Exploring crime in Toronto, Ontario with applications for law enforcement planning: Geographic analysis of hot spots and risk factors for expressive and acquisitive crimes

by

Matthew Quick

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AUTHOR'S DECLARATION

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

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Abstract

This thesis explores crime hotspots and identifies risk factors of expressive and acquisitive crimes in Toronto, Ontario at the census tract scale using official crime offence data from 2006. Four research objectives motivate this thesis: 1) to understand a number of local spatial cluster detection tests and how they can be applied to inform law enforcement planning and confirmatory research, 2) explore spatial regression techniques and applications in past spatial studies of crime, 3) to examine the influence of social disorganization and non-residential land use on expressive crime at the census tract scale, and 4) integrate social disorganization and routine activity theories to understand the small-area risk factors of acquisitive crimes. Research chapters are thematically linked by an intent to recognize crime as a spatial phenomenon, provide insight into the processes and risk factors associated with crime, and inform efficient and effective law enforcement planning.

The first research section explores four local spatial cluster detection methods applied to drug offence rate at the census tract scale. Considering little research has compared the utility of cluster detection methods to study crime, we attempt to understand the advantages and disadvantages of each method in both practical and academic contexts. We observe clusters located in downtown Toronto and close to highways, suggesting that drug offences may occur in areas where there are large numbers of potential customers with easy accessibility to drug markets. The spatial scan statistic detected the largest clusters, indicating that this technique may be most suitable for large scale observations to inform law enforcement planning, such as targeting areas with police patrols focused on altering drug market activity. In contrast, Local Moran's I detected only one small cluster in downtown Toronto, suggesting that this method is most appropriate for identifying locations for resource intensive law enforcement planning such as crackdowns and problem-oriented policing.

Second, three spatial regression techniques are explored. Providing a background to the confirmatory methods used in the following chapters, spatial error, spatial lag independent variable, and spatial lag dependent variable regression methods are illustrated and the theoretical and practical implications of using each method are discussed.

Third, we investigate the influence of social disorganization and non-residential land use on five expressive crime types. We hypothesize that in addition to measures of social disorganization, non-residential land uses are associated with census tract expressive crime rates through the attraction of many non-residents, which increases anonymity and impedes the realization of common values and norms among residents and non-residents. Employing spatial error regression models, it is found that variables representing social disorganization and non-residential land uses are associated with expressive crime types. Applying these findings to land use planning, areas exhibiting risk factors can identified as potential sites for building-specific crime prevention through environmental design initiatives. Further, development of land uses that have been shown to increase sense of ownership and social cohesion among residents should be targeted to high risk areas.

Fourth, we integrate both social disorganization and routine activity theories to explore eight acquisitive crime types and two non-expressive, non-acquisitive crime types. Employed in past research, an integrated perspective assumes that social disorganization estimates baseline victimization risk, while routine activity variables, operationalized through non-residential and residential land uses, modifies risk. Spatial regression results indicate that each crime type has relatively unique determinants, often including variables from both social disorganization and routine activity theories. Possible explanations for the findings are discussed as well as how the best fitting regression model, spatial lag dependent variable, informs our understanding of the processes influencing acquisitive crime offences. Applications of results to law enforcement planning include incorporating principles of building-specific crime prevention through environmental design in high risk areas, geographical targeting of crime prevention initiatives, and evaluating municipal land use plans such that crime risk related to land use is reduced.

Concluding, we discuss research limitations including the modifiable areal unit problem, ecological fallacy, and the use of official crime incident data. Also, we remark on challenges encountered during the research process, directions for future research, and clarify how the research chapters contained in this thesis are thematically linked.

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Chapter 1

Introduction

1.1.1 Motivation

Urban crime is a problem prevalent in all societies (Clemente and Kleiman, 1977). Crime threatens quality of life, limits activities, makes people feel like prisoners in their own homes, disrupts neighborhood cohesion, and worsens health (Nasar and Fisher, 1993; Nasar and Jones, 1997). Additionally, crime is a tremendous monetary, psychological, and social cost to government, social agencies and police forces, and individuals who alter daily activities and limit personal interactions because of crime or fear of crime (Andresen, 2006).

