. Clearly, then, seasonal factors, based both on weather and culture can change peoples' routine activities, and thus change the likelihood of crime occurring during specific times and at particular places.

Yet another important and popular theory relating to the spatial distribution of crime is the crime pattern theory (Brunsdon et al., 2009). This theory considers the physical infrastructure of a city or other location, and how that infrastructure shapes people's movements and causes them to converge at certain times and at specific locations (Brantingham and Brantingham, 1993). At first glance, this theory does not appear to be useful for explaining seasonal patterns of crime. However, some researchers have found that in certain locations, use of infrastructure changes on a seasonal basis (Quick et al., 2019). As such, crime pattern theory does have the potential to explain seasonal variations in crime rates.

Clearly, both of the aforementioned environmental theories of crime provide mechanisms by which the location of crime, rather than just its intensity, might change based on the seasons and other environmental variables. However, several authors have commented that the literature on spatial responses of crime to weather and seasonal variables is extremely limited in comparison to studies focusing on the intensity of crime over time (Brunsdon et al., 2009; Linning, 2015; Haberman et al., 2018). In fact, we are aware of only one study that considers the location of crime as a response to different weather variables; Brunsdon et al. (2009) found that both temperature and humidity were related to the location of crimes in an unidentified UK city.

Investigations into the effect of season on crime location are more frequent. For example, Ceccato (2005) found evidence to support the hypothesis that crime in Sao Paulo, Brazil, clusters in different locations during different times of year. Szkola et al. (2019) took a predictive approach, using risk terrain modelling to determine the risk of firearms crime at different times and locations in Baltimore, MD, and found that for most locations, risk varied throughout the year. While neither of these two approaches explicitly aim to assess similarity in crime patterns over time, they nevertheless indicate that crime location is not always fixed, and that dissimilarity in crime patterns may exist between seasons.

Andresen & Malleson (2013) sought to determine the degree of similarity in crime patterns occurring between different seasons in Vancouver, BC. The results of their investigation found little similarity between the seasonal patterns of all the crime types they investigated. However, another study of Vancouver, conducted with the same technique but at a different scale, found an opposite result, indicating similarity between seasonal patterns of crime (Linning, 2015). Consequently, the question of scale appears to be an important factor for consideration in spatial studies of crime patterns.

Other spatial studies have taken a narrower focus, linking crime seasonality to demographic and economic variables, as well as features of the built environment. Sorg and Taylor (2011) found evidence that the socioeconomic status of neighborhoods in Philadelphia was linked to the degree of seasonality evident in their crime patterns. Breetzke and Cohn (2012) found a similar pattern in South Africa. Haberman et al. (2018) assessed whether the effect of certain kinds of criminogenic places, as well as demographic variables, changed between the seasons, to find that only high schools and higher educational institutions demonstrated a seasonal effect on crime activities. More recently, Quick et al. (2019) conducted a similar study and found that parks, restaurants and bars were associated with seasonal changes in crime rates, whereas high schools were not. In all of the aforementioned studies, the authors examine their results in light of the routine activities theory.

Much of the literature discussed thus far has been explicitly spatial. However, there are some themes from non-spatial weather and crime research that should be considered in this context, but do not seem to have received much attention. First, crime appears to interact differently with the weather and seasons in different cities (Hipp et al., 2004; Linning et al., 2017). These relationships may be mediated by a number of different factors, from population density to the degree of seasonality present in a city's weather patterns (Hipp et al., 2004). Further to this point, local culture can change how crime interacts with seasonality, as not all locations will have the same holidays and festivals, and even differing sources of employment can change peoples' routine activities (de Melo et al., 2018). Second, not all types of crime will respond in the same way to changes of weather and season. This is apparent in reviews of the early literature on this topic (Cohn, 1990), as well as more recent studies (Towers et al., 2018).

Also notable in the literature is a lack of research on patterns of crime, spatial and otherwise, in smaller urban centers. To the best of our knowledge, the smallest study area used in research related to seasonal spatial patterns of crime is Waterloo, Ontario, from Quick et al.'s (2019) study. The population of Waterloo itself was roughly 105,000 in 2016. However, the aforementioned study also includes the neighboring cities of Kitchener and Cambridge, as well as some outlying areas, forming the Regional Municipality of Waterloo, with a combined population of approximately 535,000 in 2016. Additionally, there appear to be no such studies for northern urban centers, which experience greater extremes in seasonal temperatures than the previous study areas. The present study aims to address this gap in the literature. Using five years of calls for service data from the city of North Bay, Ontario, a small northern urban center, we will first explore seasonal differences in crime concentration at the street segment level. Then, we will map seasonal patterns of crime using kernel density estimation. Finally, we use Andresen's SPPT to look for statistical evidence of difference in seasonal spatial patterns of crime at four spatial scales.

3.3 Data and Methods

3.3.1 Study Area

North Bay is a small city located in northern Ontario, Canada, that occupies an area of 327.43 km^2, much of which is forested. The populated areas of the city are concentrated between Lake Nipissing and Trout Lake (see figure 1). The population as of the 2016 census was recorded as 50,396, a decrease of roughly 2,000 since the preceding census of 2011. Despite the decrease in population, concerns about crime have been increasing, particularly in the downtown core (BayToday Staff, 2019; Pickrell, 2020; Campaigne, 2021). The city is served by its own municipal police force, the North Bay Police Service (NBPS).

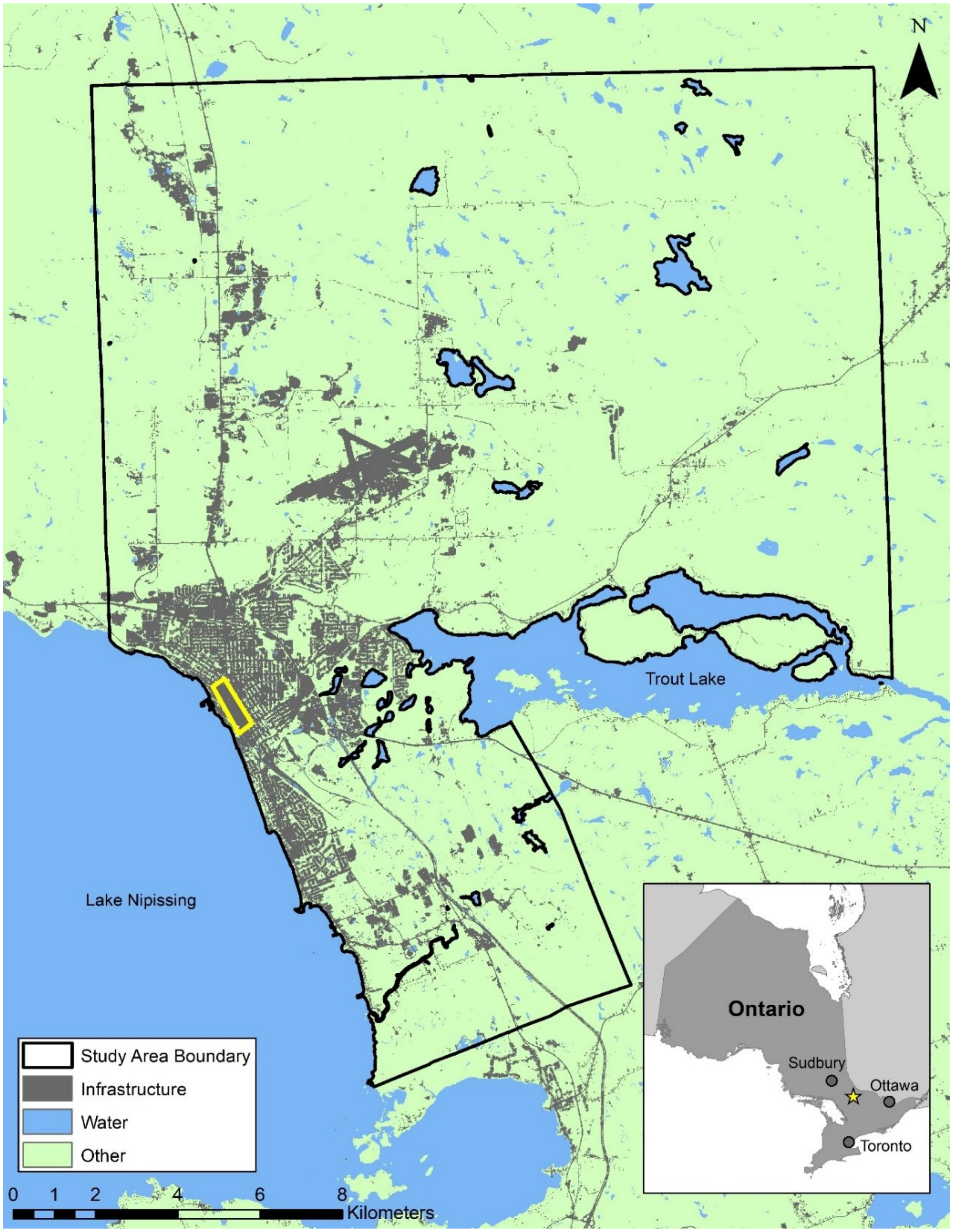

Fig. 1 Land cover in the city of North Bay, classified from Sentinel 2 imagery captured in June 2018. The location of the downtown core is highlighted in yellow.

North Bay experiences four distinct seasons. This study adopts a meteorological definition of seasonality. This definition is based on groupings of months with relatively similar mean temperatures, rather than the dates of solstices and equinoxes (Trenberth, 1983), and results in winter being defined as December to February, spring as March to May, summer as June to August, and autumn as September to November. These groupings of months are used by the Canadian government (Environment and Climate Change Canada, 2016), as well as other investigators (e.g. Cohn & Rotton, 2000; Haberman et al., 2018). The mean seasonal temperatures for North Bay are presented in table 1, which illustrates the distinct seasons typical to Northern Ontario. Summers in North Bay are frequently hot, with temperatures sometimes exceeding 30°C, and relatively little precipitation. Winters tend to be cold, with temperatures remaining well below freezing, and frequent snow fall events. Spring and autumn are more moderate in their mean temperatures but quite variable overall, with both rain and snow events being common.

Table 1 Seasonal temperatures in North Bay based on 2015-2019 weather station records

Season	Duration	Temperature (°C)		
		Mean	Standard Deviation	Range
Winter	December – February	-9.8	8.3	-34.2, 13. 2
Spring	March – May	2.5	9.3	-25.1, 29.5
Summer	June – August	17.9	4.6	2.9, 30.9
Autumn	September – November	6.8	8.7	-22.0, 28.5

3.3.2 Crime Data

Five years of calls for service data, spanning the period from January 2015 to December 2019, were provided by the NBPS. Calls for service include all incidents reported to the NBPS, both directly and through 911 (emergency services number), as recorded by the computer aided dispatch system (CAD). As such, they do not only represent crimes, but include such things as wellness checks and the very broad category "911 call". They also represent crime as reported to the police, and so can over or underestimate true crime rates to a degree that varies across the study area (Brower and Carroll, 2007; Buil-Gil et al., 2021). Despite this, calls for service are frequently used as a proxy for crime data, and may in fact have some advantages over other sources of crime data (Cohn, 1990), most especially in their temporal specificity (Brunsdon et al., 2009) and inclusion of location data (Andresen and Malleson, 2013). The North Bay dataset includes the date, time, reported incident type, and coordinates for each call. Some calls also have an associated street address, and an additional field for incident type as reported by the attending officer where this differs from the original call.

No information is available regarding the accuracy of the reported coordinates; however, two anomalous concentrations of calls were visible during initial data exploration. The first occurred at the NBPS's headquarters, and the second on a single street segment in the center of the city, 5 blocks north of the downtown core. The NBPS stated that neither of these concentrations represented known crime hotspots, and that the calls had therefore been erroneously assigned to these locations. As a result, calls at both the police headquarters and on the affected street segment were removed from this analysis, a total of 13,083 calls, representing 8.7% of the 151,031 calls in the original dataset.

The call types chosen for this analysis are those which are likely to be related to an actual crime, and which have more than 300 occurrences. Incident counts for each of these call types over the five year period are presented in table 2. Certain call types which would otherwise meet these criteria but whose patterns are likely to be determined by enforcement activities rather than the underlying pattern of crimes, such as narcotics crime, were excluded (Towers et al., 2018). Despite low incidence counts for several call types, we chose not to aggregate the calls into categories such as violent vs. non-violent. The rationale for this decision is that different crime types result from different underlying processes and thus display different patterns, which would be obscured by aggregating them into broader categories (Andresen, 2009; Andresen and Linning, 2012).

Table 2 Seasonal counts for calls for police service in the city of North Bay, 2015-2019

Call Type	TOTAL	Spring	Summer	Autumn	Winter
Theft	7251	1719	2304	1944	1284
Domestic Dispute	3713	895	1020	961	837
Break and Enter	1887	386	586	534	381
Assault	1875	480	459	503	433
Threats	1470	391	360	399	320
Family Dispute	1307	280	366	352	309
Neighbor Dispute	1023	239	330	234	220
Shoplifting	746	207	183	185	171
Sexual Assault	401	127	108	90	76
Theft of Motor Vehicle	342	80	96	90	76
Sum	20015	4804	5812	5292	4107

3.3.3 *Areal Units*

Part of this investigation requires the aggregation of crime incidents into polygons, which may be of various spatial scales. According to Weisburd (2015), the law of crime concentration states that crime will tend to concentrate in a few micro-places; that is, a very small proportion of locations in a city will account for a very large proportion of its crime incidents. These micro-places and their associated crime hotspots are generally quite small, consisting of a street segment or even just a building (Bernasco and Block, 2011). This would seem to imply that small areal units would be best able to capture the spatial patterns of crime in any given city, as large aggregation units have greater potential to obscure the actual locations of crime hotspots, or combine multiple hotspots that are in reality distinct. However, smaller areal units will generally contain fewer crimes, which can make it difficult to determine statistical significance, and also lead to volatility in the results (Malleson et al., 2019). In reality, there is no single most appropriate scale for crime aggregation; the most appropriate scale for any given study will depend on the research question, the crime type being analyzed, and the underlying processes responsible for the distribution of that crime (Hipp, 2007; Malleson et al., 2019).

In addition to concerns regarding the number of incidents in each polygon, it is important to be aware that any analysis relying on aggregation of incidents to larger polygons is vulnerable to the modifiable areal unit problem (MAUP) (Ratcliffe and McCullagh, 1999; Gerell, 2017). Both the size of the chosen polygons and the location of their boundaries, which are often arbitrary in nature, can influence the results of analysis. Gerell (2017) found that analyses using smaller polygons generally showed less evidence of the MAUP, as did those performed with administrative boundaries rather than random polygons. Several other authors agree that it is preferable to choose aggregation units which in some way represent the underlying structure and function of the city (Malleson et al., 2019; Vandeviver and Steenbeek, 2019). With this in mind, census polygons rather than a regular grid were chosen for this analysis. These polygons are defined by Statistics Canada based on areas of relatively homogenous socioeconomic characteristics, and where possible are bounded by physical features such as roads and waterways.

Several sizes of census polygons were considered for use as aggregation units. These were dissemination blocks, dissemination areas, and census tracts. In addition, a set of neighborhood polygons were digitized based on local real estate maps. These neighborhoods were of interest because they correspond to the way residents and local media frequently describe the different spaces of the city. They are also more consistent in area than any of the census polygons (see figure 2 and table 3). Given that the number of many call types in North Bay was quite low even before being split by season, low number problems were of particular concern for the present study. As such, census tracts were the favored aggregation unit for this analysis, in order to create the largest possible call count per areal unit. However, analysis was conducted at four scales to better understand what, if any, impact scale would have on crime similarity as measured by the SPPT.

Fig. 2 Aggregation polygons considered for spatial analysis of crime in North Bay. Top left: census tracts, top right: neighborhoods, bottom left: dissemination areas, bottom right: dissemination blocks.

Table 3 Summary statistics for aggregation polygons used in this investigation

Polygon Type	Number	Area (hectares)	
		Mean	Standard Deviation
Census tracts	17	1883.7	4871.5
Neighborhoods	25	1282.3	1390.6
Dissemination Areas	100	320.2	1183.6
Dissemination Blocks	639	50.1	335.7

3.3.4 Analytic Strategy

3.3.4.1 Descriptive Statistics and Exploratory Data Analysis

As a preliminary step, standard summary statistics relating to crime concentration were calculated for each call type in each season of the year. These statistics are the percentage of street segments in the study area which account for 50% of crime and the percentage of street segments for which any crime occurs. While these statistics are global, applying to the whole study area and providing no indication of where these concentrations of crime occur, they do provide a first glimpse of potential seasonal changes. They can also be interpreted in concert with later mapping for a fuller understanding of crime patterns in the study area.

To visualize seasonal crime patterns in North Bay, kernel density estimation (KDE) was used to map crime by season. This analysis was conducted in ArcMap 10.8, and a search radius of 650 m and a grid cell size of 10 m were used for all call types and all seasons in order to produce the most consistent maps possible. Although this procedure does not result in a statistical measure of difference in spatial patterns, the resulting maps allow us to compare crime patterns on a visual basis without aggregating to polygons, thus avoiding the MAUP and revealing details that might be hidden at the coarser resolution of the aggregation polygons.

3.3.4.2 Andresen's Spatial Point Pattern Test

While visual examination of the kernel density maps provides some idea of whether crime patterns in North Bay differ between seasons, such interpretation is limited; it is by nature subjective and cannot produce any numeric metric of similarity (Long and Robertson, 2017). To produce such a metric we employed Andresen's Spatial Point Pattern Test (SPPT). All versions of this test compare two point patterns occurring within a set of aggregation units to produce both local and global measures of similarity (Andresen, 2016; Steenbeek & Wheeler, 2020). For each aggregation unit, the most recent version of the SPPT conducts a test of the difference in proportions of points occurring inside and outside of the unit in each pattern. If the proportion of points occurring within the aggregation unit is significantly different between patterns, this unit is considered to be dissimilar at the local level (Steenbeek & Wheeler, 2020). Several difference in proportion tests are available; given concerns about low incidence counts, this study uses Fisher's Exact Test. We also chose to use the robust version of the SPPT, which ignores aggregation areas which contain no crimes in either point pattern. This is especially important for call types which cannot occur in certain aggregation areas, and prevents areas where crime cannot occur from falsely inflating the overall similarity index (Vandeviver and Steenbeek, 2019).

To compute the global similarity statistic, or S Index, the SPPT assigns a value of 1 to those aggregation units considered similar between the two patterns, and a value of 0 to those considered dissimilar. It then calculates the average of these values across the study area, which is equivalent to the percentage of aggregation units in the study area displaying similarity (Andresen, 2009). A value of 0.80 or above is considered to indicate similarity in the study area as a whole, while values below this are assumed to indicate dissimilarity (Andresen & Linning, 2012). It is important to note that this is a rule of thumb; the index indicates the degree of similarity and is not useful in a binary context, such as determining whether the similarity of two patterns is statistically significant or not (Andresen, 2016).

For each call type, we used the SPPT to conduct pairwise comparisons between the point pattern occurring during each season of the year. Where the global S Index indicated that some aggregation areas are dissimilar at the local level, we produced maps to visualize the location of this dissimilarity.

3.4 Results

3.4.1 Descriptive Statistics and Exploratory Data Analysis

3.4.1.1 Crime Concentration

The descriptive statistics calculated for the study area, presented in table 4, indicate that crimes appear to occur at relatively few places in the city of North Bay. Of all the call types under consideration, shoplifting is most concentrated. The degree of concentration varies for other call types, with sex assaults being the next most concentrated, and thefts and break and enters being most widespread. Within crime types, concentration does vary somewhat between seasons, with calls being most dispersed in either spring or summer. However, while these measures of concentration hint that there might be differences in the spatial pattern of crime between seasons, they do not indicate where these differences occur, or whether they are a matter of intensity or location.

Table 4 Crime concentration, described as percentage of street segments (N = 2915) that account for all calls, and for 50% of calls, 2015-2019

Call Type	% of Street Segments with any Crime				% of All Street Segments Accounting for 50% of Crime			
	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter
Threats	7.82	8.16	8.16	7.38	1.82	2.20	1.82	1.89
Assault	8.27	8.95	9.19	7.55	1.27	1.82	1.72	1.41
Sexual Assault	3.16	2.78	2.47	2.13	0.96	0.93	0.93	0.82
Break and Enter	9.09	13.34	11.87	9.19	2.50	3.70	3.19	2.64
Neighbor Dispute	4.84	6.72	5.35	5.11	1.30	1.65	1.34	1.37
Family Dispute	6.17	7.75	7.41	6.69	1.65	2.09	1.89	1.65
Domestic Dispute	14.10	16.50	14.31	14.00	2.71	3.46	2.81	2.78
Shoplifting	0.55	0.65	0.48	0.58	0.03	0.03	0.03	0.03
Motor Vehicle Theft	2.54	2.85	2.81	2.20	1.17	1.20	1.27	0.89
Theft	22.74	29.37	26.79	17.63	2.98	4.22	4.01	2.16

3.4.1.2 Spatial Patterns of Crime

The kernel density maps can help to clarify whether the differences in concentration between the seasons constitute a change in intensity or a change in locations, and are presented here in order from most voluminous call type to least (figures 3 to 12). The consistency between spatial patterns varies for each call type; many of the most frequent calls, such as thefts (figure 3), domestic disputes (figure 4) and assaults (figure 6) display a relatively consistent pattern despite changes in intensity between the seasons. Other call types, such as motor vehicle theft, exhibit visually distinct patterns between the seasons (figure 12). The call type with the most consistent location across seasons, however, is shoplifting (figure 10), despite its relatively low occurrence rate. Many call types are concentrated in the downtown area of the city and the adjacent residential area, though some are more widespread, with smaller concentrations occurring throughout the city. Note that, while the seasonal maps within each call type use a common scale of density, the different call types do not use the same scale, so a high density of motor vehicle thefts does not indicate the same density of incidents as a high density of thefts.

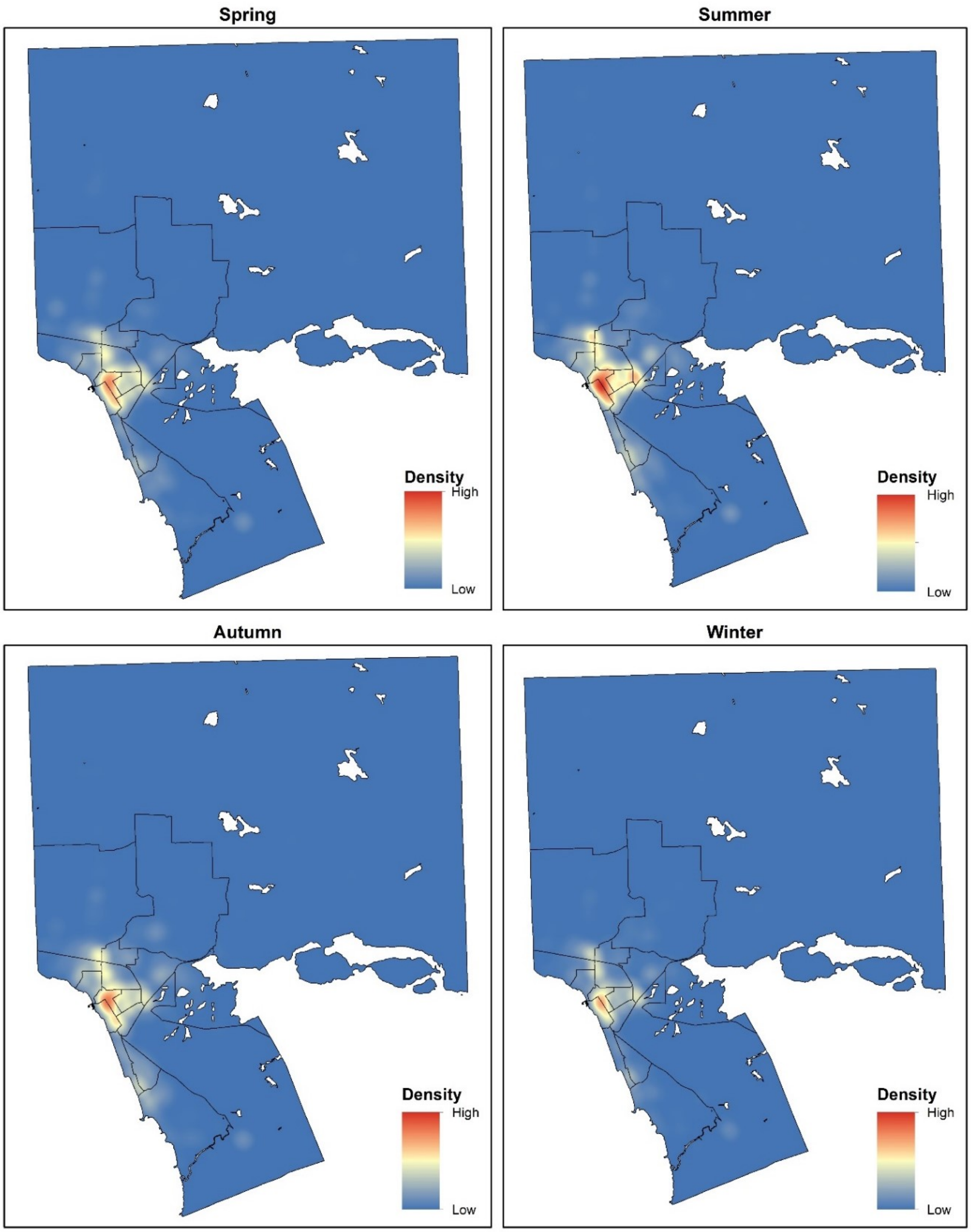

Fig. 3 Kernel density maps of thefts in North Bay overlain on census tracts, 2015-2019

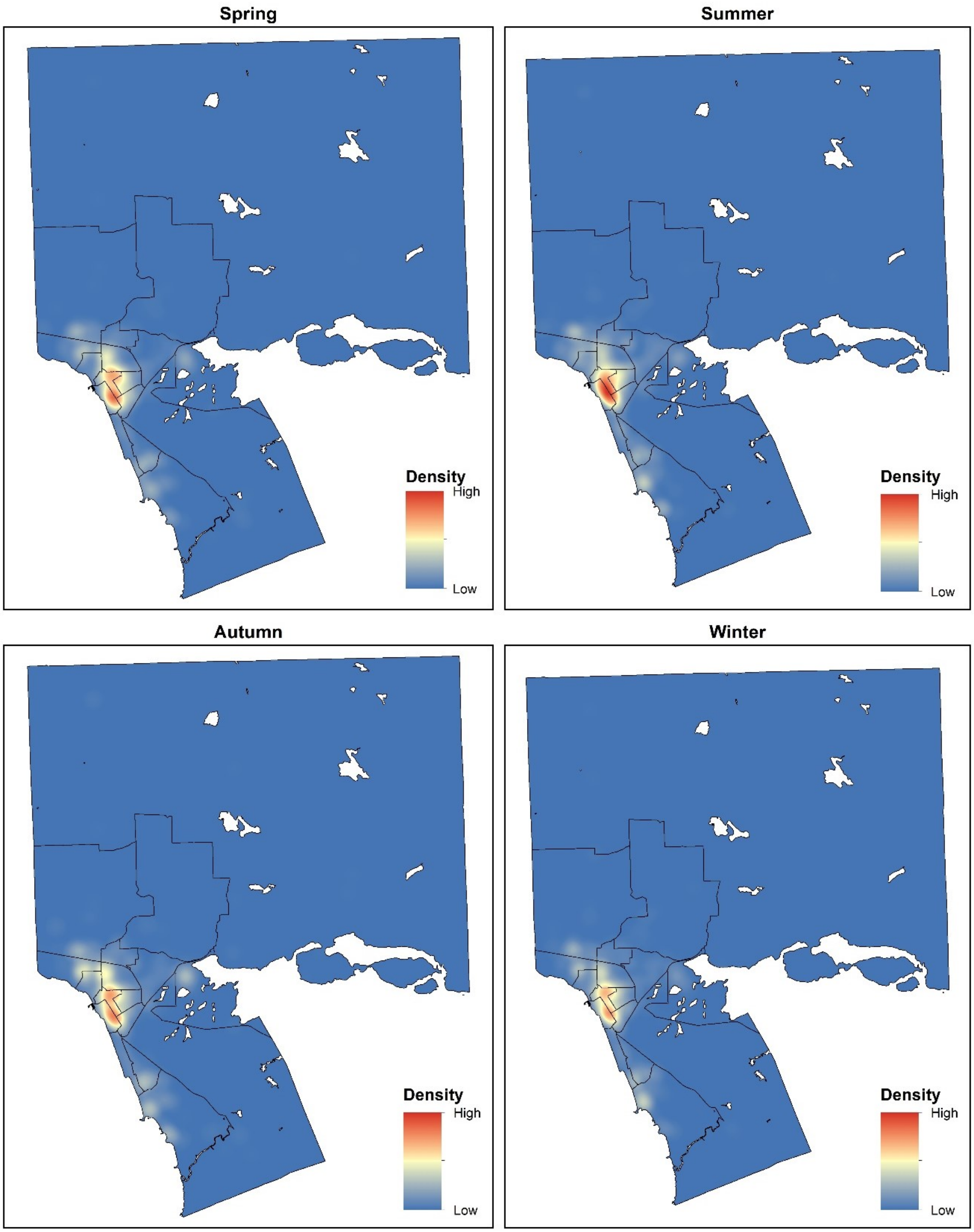

Fig. 4 Kernel density maps of domestic disputes in North Bay overlain on census tracts, 2015-2019

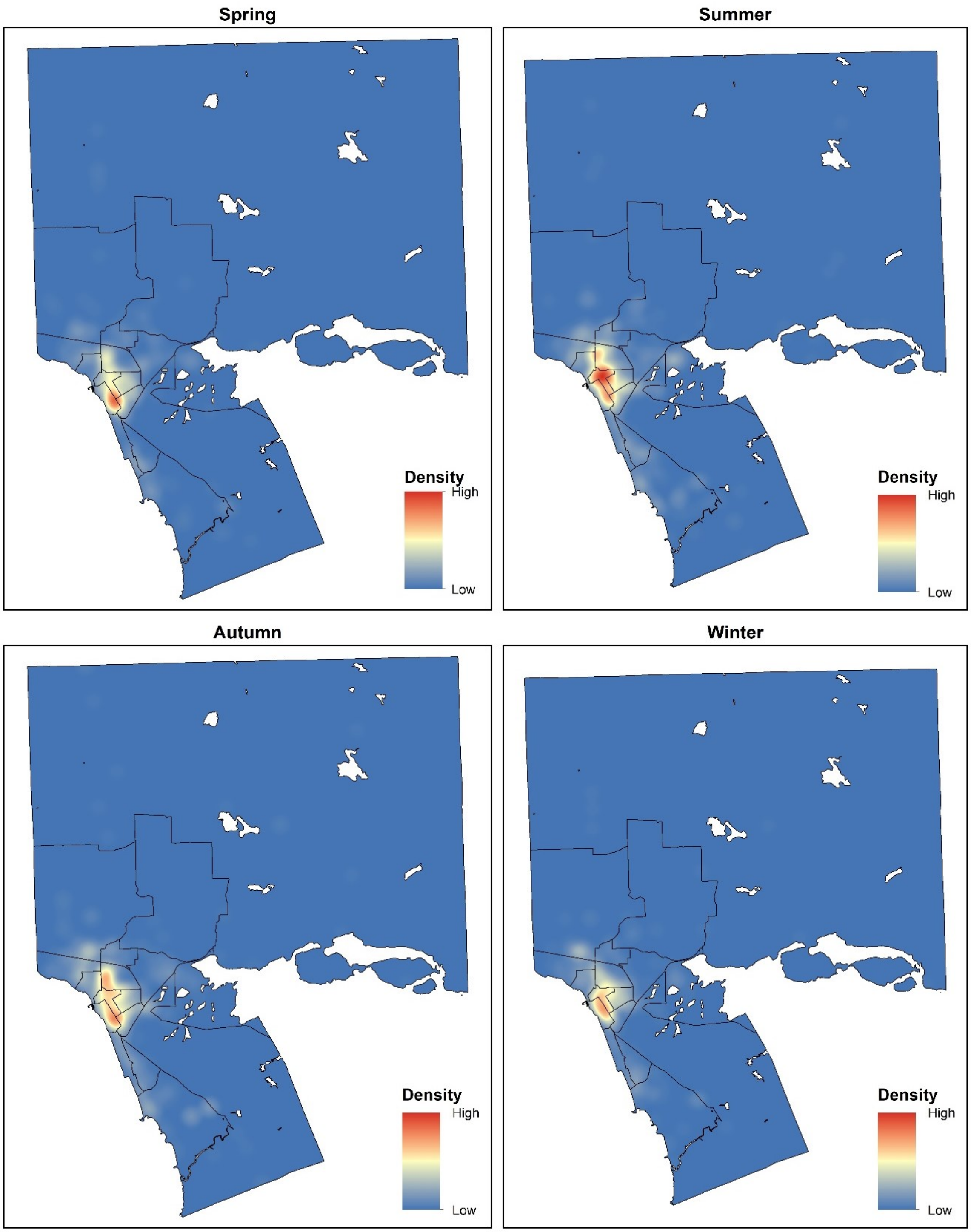

Fig. 5 Kernel density maps of break and enters in North Bay overlain on census tracts, 2015-2019

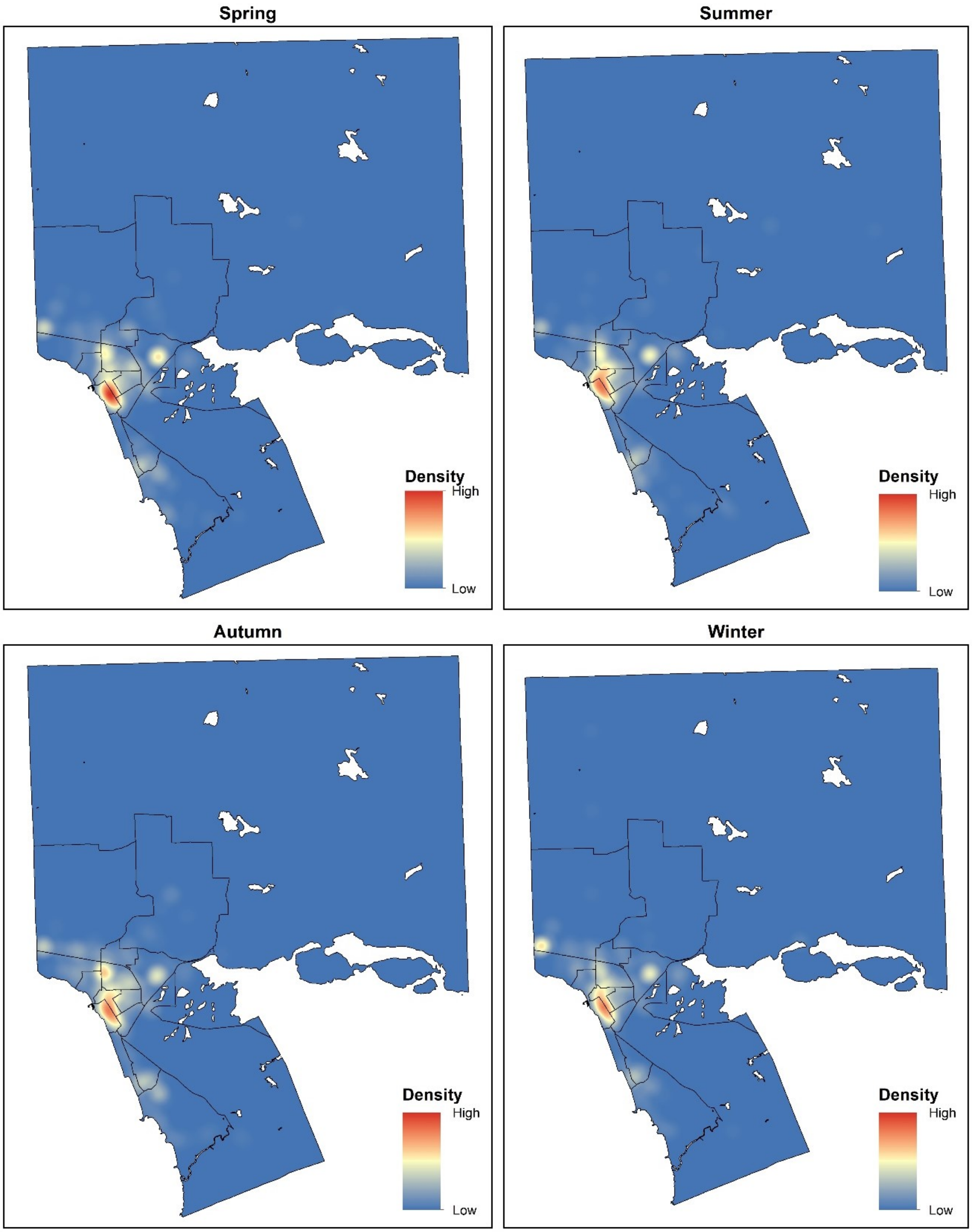

Fig. 6 Kernel density maps of assaults in North Bay overlain on census tracts, 2015-2019