The research objective motivating this thesis is to locate hotspots and identify risk factors for expressive and acquisitive crimes using methods of geographical analysis. Concisely, the research questions can be considered as such: Where are the locations of crime hotspots, and what are risk factors for high crime areas in Toronto? How can these findings be applied to inform practical efforts such as law enforcement planning? While this thesis takes the form of three chapters containing relatively distinct research focused on explaining the spatial dimensions of crime in Toronto, they are thematically linked through three research goals: to recognize crime as an inherently spatial process, to contribute to understanding the processes and associated risk factors of crime, and to inform efficient and effective law enforcement planning (Anselin, 2001).

Recognizing that crime varies substantially in geographic space and is closely intertwined with urban environments, research interest in the geography of crime has grown rapidly in recent years (Anselin et al., 2001). Indeed, crime is distributed such that some areas experience disproportionately large amounts of crime while other areas experience little to no criminal activity (Kinney et al., 2008; Eck and Weisburd, 1995). To appropriately address the geography of crime, we employ both theories and methods that incorporate explicitly spatial perspectives.

Furthering an understanding of the processes and risk factors of crime, this thesis provides novel insight into criminological theories and identifies specific small-area characteristics that influence crime. By operationalizing both socio-economic and built environment risk factors, confirmatory research advances knowledge regarding the determinants of crime. For instance, social disorganization theory, a perspective that is inherently spatial, has found general support in past criminological research (Shaw and McKay, 1942; Veysey and Messner, 1999), yet little past research has attempted to understand the influence of land use on social disorganization. In Chapter 6, we supplement past research using perceived crime data by operationalizing non-residential land use as a risk factor for expressive crimes and find a positive relationship with expressive crimes, suggesting that land use reduces informal social control.

The third research goal that unifies research chapters is the application of results to inform efficient and effective law enforcement planning. Law enforcement planning is the integration of law enforcement and other public agencies to share information, best practices, and research, and provide multidisciplinary perspectives on issues of crime and safety (OALEP, 2012). In addition to police, fields relevant to law enforcement planning include public health (Robinson and Keithley, 2000), economists and public policy makers (DiIulio Jr., 1995) and land use planners.

Findings from this research applied to law enforcement planning can be used to improve resource allocation, inform policing and crime prevention, and develop initiatives designed to promote the willingness of community members to work with police (Angel, 1968). Identifying the location of high crime clusters through comparing outputs of exploratory spatial cluster detection methods (Chapter 3), for instance, provides evidence informing the geographical allocation of law enforcement resources such as police patrols and community outreach. Further, law enforcement resources can be tailored to address unique area-specific risk factors to improve effectiveness. For example, when law enforcement is knowledgeable about the positive relationship between ethnic heterogeneity and violent crime (Chapter 5), operations can be designed to incorporate many languages and address a range of cultural differences regarding crime and safety.

Given the operationalization of variables representing both residential and non-residential land uses, results from this thesis are particularly relevant to land use planning. Potential applications include targeting high risk areas with land uses known to deter or reduce crime and complementing small-area law enforcement operations with building and area-specific crime prevention measures.

1.1.2 Outline

Following this introduction, Chapter 2 will provide an overview of the theoretical background of this thesis, focusing on environmental criminology in general, and social disorganization and routine activity theories in particular. Chapter 3 briefly describes the city of Toronto, Ontario, and details crime data and explanatory socio-economic and land use variables used in this thesis.

Chapter 4, the first research chapter, is a methodological exploration of local spatial cluster detection techniques. Comparing high drug offence clusters that result from four local cluster detection tests, the utility of each test is discussed as they apply to research, for example informing hypothesis generation and variable selection, as well as practical operations including law enforcement planning, policing, and crime prevention.

Chapter 5 provides an overview of confirmatory regression techniques employed in Chapters 6 and 7, including spatial error, spatial lag dependent variable, and spatial lag independent variable models. Theoretical and practical justifications for spatial regression models are discussed and the contributions of these models to understanding the spatial dimensions of crime are highlighted.

Chapter 6 investigates the influence of social disorganization and non-residential land use on five expressive crime types in Toronto. We recognize the relevance of expressive crimes to both crime and public health fields; expressive crimes have direct health effects, for example injury of victims, and indirect effects, such as small-area community health issues such as mental illness and children born with low birth weight. Results suggest that both social disorganization and non-residential land uses are related to expressive crime rates. Possible explanations for findings are discussed with a particular focus on the contribution of non-residential land use on small-area social disorganization and how this can be addressed by law enforcement, land use planning, and public health professionals.