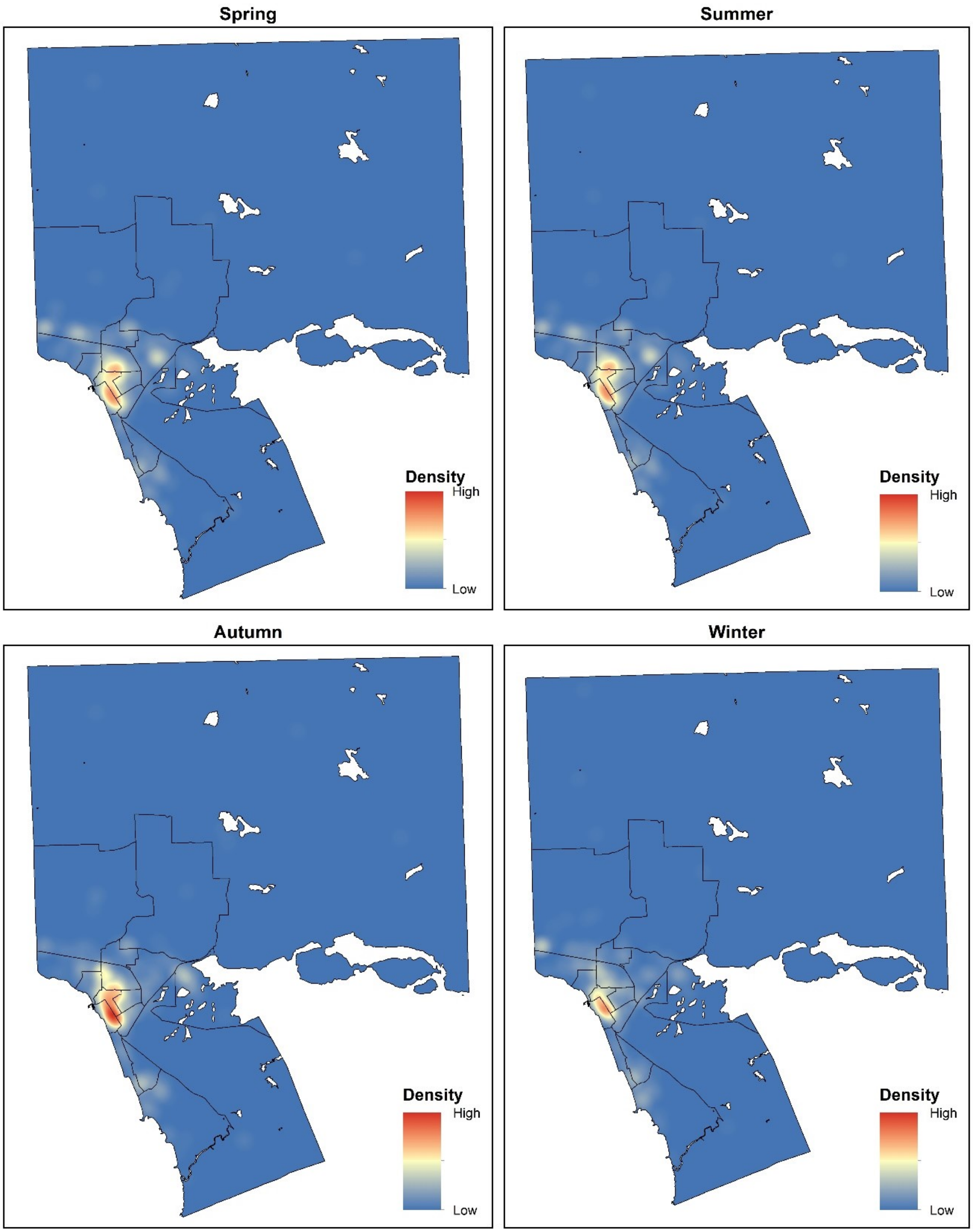

Fig. 7 Kernel density maps of threats in North Bay overlain on census tracts, 2015-2019

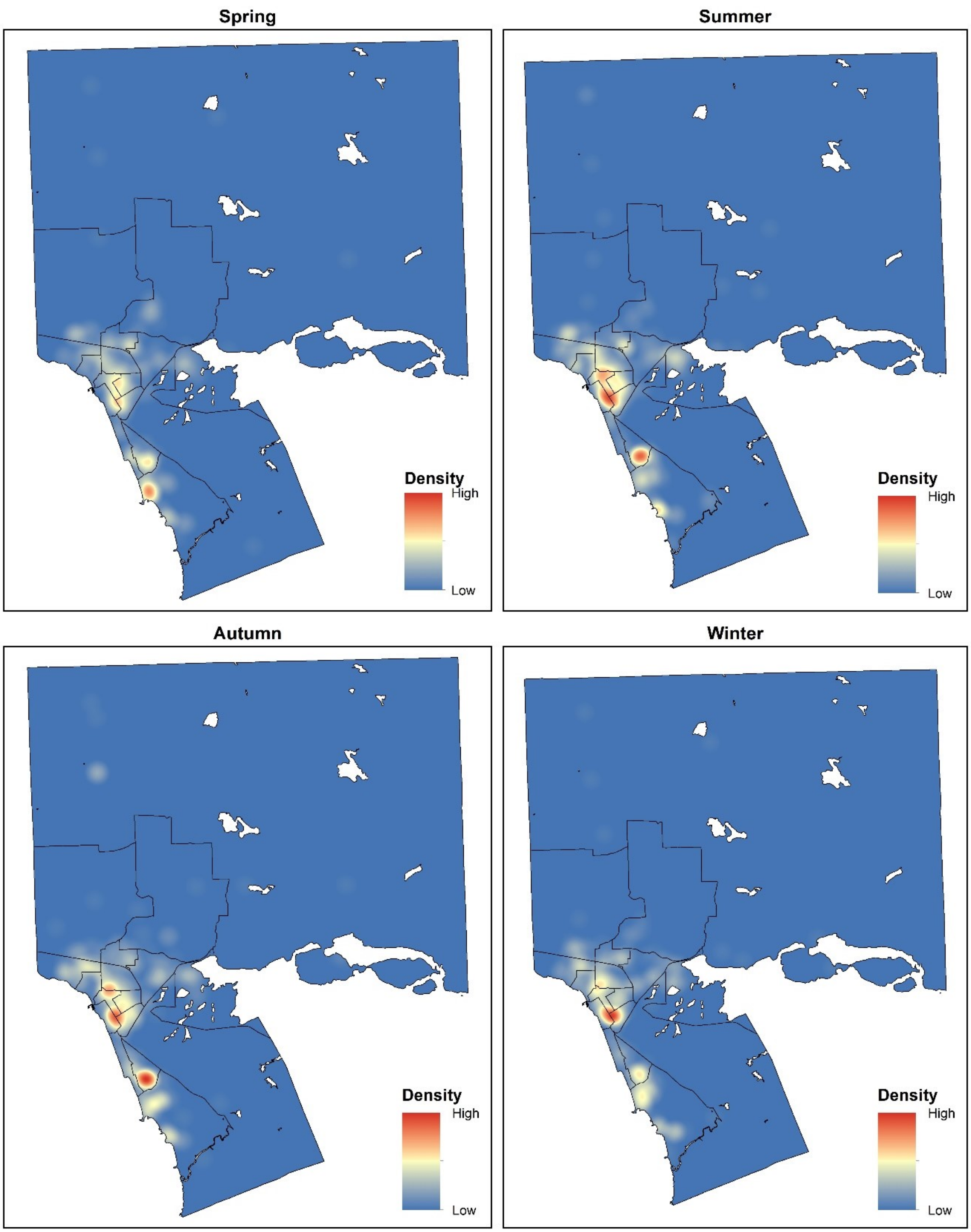

Fig. 8 Kernel density maps of family disputes in North Bay overlain on census tracts, 2015-2019

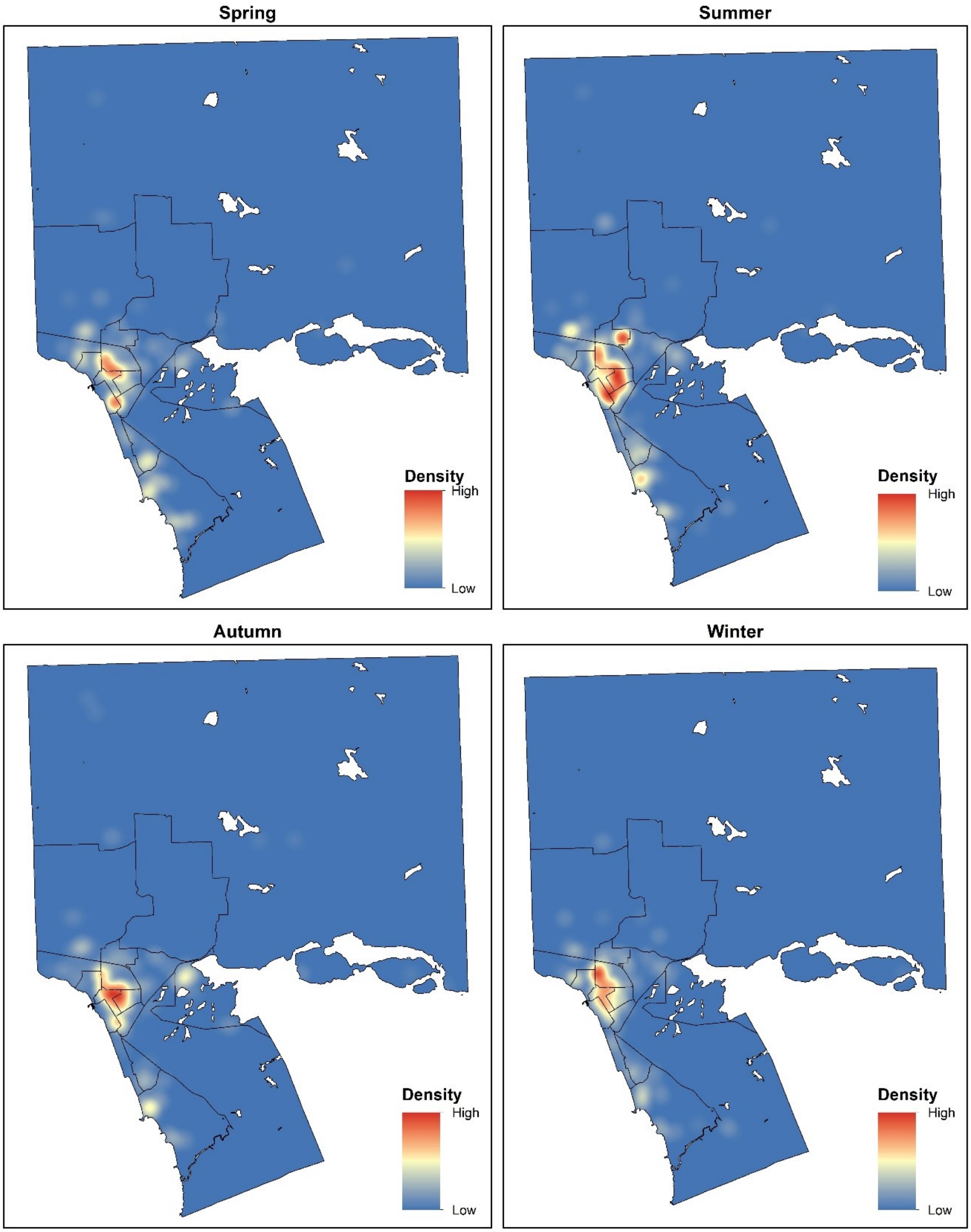

Fig. 9 Kernel density maps of neighbor disputes in North Bay overlain on census tracts, 2015-2019

Fig. 10 Kernel density maps of sex assaults in North Bay overlain on census tracts, 2015-2019

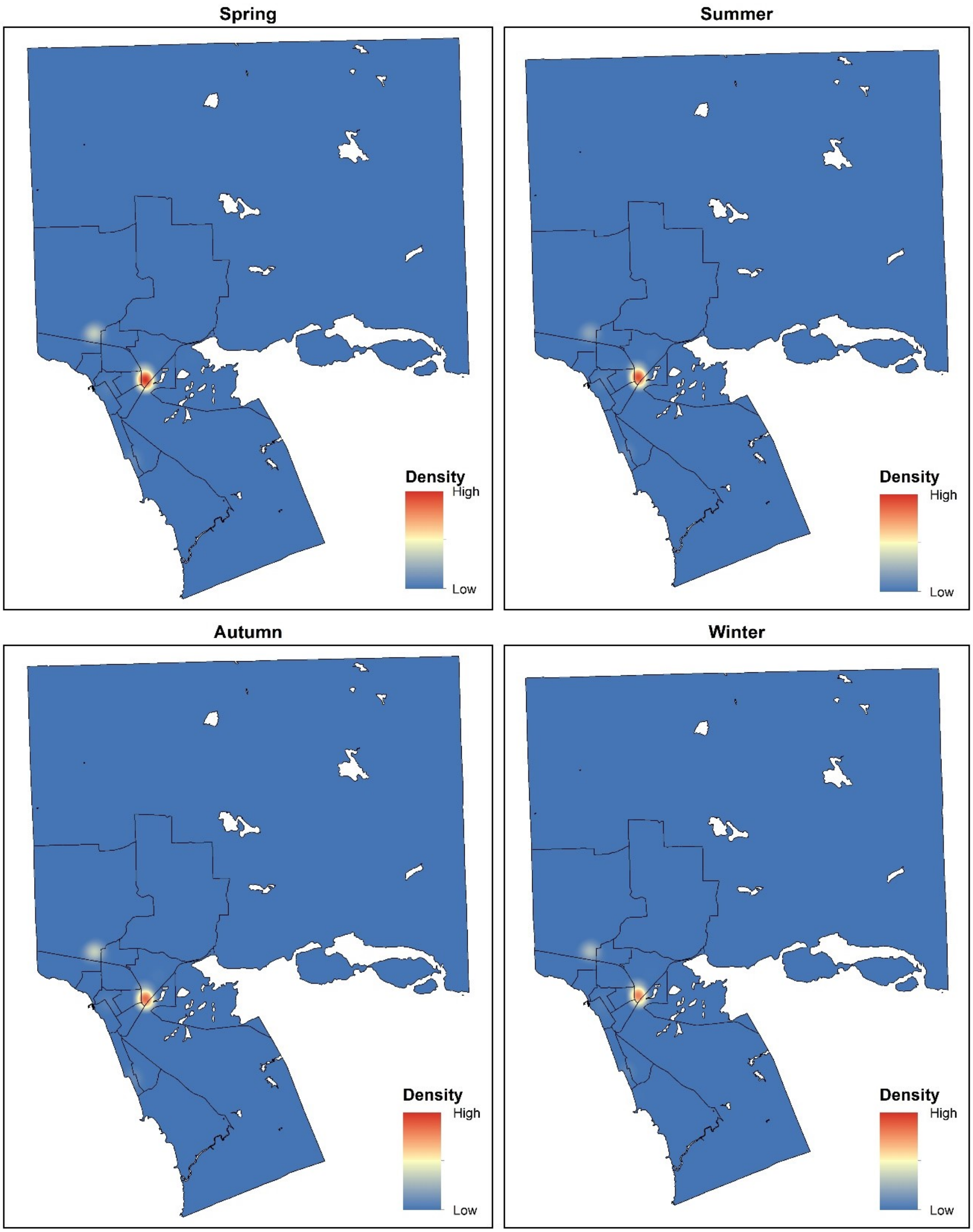

Fig. 11 Kernel density maps of shoplifting in North Bay overlain on census tracts, 2015-2019

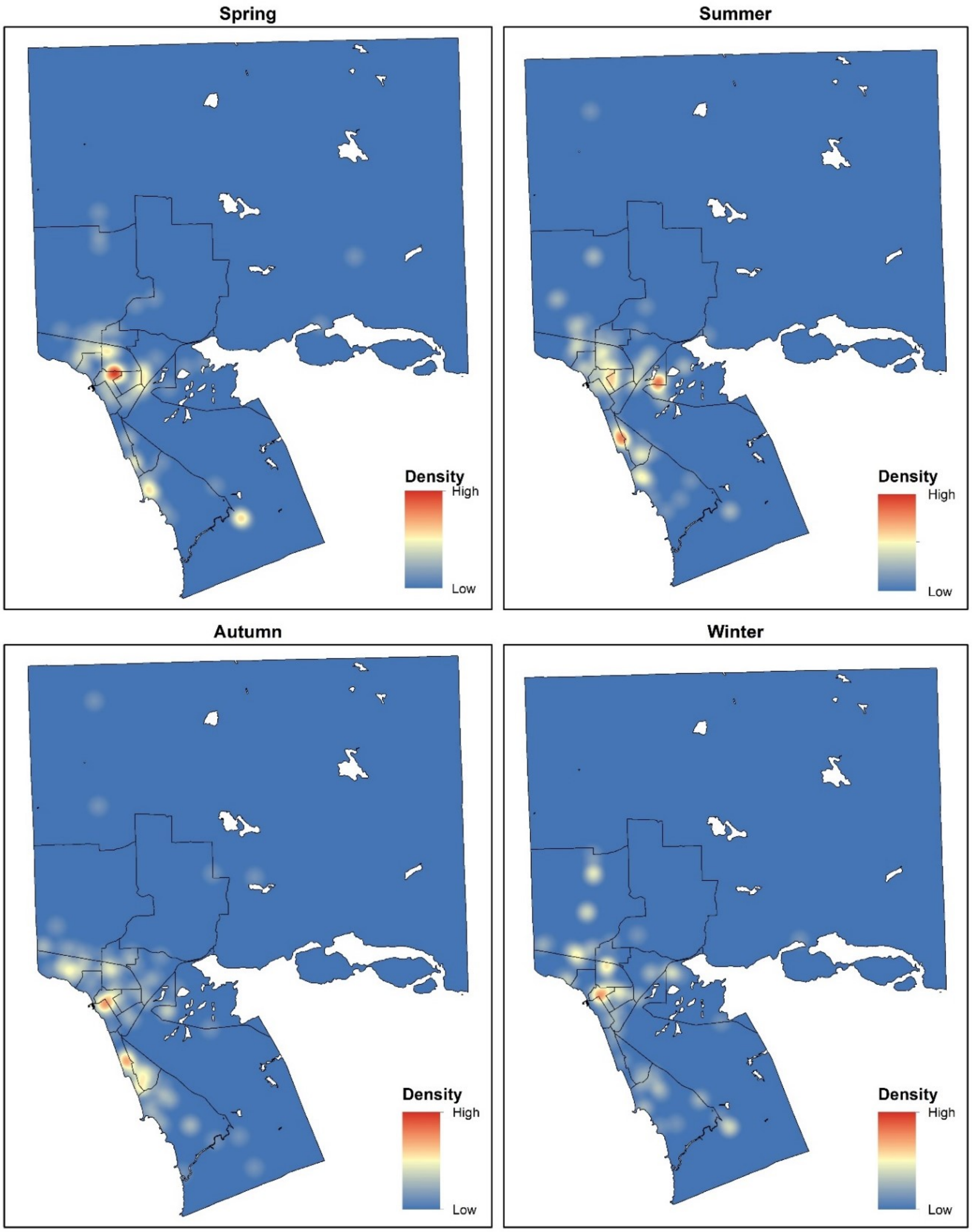

Fig. 12 Kernel density maps of motor vehicle thefts in North Bay, 2015-2019

3.4.2 Andresen's Spatial Point Pattern Test

The numeric results of a series of pairwise comparisons conducted using the SPPT, representing the degree of similarity between call patterns between seasons, are presented in table 5. The majority of call types display perfect similarity in pattern, indicated by an S index of 1, at all scales and between all seasons. In those instances where the degree of similarity is not perfect, the S Index still never reaches the rule of thumb value of 0.80 which would indicate dissimilarity between the spatial patterns. Most of the comparisons which do not indicate perfect similarity are at the census tract scale. Thus, despite small differences in the S Index of some call types, we find no evidence of dissimilarity in the seasonal pattern of calls in the city as a whole, at any of the scales tested.

Table 5 S index values for comparisons of seasonal crime patterns indicating less than a perfect degree of similarity

Call Type	Seasons	Scale	S Index
Break and Enter	Spring vs. Summer	Neighborhood	0.952
	Summer vs. Winter	Census Tract	0.941
Theft	Spring vs. Winter	Census Tract	0.882
	Summer vs. Winter	Census Tract	0.941
	Autumn vs. Winter	Census Tract	0.941
Neighbor Dispute	Autumn vs. Winter	Census Tract	0.941
	Summer vs. Autumn	Census Tract	0.941
	Summer vs. Autumn	Dissemination Block	0.995
	Summer vs. Autumn	Dissemination Area	0.989

Maps of local similarity are presented for call types and seasons displaying less than perfect similarity (figures 13 to 17). Notably, the location of changes in proportions of neighbor disputes in summer vs. autumn is consistent across several scales. At first reading, this might suggest that the MAUP is not a concern for neighbor disputes during these seasons, even at the local level. However, an examination of the maps for this particular call type (figure 13) shows that the boundaries of the polygon in question remain roughly the same across scales, possibly accounting for the consistency. Also of interest, the proportion of thefts occurring in the downtown polygon is significantly lower in winter than in any of the other seasons (figure 14).

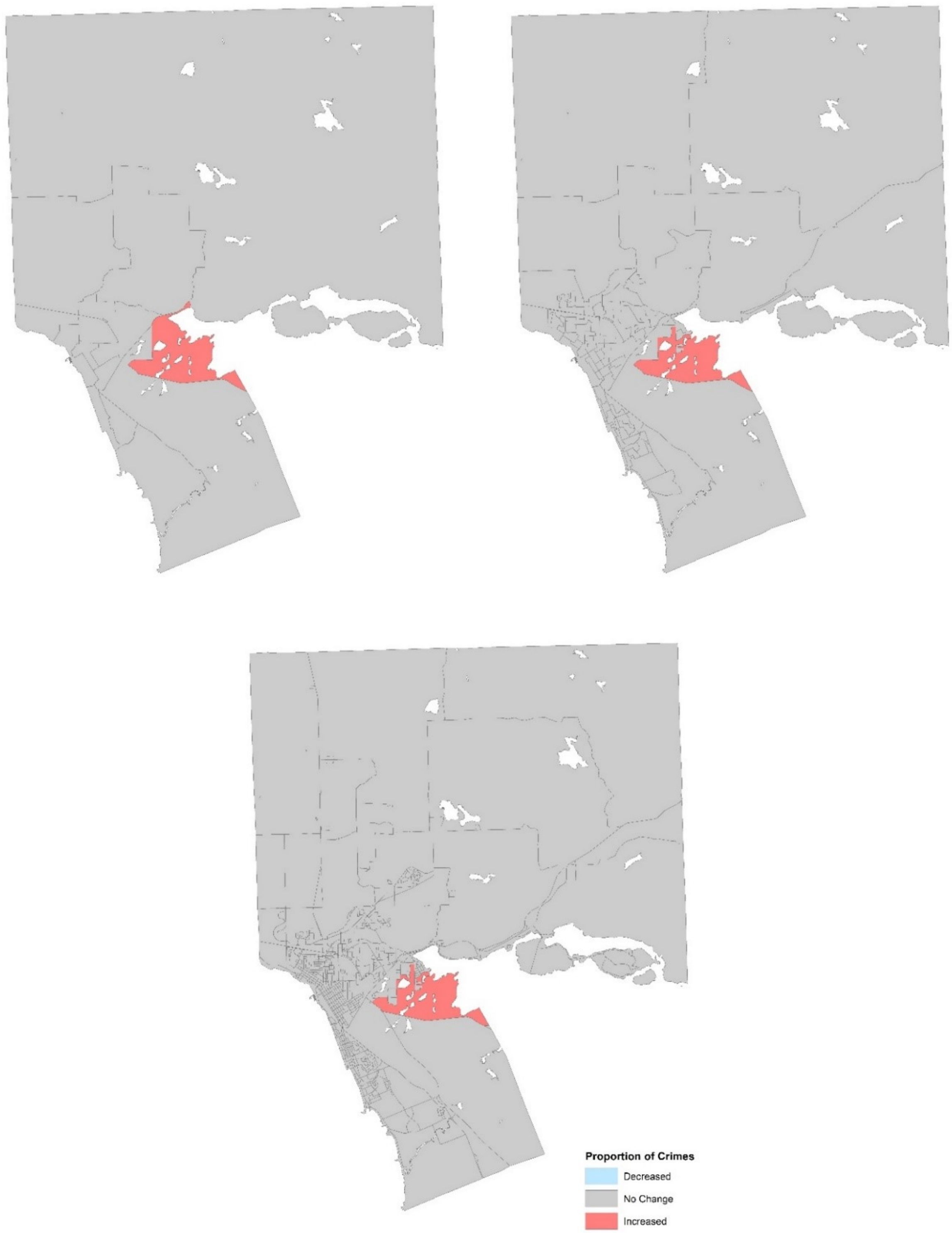

Fig. 13 Changes to the proportion neighbor disputes occurring in North in summer as compared to autumn. Top left: census tracts, top right: dissemination areas, bottom: dissemination blocks

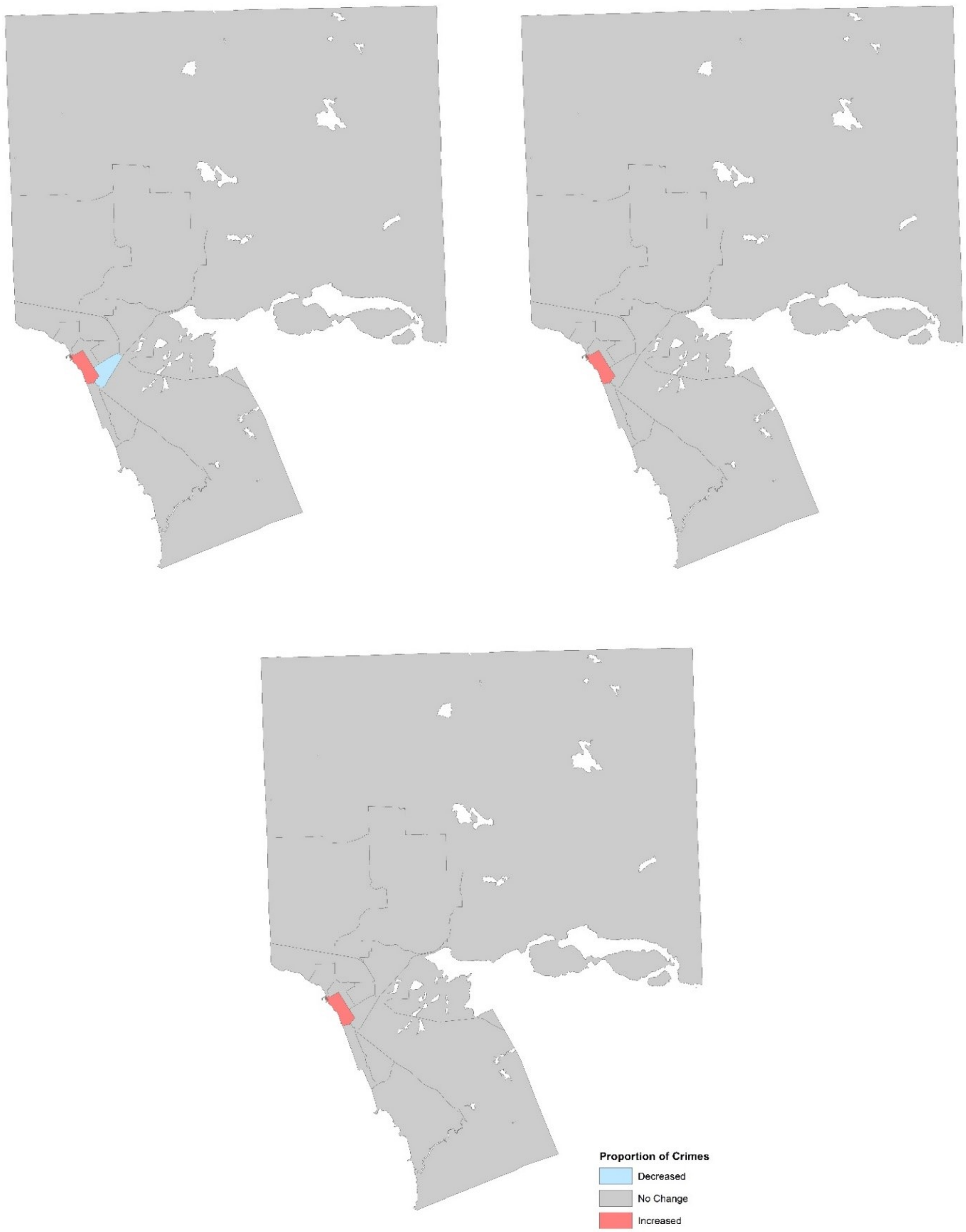

Fig. 14 Changes to the proportion thefts occurring in North Bay census tracts, as compared to winter. Top left: spring, top right: summer, bottom: autumn.

Fig. 15 Changes to the proportion of break and enters occurring in North Bay census tracts, in summer as compared to winter

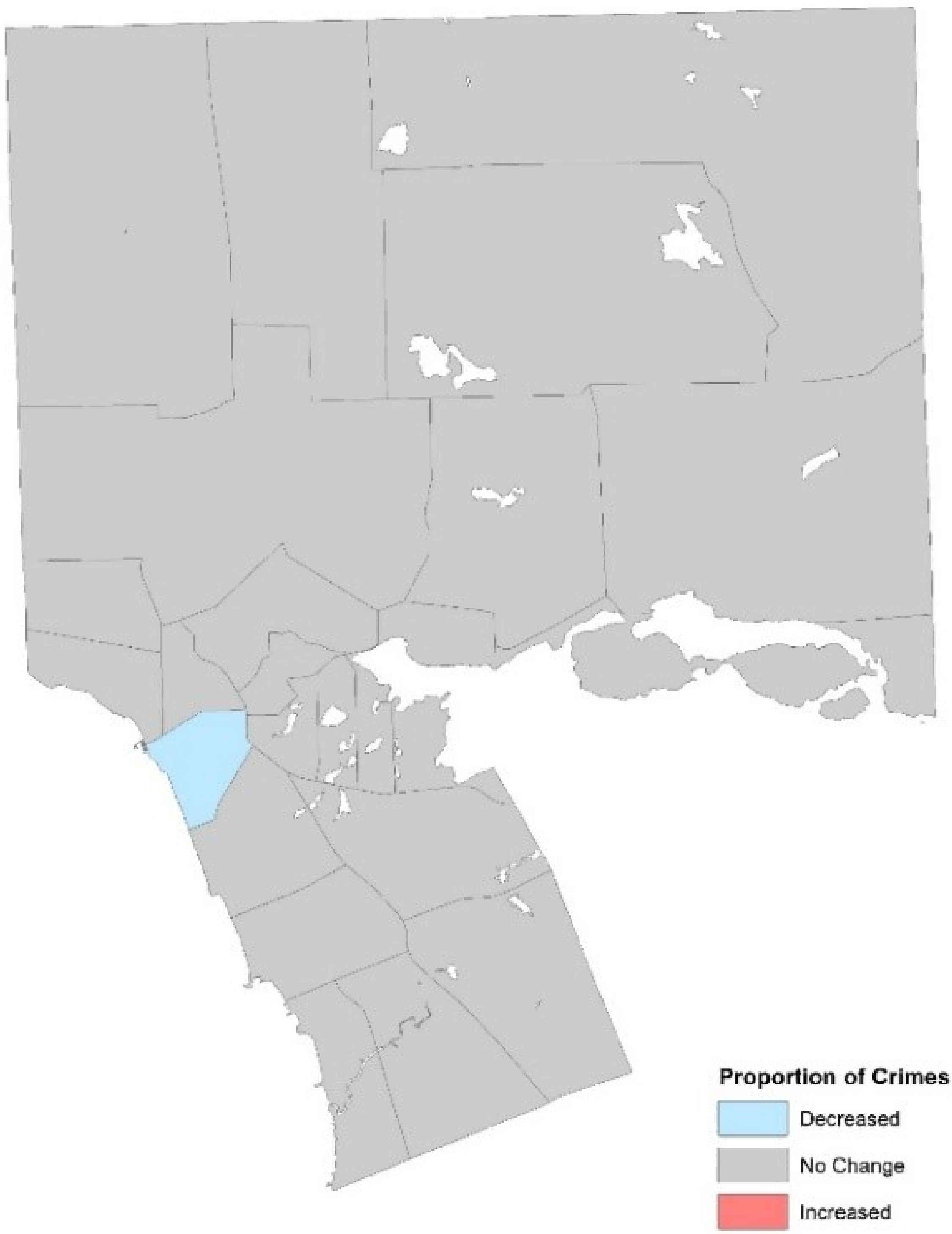

Fig. 16 Changes to the proportion of break and enters occurring in North Bay neighborhoods, in spring as compared to summer

Fig. 17 Changes to the proportion neighbor disputes occurring in North Bay census tracts, in autumn as compared to winter

3.5 Conclusion and Discussion

3.5.1 Crime Concentration

The crime concentration statistics summarized in table 4 agree with Weisburd's law of crime concentration; crime in North Bay is concentrated at relatively few places. In addition, changes in crime concentration do appear to occur across the seasons for many call types, which would imply a change in the locations of crimes. We do not apply significance testing to these values, but rather present them as an exploratory step in our data analysis.

The crime type which changes its concentration the least across seasons is shoplifting. This is also the most concentrated call type. That shoplifting should be more concentrated than other call types is logical given that it can only occur on street segments with retail establishments, which excludes much of the city. Those crimes that can occur in residences or public spaces have the potential to be distributed across a far greater proportion of places in North Bay. All but one of the other call types are least concentrated in summer, indicating that crime occurs in a greater number of places during this season. This finding is in line with routine activities theory, as people should be more likely to participate in outdoor leisure activities during the summer when the weather is hot, thus increasing their contact with others, and also the number of places that they visit. Both of these factors would increase not only the number of crimes, but also the number of places crimes occur.

3.5.2 Spatial Patterns of Crime

Some interesting trends are apparent in the kernel density mapping. First, the five most frequent call types are heavily concentrated in the downtown core of the city and adjacent densely populated neighborhoods (see figure 18), regardless of season. North Bay's downtown core is characterized by a mixture of small independent retailers and abandoned storefronts, mixed with some housing. At the census tract level, it also incorporates the city's transit terminal, museum, library, and waterfront. The waterfront has been developed as a popular recreation area, and includes a marina, a walking trail, a bar, and extensive green spaces. Any of these features could attract people to visit the area, thus increasing both the pool of both potential offenders and victims, and the number of crimes that occur. The extension of these concentrations of crime into the most densely populated areas of the city also suggests that the convergence of people in time and space might be responsible for this general pattern. However, we note that most of the aforementioned crime concentrations are a little way inland from the lake, and thus more likely to be associated with the main street than the waterfront and its recreational amenities. Given the large numbers of abandoned businesses downtown, this raises the possibility that broken windows theory is also at play (Welsh et al., 2015). In its original conception, this theory posited that physical and social disorder in a neighborhood increase fear, causing families to leave and other residents to isolate themselves, leading to a lack of social control and an increase in crime. A number of studies have shown that offenders operating in the vicinity of decayed or abandoned properties tend to worry less about the attention of police or residents (Valasik et al., 2019), whether or not this lack of concern stems from fear and isolation. Taken together, this would seem to indicate that there is a perceived lack of guardianship in areas with physical disorder, thus linking broken windows and routine activities theory.

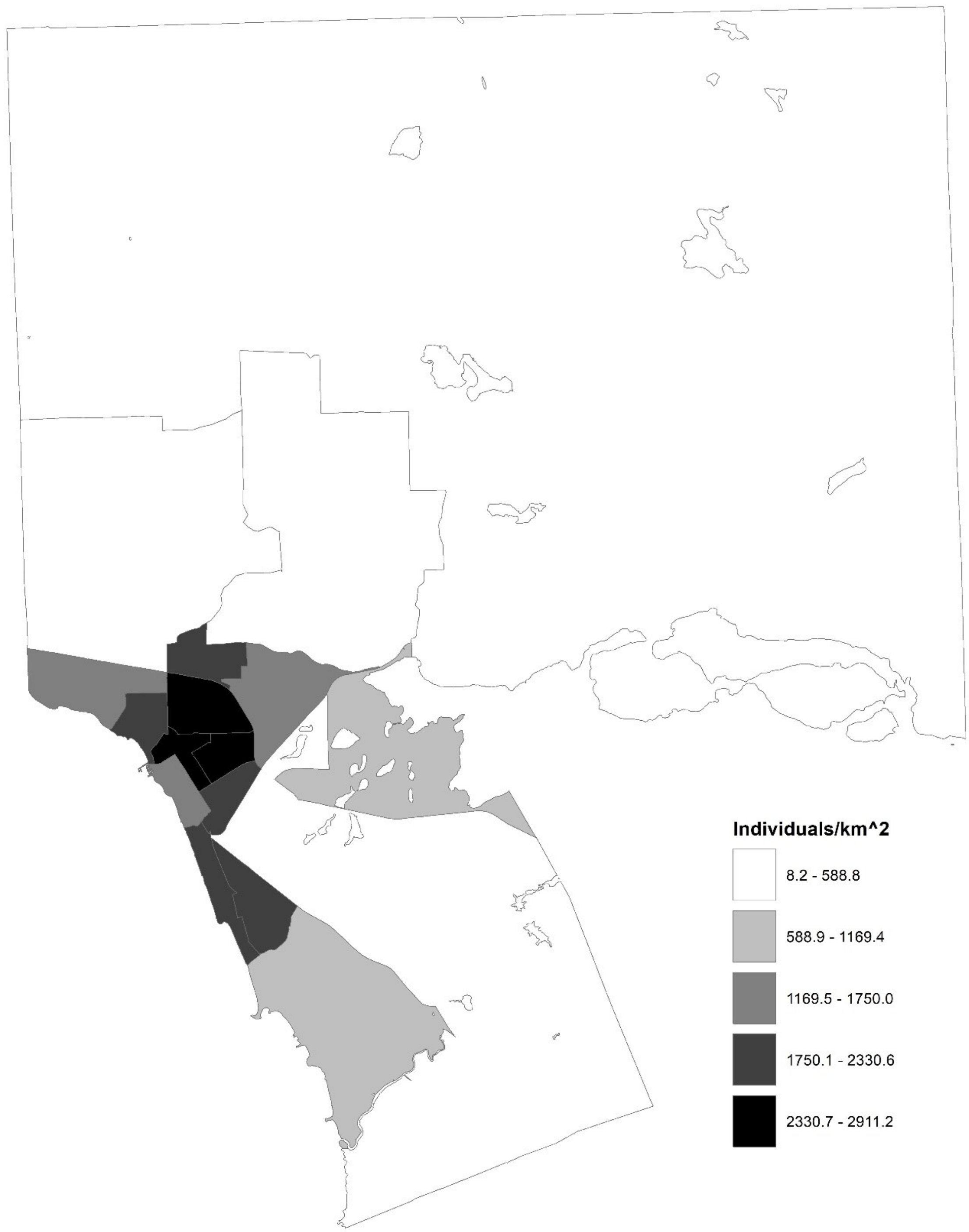

Fig. 18 Population density in North Bay census tracts, 2016. With data from Statistics Canada.

Those call types which are not concentrated downtown are not especially similar to one another, and defy description as a group. For example, shoplifting (figure 11) has only two concentrations in the whole city. The denser of the two is associated with the city's largest indoor shopping mall, while the less dense is located in a shopping district containing a grocery store, pharmacy, dollar store and several restaurants. Motor vehicle theft (figure 12), on the other hand, is distributed throughout the city, including both residential and commercial areas.

In terms of seasonal trends, many of the hotspots visible in the density maps change in intensity over the seasons, but not in location. This is the case for thefts, domestic disputes, break and enters, assaults, threats, family disputes, and shoplifting. This is not to indicate that the spatial patterns of these crimes does not change; a shift in greatest intensity from one location to another across the seasons, as happens with family disputes (figure 8) could be described as a change in pattern. For most call types, the hotspots appear most intense during the summer. Interpreted along with the crime concentration statistics in table 4, this suggests that while crime becomes more widespread in the summer, it is not spreading far, and those street segments that experience crime only during the summer are in roughly the same locations as those which experience crime year round.

Those crimes which do appear to change in location over the seasons are neighbor disputes, sex assaults, and motor vehicle thefts. The fact that all of these are among the least voluminous call types raises some concerns. It is possible that our small sample sizes limit interpretation. This is particularly true for motor vehicle thefts (figure 12), where the changes between seasons seem more or less random, and to the best of our knowledge are not associated with any particular land use or infrastructure features.

Changes in the pattern of sex assaults (figure 10) are somewhat more coherent. In spring and summer there are three intense hotspots, which shift location slightly but remain situated in the downtown core and surrounding densely populated neighborhoods. In autumn they become less intense, and the hotspot associated with the downtown disappears entirely, while in winter the hotspots barely exist, but have shifted back towards the downtown core. As previously discussed, these changes in intensity are in line with routine activities theory, given that more people should be outside and coming into contact with one another during the warmer weather. The shift back towards the downtown during the winter could potentially be explained by university and college students visiting the downtown's two bars at this time of year. However, there is no corresponding downtown hotspot during the autumn, which one might expect if this hotspot resulted from student visits to bars and restaurants.

At first glance, the changes in neighbor disputes are more expected, in that an intense summer hotspot appears in the portion of downtown that contains the most homes, perhaps indicating that people are spending more time outside and thus have more opportunities to find fault with their neighbors. A similarly intense but more constrained hotspot also appears to the north east during this season. However, neighbor disputes presumably are most likely to occur between neighbors, that is, when all parties involved are in the vicinity of their homes. As such, there is no immediately apparent reason that they should form such distinct patterns during different seasons. There is no obvious reason, for example, that people living downtown would spend more time outside during the summer than those from other parts of the city. Downtown has some of the lowest incomes in the city (figure 19), which raises the possibility that this pattern is related to the socioeconomic status of the residents. Ceccato (2005) noted that crime patterns can change based on popular vacation times, when residents from wealthier areas tend to travel while those from poorer areas do not; while the cultural setting of this study was much different from North Bay, it is possible a similar effect is occurring here.

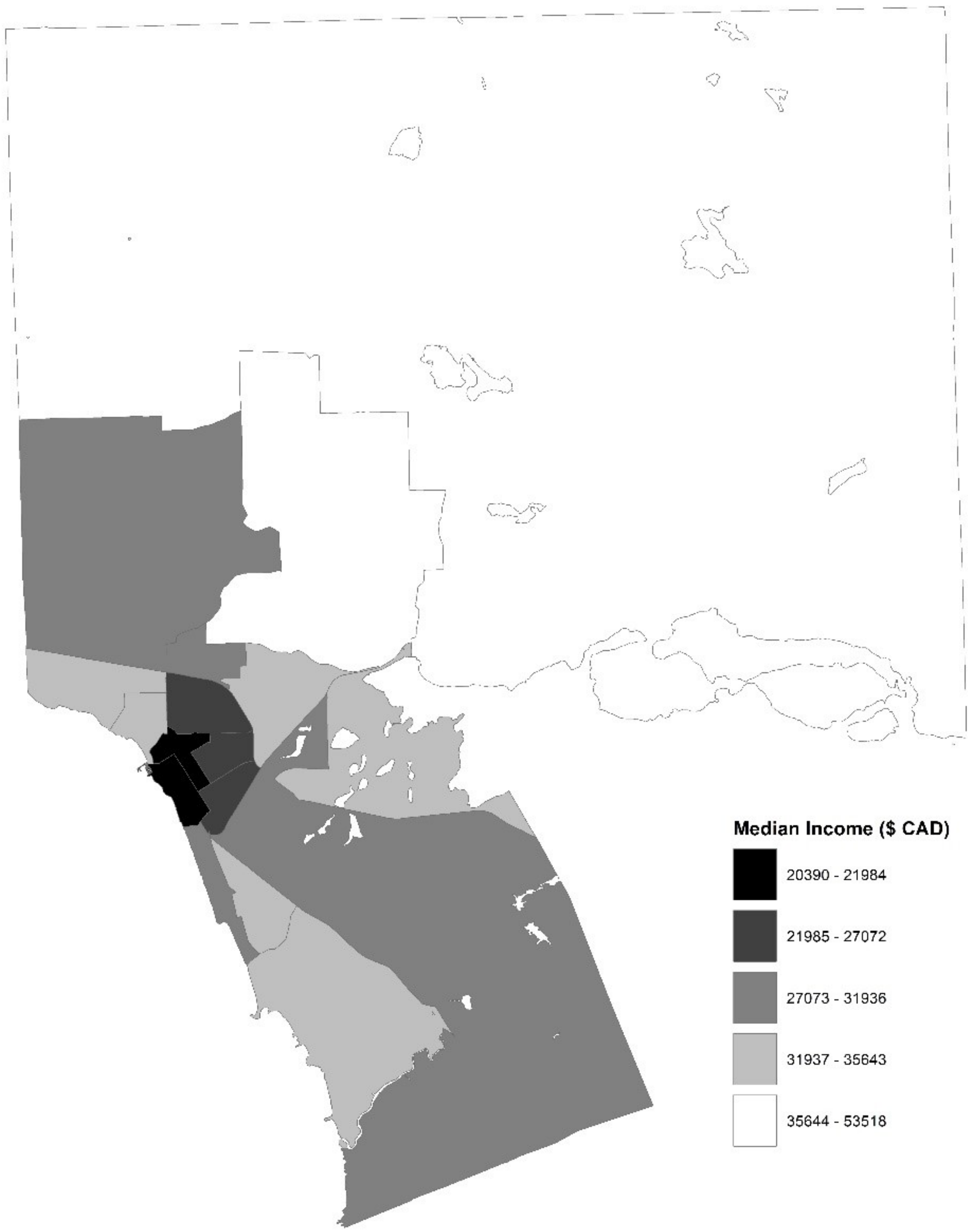

Fig. 19 Median income in North Bay census tracts, 2015. With data from Statistics Canada.

3.5.3 Andresen's Spatial Point Pattern Test

The consistency in the global similarity results across spatial scales is promising; at least for those scales tested here, changes in the size and boundaries of the aggregation polygons do not appear to be influencing our overall results. At the local level, the larger aggregation units do seem to find decreased levels of similarity. This is in line with the findings of Andresen and Malleson (2013) and Linning (2015) in their studies of Vancouver, where the larger aggregation units employed by Andresen and Malleson found considerably lower levels of similarity.

Two areas of North Bay seem to be the particular focus of dissimilarity in seasonal crime patterns. The first is the downtown core, which at the census tract scale experiences a decreased proportion of the city's thefts in winter compared to all other seasons. It also experiences a smaller proportion of break and enters in winter as compared to summer. At the neighborhood scale, the downtown core and surrounding area also experiences a decreased proportion of break and enters in spring as opposed to summer. The location of these changes in property crime is consistent with Linning's (2015) observations of motor vehicle theft in Ottawa, which similarly changed in intensity only in the downtown core, although notably motor vehicle theft itself appears not to have followed this pattern in North Bay. They are also consistent with Andresen and Malleson's (2013) results, which found increased levels of summer crime in Vancouver's central business district and other shopping areas.

Routine activities theory has excellent potential to explain the increase in crimes in the city's downtown during the summer. Previous work suggests that the parks are most likely to be associated with summer increases in crime (Quick et al., 2019), and given North Bay's climate, it is logical that the outdoor recreational areas downtown as well as the main street are likely to see more use in the warmer, drier weather of summer. Further, this area is used to host various outdoor concerts and festivals during the summer; similar events in stadiums have been shown to act as crime generators, increasing crime counts in the areas that host them (Kurland et al., 2014). The school summer break might also play a role in increasing use of the downtown area during the summer (Cohn and Rotton, 2000). This increased use would increase the likelihood of a potential offender and a suitable victim intersecting in time and space, although it should also increase the presence of capable guardianship. In particular, the parks are likely to be associated with the increase of property crimes during the summer.

In addition to its physical characteristics, discussed in section 5.2, the downtown core also has the lowest average income in North Bay (figure 19). Sorg and Taylor (2011) link low socioeconomic status to increased seasonality in street robberies in a neighborhood, and while robbery is by definition a violent crime, it also involves an element of property acquisition, and thus provides an interesting parallel to the trend of thefts in downtown North Bay. One potential area for future research would be to conduct quantitative analysis of the relationship between variables such as socioeconomic status and land use, to seasonality in crimes in North Bay, to understand by what mechanisms season and crime patterns are linked in this city.

The other area of the city that experiences local changes in crime proportion is a large aggregation unit on the shore of Trout Lake. This unit is the location of several seasonal differences to the proportion of neighbor disputes. In both summer and winter, it contains a higher proportion of the city's neighbor disputes than it does in autumn. This trend is more difficult to explain than downtown increases in property theft. In summer, at least, people are more likely to be outside and interacting with one another, and thus disputes are more likely to occur. A similar trend should not occur during the winter, however. This part of the city is both residential and industrial, with residences concentrated in the north of the aggregation polygon, and industry in the south west, connected. Further investigation, perhaps focusing on finer timescales or detailed exploratory mapping, might be able to shed light on the reason for these changes in pattern.

The rest of the city appears not to experience changes in crime patterns between the seasons, even at a coarse spatial scale, despite the existence of other locations that should theoretically see seasonal changes in use. These results are unexpected based on the kernel density mapping, which suggests changes in the location of crime hotspots between the seasons, at least for some crime types such as motor vehicle thefts. It is possible that only these two locations experience sufficient changes in their intensity of use to also affect crime rates to a degree that the SPPT finds statistically significant. They are also theoretically unexpected in that other crime types should also exhibit seasonal changes in location; this is especially true of crimes such as auto theft and assault which are less likely to be committed based on the physical characteristics of a location, and thus should be more mobile (Linning, 2015).

Given the theoretically unexpected results, there are some concerns regarding small sample size. Andresen and Malleson (2014) encountered similar problems in their analysis of crime displacement in a small study area, using an earlier version of the SPPT, and attribute the unexpectedly high similarity for some crime types to low incident counts. While steps were taken in our analysis to mitigate the potential adverse effects of low incident counts by including larger aggregation units, further research in small cities, and validation of the results based on other techniques, would be of great benefit.

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Chapter 4: Conclusion

4.1 Summary of Results

This study encompassed three main objectives. The first, which was essential in preparation for the later objectives, was to fully integrate two separate databases. The NBPS calls for service dataset contained locational data, while the weather and calendar dataset was aspatial. This objective was completed as described in section 1.6.2, and depicted in figure 3 of chapter 1. The other two objectives related to the analysis of these datasets; first, to analyze relationships between weather variables and crime, and second, to understand whether and how spatial patterns of crime differ between seasons in the city of North Bay. These objectives were also reached, and the results are outlined in the chapters 2 and 3 respectively.

At the seasonal level, the results of the aspatial analysis, objective 2, indicate significant relationships between crime and both weather and calendar variables in the city of North Bay. Specifically, in the case of property crime, the significant weather variables identified were temperature, relative humidity, and daylight hours. For violent crime, these variables as well as precipitation were found to be significant. However, the nature of these relationships vary between seasons. For property crime, for example, temperature is not significant during the summer, while the relationship to daylight hours was found to be significant in all four seasons, but is quadratic in spring and summer, and linear in autumn and winter. Temperature was found to be associated with a greater increase in spring than the other seasons. Violent crime differs again in its seasonal relationships; temperature is linear in spring and autumn but quadratic in winter, while daylight hours is again significant in all seasons, with autumn being linear and all others being quadratic.

Crime in North Bay has also been shown to have significant relationships to many calendar variables. Property crime appears to decrease on statutory holidays and over weekends. Moreover, the intensity of these relationships is largely consistent across the seasons. Violent crime, on the other hand, appears to decrease during the summer school breaks, and increase over summer weekends while remaining at normal levels on statutory holidays. Notably, the inclusion of a sequence variable in the regression analysis indicates that crime in the city, both property and violent, has been increasing over the study period. For property crime, this increase is significantly greater in spring than in any other season, while for violent crime, it is greater only in the spring in comparison to the winter.

In terms of the seasonal spatial patterns of crime, there was found to be little change between the seasons. While crime is frequently less concentrated in summer than other seasons, this does not correspond to an overall dissimilarity in the spatial pattern of crimes between seasons based on the SPPT. Based on kernel density analysis, crime in North Bay tends to be located downtown and in the surrounding residential areas, and appears to remain there regardless of the season. The exceptions to this are shoplifting, which is concentrated at the Northgate Mall, and motor vehicle theft, which is scattered across the city, though neither has any change in pattern between the seasons. Those call types which were found to exhibit a small change in pattern were break and enters, thefts, and neighbor disputes. Neighbor disputes increase in a census tract to the west of Trout Lake in summer as compared to autumn. Thefts decrease downtown during the winter as compared to every other season. Break and enters increase downtown in summer as compared to winter, and decrease to the west of Trout Lake in autumn as compared to winter.

As discussed in chapters 2 and 3, the observed relationships and patterns identified in this investigation can largely be described using the routine activities theory. The spatial findings, particularly the increase in several types of property crime downtown during the summer, likely relate to increased use of outdoor shopping and recreational areas during the warmer, drier periods of the year. The use of downtown parks for hosting festivals and events may contribute to this effect. This increased use of such places would likely bring more potential offenders and suitable targets into closer contact, increasing the likelihood of crime. In the case of break and enters, these suitable targets may in fact be the abandoned buildings downtown, rather than a person. Notably, the aspatial models found no indication of a relationship between property crime and weather or precipitation during the summer. However, this effect applies to the city as a whole, and not just to the downtown area. It is possible that crime-weather relationships differ in this location from those in the city as a whole, based on its land uses and other factors.

Not all the spatial patterns identified in this research endeavor are easily explained using crime theories. For example, neighbor disputes increase to the west of Trout Lake in several seasons, when there appears to be no reason for them to do so. More generally, though, the lack of differences in spatial pattern in other areas of the city is also puzzling. There are other locations in the city whose intensity of use might be expected to change on a seasonal basis. For example, one might expect changes around the university and the ski hill based on student seasonal residency and seasonal leisure activities respectively. Despite the fact that these changes in activities should also influence the likelihood of crime, no corresponding change in the seasonal pattern of crime in these areas appears to occur.

The aspatial results are in some ways easier to explain using the routine activities theory. For example, property crime in North Bay has a positive linear relationship to temperature in all seasons except summer, which might indicate that people are leaving their houses more in good weather, making both themselves and their homes more suitable targets for crime. The lack of a relationship during summer may simply indicate that the weather is sufficiently pleasant all the time that further increasing temperature has no impact on peoples' willingness to go outside. The same is true of daylight hours – property crime appears to increase during those time periods which have a high or moderate amount of daylight, perhaps because people are more likely to be out and about at these times, with a similar effect to increased temperatures. Notably, the routines tied to daylight hours may be obligatory, for example attending work and school, while the routines tied to temperature may be discretionary, for example recreation. The only result which is difficult to explain is the apparent quadratic relationship between property crime and relative humidity for several seasons; humidity in and of itself seems unlikely to influence peoples' activities during the cooler months when this relationship exists.

These results and explanations are also true of violent crime. Interestingly, it appears that the temperature aggression theory may not be as important for explaining the occurrence of violent crime in North Bay as the routine activities theory. If this was the dominant mechanism linking violent crime and temperature in the city, some kind of relationship between the two variables ought to exist in summer, when the highest temperatures occur. Even if the NAE model was in effect, there should be some sign of a quadratic relationship.

Finally, it is also important to discuss how calendar variables influence the observed patterns and relationships. Summer weekends have a significant positive relationship to violent crime, which may indicate more people coming into contact as described for property crime, whether in public or in their homes which coincides with the routine activities theory. However, property crime appears to have a negative relationship to both weekends and statutory holidays.

Under routine activities theory, this might simply indicate that less people are leaving home at these times, for whatever reason. However, it is also possible that this indicates a reporting bias, and that property crimes do occur at these times, but are less likely to be noticed and reported to the police until much later.

4.2 Limitations

As with any research endeavor, there are some limitations and challenges to this investigation. First, the aspatial study included aggregated crimes in the broad categories of violent crime property crime. This was done in order to avoid issues stemming from low incident counts typical of small cities like North Bay. However, previous studies have indicated that different crime types can respond differently to weather variables (Towers et al., 2018; Linning et al., 2017a). As such, it would be preferable to avoid this step wherever incident counts are large enough, as in these studies of large population centers. Second, both studies in this investigation use calls for service data rather than crime reports. While there are some advantages to doing so, in this case relating mainly to data availability, it must be noted that there can be data quality issues with calls for service. These can include multiple calls being made about the same incident (Brower and Carroll, 2007). Further, the NBPS have stated anecdotally that members of the public sometimes confuse crime types when making a call; for example, mixing up robbery, which by definition involves violence, with theft, which does not. While the responding officer has the option to update the call classification, no information is available about how frequently this is done. Additionally, there may be a difference between the time a crime is committed and the time the police are called, particularly in the case of property crimes occurring on statutory holidays or weekends. This issue seems especially likely to occur on commercial properties, which may not be staffed on these dates, meaning that property crimes could go unnoticed for some time. As such, a more detailed analysis of disaggregate crime types, particularly focusing on the difference between commercial and residential crimes, could shed some more light on this potential concern.

4.3 Directions for Future Research

While these studies have answered the original research question, they are also suggestive of some avenues for further research. As indicated in section 4.2, it would be preferable to conduct regression analysis on disaggregate crime types in order to better understand how the routine activities and temperature aggression theories play out in the city of North Bay. However, this might require aggregation to coarser time units in order to yield acceptable mean call counts. It would also be desirable to study the difference between property crime in commercial properties as opposed to residential properties. If the NBPS is unable to provide this data, it should be possible to determine which category a given crime falls into using a zoning map of the city, and the coordinates of each call.

Some other possibilities for further research would require the use of different methodologies. As indicated at the end of chapter 3, the unexpected results of the SPPT raise concerns that it may struggle with low incident counts, which do occur in the North Bay crime data. As such, it would be desirable to confirm these results with other methodologies intended to measure differences in spatial patterns. One possibility is the bivariate version of Ripley's K, which is based on the distance between points and thus avoids the MAUP, though it is subject to edge effects (Baddeley et al., 2015). Other possibilities may include several extensions of geographically weighted regression, and techniques based on image comparison (Long and Robertson, 2017).

On this note, it would be interesting to analyze how the relationships between weather and crime change across space within the city, if a methodology could be found to accomplish this task. The Bayesian time-varying regression analysis employed by Quick et al. (2019) might be worth considering in future. It may also be interesting to compare patterns of crime occurring in North Bay under different weather conditions rather than in different seasons. As discussed in section 1.4.4, this is difficult because the methodologies commonly used to compare spatial patterns are either based on pairwise comparisons, in the case of the SPPT, or simply on the detection of spatio-temporal clusters of events, in the case of Kulldorff's spatial scan test. Using the SPPT to compare crime under different weather conditions would be possible if those weather conditions were first classified into ranges. However, this requires the creation of an appropriate classification scheme, and has the potential to result in a very large number of comparisons, depending on how wide the chosen ranges are. In the case of the Kulldorff's scan test, it would be necessary to modify the test to use a continuous weather variable as the z-variable instead of time, so that if for example temperature was chosen as the weather variable, the test would detect spatio-temperature clusters rather than spatio-temporal clusters. These modifications were far beyond the scope of this initial exploratory study, but might be worth future consideration.

Finally, crime is not consistent across time, as North Bay's crime rate has increased, while in many other locations in North America crime rates have decreased. Further, the recent COVID-19 pandemic and its associated public health measures are likely to have changed routine activities in North Bay substantially. As such, it may be interesting to compare both spatial patterns of crime, and the relationships between crime and weather variables, before, during and after the pandemic, to understand what impacts these changing restrictions have had.