Chapter 7 focuses on eight acquisitive crime types and two additional crime types from a theoretical perspective that integrates social disorganization and routine activity theories. Possible explanations for statistically significant associations are observed for each crime type, highlighting the role of the built environment as it brings together offenders, targets, and limited guardianship. General applications to law enforcement planning are discussed.

Finally, Chapter 8 provides concluding thoughts on this research. In particular, we discuss research limitations such as the modifiable areal unit problem and ecological fallacy, challenges during the research process, and directions for future research that can build on, and complement, the research completed in this thesis. In conclusion, we re-visit the findings of each research chapter and expand on the thematic elements linking research chapters.

Chapter 2

Theoretical Overview

Broadly, this thesis draws from theories of environmental criminology. Environmental criminology lies at the intersection of criminology, sociology, and geography, and focuses on the spatial distribution of crime, criminals, targets, and the interaction between these components (Brantingham and Brantingham, 1981). In summarizing the four dimensions of crime - legality, offender, target, and place - Brantingham and Brantingham (1981, p.8) frame the research context of environmental criminology:

> "Environmental criminologists begin their study of crime by asking questions about where and when crimes occur. They ask about the physical and social characteristics of crime sites. They ask about the movements that bring the offender and target together at the crime site. They ask about the perceptual processes that lead to the selection of crime sites and the social processes of ecological labeling. Environmental criminologists also ask about the spatial patterning in laws and the ways in which legal rules create crime sties. They ask about the spatial distribution of targets and offenders in urban, suburban, and rural settings. Finally, environmental criminologists ask how the fourth dimension of crime [place] interacts with the other three dimensions to produce criminal events."

Environmental criminology is widely thought to have originated with macro-level studies of French criminal statistics, notably Guerry (1833) and Quetelet (1842), who mapped violent crimes and property crimes at the department level in France, respectively (Brantingham and Brantingham, 1981). The researchers found that crime was not homogenously distributed throughout the country, but that high violent crime rates were located in the rural south and property crimes were most prevalent in the urbanized north (Brantingham and Brantingham, 1981; Wortley and Mazerolle, 2008).

Two theories developed in the field of environmental criminology that can be applied to small-area studies of crime are the social disorganization theory, which attempts to understand neighborhood scale crime as a function of social processes, and routine activity theory, which interprets crime as an outcome possible when rational and motivated criminal offenders converge with suitable targets and limited guardianship.

2.1 Social Disorganization Theory

Social disorganization theory hypothesizes that neighborhoods exhibiting traits of social disorganization, generally measured through economic deprivation, residential mobility, and ethnic heterogeneity, have higher levels of crime than areas that do not exhibit these traits (Sampson and Groves, 1989; Veysey and Messner, 1999; Law and Quick, 2012). While often inferred using small-area structural variables, social disorganization assumes the breakdown of family and community as agents of informal social control leading to increased small-area crime (Hagan et al., 1978).

Social disorganization is rooted in Park and Burgess' (1925) concentric zone theory, which posited that in processes similar to the succession of natural plant species, the geography of cities evolve through stages of invasion, conflict, accommodation, and assimilation (Veysey and Messner, 1999; Roh and Choo, 2008). Over time, Park and Burgess (1925) suggested that urban environments would evolve to take the form of a number of concentric rings, with the innermost rings unable to resist invasion and conflict and exhibiting physical deterioration and disorganization. The outermost rings of a city, in contrast, resist invasion and conflict, instead exhibiting accommodation and assimilation with little disorganization and crime (Veysey and Messner, 1999).

Social disorganization theory was proposed by Shaw and McKay (1942) to explain the non-random geographic distribution of juvenile delinquency in Chicago, Illinois, at the neighborhood scale (Kubrin and Weitzer, 2003). Specifically, high juvenile delinquency occurred in the city centre or transition zone, with decreasing delinquency as distance from the centre increased. This geographic pattern was evident, it was thought, because neighborhoods in the inner center exhibited social disorganization, or an inability for communities to realize common values, solve commonly experienced problems, and maintain effective social controls (Bursik, 1988; Sampson and Groves, 1989; Kubrin, 2009). In comparison, neighborhoods on the edge of the city, conceptually equivalent to the outermost rings in Park and Burgess' concentric zone theory, were believed to exhibit less social disorganization and crime.

Shaw and McKay (1942) originally argued that social disorganization could be inferred through three neighborhood-level structural factors: low economic status, high ethnic heterogeneity, and high residential mobility (Veysey and Messner, 1999). Elaborating, it is believed that communities with low economic status lack money and resources, have a weaker organizational base than more prosperous communities, and have more socially isolated residents; ethnic heterogeneity impedes the ability of residents to achieve consensus through a segmentation of neighborhood social order; and residential mobility acts as a barrier to the development of friendship networks and disrupts community social relations (Sampson and Groves, 1989; Kubrin and Weitzer, 2003).

Despite being subject to substantial criticism because it is difficult for macro-level models to predict individual criminal actions (Kubrin, 2009) and there is no direct measurement of social disorganization (Veysey and Messner, 1999), the social disorganization theory has found tremendous support in a variety of criminological contexts. This includes, for example, juvenile delinquency (Ouimet, 2000; Jacob, 2006; Law and Quick, 2012), total victimization rate (Veysey and Messner, 1999), homicide (Morenoff et al., 2001), and violent crimes in general (Cahill and Mulligan, 2003; Andresen, 2006). Social disorganization has also been modified to contextualize modern research directions looking to expand beyond traditional measurements of disorganization. For instance, recent interpretations of social disorganization include incorporating both individual and neighborhood characteristics (Wikstrom and Loeber, 2000; Gottfredson et al., 1991), examining the importance of informal and formal networks (e.g. friendship networks and organizational participation) as mediating factors between structural measurements and crime outcomes (Sampson and Groves, 1989), and investigating the role of collective efficacy on social disorganization (Morenoff et al., 2001).

Importantly, social disorganization is generally used to investigate expressive rather than acquisitive crime types. In contrast to acquisitive crimes where offenders are assumed to act rationally to obtain tangible goods, expressive crimes are often spontaneous and conducted to exhibit aggression and violence (Miethe et al., 1987). Expressive crimes, then, are best understood through the social disorganization lens, which focuses on the factors assumed to drive expressive crimes including small-area social, economic, and interpersonal dynamics (Miethe et al., 1987).

Of particular relevance to this thesis is the role of land use in conceptualizations of social disorganization (Chapter 6). While occasionally considered in past research, only recently have the built environment and land use emerged as dimensions relevant to social disorganization, as researchers recognize the potential for land use to influence neighborhood social interactions and modify the effect of traditional variables such as economic deprivation (Stucky and Ottensman, 2009; Sampson and Raudenbush, 1999).

2.1.1 Social Disorganization and Land Use

In Shaw and McKay's (1942) formative discussion of social disorganization, they observe elevated juvenile delinquency in Chicago's city center and attribute this to the social processes that occur in urbanized areas (Veysey and Messner, 1999). Urban communities, they posit, have less capacity for social control compared to suburban and rural communities because urbanization weakens social networks and limits social participation in local affairs (Sampson and Groves, 1989; Jacob, 2006). Further, it is believed that urbanization affects the opportunity for individuals to participate in organizations, impeding the involvement of community members in organizations, which would generally work to strengthen formal and informal bonds (Veysey and Messner, 1999).

Often the operationalization of urbanization highlights relative geographical location or broad land use patterns (Stucky and Ottensman, 2009). Measures of relative geographic location, for example, include a binary indicator of urbanization, where neighborhoods in the central city are assigned a value of 1 and neighborhoods outside the city centre are assigned a value of 0 (Sampson and Groves, 1989; Veysey and Messner, 1999) or continuous measures of population density and/or population size (Jacob, 2006; Cahill and Mulligan, 2003). One variable measuring broad land use pattern is a mixed land use index, which measures the proportion of face blocks that contain mixed residential and commercial activity (Sampson and Raudenbush, 1999).

Despite rarely being included in analysis, it is possible that specific land uses contribute to social disorganization (Wilcox et al., 2004; Stucky and Ottensman, 2009). In some contexts, land uses in a small-area unit may influence social disorganization by physically altering social processes and community member relationships, making it difficult to realize common values and maintain effective social control. This is supported by Sampson and Raudenbush (1999, p.622), who note, for example, that it may be that the "capacity of residents to achieve common purpose is limited not because of lack of internal effort, but simply the structural constraint imposed by the density of commercial traffic and land use patterns inhospitable to social interaction and surveillance."