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Appendix 1: R Scripts

A2.1 Regression Analysis

```
# load required packages
# we'll do this with a function
installpack <- function(x)
{new <- x[!(x %in% installed.packages()[, 'Package'])]
if (length(new))
  install.packages(new, depend = T)
sapply(x, require, character.only = T)}

req_packages <- c('data.table', 'readxl', 'padr', 'lubridate',
'dplyr', 'tidyverse', 'StreamMetabolism', 'openair',
'DescTools', 'metR',
                  'vcd', 'MASS', 'arm', 'statmod', 'DHARMa',
'pscl', 'car', 'gridExtra')
installpack(req_packages)

# first, let's read in our crime table
# note that this data will be for NONSPATIAL ONLY - we have not
removed the Princess and 4th anomalies
# we also remove those calls from 2020, now that we've added the
covid data to our master files
# and we'll remove any records where municipality is not North
Bay
crimes <- as.data.table(read_excel("H:/Policing/Working
Data/Master Files/Combined.xlsx", "Sheet1"))
tz(crimes$TIMESTAMP) <- "US/Eastern"
attr(crimes$TIMESTAMP, "tzone") <- "UTC"
crimes <- crimes[crimes$YR != 2020, ]
crimes <- crimes[crimes$EMUN == "NTH"]


# next we need to set up our crime aggregations
# I'm assuming violent vs. property in line with the literature,
if NBPS says otherwise will need to change this
property <- c('ARSON', 'B-E', 'POSPROP', 'PROPDAM', 'THEFT',
'THEFTMV', 'THEFTSH')
violent <- c('ABDUCT', 'ASSAULT', 'ASSLTSEX', 'CHILDABUSE',
'DOMESTIC', 'ELDERABUSE', 'FAMDISP', 'NEIGH', 'ROBBERY',
'THREATS')

# now we'll assign the aggregations and remove un-aggregated
calls
crimes$type[crimes$CODE %in% property] <- 'Property'
crimes$type[crimes$CODE %in% violent] <- 'Violent'
```

```
crimes <- na.omit(crimes, "type")

# next we'll split this into two dataframes
vcrimes <- crimes[crimes$type == 'Violent', ]
pcrimes <- crimes[crimes$type == 'Property', ]

# then get our hourly counts
hourslist <- seq(from = as.POSIXct('2015-01-01 05:00:00'), to =
as.POSIXct('2020-01-01 04:00:00'), by = "hour")
tz(hourslist) <- "UTC"

vcrimeshourly <- count(vcrimes, Time1 = as.Date(TIMESTAMP), Hour
= hour(TIMESTAMP))
vcrimeshourly <- complete(vcrimeshourly, Time1 = full_seq(Time1,
1), Hour = 0:23, fill = list(n = 0))
vcrimeshourly <- vcrimeshourly[-c(seq(43830, 43848, 1),
seq(1,5,1)), ]
vcrimeshourly <- data.frame(Timestamp = hourslist, n =
vcrimeshourly$n)

pcrimeshourly <- count(pcrimes, Time1 = as.Date(TIMESTAMP), Hour
= hour(TIMESTAMP))
pcrimeshourly <- complete(pcrimeshourly, Time1 =
seq.Date(as.Date("2015-01-01"), as.Date("2020-01-01"), "day"),
Hour = 0:23, fill = list(n = 0))
pcrimeshourly <- pcrimeshourly[-c(seq(43830, 43848, 1),
seq(1,5,1)), ]
pcrimeshourly <- data.frame(Timestamp = hourslist, n =
pcrimeshourly$n)

remove(hourslist, crimes, pcrimes, vcrimes)

# then aggregate
quarterslist <- seq(from = as.POSIXct('2015-01-01 05:00:00'), to
= as.POSIXct('2020-01-01 04:00:00'), by = "6 hours")
tz(quarterslist) <- "UTC"

vquartercounts <- colSums(matrix(vcrimeshourly$n, nrow = 6))
vcrimesquarterday <- data.frame(Timestamp = quarterslist, n =
vquartercounts)
pquartercounts <- colSums(matrix(pcrimeshourly$n, nrow = 6))
pcrimesquarterday <- data.frame(Timestamp = quarterslist, n =
pquartercounts)

remove(quarterslist, pquartercounts, vquartercounts,
pcrimeshourly, vcrimeshourly)
```

```
# wonderful. next, we need to figure out the weather stuff -
have to go from hourly to six-hourly averages
# first, let's read in the hourly averages
weather <- read_excel("H:/Policing/Weather Data/Hourly
Averages.xlsx")

# and deal with a few small data formatting issues
weather$Timestamp <- with(weather, ymd(day) + hm(Time))
weather <- rename(weather, date = Timestamp)
tz(weather$date) <- "UTC"
weather <- subset(weather, select = -c(hour, day, Time,
Pressure, wind_spd, wind_dir, SolarRad, Vis))

weather$Precip <- na_if(weather$Precip, "NA")
weather$Precip <- as.numeric(weather$Precip)
weather$AirTemp <- na_if(weather$AirTemp, "NA")
weather$RH <- na_if(weather$RH, "NA")

weather <- arrange(weather, date)

# this gets us the mean of every six hours in every column
weatherquarter <- timeAverage(weather, avg.time = '6 hour',
data.thresh = 0, statistic = 'mean')

# but precip wants a sum not a mean
temp1 <- timeAverage(weather, avg.time = '6 hour', data.thresh =
0, statistic = 'sum')
weatherquarter$Precip <- temp1$Precip
weatherquarter$Precip2 <- factor(ifelse(weatherquarter$Precip >
0, 1, weatherquarter$Precip))

remove(temp1, weather)

# great. next, let's figure out hours of daylight per time
period
tz(weatherquarter$date) <- "UTC"
weatherquarter <- rename(weatherquarter, StartTime = date)
weatherquarter$EndTime <- weatherquarter$StartTime + 6*60*60

sun <- sunrise.set(46.3091, -79.4608, "2014-12-31", "UTC", 1828)
period <- data.frame(weatherquarter$StartTime,
weatherquarter$EndTime)

setDT(sun)[, join_date := sunrise]
setDT(period)[, join_date := weatherquarter.StartTime]
test <- sun[period, on = .(join_date), roll = 'nearest']
test <- subset(test, select = -c(join_date))
```

```
test1 <- data.frame(test$sunrise, test$sunset)
test2 <- data.frame(test$weatherquarter.StartTime,
test$weatherquarter.EndTime)
test1 <- as.matrix(sapply(test1, as.numeric))
test2 <- as.matrix(sapply(test2, as.numeric))
weatherquarter$lighthours <- (Overlap(test1, test2)/3600)
weatherquarter <- subset(weatherquarter, select = -c(EndTime))

remove(sun, period, test, test1, test2)

# next we'll make a sequence of weekend dates
weekend <- seq(as.Date("2015-01-01"), as.Date("2020-01-01"), 1)
weekend <- data.frame(weekend,is.weekend(weekend))
colnames(weekend)[1] <- "date"
colnames(weekend)[2] <- "weekend"
weekend <- weekend[!(weekend$weekend == FALSE),]
weekend <- weekend$date

# then read in our holidays
holidays <- read_excel("H:/Policing/Weather Data/Holidays.xlsx",
"Stat")
stathols <- as.Date(holidays$Dates)

holidays <- read_excel("H:/Policing/Weather Data/Holidays.xlsx",
"School")
schoolhols <- as.Date(holidays$Dates)

remove(holidays)

# next we're going to attempt joining the above to our weather
data
# first, coerce to the same timezone
weatherquarter <- rename(weatherquarter, Timestamp = StartTime)
attr(weatherquarter$Timestamp, "tzone") <- "US/Eastern"
weatherquarter$ETDay <- as.Date(weatherquarter$Timestamp, tz =
"US/Eastern")

# then we'll do a lookup rather than a true join
weatherquarter$stat <- weatherquarter$ETDay %in% stathols
weatherquarter$stat <- factor(as.numeric(weatherquarter$stat))

weatherquarter$school <- weatherquarter$ETDay %in% schoolhols
weatherquarter$school <-
factor(as.numeric(weatherquarter$school))

weatherquarter$weekend <- weatherquarter$ETDay %in% weekend
```

```
weatherquarter$weekend <-
factor(as.numeric(weatherquarter$weekend))

# next we're going to extract our calendar variables
weatherquarter$day <- factor(wday(weatherquarter$Timestamp))
weatherquarter$month <- factor(month(weatherquarter$Timestamp))
weatherquarter$season <-
factor(season(weatherquarter$Timestamp))
attr(weatherquarter$Timestamp, "tzone") <- "UTC"
weatherquarter <- subset(weatherquarter, select = -c(ETDay))

# we'll also add our sequence variable now
weatherquarter$seq <- seq.int(nrow(weatherquarter))

# and then we can do our join
setDT(weatherquarter)[, join_date := Timestamp]
setDT(pcrimesquarterday)[, join_date := Timestamp]
setDT(vcrimesquarterday)[, join_date := Timestamp]
meteopcrime <- weatherquarter[pcrimesquarterday, on =
.(join_date), roll = 'nearest']
meteovcrime <- weatherquarter[vcrimesquarterday, on =
.(join_date), roll = 'nearest']

remove(pcrimesquarterday, vcrimesquarterday, weatherquarter)

# and then, I think, we can make a start on the regression
# unfortunately, we do need to remove all our NA values first
meteopcrime <- na.omit(meteopcrime)
meteovcrime <- na.omit(meteovcrime)

# this term will allow you to subset by season if you so desire
meteopcrime <- meteopcrime[meteopcrime$season == "MAM", ]
meteovcrime <- meteovcrime[meteovcrime$season == "MAM", ]

# here are your basic summary stats for the crime counts
sum(meteopcrime$n)
min(meteopcrime$n)
max(meteopcrime$n)
mean(meteopcrime$n)
sd(meteopcrime$n)

sum(meteovcrime$n)
min(meteovcrime$n)
max(meteovcrime$n)
mean(meteovcrime$n)
sd(meteovcrime$n)
```

```
# we can run a statistical test (with graphs!) for goodness of
fit to a Poisson dist
# want the summary to have a low p value
# and the rootogram to have bars that sit right on the 0 of the
y axis
summary(goodfit(meteopcrime$n))
rootogram(goodfit(meteopcrime$n))

summary(goodfit(meteovcrime$n))
rootogram(goodfit(meteovcrime$n))


# PROPERTY CRIME


pweathermodel <- glm.nb(n ~ AirTemp + Precip2 + RH + lighthours,
                       data = meteopcrime)

ptempweathermodel <- glm.nb(n ~ AirTemp + Precip2 + RH +
lighthours +
                             stat + school + weekend + seq,
                           data = meteopcrime)

ptempmodel <- glm.nb(n ~ stat + school + weekend + seq,
                    data = meteopcrime)

pfullmodel <- glm.nb(n ~ Precip2 + poly(AirTemp, 2, raw = T) +
poly(RH, 2, raw = T) + poly(lighthours, 2, raw = T) +
                      stat + school + weekend + seq +
                      AirTemp:Precip2 + AirTemp:stat +
AirTemp:school + AirTemp:weekend + AirTemp:lighthours +
AirTemp:RH +
                      Precip2:lighthours + Precip2:stat +
Precip2:school + Precip2:weekend +
                      seq:AirTemp + seq:Precip2 + seq:RH +
seq:lighthours,
                    data = meteopcrime)

summary(pfullmodel)

# you need to modify the final model seperately for each season,
based on the p values in the full model
pfinalmodel <- glm.nb(n ~ AirTemp + Precip2 + poly(RH, 2, raw =
T) + lighthours +
                             stat + school + weekend + seq,
                           data = meteopcrime)
```

```
# write the model results
write.csv(summary(pweathermodel)$coefficients,
"H:/Policing/Temporal Analysis/Quarterly/pcrimeweather.csv")
write.csv(summary(ptempmodel)$coefficients,
"H:/Policing/Temporal Analysis/Quarterly/pcrimetemp.csv")
write.csv(summary(ptempweathermodel)$coefficients,
"H:/Policing/Temporal Analysis/Quarterly/pcrimetempweather.csv")
write.csv(summary(pfinalmodel)$coefficients,
"H:/Policing/Temporal Analysis/Quarterly/pcrimefinal.csv")

# let's check our multicollinearity, see if we need to worry
about stepwise model selection or anything
# ideally we want no values greater than 5
write.csv(vif(pfinalmodel), "H:/Policing/Temporal
Analysis/Quarterly/pvif.csv")

# this is how we test for goodness of fit
# we want a result of not statistically significant, or p > 0.05
test <- sum(resid(pweathermodel, type = 'pearson')^2)
with(pweathermodel, cbind(res.deviance = deviance,
                         df = df.residual,
                         x = qchisq(0.95,
pweathermodel$df.resid),
                         p = pchisq(deviance, df.residual,
lower.tail=FALSE),
                         px = 1 - pchisq(test,
pweathermodel$df.resid),
                         AIC = AIC(pweathermodel)))
test <- sum(resid(ptempmodel, type = 'pearson')^2)
with(ptempmodel, cbind(res.deviance = deviance,
                      df = df.residual,
                      x = qchisq(0.95, ptempmodel$df.resid),
                      p = pchisq(deviance, df.residual,
lower.tail=FALSE),
                      px = 1 - pchisq(test,
ptempmodel$df.resid),
                      AIC = AIC(ptempmodel)))
test <- sum(resid(ptempweathermodel, type = 'pearson')^2)
with(ptempweathermodel, cbind(res.deviance = deviance,
                             df = df.residual,
                             x = qchisq(0.95,
df.residual(ptempweathermodel)),
                             p = pchisq(deviance, df.residual,
lower.tail=FALSE),
                             px = 1 - pchisq(test,
ptempweathermodel$df.resid),
                             AIC = AIC(ptempweathermodel)))
```

```
test <- sum(resid(pfinalmodel, type = 'pearson')^2)
with(pfinalmodel, cbind(res.deviance = deviance,
                       df = df.residual,
                       x = qchisq(0.95,
df.residual(pfinalmodel)),
                       p = pchisq(deviance, df.residual,
lower.tail=FALSE),
                       px = 1 - pchisq(test,
pfinalmodel$df.resid),
                       AIC = AIC(pfinalmodel)))

remove(pweathermodel, ptempmodel, ptempweathermodel, pfullmodel)

# some DHARMa testing
allresid <- simulateResiduals(fittedModel = pfinalmodel, plot =
F)
plot(allresid)
testZeroInflation(allresid, plot = F)
testTemporalAutocorrelation(allresid, meteopcrime$Timestamp,
plot = F)

# a residual plot for the final model
resid <- resid(pfinalmodel, type = 'pearson')
fitted <- fitted(pfinalmodel)
df <- data.frame(resid, fitted)
ggplot(df, aes(fitted, resid)) +
  geom_point() +
  ylab("Pearson Residuals") +
  xlab("Fitted Values") +
  ggtitle("Property Crime Residuals")

plot(density(qresid(pfinalmodel)))
scatter.smooth(1:nrow(meteopcrime), qresid(pfinalmodel),
col='gray')
scatter.smooth(predict(pfinalmodel, type='response'),
qresid(pfinalmodel), col='gray')
scatter.smooth(predict(pfinalmodel), resid(pfinalmodel, type =
'working'), col = 'gray')
qqnorm(qresid(pfinalmodel));qqline(qresid(pfinalmodel))
influencePlot(pfinalmodel)
plot(cooks.distance(pfinalmodel), pch = '*', cex = 2, main =
'Influential Obs by Cooks Distance')
abline(h = 4/nrow(meteopcrime), col = 'red')
influence <- cooks.distance(pfinalmodel)
influence <- data.frame(influence)
influence$outlier <- ifelse(influence < 4/nrow(meteopcrime), 0,
1)
```

```
sum(influence$outlier)

par(mfrow=c(1,2))
scatter.smooth(meteopcrime$AirTemp, qresid(pfinalmodel),
col='gray')
scatter.smooth(meteopcrime$Precip2, qresid(pfinalmodel),
col='gray')

scatter.smooth(meteopcrime$RH, qresid(pfinalmodel), col='gray')
scatter.smooth(meteopcrime$lighthours, qresid(pfinalmodel),
col='gray')

scatter.smooth(meteopcrime$stat, qresid(pfinalmodel),
col='gray')
scatter.smooth(meteopcrime$school, qresid(pfinalmodel),
col='gray')

scatter.smooth(meteopcrime$weekend, qresid(pfinalmodel),
col='gray')
scatter.smooth(meteopcrime$seq, qresid(pfinalmodel), col='gray')
par(mfrow=c(1,1))

# VIOLENT CRIME


vweathermodel <- glm.nb(n ~ AirTemp + Precip2 + RH + lighthours,
                        data = meteovcrime)

vtempweathermodel <- glm.nb(n ~ AirTemp + Precip2 + RH +
lighthours +
                              stat + school + weekend + seq,
                            data = meteovcrime)

vtempmodel <- glm.nb(n ~ stat + school + weekend + seq,
                     data = meteovcrime)

vfullmodel <- glm.nb(n ~ Precip2 + poly(AirTemp, 2, raw = T) +
poly(RH, 2, raw = T) + poly(lighthours, 2, raw = T) +
                       stat + school + weekend + seq +
                       AirTemp:Precip2 + AirTemp:stat +
AirTemp:school + AirTemp:weekend + AirTemp:lighthours +
AirTemp:RH +
                       Precip2:lighthours + Precip2:stat +
Precip2:school + Precip2:weekend +
                       seq:AirTemp + seq:Precip2 + seq:RH +
seq:lighthours,
                     data = meteovcrime)
```

```
summary(vfullmodel)

# you need to modify the final model seperately for each season,
based on the p values in the full model
vfinalmodel <- glm.nb(n ~ poly(AirTemp, 2, raw = T) + Precip2 +
poly(RH, 2, raw = T) + poly(lighthours, 2, raw = T) +
                        stat + school + weekend + seq +
AirTemp:RH,
                      data = meteovcrime)

# read the model results
write.csv(summary(vweathermodel)$coefficients,
"H:/Policing/Temporal Analysis/Quarterly/vcrimeweather.csv")
write.csv(summary(vtempmodel)$coefficients,
"H:/Policing/Temporal Analysis/Quarterly/vcrimetemp.csv")
write.csv(summary(vtempweathermodel)$coefficients,
"H:/Policing/Temporal Analysis/Quarterly/vcrimetempweather.csv")
write.csv(summary(vfinalmodel)$coefficients,
"H:/Policing/Temporal Analysis/Quarterly/vcrimefinal.csv")

# let's check our multicollinearity, see if we need to worry
about stepwise model selection or anything
# ideally we want no values greater than 5
write.csv(vif(vfinalmodel), "H:/Policing/Temporal
Analysis/Quarterly/vvif.csv")

# this is how we test for goodness of fit
# we want a result of not statistically significant, or p > 0.05
test <- sum(resid(vweathermodel, type = 'pearson')^2)
with(vweathermodel, cbind(res.deviance = deviance,
                          df = df.residual,
                          x = qchisq(0.95,
df.residual(vweathermodel)),
                          p = pchisq(deviance,
df.residual(vweathermodel), lower.tail=FALSE),
                          px = 1 - pchisq(test,
vweathermodel$df.resid),
                          AIC = AIC(vweathermodel)))
test <- sum(resid(vtempmodel, type = 'pearson')^2)
with(vtempmodel, cbind(res.deviance = deviance,
                       df = df.residual,
                       x = qchisq(0.95,
df.residual(vtempmodel)),
                       p = pchisq(deviance,
df.residual(vtempmodel), lower.tail=FALSE),
```

```
                       px = 1 - pchisq(test, 
vtempmodel$df.resid),
                       AIC = AIC(vtempmodel)))
test <- sum(resid(vtempweathermodel, type = 'pearson')^2)
with(vtempweathermodel, cbind(res.deviance = deviance,
                              df = df.residual,
                              x = qchisq(0.95, 
df.residual(vtempweathermodel)),
                              p = pchisq(deviance, df.residual, 
lower.tail=FALSE),
                              px = 1 - pchisq(test, 
vtempweathermodel$df.resid),
                              AIC = AIC(vtempweathermodel)))
test <- sum(resid(vfinalmodel, type = 'pearson')^2)
with(vfinalmodel, cbind(res.deviance = deviance,
                        df = df.residual,
                        x = qchisq(0.95, 
df.residual(vfinalmodel)),
                        p = pchisq(deviance, df.residual, 
lower.tail=FALSE),
                        px = 1 - pchisq(test, 
vfinalmodel$df.resid),
                        AIC = AIC(vfinalmodel)))

remove(vweathermodel, vtempmodel, vtempweathermodel, vfullmodel)

# a residual plot for the final model
allresid <- simulateResiduals(fittedModel = vfinalmodel, plot = 
F)
plot(allresid)
testZeroInflation(allresid, plot = F)
testTemporalAutocorrelation(allresid, meteovcrime$Timestamp, 
plot = F)
remove(allresid)

resid <- resid(vfinalmodel, type = 'pearson')
fitted <- fitted(vfinalmodel)
df <- data.frame(resid, fitted)
ggplot(df, aes(fitted, resid)) +
  geom_point() +
  ylab("Pearson Residuals") +
  xlab("Fitted Values") +
  ggtitle("Violent Crime Residuals")
remove(df)

plot(density(qresid(vfinalmodel)))
```

```
scatter.smooth(1:nrow(meteovcrime), qresid(vfinalmodel),
col='gray')
scatter.smooth(predict(vfinalmodel, type='response'),
qresid(vfinalmodel), col='gray')
scatter.smooth(predict(vfinalmodel), resid(vfinalmodel, type =
'working'), col = 'gray')
qqnorm(qresid(vfinalmodel));qqline(qresid(vfinalmodel))
influencePlot(vfinalmodel)
plot(cooks.distance(vfinalmodel), pch = '*', cex = 2, main =
'Influential Obs by Cooks Distance')
abline(h = 4/nrow(meteovcrime), col = 'red')
influence <- cooks.distance(vfinalmodel)
influence <- data.frame(influence)
influence$outlier <- ifelse(influence < 4/nrow(meteocrime), 0,
1)
sum(influence$outlier)


par(mfrow=c(1,2))
scatter.smooth(meteovcrime$AirTemp, qresid(vfinalmodel),
col='gray')
scatter.smooth(meteovcrime$Precip2, qresid(vfinalmodel),
col='gray')

scatter.smooth(meteovcrime$RH, qresid(vfinalmodel), col='gray')
scatter.smooth(meteovcrime$lighthours, qresid(vfinalmodel),
col='gray')

scatter.smooth(meteovcrime$stat, qresid(vfinalmodel),
col='gray')
scatter.smooth(meteovcrime$school, qresid(vfinalmodel),
col='gray')

scatter.smooth(meteovcrime$weekend, qresid(vfinalmodel),
col='gray')
scatter.smooth(meteovcrime$seq, qresid(vfinalmodel), col='gray')
par(mfrow=c(1,1))
```

A2.2 Spatial Point Pattern Test

```
# load required packages
# we'll do this with a function
installpack <- function(x)
{new <- x[!(x %in% installed.packages()[, 'Package'])]
if (length(new))
  install.packages(new, depend = T)
```

```
sapply(x, require, character.only = T)}

req_packages <- c('GISTools', 'rgdal', 'raster', 'tmap',
'classInt', 'xtable', 'hydroGOF', 'parallel', 'pbapply',
'ggplot2', 'gridExtra',
                  'statmod', 'spatstat', 'maptools', 'sppt',
'data.table', 'readxl', 'grid', 'xlsx')
installpack(req_packages)

# so. first let's read in all our spatial bits
# note that I have already projected all of these appropriately,
but you should always check your data
Crimes <- readOGR("H:/Policing/Working Data",
"NBPointsforRProj")
NH <- readOGR('H:/Policing/Working Data', "Neighbourhood")
CT <- readOGR('H:/Policing/Working Data', "CTFinal")
DA <- readOGR('H:/Policing/Working Data', "DAfinal")
DB <- readOGR('H:/Policing/Working Data', "DBfinal")

# we're only interested in certain crime types, so let's sort
that out now
types <- c('B-E', 'THEFT', 'THEFTMV', 'THEFTSH', 'ASSAULT',
'DOMESTIC', 'FAMDISP', 'NEIGH', 'THREATS', 'ASSLTSEX')

# we need to make ourselves a dataframe to store the results
SPPTResult <- data.frame(Calls = character(),
                         Spring = double(),
                         Summer = double(),
                         Autumn = double(),
                         Winter = double(),
                         stringsAsFactors = FALSE)

# then I guess we run the thing
# I know this is inelegant and I should set up nested loops,
something to consider for next time
for (i in types) {
  type <- Crimes[Crimes$CODE == i, ]
  Test <- type[type$SEASON == 'Spring', ]
  Base <- type[type$SEASON == 'Summer', ]
  SPPTss <- sppt_diff(Test, Base, CT, test = 'Fisher')
  SPPTResultss <- mean(SPPTss$globalS)
  SPPTssin <- length(which(SPPTss$localS.robust == 1))
  SPPTssde <- length(which(SPPTss$localS.robust == -1))
  SPPTssnull <- length(which(SPPTss$localS.robust == 0))
  SPPTssmiss <- sum(is.na(SPPTss$localS.robust))

  Test <- type[type$SEASON == 'Spring', ]
```

```
Base <- type[type$SEASON == 'Autumn', ]
SPPTsa <- sppt_diff(Test, Base, CT, test = 'Fisher')
SPPTResultsa <- mean(SPPTsa$globalS)
SPPTsain <- length(which(SPPTsa$localS.robust == 1))
SPPTsade <- length(which(SPPTsa$localS.robust == -1))
SPPTsanull <- length(which(SPPTsa$localS.robust == 0))
SPPTsamiss <- sum(is.na(SPPTsa$localS.robust))

Test <- type[type$SEASON == 'Spring', ]
Base <- type[type$SEASON == 'Winter', ]
SPPTsw <- sppt_diff(Test, Base, CT, test = 'Fisher')
SPPTResultsw <- mean(SPPTsw$globalS)
SPPTswin <- length(which(SPPTsw$localS.robust == 1))
SPPTswde <- length(which(SPPTsw$localS.robust == -1))
SPPTswnull <- length(which(SPPTsw$localS.robust == 0))
SPPTswmiss <- sum(is.na(SPPTsw$localS.robust))

Test <- type[type$SEASON == 'Summer', ]
Base <- type[type$SEASON == 'Autumn', ]
SPPTsua <- sppt_diff(Test, Base, CT, test = 'Fisher')
SPPTResultsua <- mean(SPPTsua$globalS)
SPPTsuain <- length(which(SPPTsua$localS.robust == 1))
SPPTsuade <- length(which(SPPTsua$localS.robust == -1))
SPPTsuanull <- length(which(SPPTsua$localS.robust == 0))
SPPTsuamiss <- sum(is.na(SPPTsua$localS.robust))

Test <- type[type$SEASON == 'Summer', ]
Base <- type[type$SEASON == 'Winter', ]
SPPTsuw <- sppt_diff(Test, Base, CT, test = 'Fisher')
SPPTResultsuw <- mean(SPPTsuw$globalS)
SPPTsuwin <- length(which(SPPTsuw$localS.robust == 1))
SPPTsuwde <- length(which(SPPTsuw$localS.robust == -1))
SPPTsuwnull <- length(which(SPPTsuw$localS.robust == 0))
SPPTsuwmiss <- sum(is.na(SPPTsuw$localS.robust))

Test <- type[type$SEASON == 'Autumn', ]
Base <- type[type$SEASON == 'Winter', ]
SPPTaw <- sppt_diff(Test, Base, CT, test = 'Fisher')
SPPTResultaw <- mean(SPPTaw$globalS)
SPPTawin <- length(which(SPPTaw$localS.robust == 1))
SPPTawde <- length(which(SPPTaw$localS.robust == -1))
SPPTawnull <- length(which(SPPTaw$localS.robust == 0))
SPPTawmiss <- sum(is.na(SPPTaw$localS.robust))

SPPTResult <- rbind(SPPTResult, data.frame(Calls = i,
```

```
                                                     SpringSummer =
SPPTResultss, SSmiss = SPPTssmiss, SSincresase = SPPTssin,
SSdecrease = SPPTssde, SStatic = SPPTssnull,
                                                     SpringAutumn =
SPPTResultsa, SAmiss = SPPTsamiss, SAincresase = SPPTsain,
SAdecrease = SPPTsade, SAstatic = SPPTsanull,
                                                     SpringWinter =
SPPTResultsw, SWmiss = SPPTswmiss, SWincresase = SPPTswin,
SWdecrease = SPPTswde, SWstatic = SPPTswnull,
                                                     SummerAutumn =
SPPTResultsua, SuAmiss = SPPTsuamiss, SuAincresase = SPPTsuain,
SuAdecrease = SPPTsuade, SuAstatic = SPPTsuanull,
                                                     SummerWinter =
SPPTResultsuw, SuWmiss = SPPTsuwmiss, SuWincresase = SPPTsuwin,
SuWdecrease = SPPTsuwde, SuWstatic = SPPTsuwnull,
                                                     AutumnWinter =
SPPTResultaw, AWmiss = SPPTawmiss, AWincresase = SPPTawin,
AWdecrease = SPPTawde, AWstatic = SPPTawnull,
                                                     stringsAsFactors =
FALSE))
  SSmap <- tm_shape(SPPTss) +
    tm_polygons(col = 'localS.robust',
                style = 'cat',
                palette = 'Greys',
                n = 3,
                contrast = c(0,1),
                title = i)

  SAmap <- tm_shape(SPPTsa) +
    tm_polygons(col = 'localS.robust',
                style = 'cat',
                palette = '-Greys',
                n = 3,
                contrast = c(0,1),
                title = i)

  SWmap <- tm_shape(SPPTsw) +
    tm_polygons(col = 'localS.robust',
                style = 'cat',
                palette = '-Greys',
                n = 3,
                contrast = c(0,1),
                title = i)

  SuAmap <- tm_shape(SPPTsua) +
    tm_polygons(col = 'localS.robust',
                style = 'cat',
```

```
              palette = '-Greys',
              n = 3,
              contrast = c(0,1),
              title = i)

  SuWmap <- tm_shape(SPPTsuw) +
    tm_polygons(col = 'localS.robust',
              style = 'cat',
              palette = '-Greys',
              n = 3,
              contrast = c(0,1),
              title = i)

  AWmap <- tm_shape(SPPTaw) +
    tm_polygons(col = 'localS.robust',
              style = 'cat',
              palette = '-Greys',
              n = 3,
              contrast = c(0,1),
              title = i)

  grid.newpage()

  pushViewport(viewport(layout = grid.layout(2,3)))

  print(SSmap, vp = viewport(layout.pos.row = 1, layout.pos.col
= 1))
  print(SAmap, vp = viewport(layout.pos.row = 1, layout.pos.col
= 2))
  print(SWmap, vp = viewport(layout.pos.row = 1, layout.pos.col
= 3))
  print(SuAmap, vp = viewport(layout.pos.row = 2, layout.pos.col
= 1))
  print(SuWmap, vp = viewport(layout.pos.row = 2, layout.pos.col
= 2))
  print(AWmap, vp = viewport(layout.pos.row = 2, layout.pos.col
= 3))
}

write.xlsx(SPPTResult,"H:/Policing/Spatial
Analysis/NHTake2.xlsx")
```

Appendix 2: Python Scripts

A1.1 Subsetting

```
# Import system modules
import arcpy
import os
from arcpy import env

# Set workspace
env.workspace = "H:\Policing\Working Data"

# Define output folder
outputFolder = "H:\Policing\Subset\Seasons"

# Create loop
in_features = "H:\Policing\Working Data\NBPointsforRProj.shp"
out_name =
os.path.join(outputFolder,os.path.splitext(os.path.basename(in_f
eatures))[0]+"_Spring.shp")
where_clause = '"SEASON" = "Spring"'

# Execute Select
arcpy.Select_analysis(in_features, out_name, where_clause)

# Create loop
in_features = "H:\Policing\Working Data\NBPointsforRProj.shp"
out_name =
os.path.join(outputFolder,os.path.splitext(os.path.basename(in_f
eatures))[0]+"_Summer.shp")
where_clause = '"SEASON" = "Summer"'

# Execute Select
arcpy.Select_analysis(in_features, out_name, where_clause)

# Create loop
in_features = "H:\Policing\Working Data\NBPointsforRProj.shp"
out_name =
os.path.join(outputFolder,os.path.splitext(os.path.basename(in_f
eatures))[0]+"_Autumn.shp")
where_clause = '"SEASON" = "Autumn"'

# Execute Select
arcpy.Select_analysis(in_features, out_name, where_clause)

# Create loop
in_features = "H:\Policing\Working Data\NBPointsforRProj.shp"
```

```
out_name =
os.path.join(outputFolder,os.path.splitext(os.path.basename(in_f
eatures))[0]+"_Winter.shp")
where_clause = '"SEASON" = "Winter"'

# Execute Select
arcpy.Select_analysis(in_features, out_name, where_clause)

# Set workspace
env.workspace = "H:\Policing\Subset\Seasons"

# List desired attribute values
attlist = ['THEFT', 'THEFTMV', 'THEFTSH', 'ASSAULT',
           'DOMESTIC', 'NEIGH', 'THREATS', 'BE']

# Create loop
for att in attlist:
    in_features =
"H:\Policing\Subset\Seasons\NBPointsforRProj_Spring.shp"
    out_name = "{}spring.shp".format(att)
    where_clause = '"CODE" = \'{}\''.format(att)

    # Execute Select
    arcpy.Select_analysis(in_features, out_name, where_clause)

for att in attlist:
    in_features =
"H:\Policing\Subset\Seasons\NBPointsforRProj_Summer.shp"
    out_name = "{}summer.shp".format(att)
    where_clause = '"CODE" = \'{}\''.format(att)

    # Execute Select
    arcpy.Select_analysis(in_features, out_name, where_clause)

for att in attlist:
    in_features =
"H:\Policing\Subset\Seasons\NBPointsforRProj_Autumn.shp"
    out_name = "{}autumn.shp".format(att)
    where_clause = '"CODE" = \'{}\''.format(att)

    # Execute Select
    arcpy.Select_analysis(in_features, out_name, where_clause)

for att in attlist:
    in_features =
"H:\Policing\Subset\Seasons\NBPointsforRProj_Winter.shp"
    out_name = "{}winter.shp".format(att)
```

```
    where_clause = '"CODE" = \'{}\''.format(att)

    # Execute Select
    arcpy.Select_analysis(in_features, out_name, where_clause)
```

A1.2 Join Points to Polygons

```
import arcpy
import os

# Set workspace
arcpy.env.workspace= " H:\Policing\Subset\Crimes"

# Loop through files and save under a different name
crimes = arcpy.ListFiles("*.shp")
outputFolder = "H:\Policing\Polygons"
for crime in crimes:
     target_features = "H:\Policing\Working Data\DAfinal.shp"
     join_features = crime
     out_feature_class =
     os.path.join(outputFolder,os.path.splitext(os.path.basename
     (crime))[0]+"DA.shp")

     arcpy.SpatialJoin_analysis(target_features, join_features,
     out_feature_class)

     target_features = "H:\Policing\Working Data\DBfinal.shp"
     join_features = crime
     out_feature_class =
     os.path.join(outputFolder,os.path.splitext(os.path.basename
     (crime))[0]+"DB.shp")

     arcpy.SpatialJoin_analysis(target_features, join_features,
     out_feature_class)
```

A1.3 Join Points to Nearest Lines

```
# THIS SCRIPT MUST BE RUN IN ARCMAP, NOT IDLE
import arcpy
import os

# CREATE NEAR TABLE
# Set workspace and output location
arcpy.env.workspace= "H:\Policing\Subset\Crimes"
outputFolder = "H:\Policing\Lines"
```

```
# This prevents tables and layers being loaded to your map,
which would stop you moving the files
arcpy.env.addOutputsToMap = 0

# List inputs
crimes = arcpy.ListFiles("*.shp")

for crime in crimes:

     Input_Features = crime
     Near_Features = "H:\Policing\Working Data\RoadClip.shp"
     Out_Table =
     os.path.join(outputFolder,os.path.splitext(os.path.basename
     (crime))[0]+".dbf")

     arcpy.GenerateNearTable_analysis(Input_Features,
     Near_Features, Out_Table)

# SUMMARIZE NEAR TABLES
# Set workspace and output location
arcpy.env.workspace = "H:\Policing\Lines"
outputFolder = "H:\Policing\Working Folder\Tables"

# List inputs
tables = arcpy.ListFiles("*.dbf")

for table in tables:
     # This prevents tables and layers being loaded to your map,
     which would stop you moving the files
     arcpy.env.addOutputsToMap = 0

    # Summarize Near Table
     InTable = table
     OutTable =
     os.path.join(outputFolder,os.path.splitext(os.path.basename
     (table))[0]+".dbf")

     arcpy.Statistics_analysis(InTable, OutTable,
     [["NEAR_FID","COUNT"]],"NEAR_FID")

# JOIN TABLES TO ROADS

import arcpy
import os

# This turns on automatic loading of layers, etc.
```

```
arcpy.env.addOutputsToMap = 1

# Set workspace
arcpy.env.workspace = "H:\Policing\Working Folder\Tables"

# List inputs
tables = arcpy.ListFiles("*.dbf")

# Add files to map document
mxd = arcpy.mapping.MapDocument("CURRENT")
df = arcpy.mapping.ListDataFrames(mxd, "Layers")[0]
newlayer = arcpy.mapping.Layer("H:\Policing\Working
Data\RoadClip.shp")
arcpy.mapping.AddLayer(df, newlayer, "AUTO_ARRANGE")

for table in tables:
    mxd = arcpy.mapping.MapDocument("CURRENT")
    df = arcpy.mapping.ListDataFrames(mxd, "Layers")[0]
    newtable = arcpy.mapping.TableView(table)
    arcpy.mapping.AddTableView(df, newtable)

arcpy.RefreshActiveView()
arcpy.RefreshTOC()

# Convert roads to a layer file
inFeature = "H:\Policing\Working Data\RoadClip.shp"
layerName = "RoadLayer"

arcpy.MakeFeatureLayer_management (inFeature,  layerName)

# Set output folder
OutputFolder = "H:\Policing\Lines2"

# Create join
for table in tables:
     layerName = "RoadLayer"
     inField = "FID"
     joinTable = table
     joinField = "NEAR_FID"
     outFeature =
     os.path.join(OutputFolder,os.path.splitext(os.path.basename
     (table))[0]+".shp")

     # Join
     arcpy.AddJoin_management(layerName, inField, joinTable,
     joinField)
```

```
    # Export
    arcpy.CopyFeatures_management(layerName, outFeature)

    # Remove Join
    arcpy.RemoveJoin_management(layerName,os.path.splitext(os.p
    ath.basename(table))[0])
```

A1.4 Kernel Density Estimation

```
import arcpy
arcpy.CheckOutExtension("Spatial")
from arcpy.sa import *
import os

# Set workspace and output folder
arcpy.env.workspace= 'H:\Policing\Subset\Crimes'
outputFolder = "H:\Policing\KDE"

# Set output extent
arcpy.env.extent = "H:\Policing\Working Data\NorthBayErase.shp"
arcpy.env.mask = "H:\Policing\Working Data\NorthBayErase.shp"

# Create list
crimes = arcpy.ListFiles("*.shp")

# Create loop
for crime in crimes:
    in_features = crime
    outraster =
    os.path.join(outputFolder,os.path.splitext(os.path.basename
    (crime))[0]+"Density.tif")

    outKDens = KernelDensity(in_features, "NONE", 10, 650,
    "SQUARE_KILOMETERS")
    outKDens.save(outraster)

arcpy.CheckInExtension("Spatial")
```

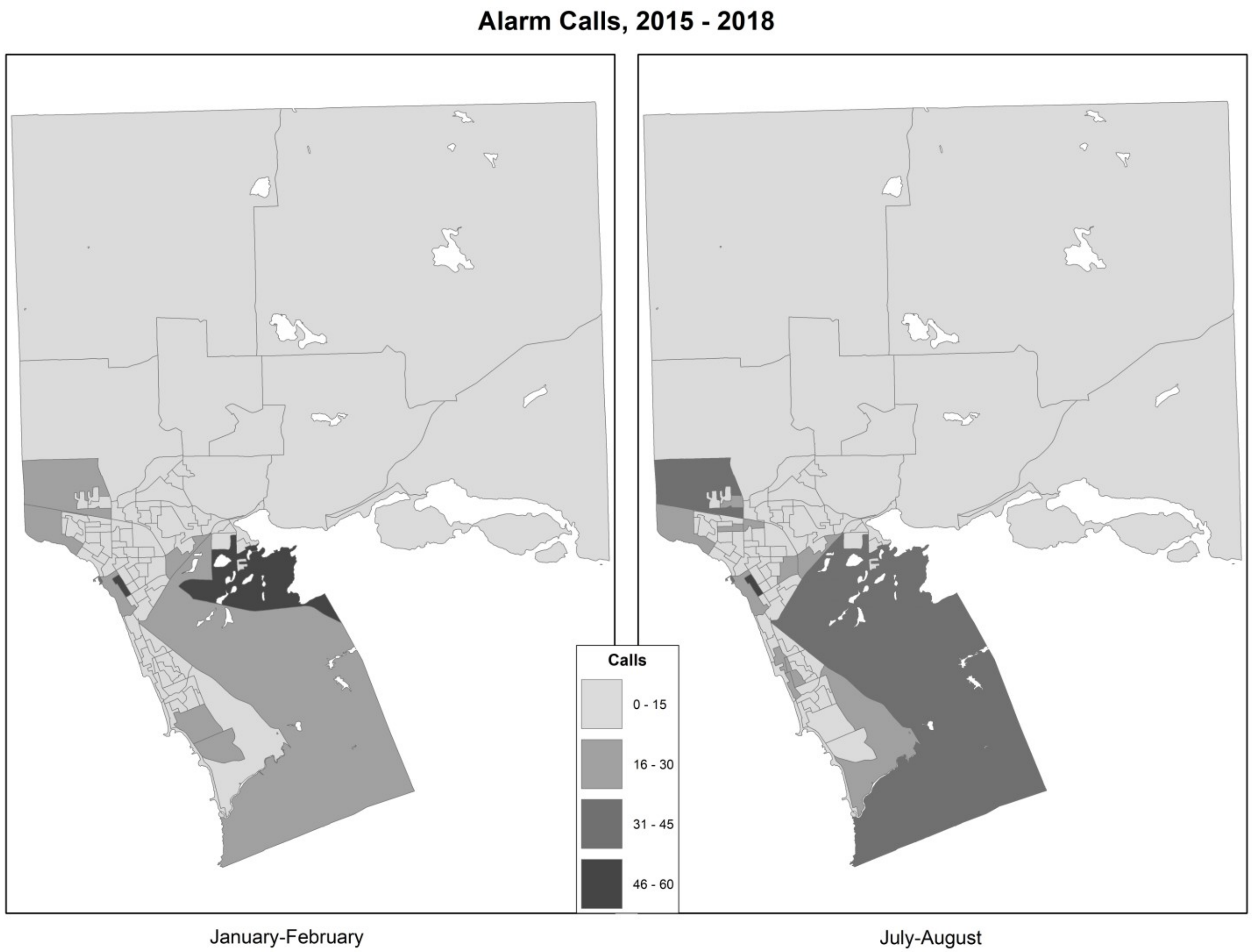
A1.5 Optimized Hotspot Analysis

```
# Import system modules
import arcpy
import os
from arcpy import env
```

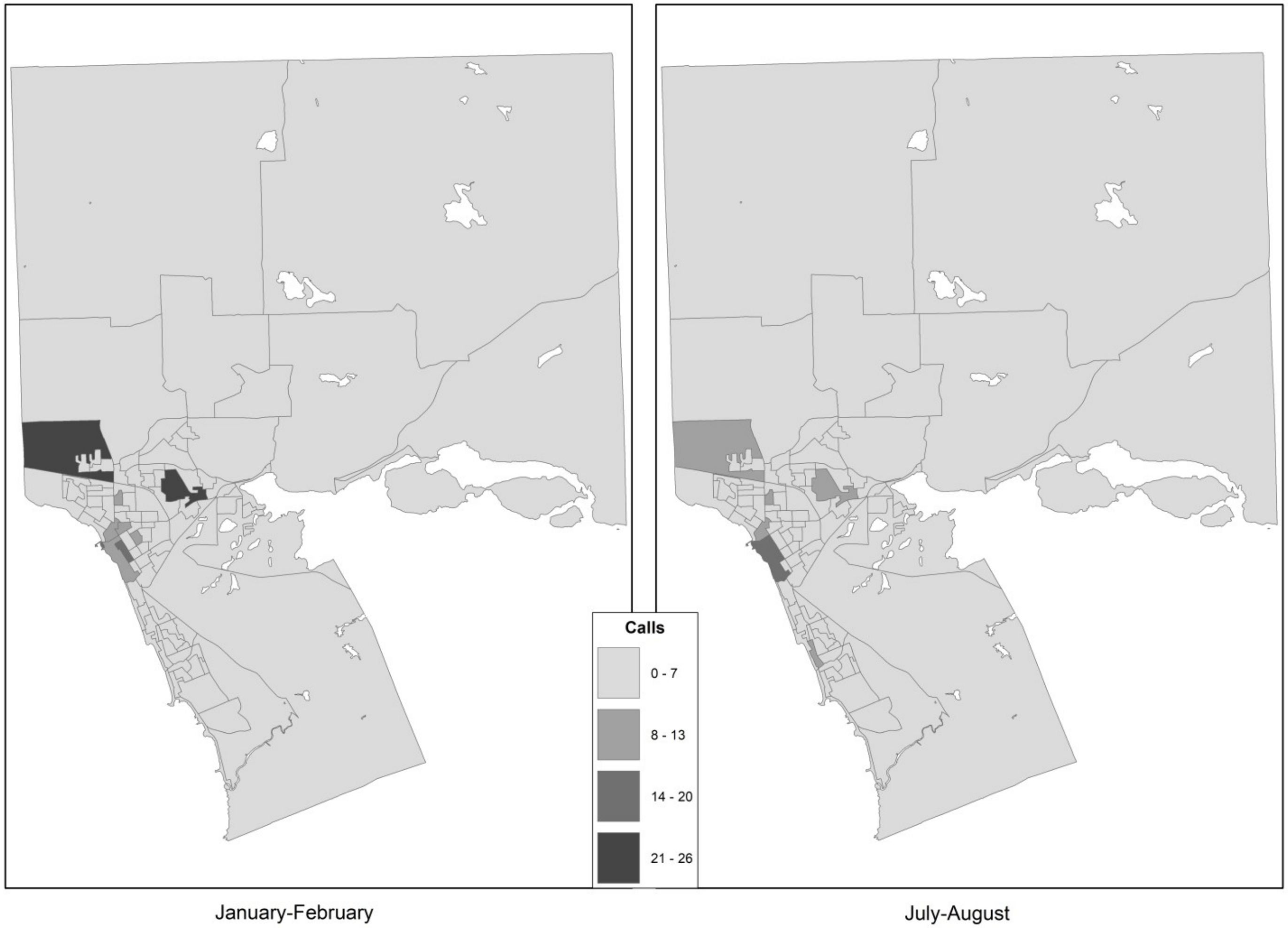
```
# Set workspace and outputs
arcpy.env.workspace = "H:\Policing\Subset\Crimes"
outputFolder = "H:\Policing\Spatial Analysis\GI"

# Set mask and extent
arcpy.env.extent = "C:\Users\Lab R220\Desktop\Working
Folder\Working Data\NorthBayErase.shp"
arcpy.env.mask = "C:\Users\Lab R220\Desktop\Working
Folder\Working Data\NorthBayErase.shp"

# List inputs
crimes = arcpy.ListFiles("*.shp")

try:
    for crime in crimes:
          # Fishnet polygons
          Input_Features = crime
          Output_Features =
          os.path.join(outputFolder,os.path.splitext(os.path.bas
          ename(crime))[0]+"fishnet.shp")

          arcpy.OptimizedHotSpotAnalysis_stats(Input_Features,
          Output_Features, "#",
          "COUNT_INCIDENTS_WITHIN_FISHNET_POLYGONS",
          "H:\Policing\Working Data\NorthBayErase.shp", "#",
          "#", Cell_Size = "30 METERS", "#")

          # Aggregate to dissemination areas
          Input_Features = crime
          Output_Features =
          os.path.join(outputFolder,os.path.splitext(os.path.bas
          ename(crime))[0]+"DA.shp")

          arcpy.OptimizedHotSpotAnalysis_stats(Input_Features,
          Output_Features, "#",
          "COUNT_INCIDENTS_WITHIN_AGGREGATION_POLYGONS",
          "H:\Policing\Working Data\NorthBay.shp",
          "H:\Policing\Working Data\DAfinal.shp", "#")

except:
    pass
```