Unlike the routine activity framework (reviewed in Section 2.2) - which constitutes most of the literature examining the relationships between land use and crime and interprets land uses as facilitators of criminal opportunity (Lorenc et al., 2012; Stucky and Ottensman, 2009) - research focused on the role of specific land uses in social disorganization is undeveloped. To this, when research does investigate land use and social disorganization, it is generally focused on one specific land use type and does not account for other nearby land uses or previously supported socio-economic variables. Examples include mixed land use (Browning et al., 2010), public housing projects (McNulty and Holloway, 2000; Sampson, 1989) and the presence of local institutions such as recreation centers (Peterson et al., 2000).

Some past research has included a variety of specific land uses in analysis. Lockwood’s (2007) study on violent crime in Savannah, Georgia, for example, finds that retail/office/commercial and public/institutional land uses are positively associated with assault. Despite making claims to social disorganization, Lockwood (2007) includes only two structural measures of social disorganization, so the influence of land use in the presence of other possibly related social disorganization variables (e.g. population turnover, ethnic heterogeneity, immigration) is not explored. Stucky and Ottensman (2009) also investigate the relationship between specific land uses and violent crime, finding that socio-economic disadvantage, percent black, and percent Hispanic are all positively related to a violent crime index. This article uses mismatched spatial scales, however, combining crime data for fixed-area grid cells and census data for census tracts, assuming a constant distribution of census characteristics throughout finer resolution grid cells. Sparks (2011) also investigates measures of social disorganization and land use to explain violent crime in San Antonio, Texas, using Bayesian spatial models. He observes that violent crime is influenced by poverty, vacant housing, and land use diversity, but notes that land use diversity does not contribute substantively to the model. Sparks (2011) fails to elaborate on the mechanisms by which these land uses contribute to social disorganization, instead suggesting that this become the focus of future research.

2.2 Routine Activity Theory

In an attempt to explain the substantial increase in crime between 1960 and 1975 in postwar United States, Cohen and Felson (1979) proposed the routine activity theory. Cohen and Felson (1979) suggested that the changing location of lifestyles or routine activities from inside the household to public locations contributed to the increase in crime because there were more frequent convergences of criminal elements, specifically: 1) motivated offenders, 2) suitable targets, and 3) the absence of capable guardians against crime (Felson, 1987; Sherman et al., 1989; Maxfield, 1987). Assuming that criminals act rationally, areas where these three elements converge have higher risk for crimes than areas that do not bring together motivated offenders and suitable targets with limited guardianship.

Explanatory variables employed to operationalize routine activities include demographic measures to encompass the number of likely offenders and suitable targets as well as land uses where these elements converge. For example, measures of likely offenders include population density (e.g. Andresen, 2006), proportion of young males, and percentage of unmarried families (Miethe et al., 1987). Measures of land use can also be employed under the assumption that some land uses more than others will act as sites for the frequent convergence offender and target with little guardianship. For example, it is reasonable to expect that an area with a mix of commercial, residential, and public spaces will bring together more likely offenders and targets than areas that are rural or predominantly residential. Moreover, areas with many offenders and targets also likely have large populations, which may increase perceived anonymity and limit guardianship (LaGrange, 1999).

The routine activity theory has been studied at a variety of spatial scales ranging from the individual to macro-level (Groff, 2007) and has been employed primarily to explain acquisitive or property crimes such as street robbery, burglary, and motor vehicle theft (Miethe et al., 1987; Groff, 2007). Acquisitive crimes are often studied through the routine activity lens because they are believed to occur when offenders act rationally in the presence of suitable targets and limited guardianship. So, the factors contributing to acquisitive crimes can be considered with respect to how they bring these three elements together.

2.3 Integrating Social Disorganization and Routine Activity Theories

Recognizing that social disorganization and routine activity theories may not operate exclusively to influence small-area crime, past research has integrated these two theories to further interpretations of acquisitive crime types (Smith et al., 2000). Specifically, many social disorganization variables also apply to, and in some cases are interdependent on, those measured for the routine activity theory (Smith et al., 2000; Andresen, 2006; Groff, 2007). For example, small-area unemployment, a measure of economic deprivation in the social disorganization framework, may also reflect local employment opportunities (e.g. the presence of industrial or commercial land uses) and residential typology (e.g. rental apartment dwellings), which can simultaneously be considered under the routine activity lens as locations that bring together offenders, targets, and limited guardianship.

One way to interpret the integration of these two theoretical perspectives is for social disorganization to estimate baseline small-area crime risk with routine activity land uses modifying this baseline risk (Smith et al., 2000). For example, given a level of social disorganization, an area with many commercial institutions is more likely to exhibit a high theft rate than an area that is comprised of mostly industrial land uses because we assume that commercial land uses attract larger numbers of offenders and targets. Likewise, given the same land uses among two census tracts, the area with higher social disorganization (i.e. more low income families, higher ethnic heterogeneity, etc.) can be expected to have a higher acquisitive crime rate because of a relatively higher baseline crime risk.

Integrating these two theories has been found to be particularly informative when used to study acquisitive or property crimes (Miethe et al., 1987; Kennedy and Forde, 1990; Sampson and Wooldredge, 1987). Applied in the Canadian context, both Kennedy and Forde (1990) and Andresen (2006) observe the utility of synthesizing social disorganization and routine activity theories in their studies on property crime and break and enter, respectively. Social disorganization and routine activity theories are considered simultaneously in Chapter 7 to investigate eight acquisitive crime types including break and enter, robbery, and shoplifting and two other crime types, criminal harassment and drug offences.

Chapter 3
Study Region and Data

3.1 City of Toronto, Ontario

Toronto, Ontario is located on the north shore of Lake Ontario and is the most populous Canadian Census Metropolitan Area (CMA). In 2006, Toronto had a residential population of approximately 2.5 million people distributed over 524 census tracts (Charron, 2009). Toronto is the major urban centre in the Greater Toronto Area, which is home to over 5.5 million people. For reference, downtown Toronto is marked on Fig. 3.1.1.1 with a dashed line and is approximately bounded by Bloor St. to the north, the Don Valley Parkway to the east, Lake Ontario to the south, and Bathurst St. to the west. Highways 401, 400, 427, the Gardiner Expressway (GE), and the Don Valley Parkway (DVP) are also labelled in Fig. 3.1.1.1.

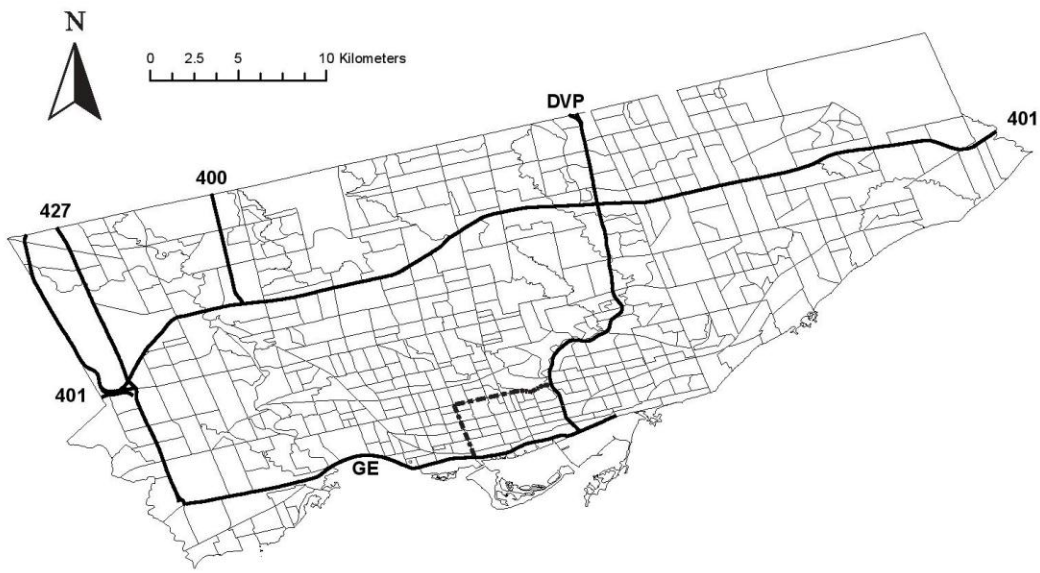

Figure 2.1.1.1. Map of Toronto, Ontario. For reference, downtown Toronto is bounded by a dashed line and prominent highways are highlighted.