Appendix 3: Additional Maps

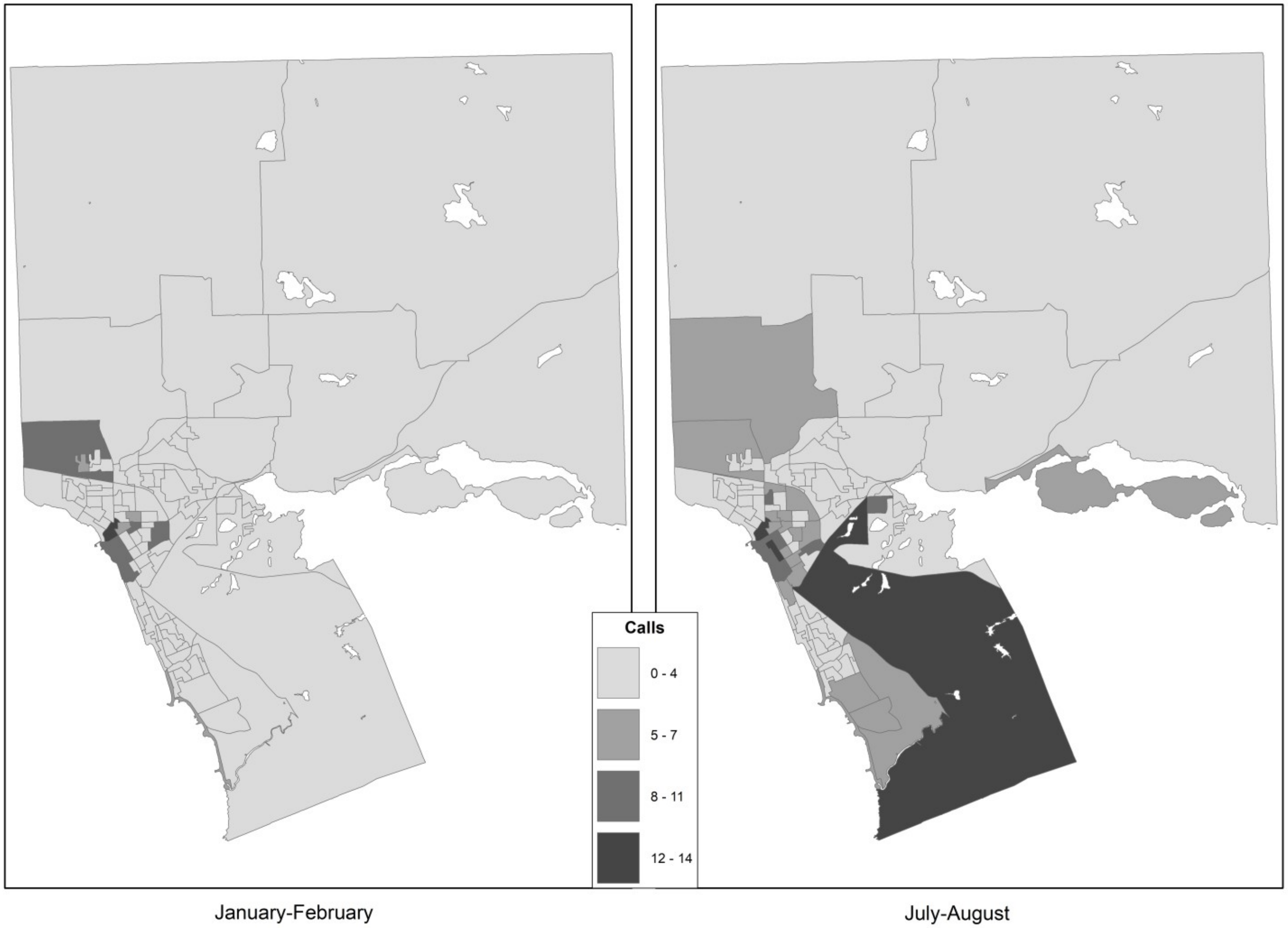
A3.1 Crime Counts by Dissemination Area



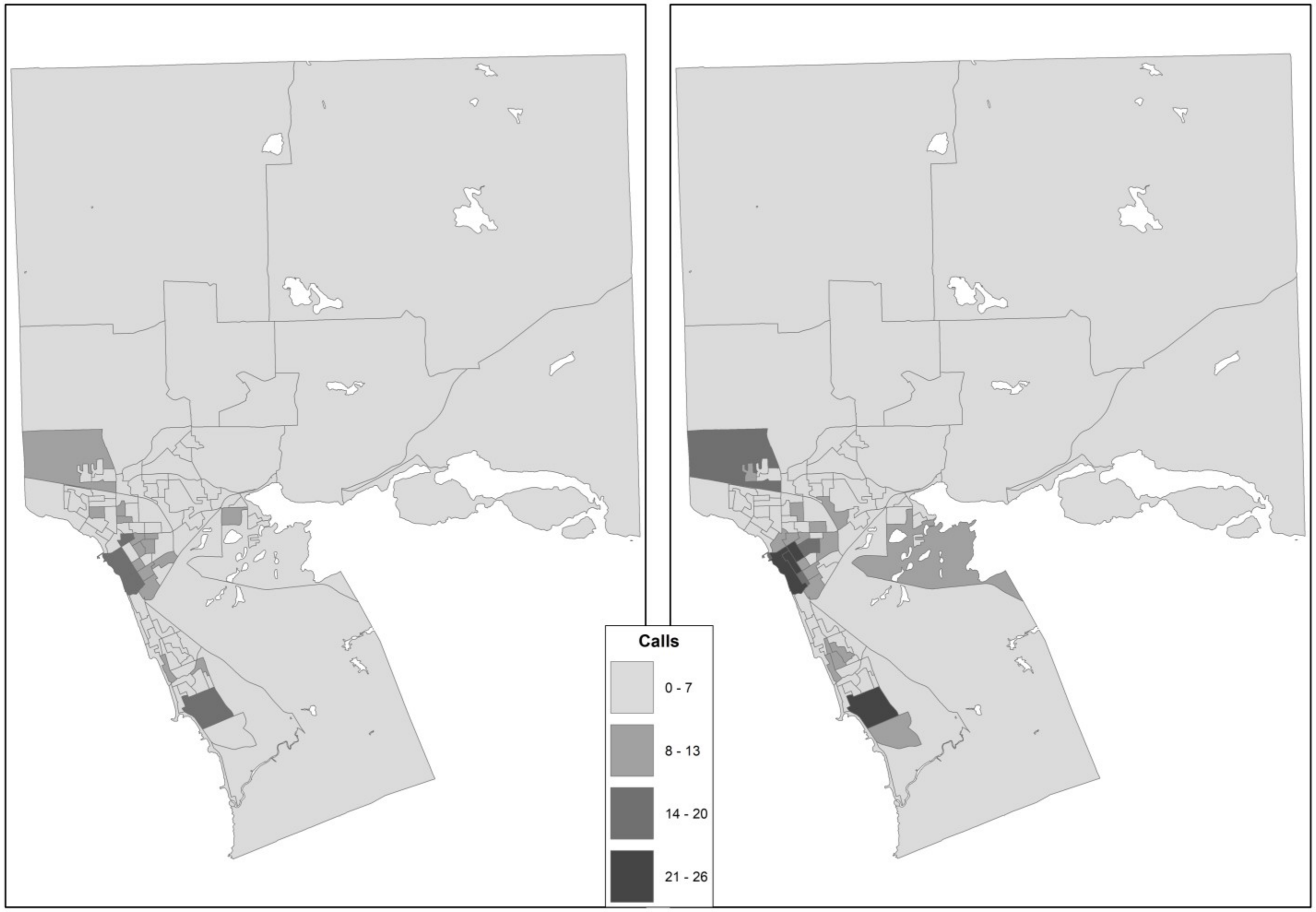
Assault Calls, 2015 - 2018



Break and Enter Calls, 2015 - 2018



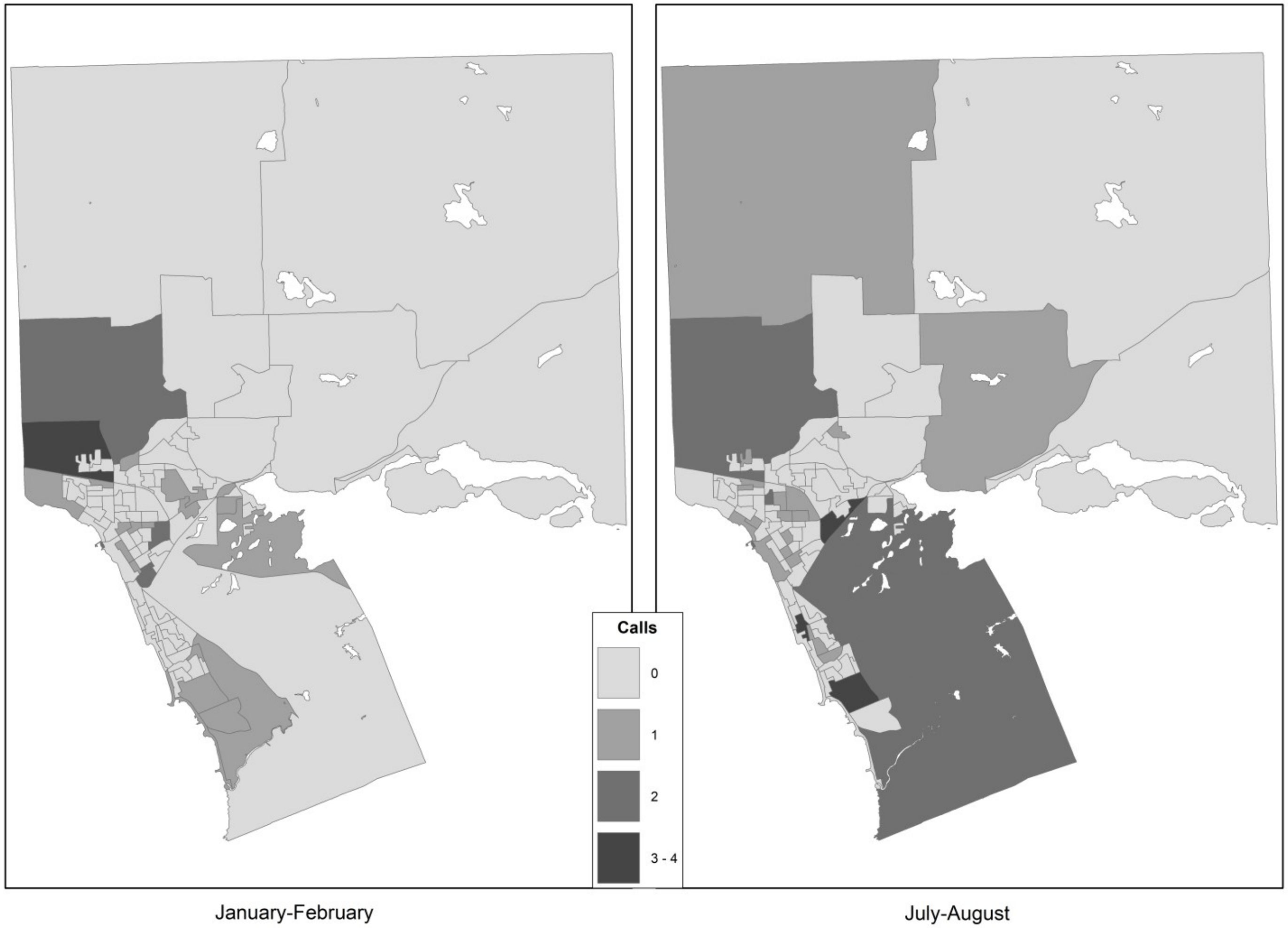
Domestic Dispute Calls, 2015 - 2018



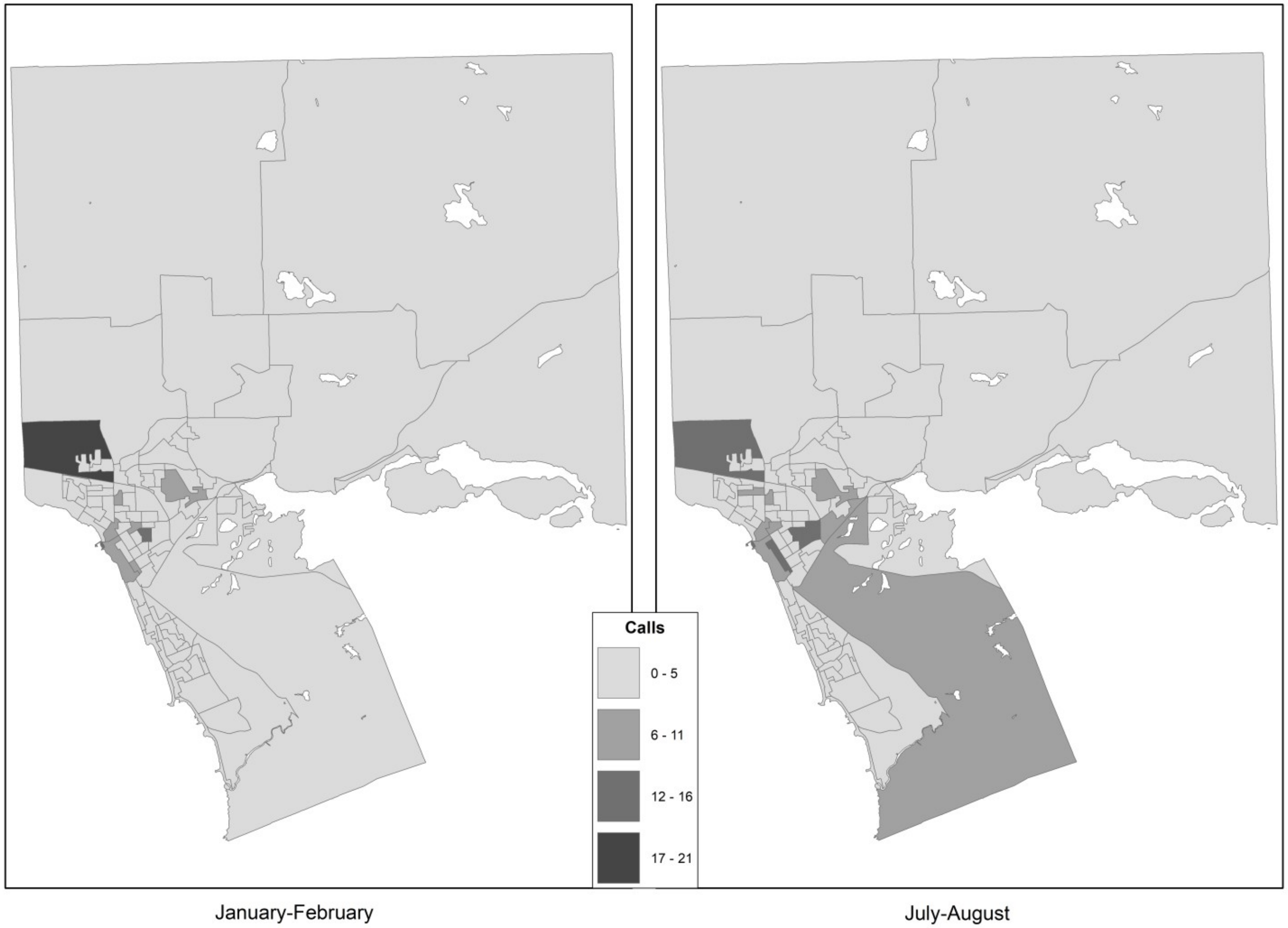
January-February

July-August

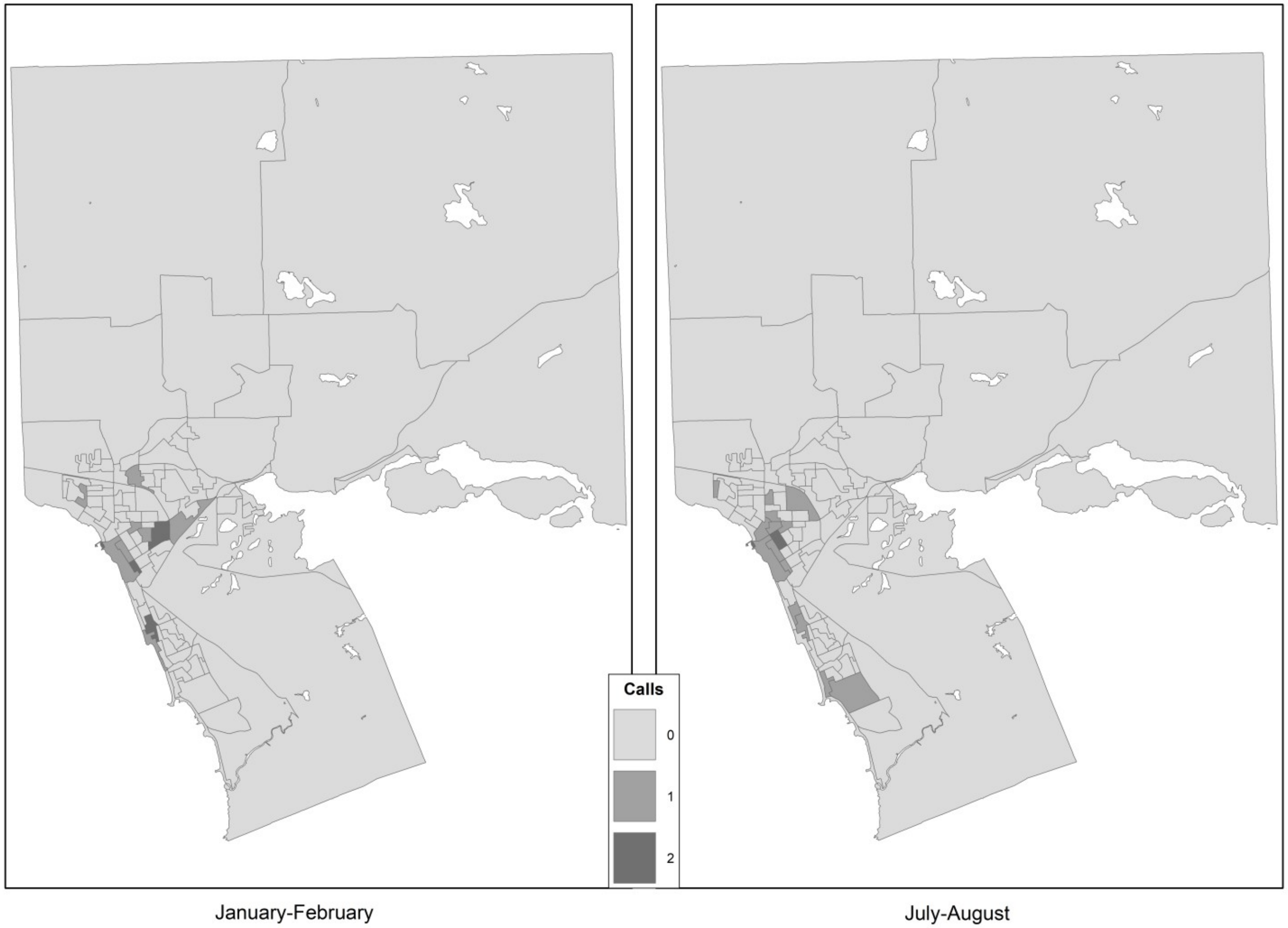
Motor Vehicle Theft Calls, 2015 - 2018



Narcotics Calls, 2015 - 2018



Robbery Calls, 2015 - 2018

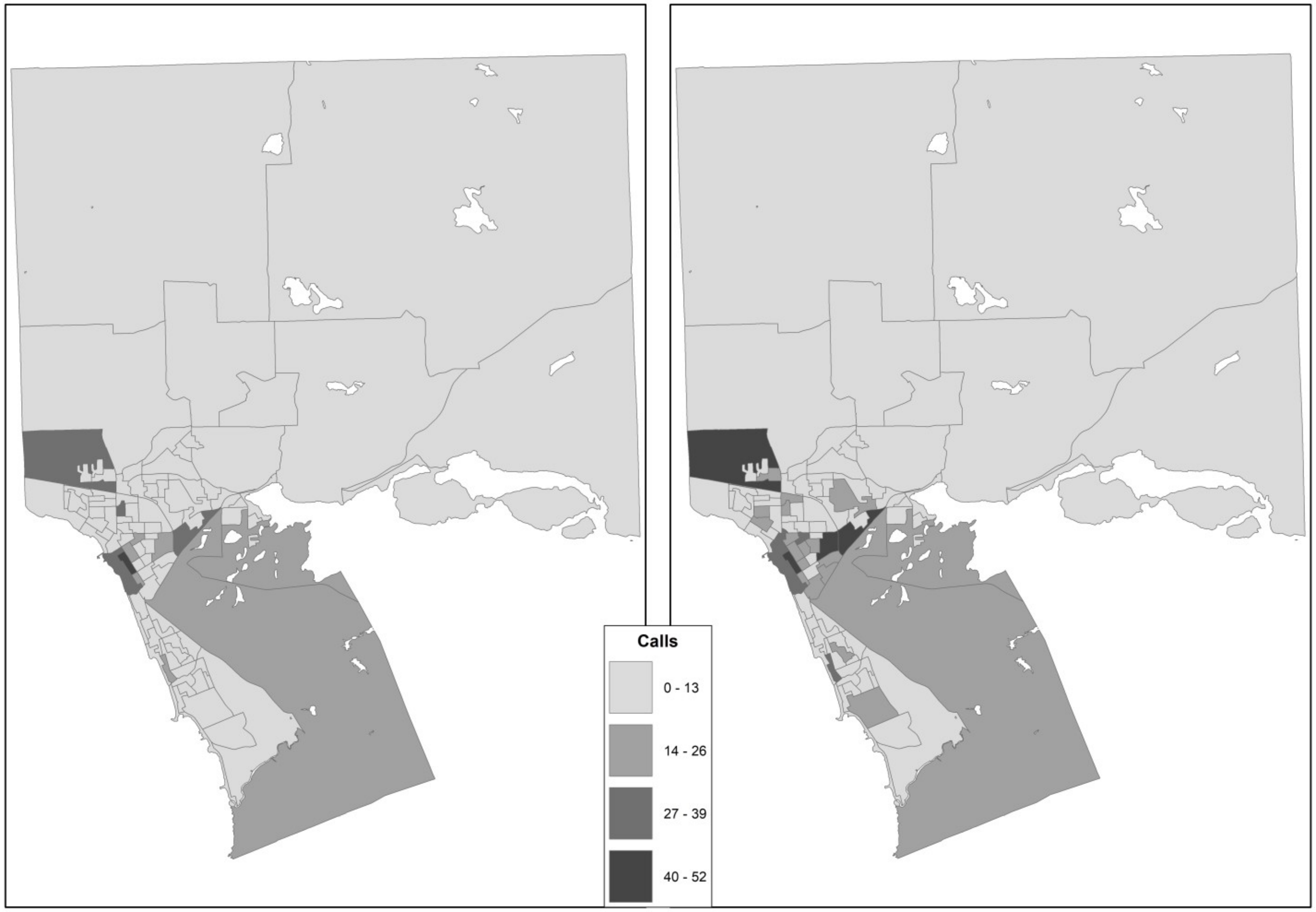


Shoplifting Calls, 2015 - 2018

January-February

July-August

Theft Calls, 2015 - 2018

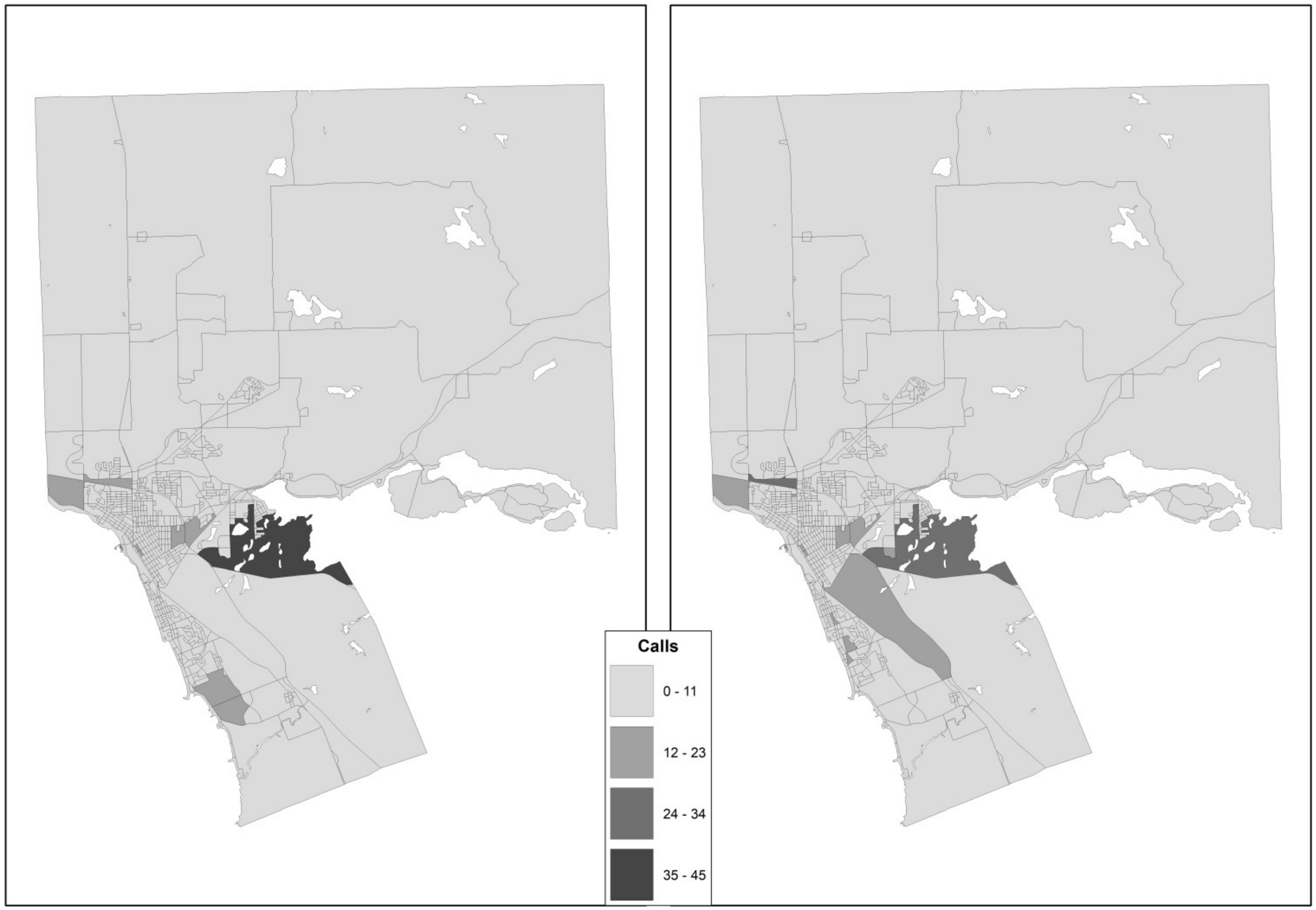


January-February

July-August

A3.2 Crime Counts by Dissemination Block

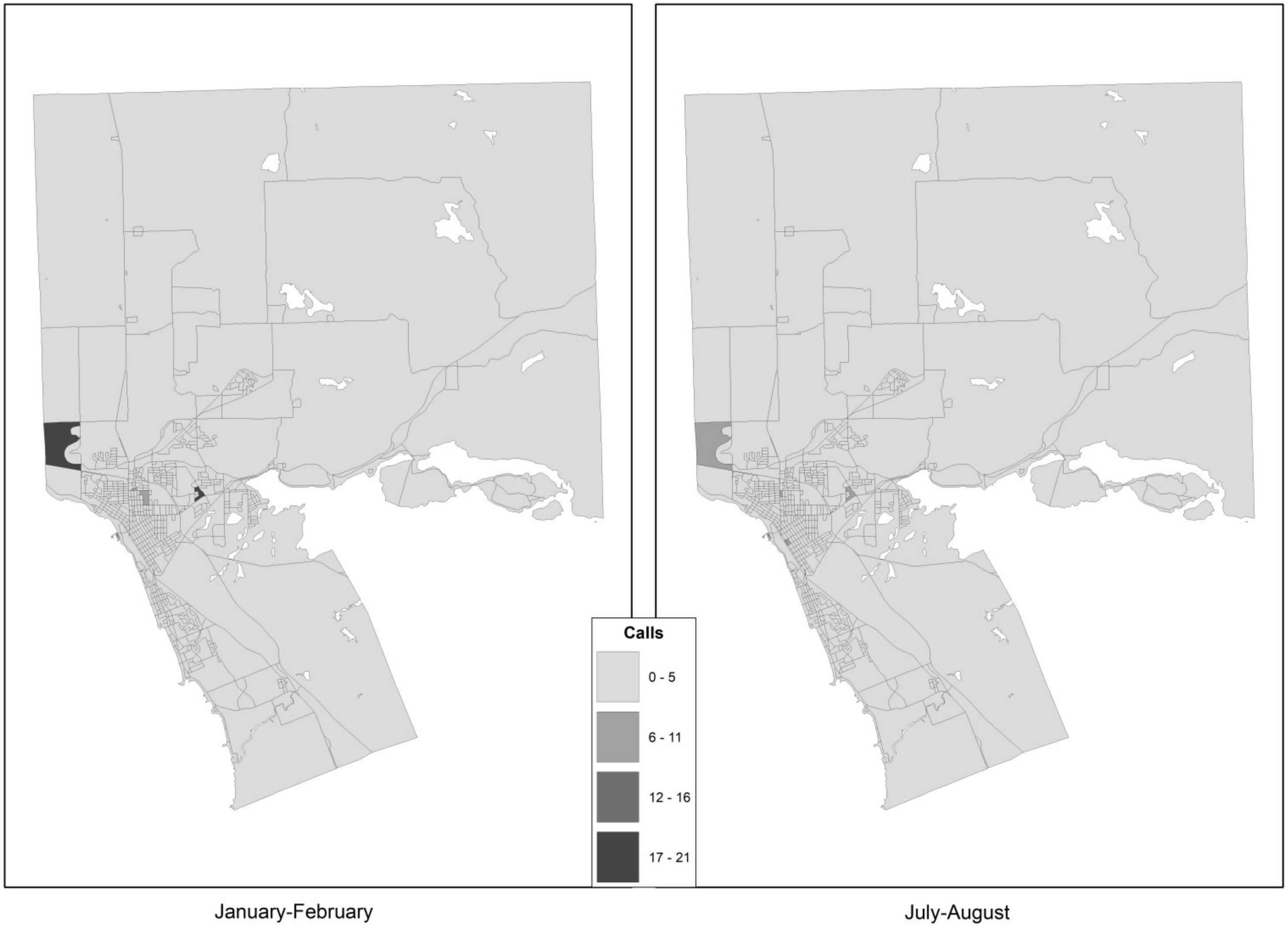
Alarm Calls, 2015 - 2018