3.1.1 Spatial Unit of Analysis – Census Tract

All analysis in this thesis was conducted at the census tract scale. Census tracts are small-area units delineated by Statistics Canada (2012) in cities with populations larger than 50,000. Generally, census tracts have populations between 2,500 and 8,000 people with boundaries that follow permanent and recognizable physical features (Statistics Canada, 2012).

The census tract was chosen as the spatial unit of analysis for three reasons. First, Toronto crime data was only available at the census tract scale. This scale aligns with the scale of Canadian census data, allowing for census tract population data to be used in analysis. Second, both social disorganization and routine activity theories can be used to interpret small-area crime. That is, both social disorganization theory hypothesize that small-area characteristics influence crime rather than broader (i.e. at regional or national scale) or more precise attributes (i.e. at individual or street corner scale). Third, there is tremendous practical relevance of analysis at the census tract scale to law enforcement planning because high risk areas can be identified and targeted at a suitable spatial scale. In fact, census tracts are approximately the size of secondary plans and area-specific policies (City of Toronto, 2010), so results from census tract analysis can be directly applied to land use planning and used to inform plans and policies.

3.2 Crime in Toronto, 2006

Crime data was extracted from the 2006 Uniform Crime Reporting Survey (UCR) (Statistics Canada, 2006a). The 2006 UCR collected crime data spanning the period from January 1, 2006 to December 31, 2006 and is an incident-based reporting system designed to capture "incident-level information on the characteristics of the criminal incident and the accused persons involved (Statistics Canada, 2006b, p.4)."

When arrests are made, offence type and location are recorded and coded by the police. Only crimes that come to the attention of police are included, so the UCR is not a record of all crimes in Canada since some crimes are never reported to, or recorded by, the police (Statistics Canada, 2006b). Of note, in cases where one or more offence is recorded (e.g. shoplifting incident also involving assault), only the most serious offence as determined by the longest maximum sentence under the Criminal Code of Canada is recorded (Statistics Canada, 2006b). This leads to a general under-counting of less serious, often non-violent, offences. UCR data is recorded by police forces across Canada and aggregated and distributed by the Canadian Centre for Justice Statistics and Statistics Canada.

The 2006 UCR dataset used for this thesis contained crime counts and the sum of residential and working populations at the census tract scale for Toronto, Ontario. In the dataset, crime counts greater than zero and less than five were rounded up to five for confidentiality purposes. Crime data was obtained from the University of Waterloo Map Library.

3.2.1 Expressive Crimes

Fifteen crimes were included in the 2006 UCR (Statistics Canada, 2006a). For analysis, crime types were separated into three categories based on motivation. Expressive crimes, which are analysed in Chapter 6, involve violence and aggression and are often spontaneous and motivated by a desire to express emotion (Cohn and Rotton, 2003; Miethe et al., 1987). Five expressive crimes were identified: major, minor, and sexual assaults, uttering threats, and violent crimes (Table 3.2.1).

Table 3.2.1. Descriptive statistics for five expressive crime types.

	Criminal Incident (count)		**Crime Rate (per 1,000 residential population)**			
	Sum	**Mean**	**Mean**	**Min**	**Max**	**St. Dev.**
Major assault	3, 976	7.59	1.74	0	26.27	2.25
Minor assault	11, 648	22.23	5.07	0	89.42	6.05
Sexual assault	1, 116	2.13	0.46	0	9.12	0.77
Uttering threats	5, 497	10.50	2.38	0	47.44	2.75
Violent crime	25, 985	49.59	11.47	0	224.45	14.23

Expressive crime rates were calculated using residential population as the population at risk because we assume that expressive crimes are mostly conducted by offenders close to their home (Morenoff et al., 2001) and in their residential neighborhood (Steenbeck et al., 2012). This assumption concurs with Wikstrom and Dolmen’s (1990) choice of residential population as the crime rate denominator for their study of crimes against the person, where they justify that residential population best controls for at risk targets of violent crimes.