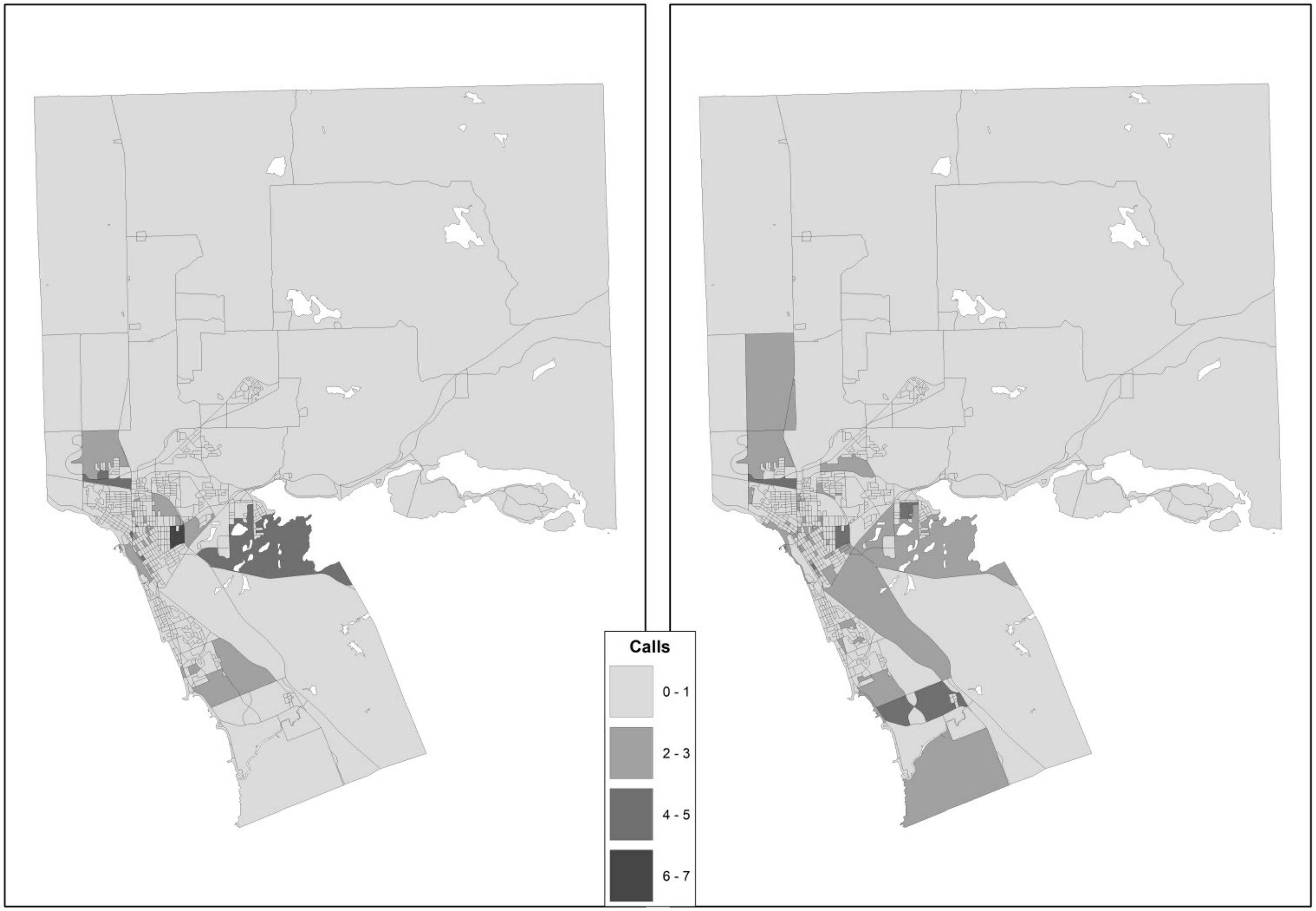
January-February

July-August

Assault Calls, 2015 - 2018



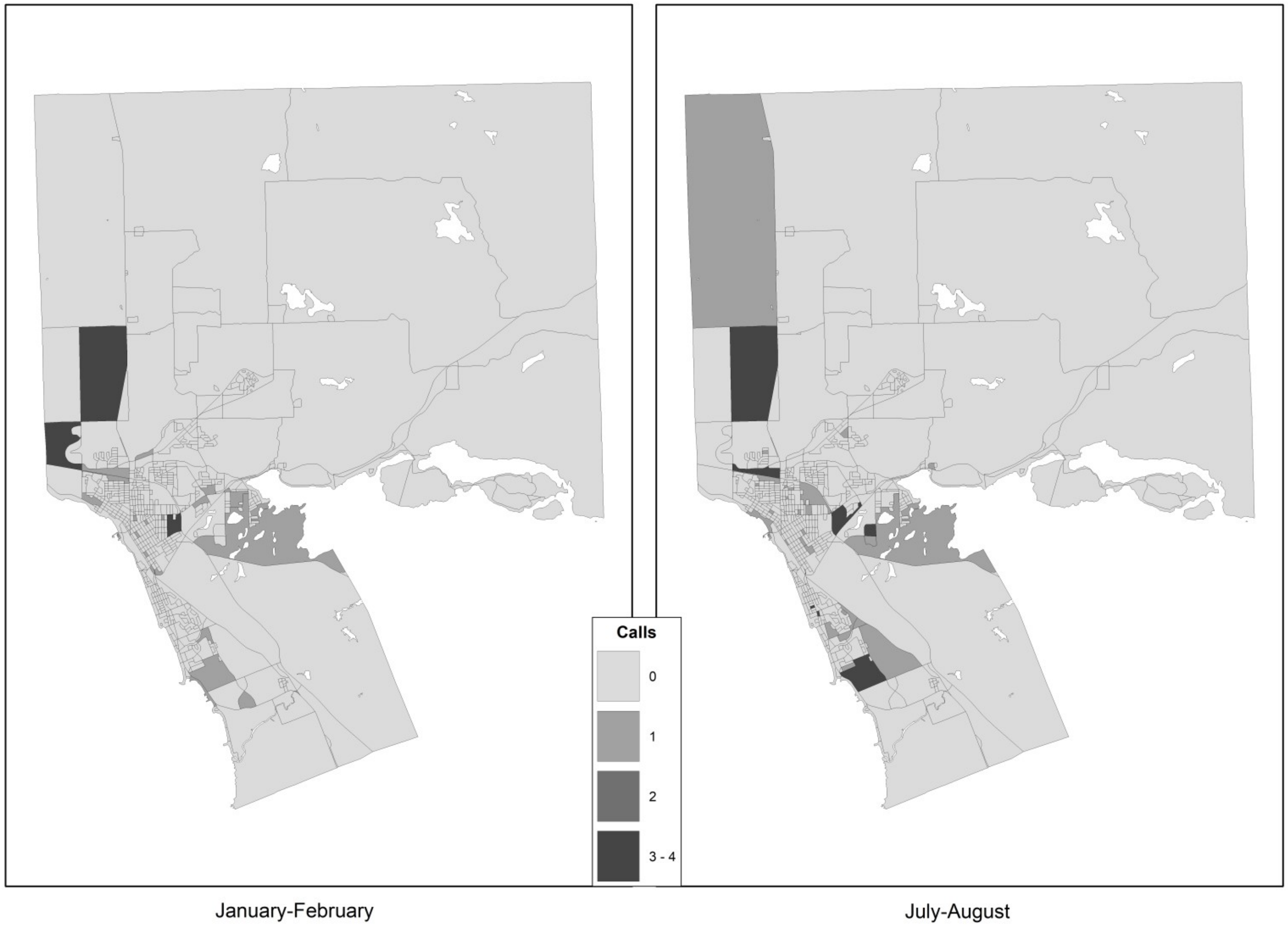
Break and Enter Calls, 2015 - 2018



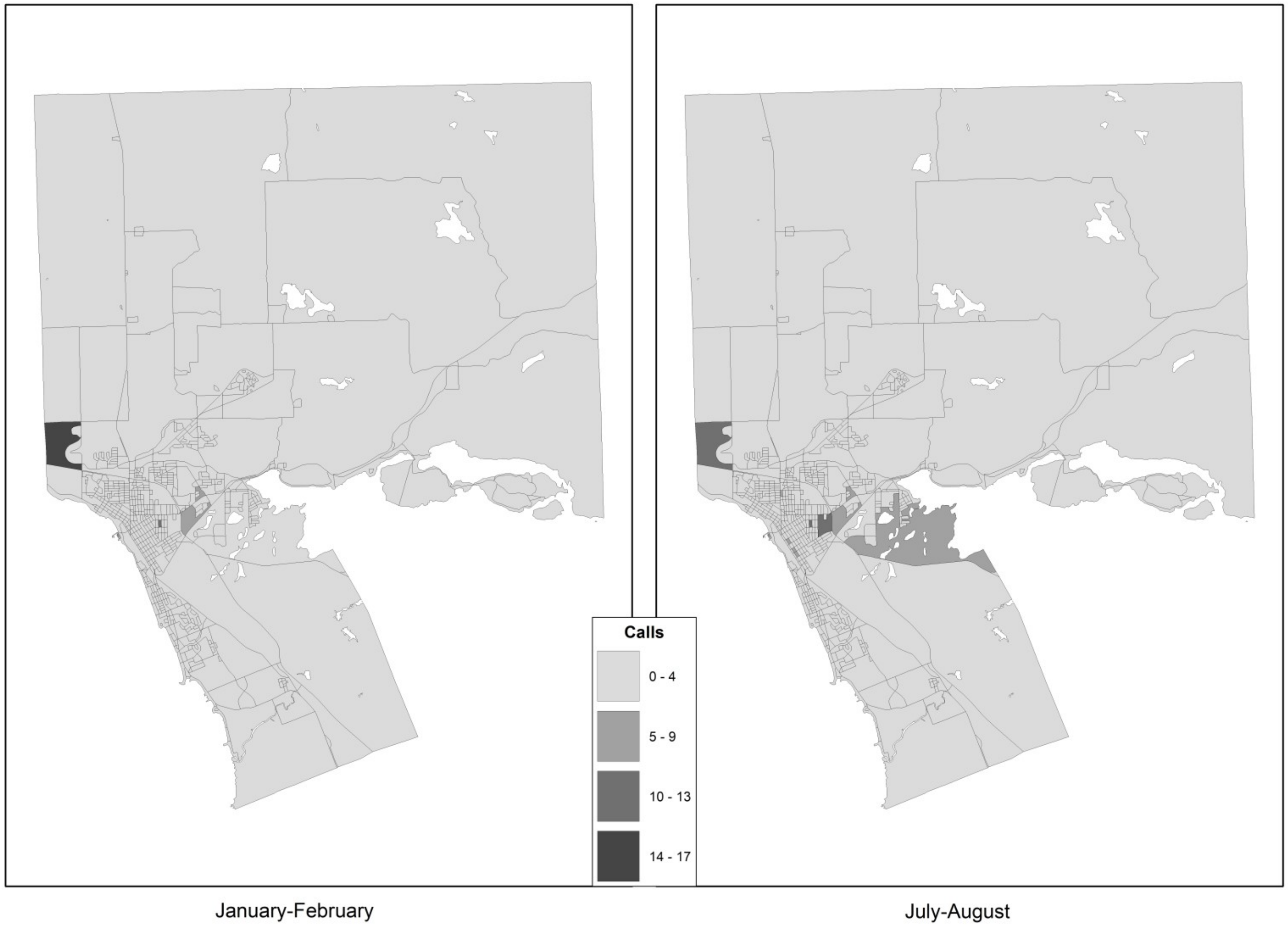
January-February

July-August

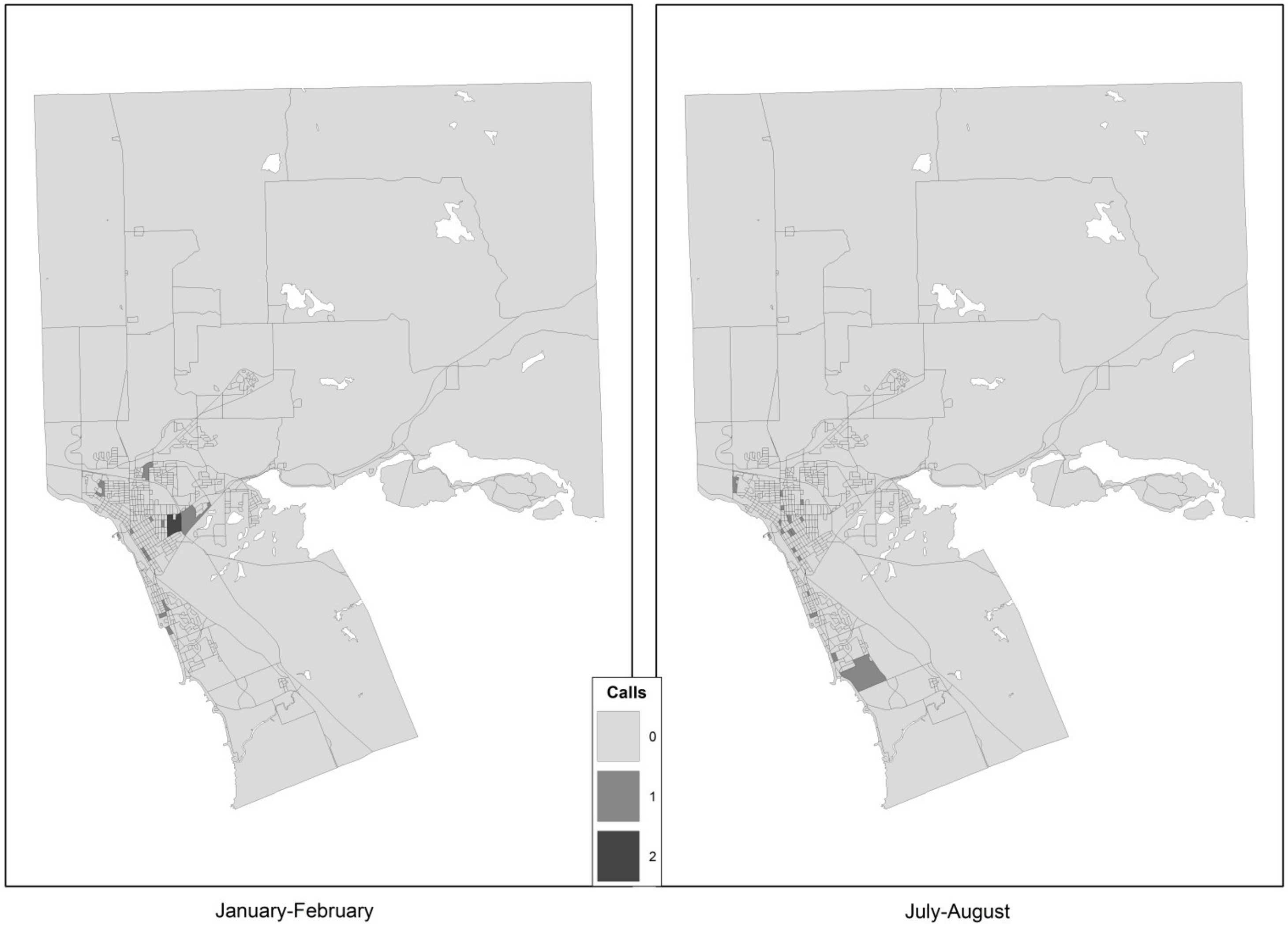
Motor Vehicle Theft Calls, 2015 - 2018



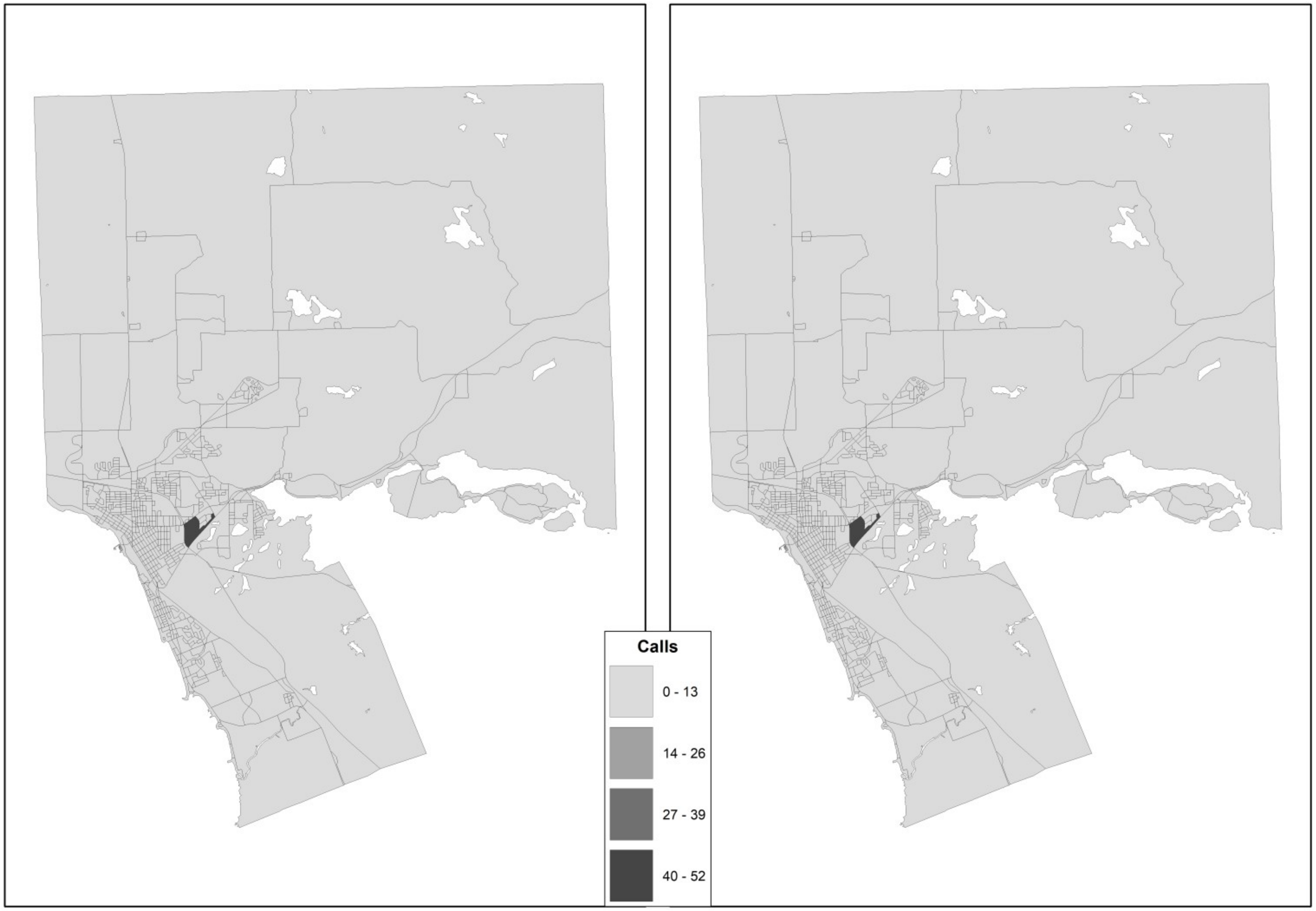
Narcotics Calls, 2015 - 2018



Robbery Calls, 2015 - 2018



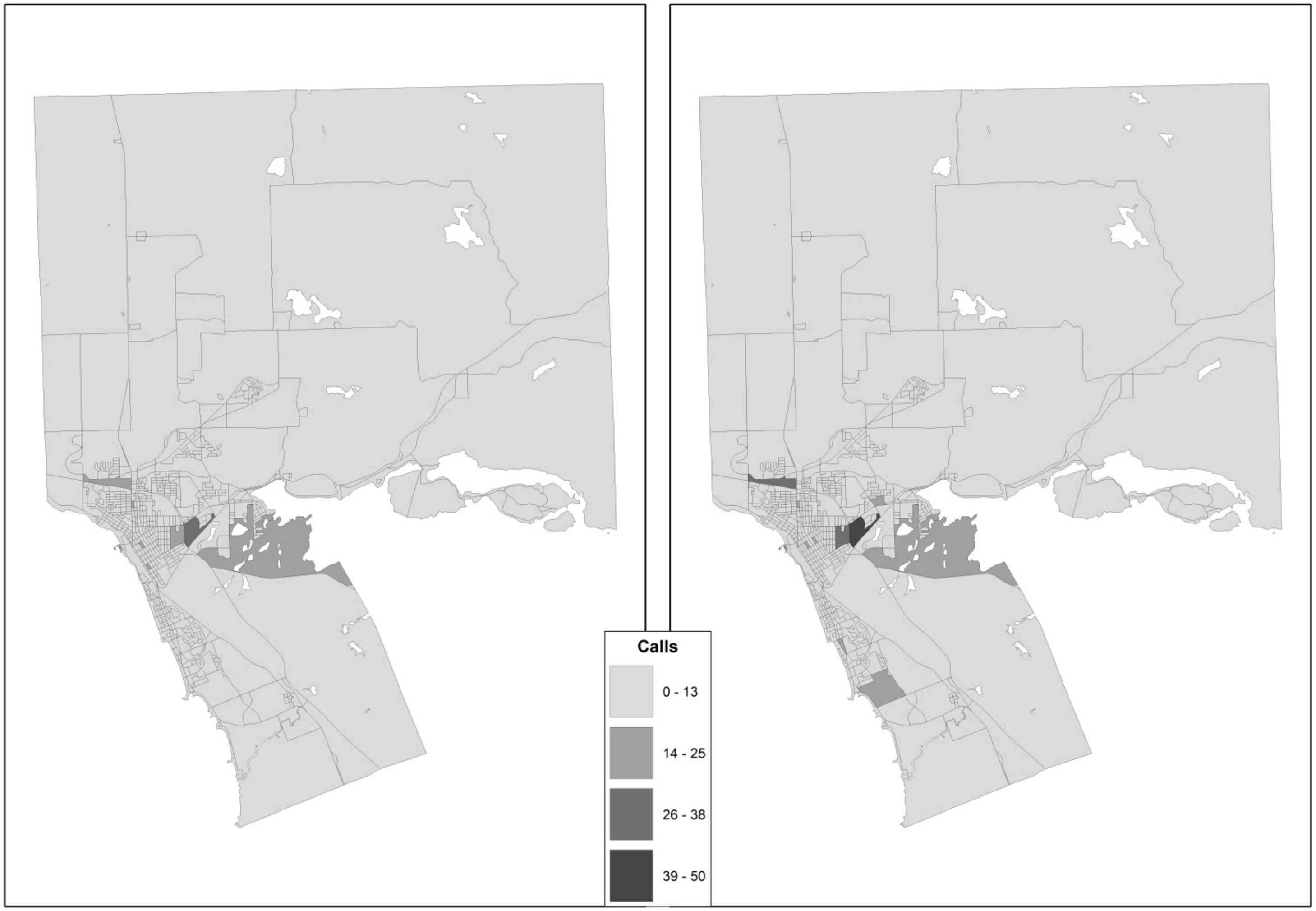
Shoplifting Calls, 2015 - 2018



January-February

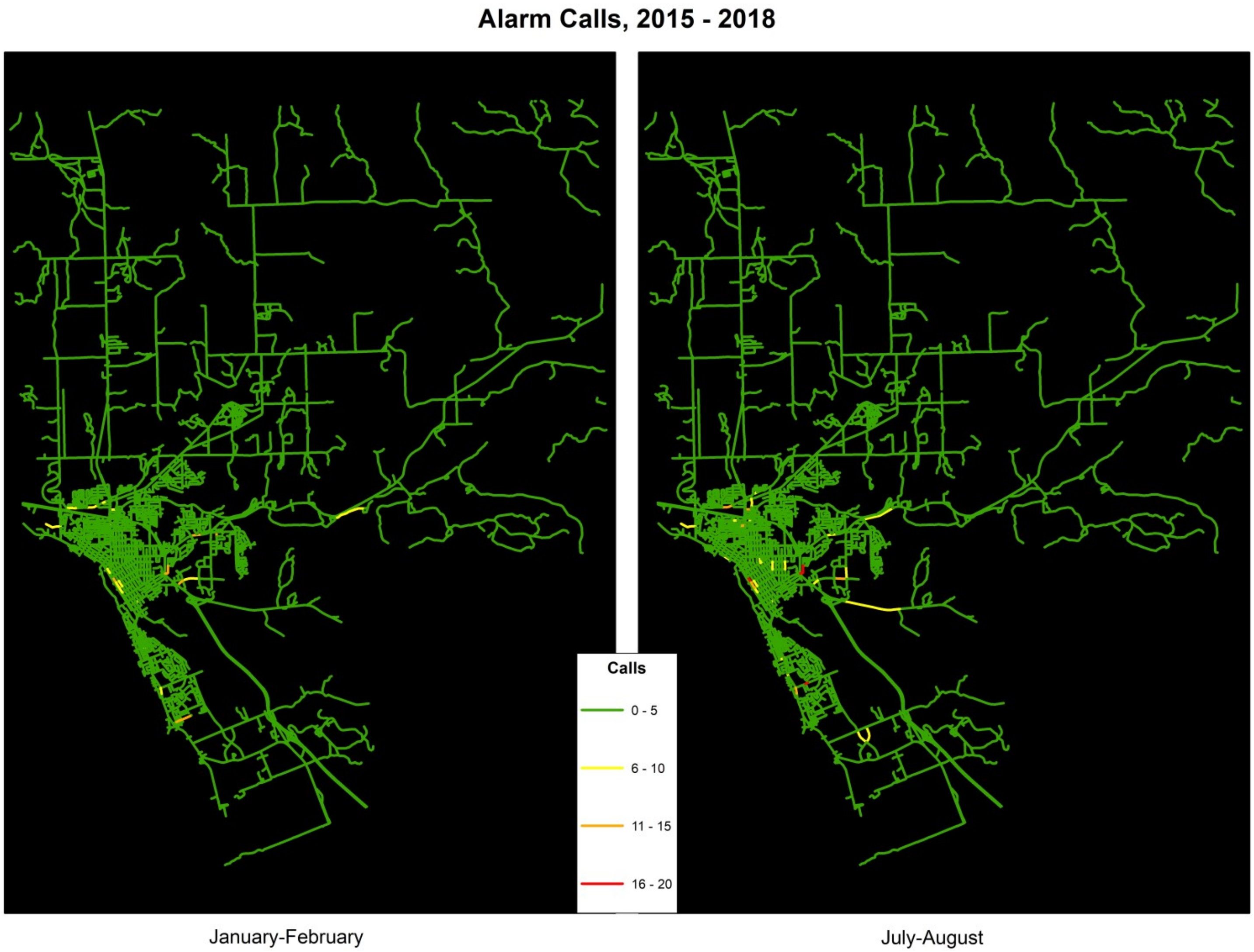
July-August

Theft Calls, 2015 - 2018

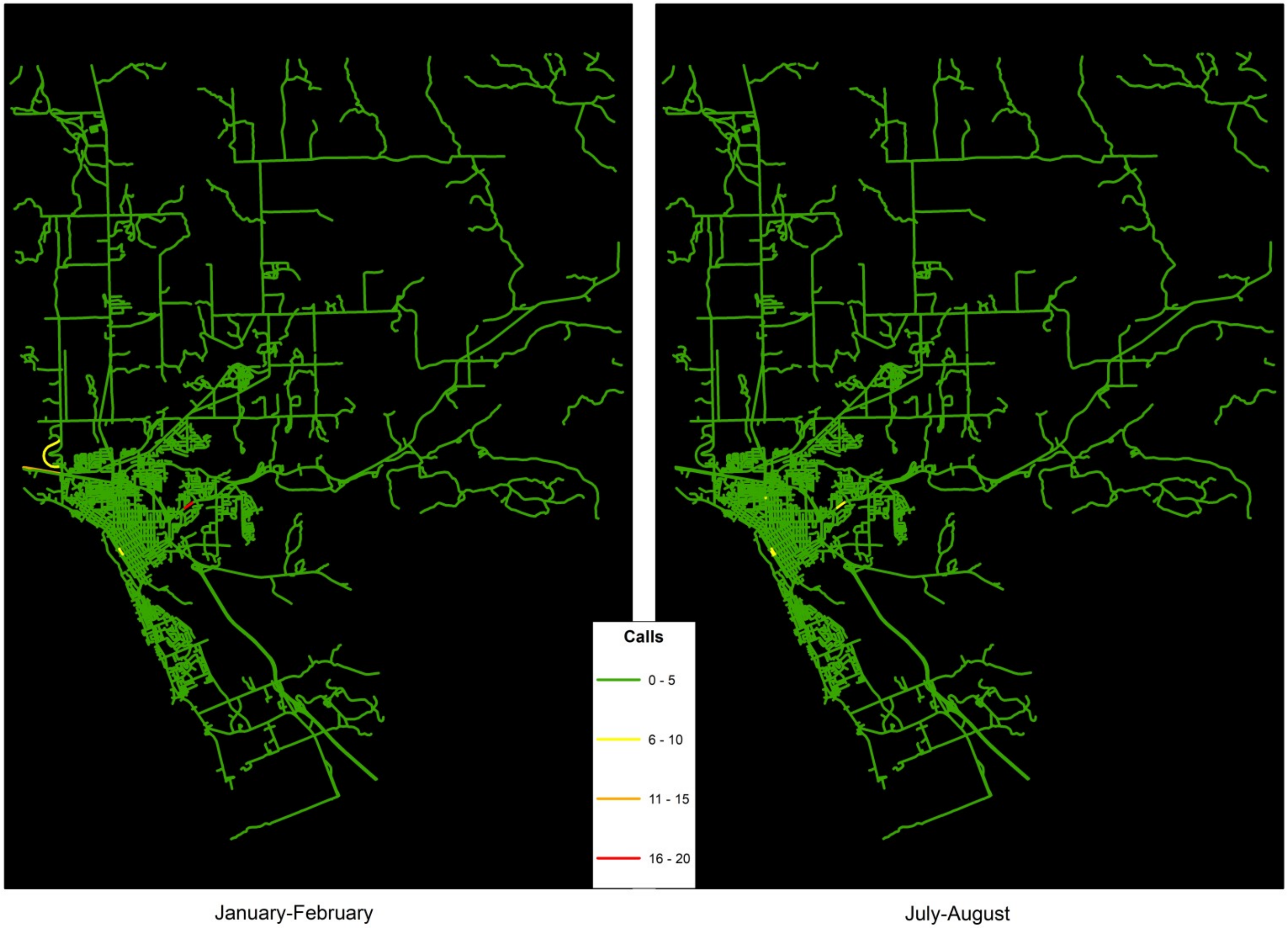


January-February July-August

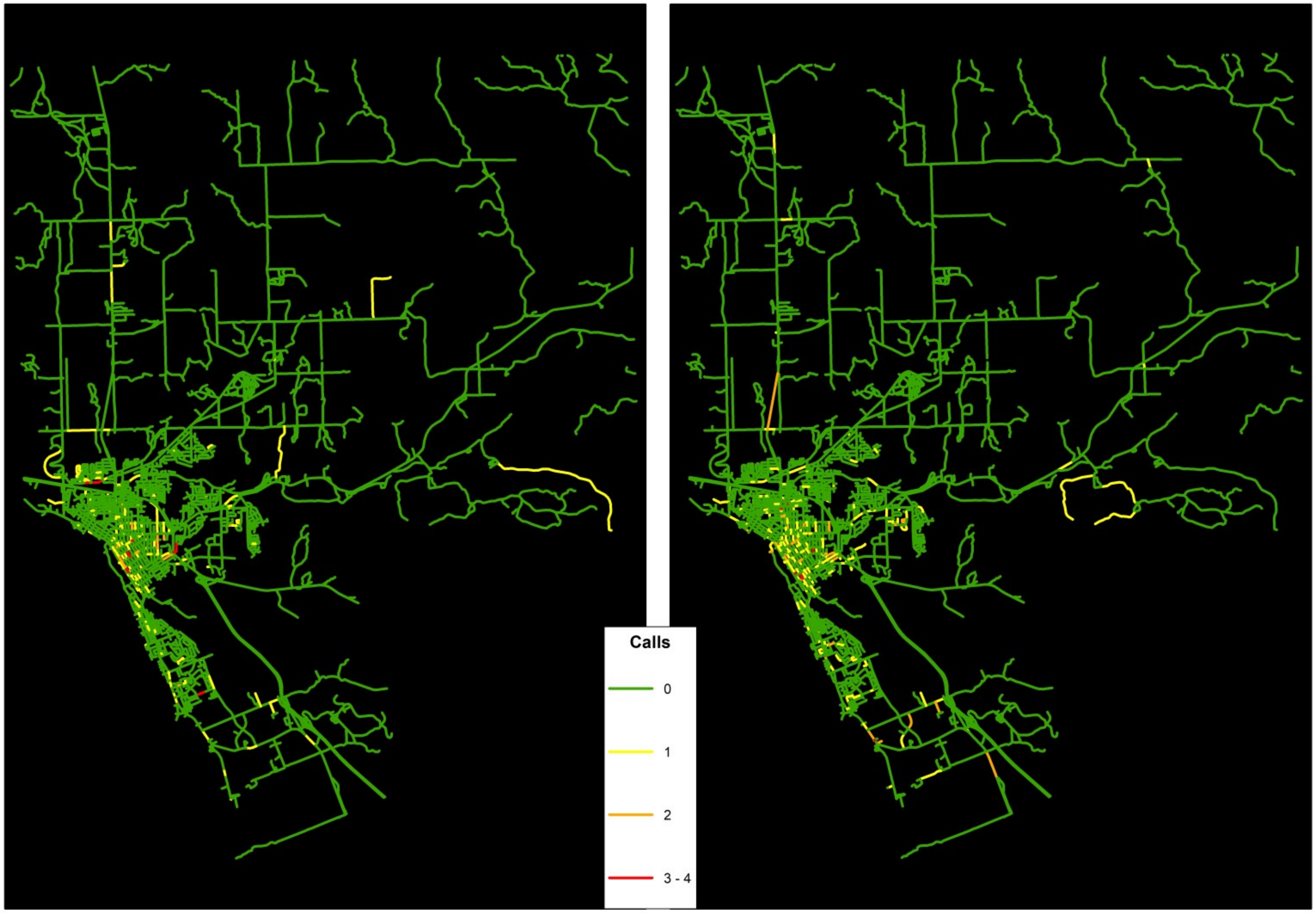
A3.3 Crime Counts by Street Segment



Assault Calls, 2015 - 2018



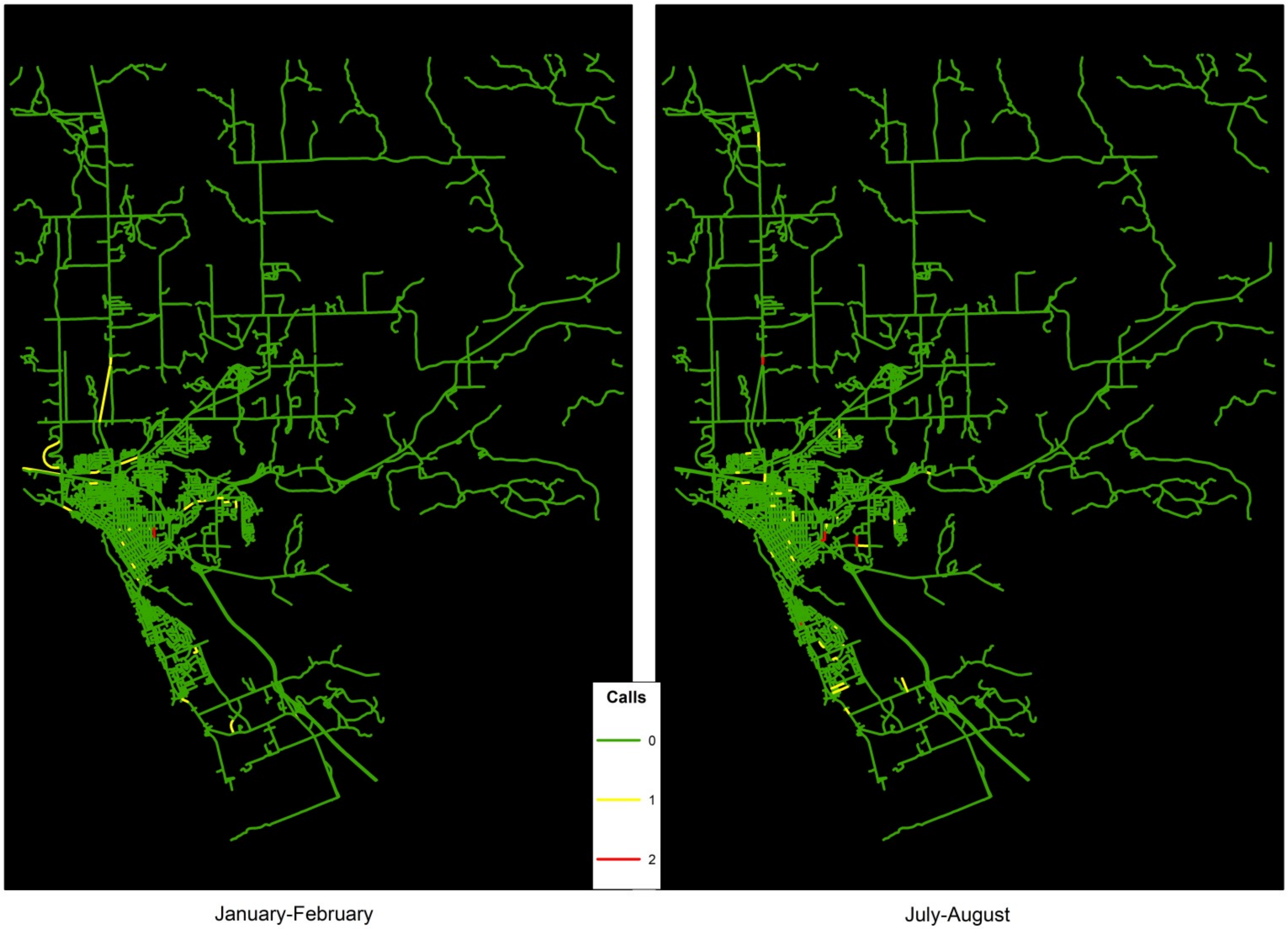
Break and Enter Calls, 2015 - 2018



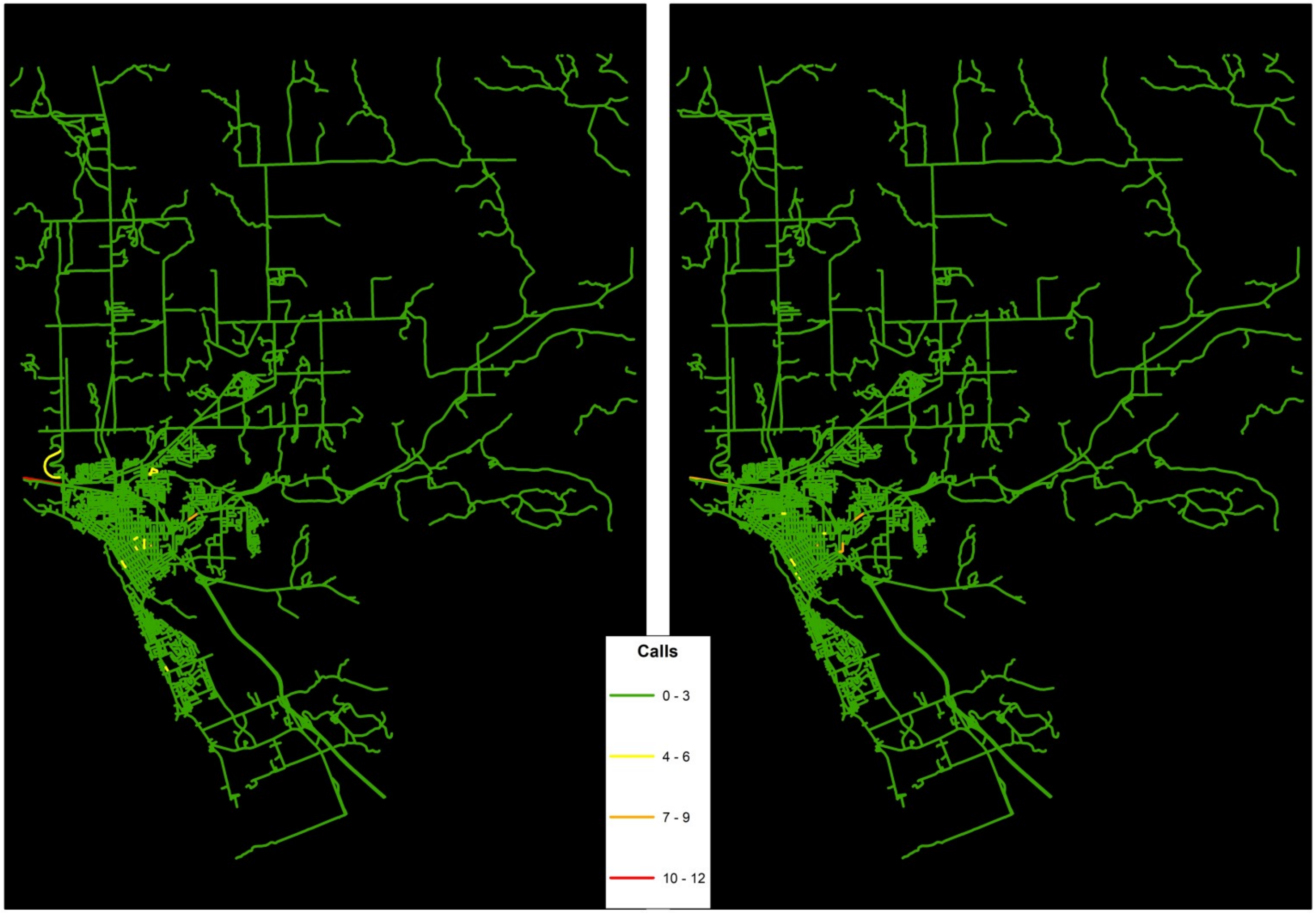
January-February

July-August

Motor Vehicle Theft Calls, 2015 - 2018



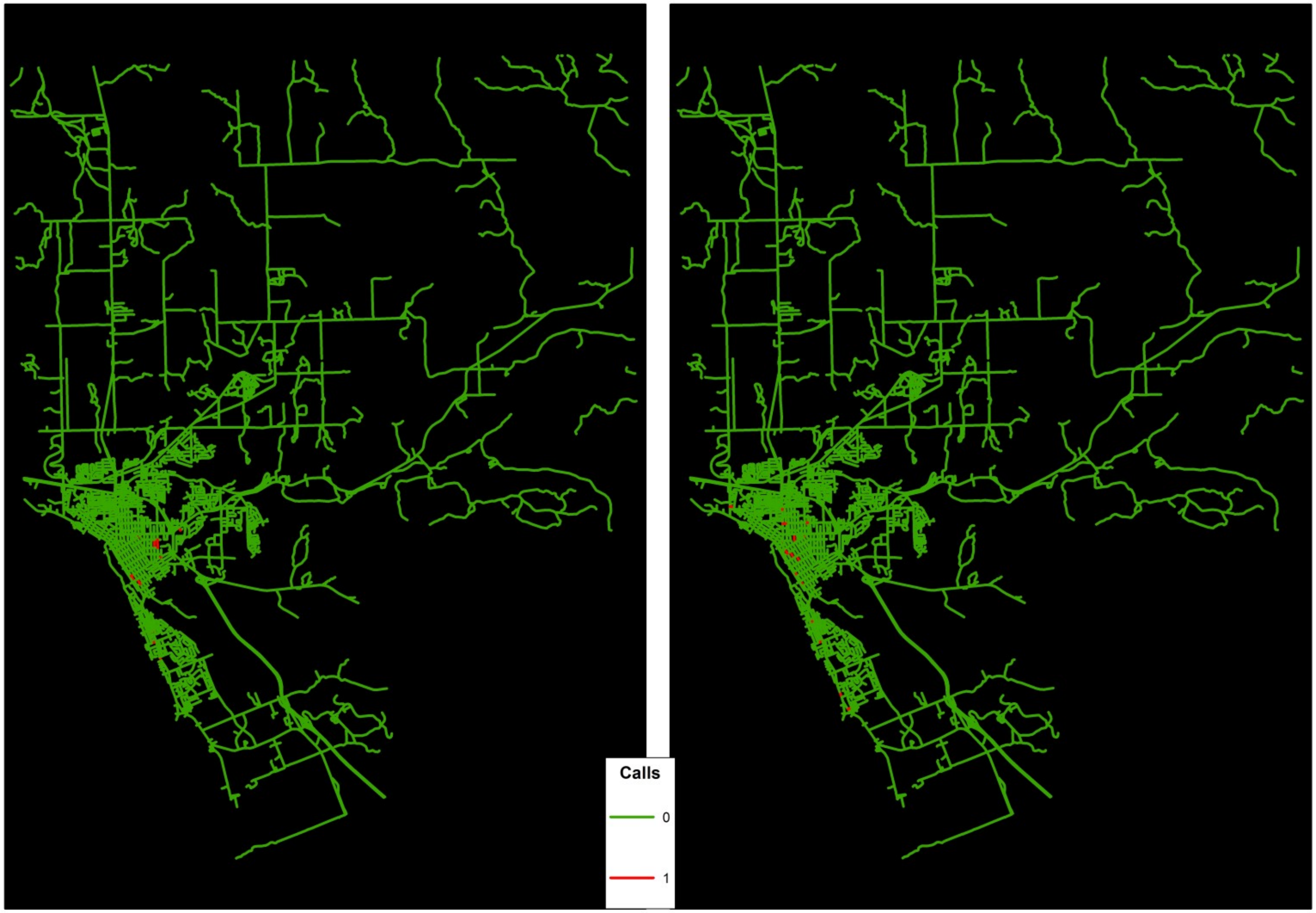
Narcotics Calls, 2015 - 2018



January-February

July-August

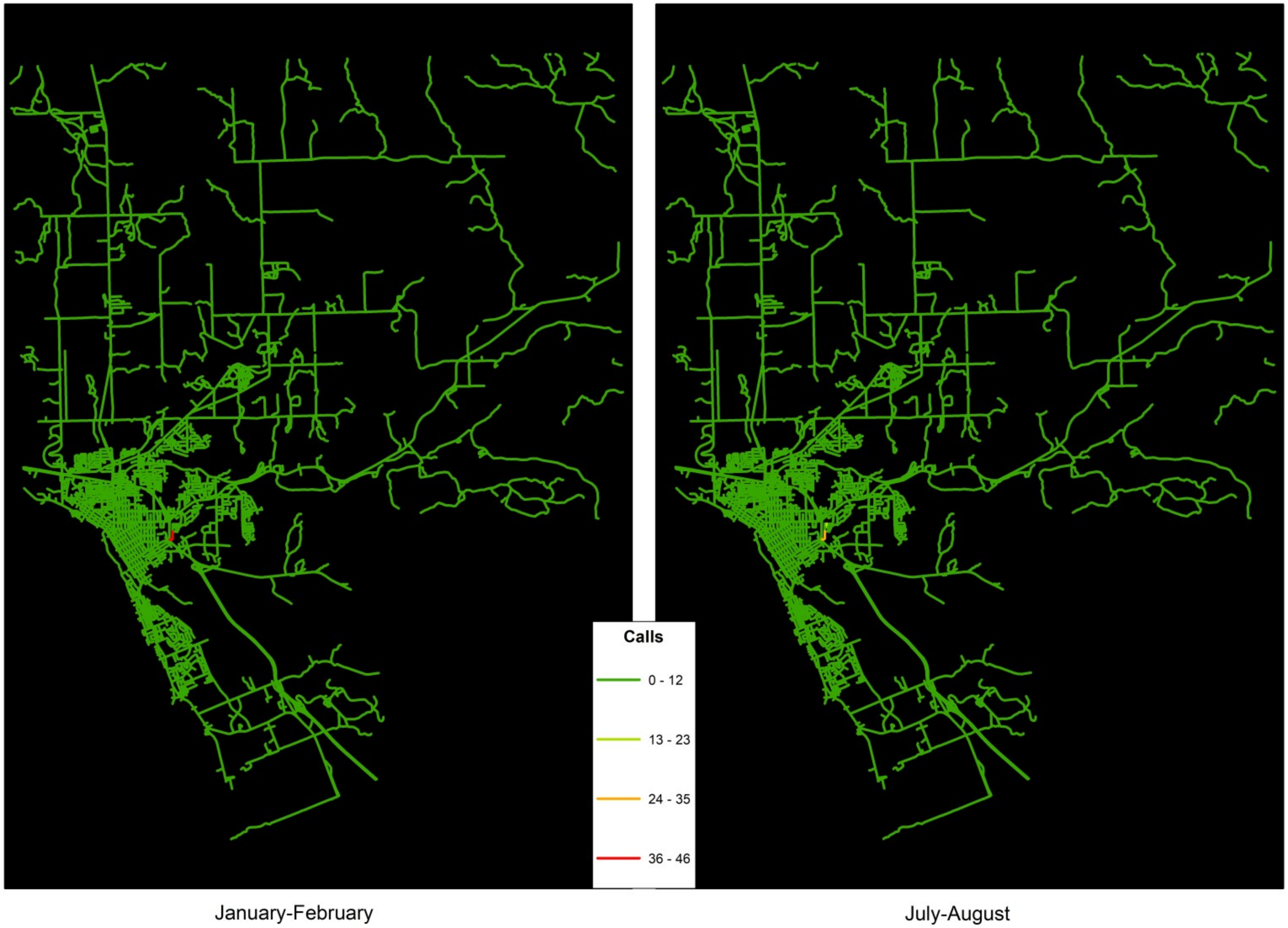
Robbery Calls, 2015 - 2018



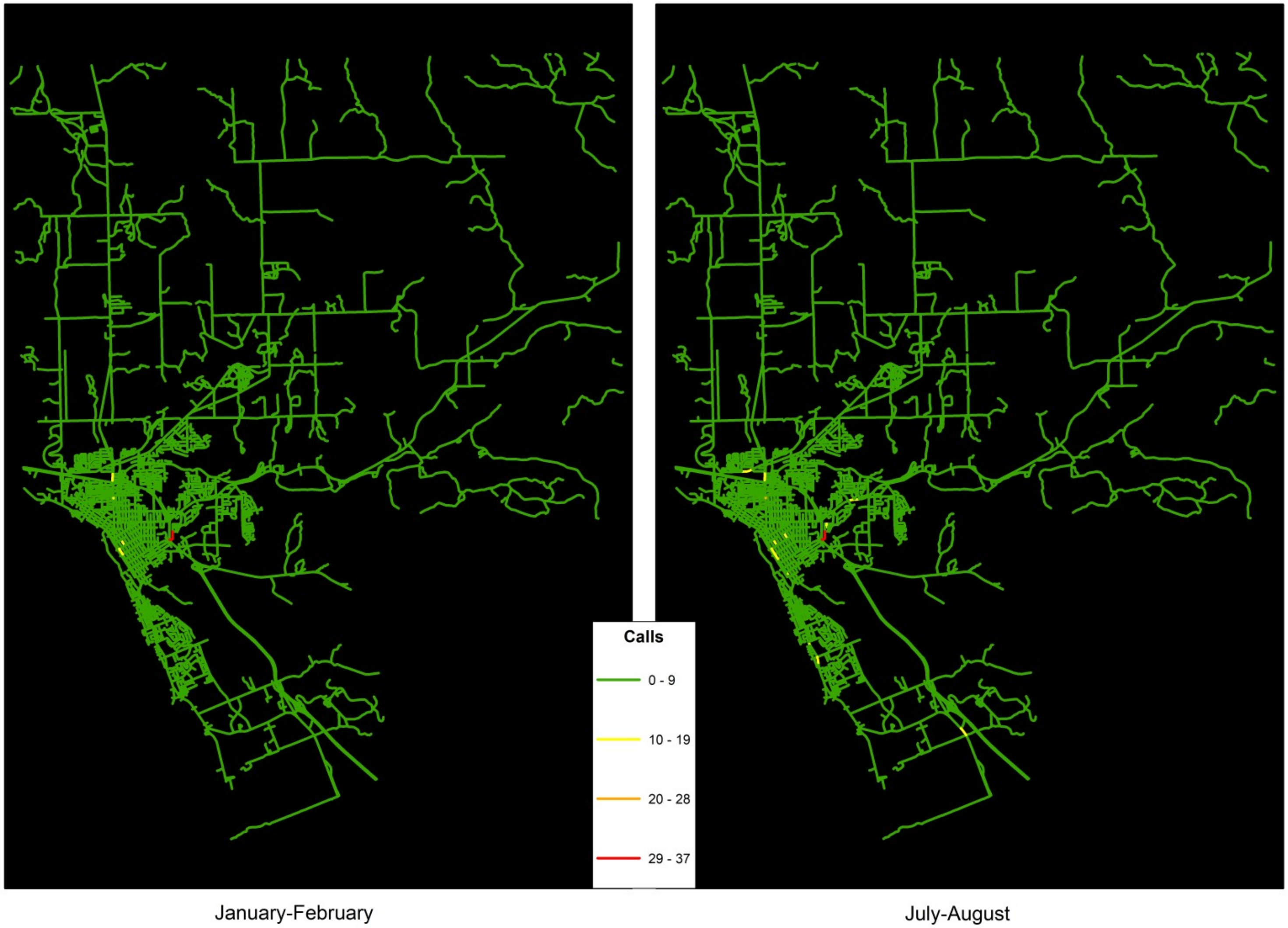
January-February

July-August

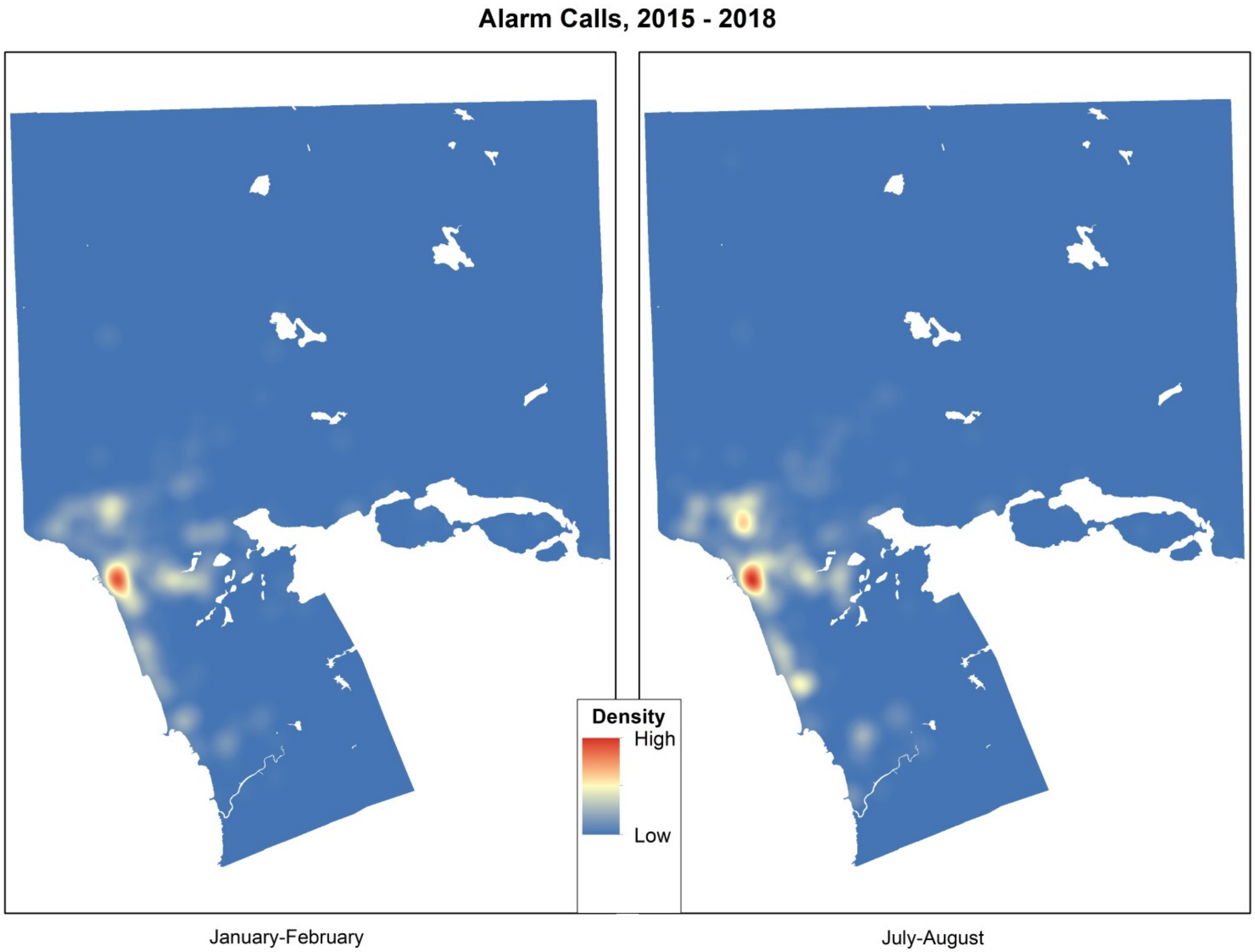
Shoplifting Calls, 2015 - 2018



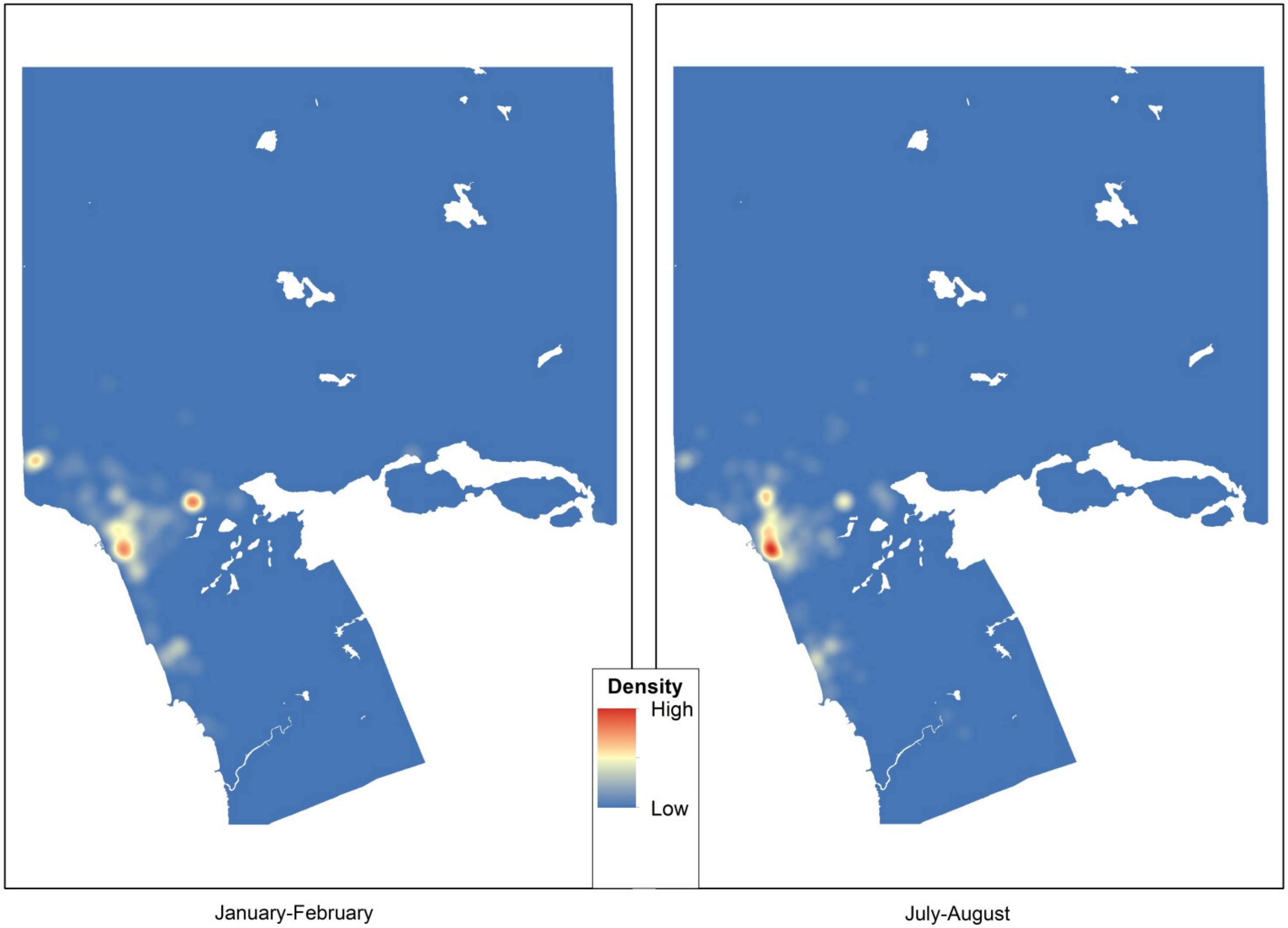
Theft Calls, 2015 - 2018



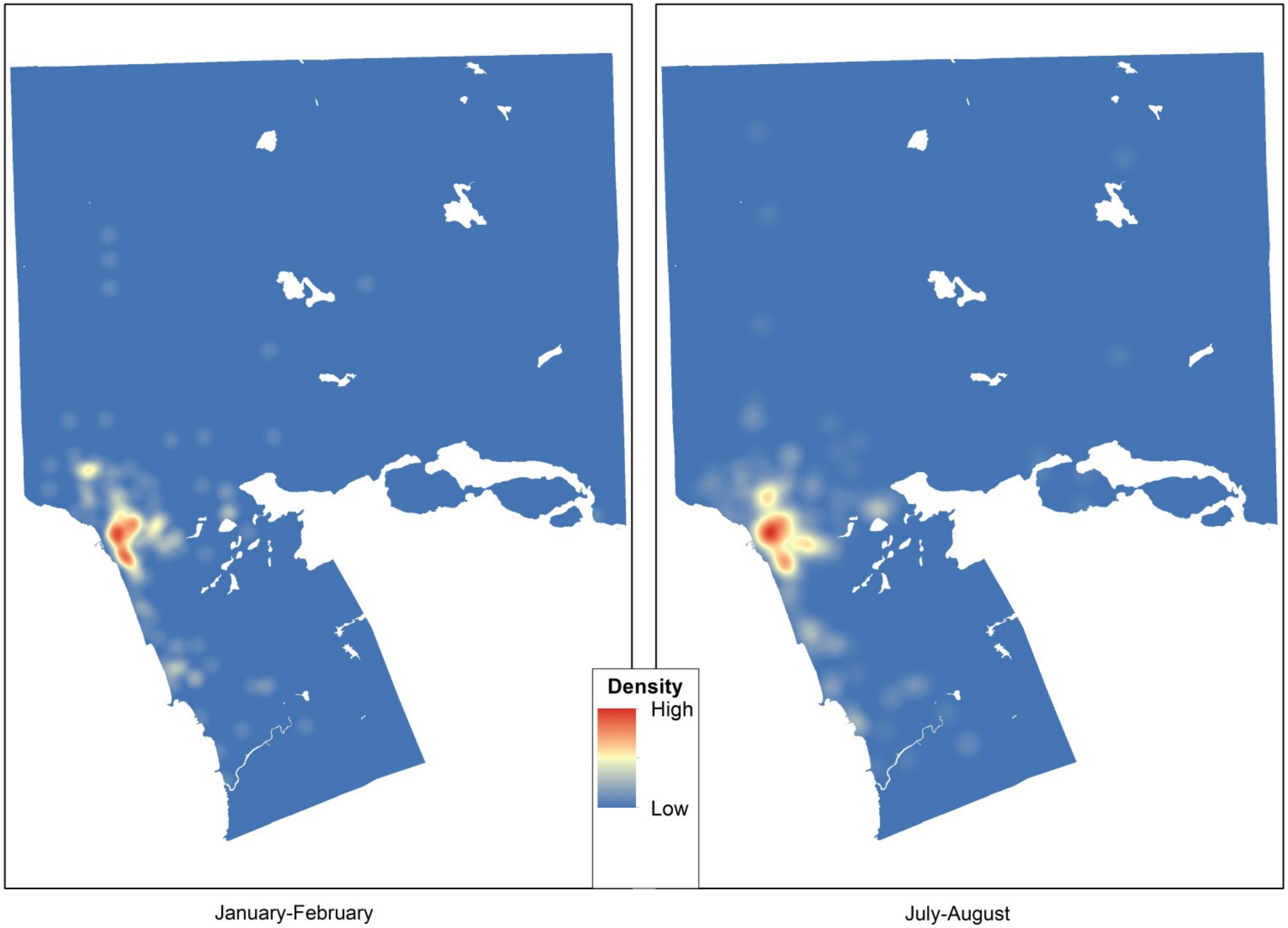
A3.4 Kernel Density Mapping

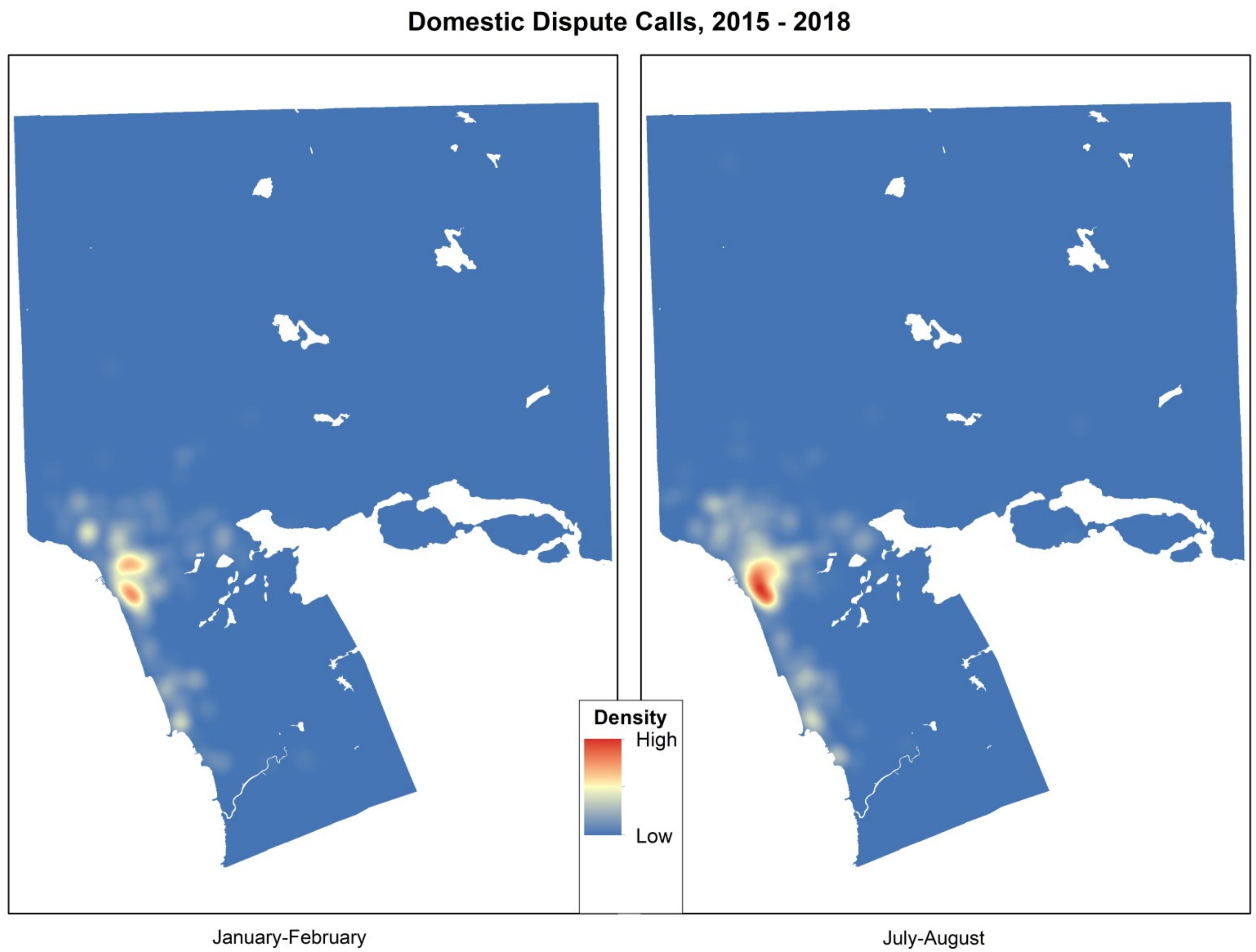


Assault Calls, 2015 - 2018

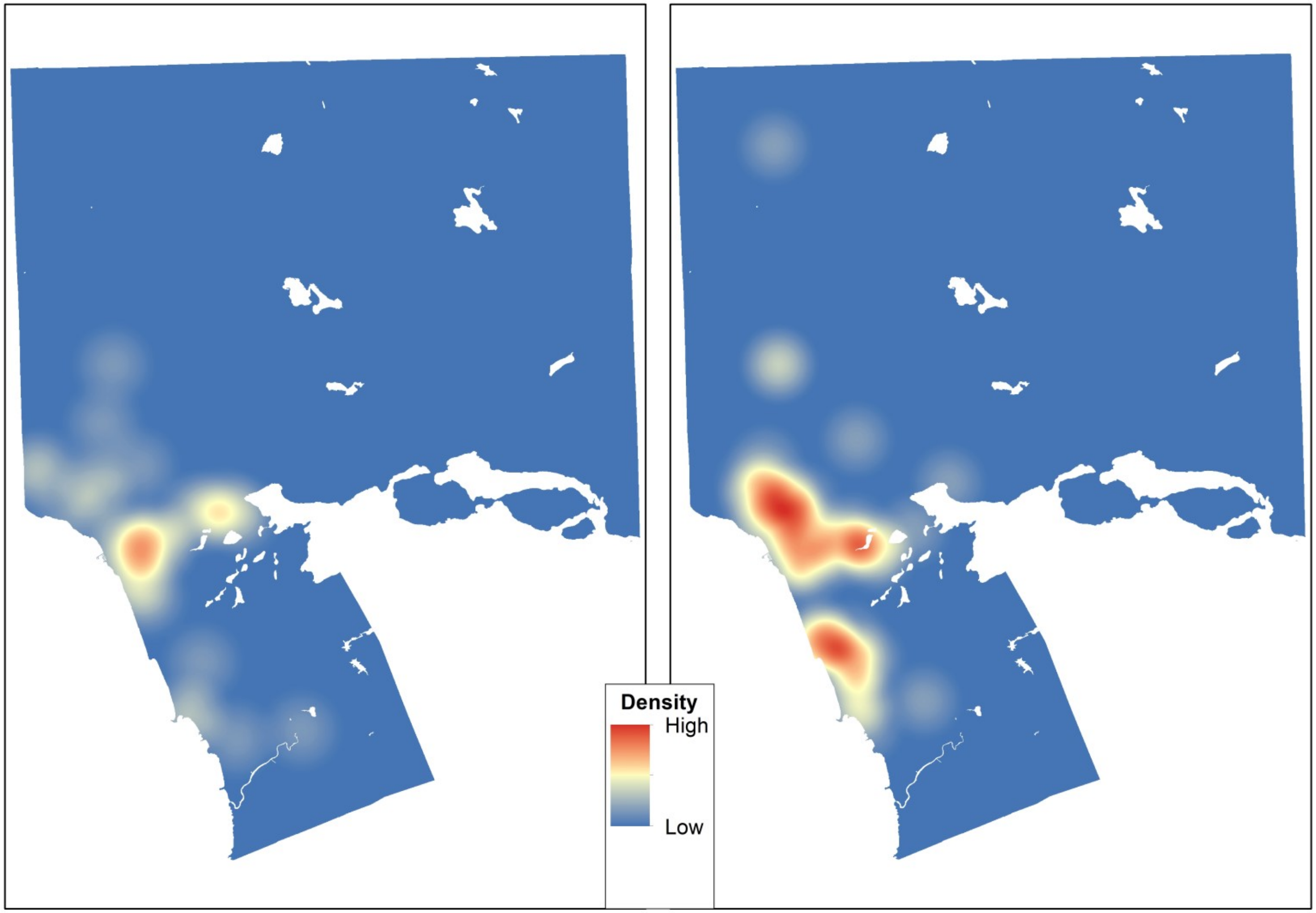


Break and Enter Calls, 2015 - 2018



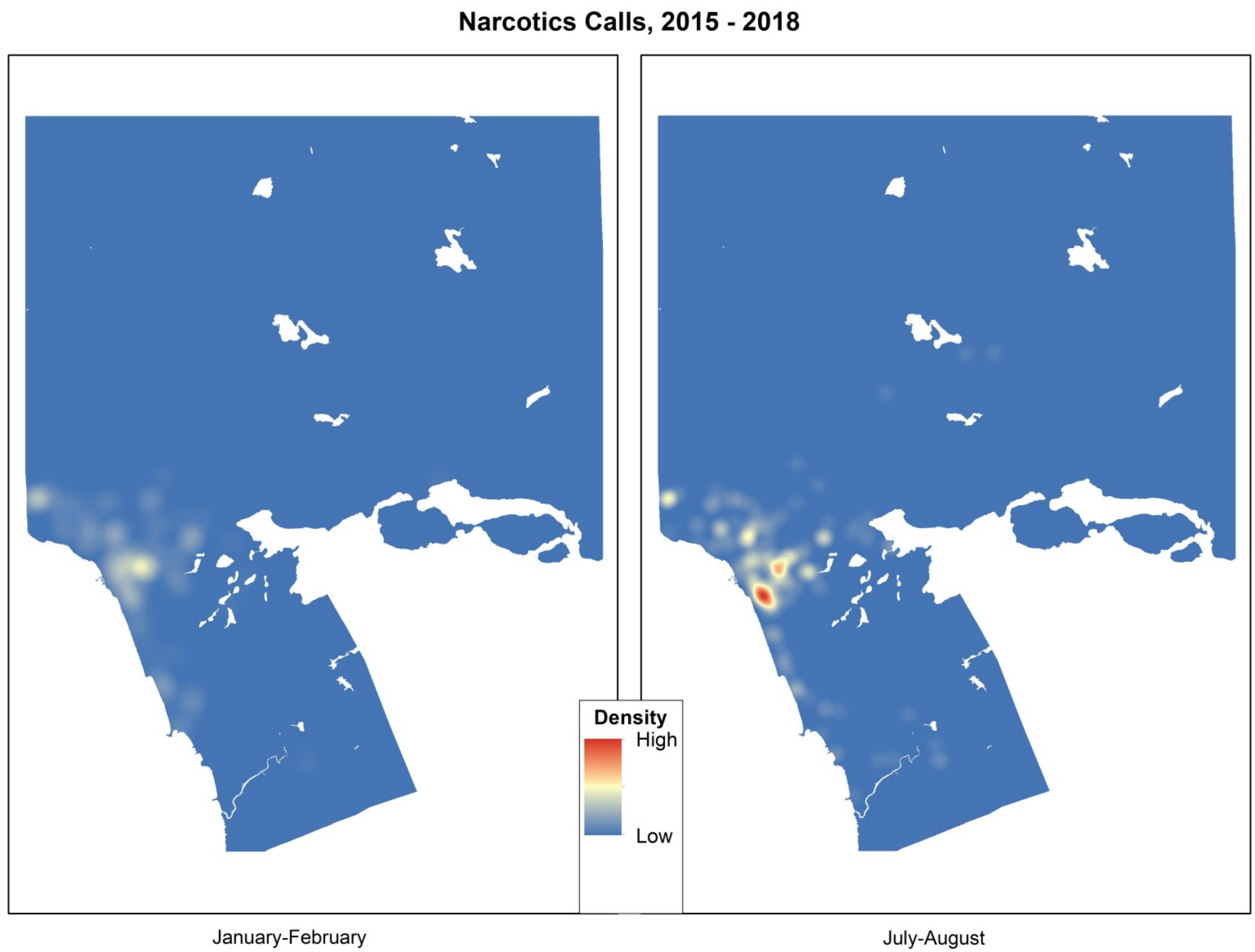

Domestic Dispute Calls, 2015 - 2018
Density
High
Low
January-February
July-August

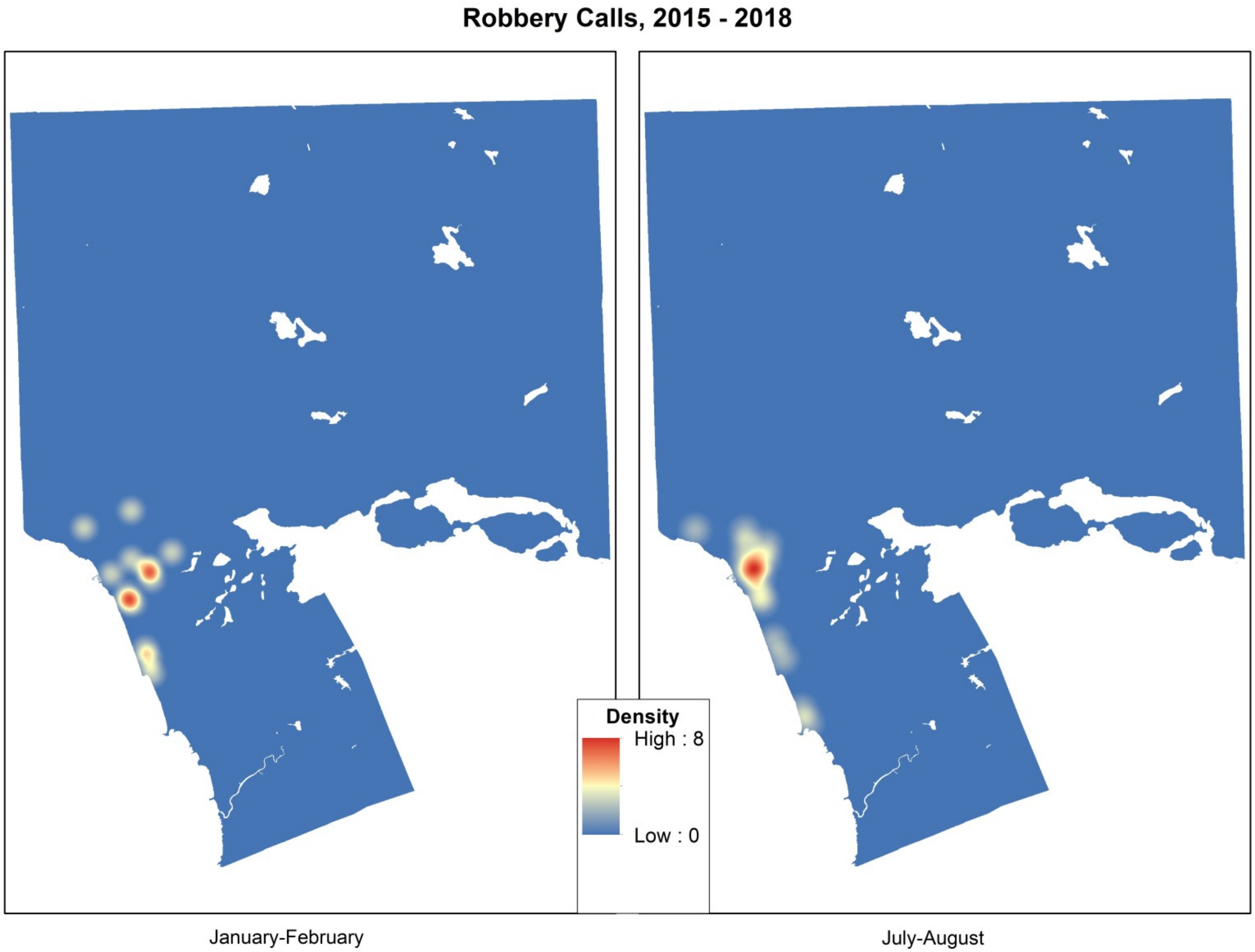
Motor Vehicle Theft Calls, 2015 - 2018

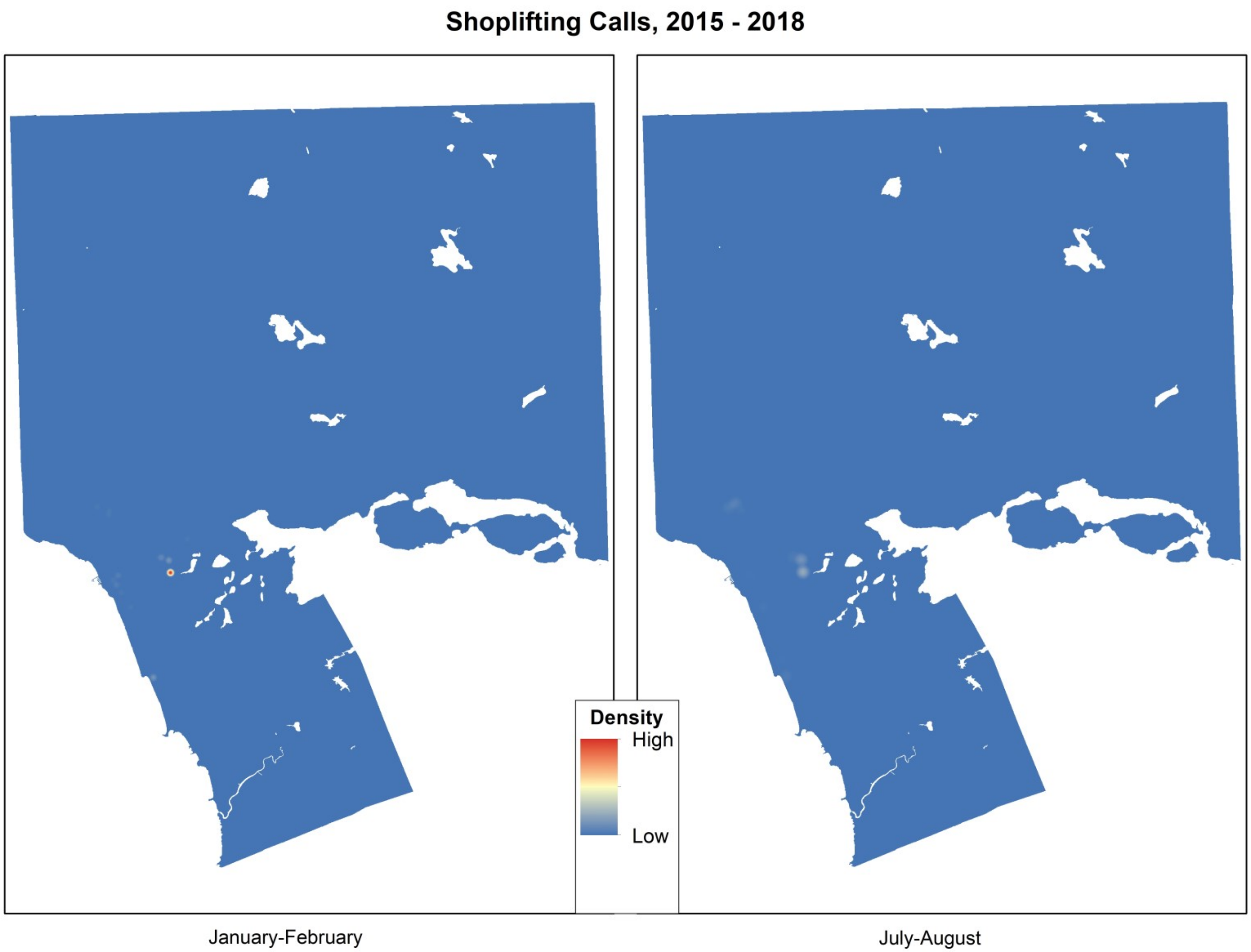


January-February

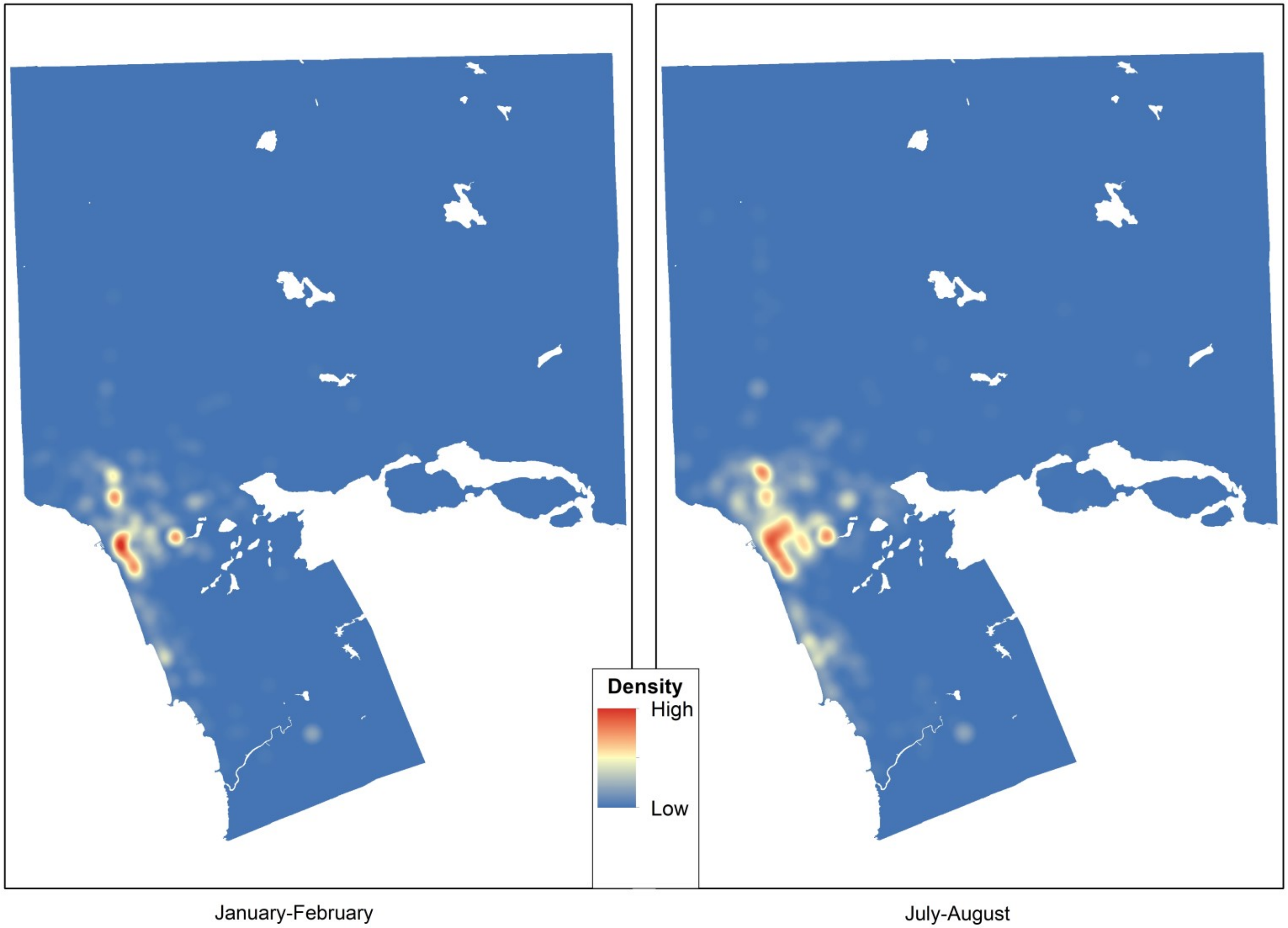
July-August


Narcotics Calls, 2015 - 2018
Density
High
Low
January-February
July-August

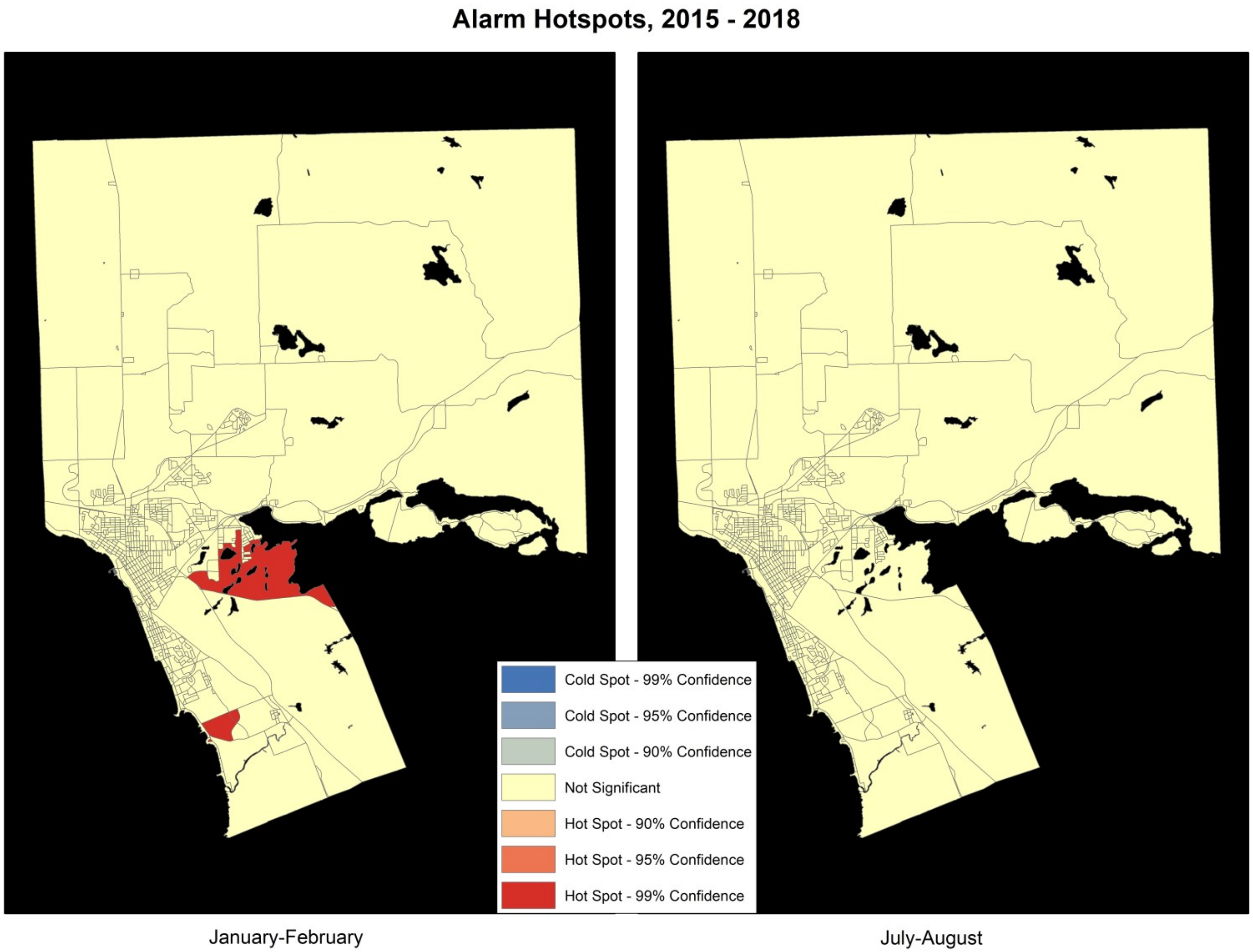

Robbery Calls, 2015 - 2018
Density
High : 8
Low : 0
January-February
July-August


Shoplifting Calls, 2015 - 2018
Density
High
Low
January-February
July-August

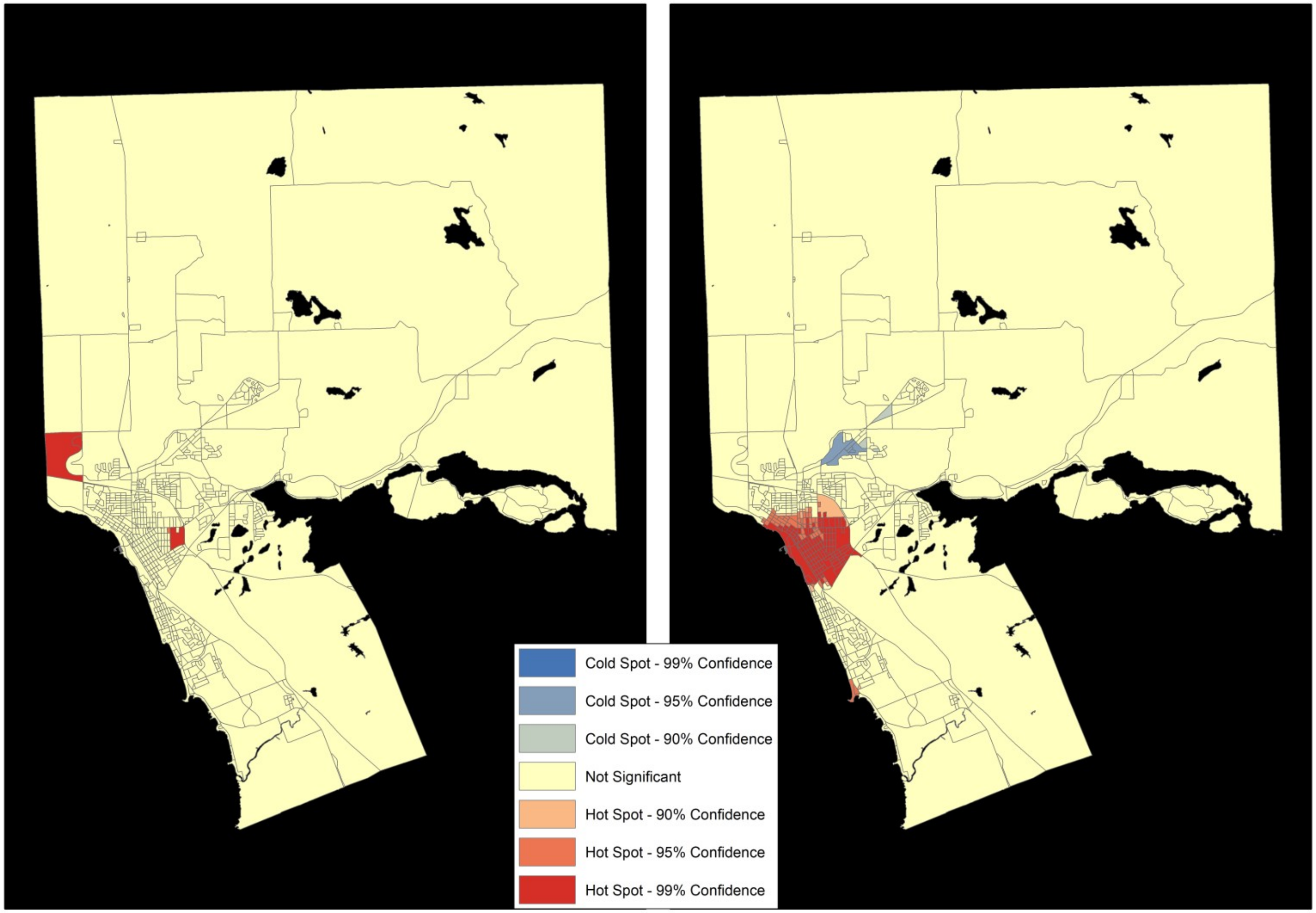
Theft Calls, 2015 - 2018



A3.5 Hotspot Analysis by Dissemination Block

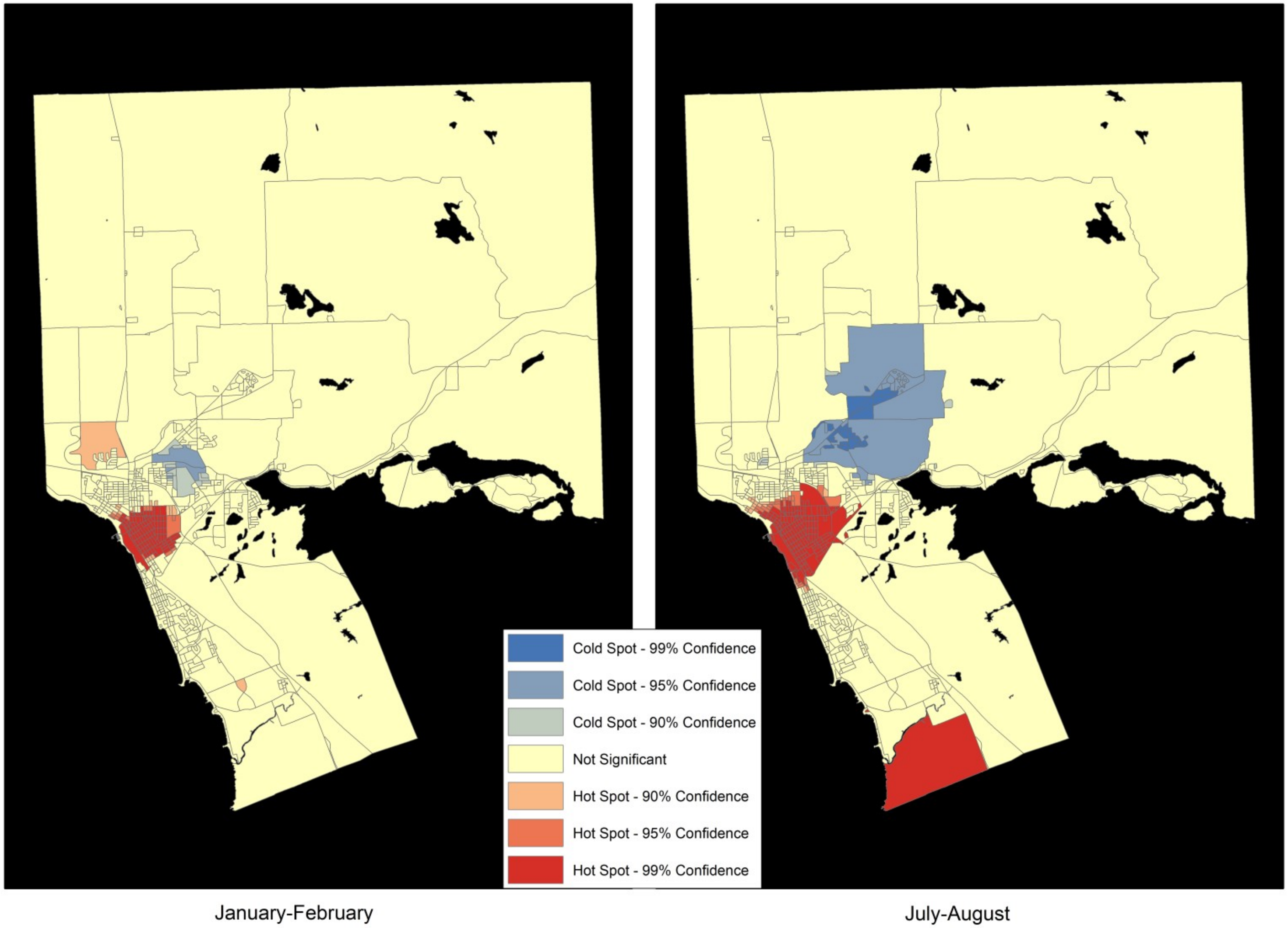


Assault Hotspots, 2015 - 2018

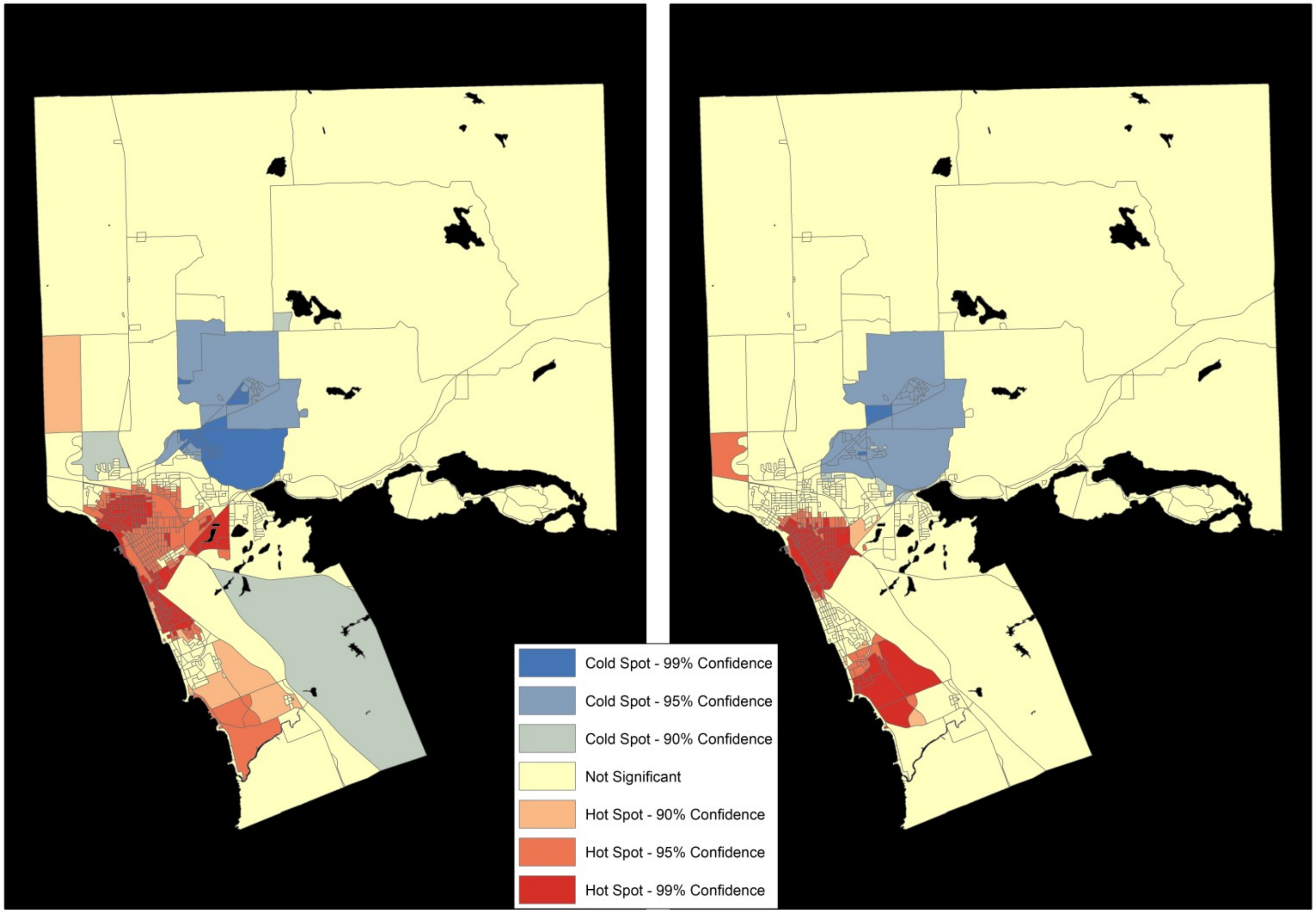


January-February July-August

Break and Enter Hotspots, 2015 - 2018



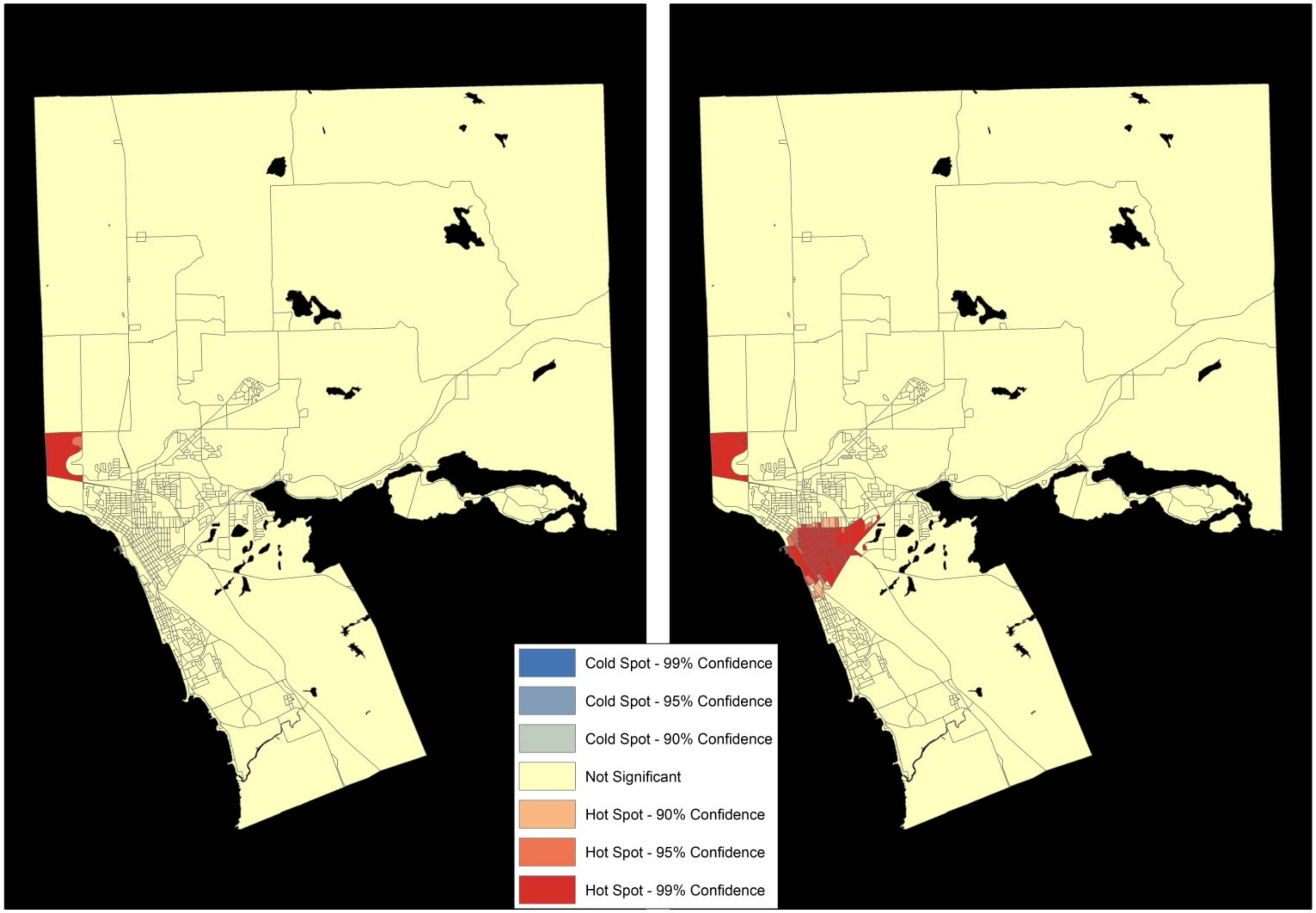
Domestic Dispute Hotspots, 2015 - 2018



January-February

July-August

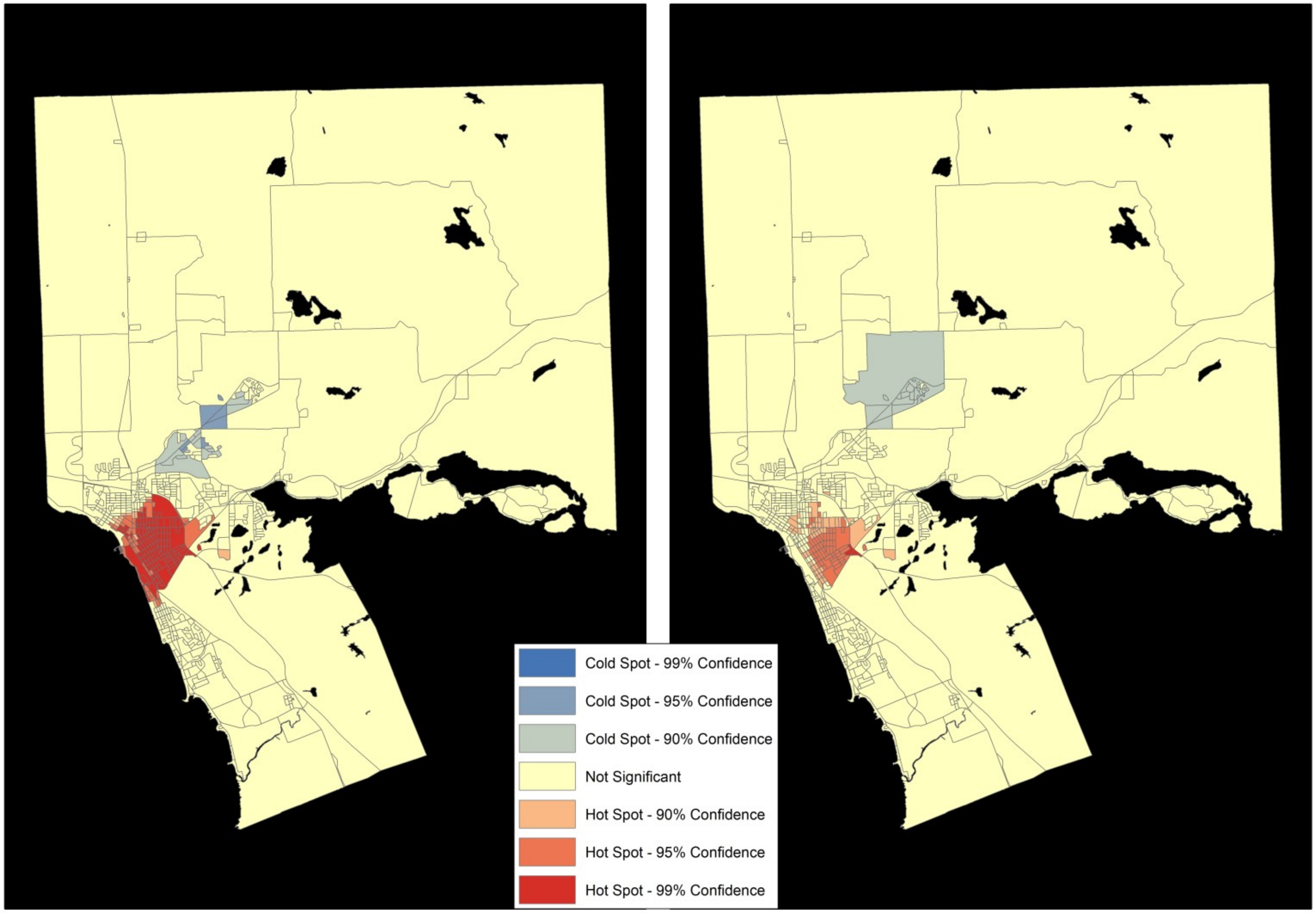
Narcotics Call Hotspots, 2015 - 2018



January-February

July-August

Theft Hotspots, 2015 - 2018



January-February

July-August