3.2.2 Acquisitive Crimes

Acquisitive crimes, also termed instrumental crimes, are motivated to achieve a tangible goal, such as obtaining a physical good through theft (Cohn and Rotton, 2003). Acquisitive crimes are generally assumed to be planned and committed by rational offenders who evaluate and respond to expected rewards and punishments (Miethe et al., 1987; Hechter and Kanazawa, 1997). Eight acquisitive crimes were included in the 2006 UCR: break and enter, mischief, other theft, property crime, robbery, shoplifting, theft from a motor vehicle, and theft of a motor vehicle (Table 3.2.2).

Table 3.2.2.1. Descriptive statistics for eight acquisitive crime types.

	Criminal Incident (count)		Crime Rate (per 1,000 summed residential and working population)			
	Total	**Mean**	**Mean**	**Min**	**Max**	**Std. Dev.**
Break and enter	11, 557	22.06	3.22	0	9.45	1.73
Mischief	14, 389	27.46	4.03	0	17.60	2.24
Other theft	19, 950	38.07	4.74	0	23.65	3.16
Property crime	74, 852	142.85	18.82	4.35	59.73	9.57
Robbery	4, 204	8.02	1.21	0	5.95	1.02
Shoplifting	9, 053	17.28	1.79	0	36.48	4.41
Theft from a motor vehicle	15, 663	29.89	4.00	0	18.99	2.61
Theft of a motor vehicle	5, 806	11.08	1.47	0	11.77	1.10

3.2.3 Other Crime Types

Two crime types, criminal harassment and drug offences, do not exhibit traits of either expressive or acquisitive crimes as they are not intended to express emotion or to obtain a tangible good (Table 3.2.3).

Table 3.2.3.1. Descriptive statistics for two other crime types.

	Criminal Incident	Crime Rate (per 1,000 summed residential

			and working population)			
	Total	**Mean**	**Mean**	**Min**	**Max**	**Std. Dev.**
Criminal Harassment	1, 688	3.22	0.49	0	3.48	0.52
Drug Offences	2, 942	5.62	0.81	0	13.87	1.17

Acquisitive and other crime type rates were calculated using the sum of residential and working population as the denominator because the sum of populations is the best indicator for the total number of at risk targets. We assume that the nature of acquisitive crimes often takes offenders outside their residential or employment location to areas where there are many non-mobile at risk targets (i.e. shops and residences) (Wikstrom and Dolmen, 1990), so working or residential populations alone are not appropriate. For mobile targets such as motor vehicles, the number of targets was not available so we assume that the sum of residential and working population provides a reasonable proxy indicator for the total number of motor vehicles in a census tract.

3.3 Explanatory Variables

Explanatory variables were selected to represent social disorganization and routine activity theories. All data was made available by the University of Waterloo Map Library.

3.3.1 Social disorganization

Following the variable selection of Law and Quick (2012), nine social disorganization variables were chosen to encompass four dimensions of social disorganization: family disruption, ethnic heterogeneity, population turnover, and economic deprivation. Family disruption was measured through the proportion of lone parent families. Ethnic heterogeneity was operationalized through proportion of aboriginal residents, proportion of immigrant residents, and an index of ethnic heterogeneity. Population turnover was measured through one- and five-year residential mobility rates, and economic deprivation through percentage of low family income families, percentage of families receiving government transfer payments, and unemployment rate.

Descriptive statistics for social disorganization variables can be seen in Table 3.3.1.1. All variables were extracted from the 2006 Canadian Census (Statistics Canada, 2006c) at the census tract scale.

Table 3.3.1.1. Descriptive statistics for social disorganization variables.

	Description	Min	Mean	Max	Std. Dev.
Family Disruption					
Lone parent families	No. of lone-parent families / No. of census families	0	0.20	0.51	0.07
Ethnic Heterogeneity					
Aboriginal residents	No. of aboriginal identity population / census tract population	0	0.01	0.04	0.01
Immigrant residents	No. of immigrants / census tract population	0	0.48	0.80	0.16
Index of ethnic heterogeneity	1 – (sum of the squared ethnic proportions) 1 - $\sum W_i^2$ (where W_i is the proportion of residents in ethnic group i) (adapted from Hirschfield and Bowers, 1997)	0.01	0.63	0.86	0.13
Population Turnover					
One-year residential mobility	Number of residential movers in last	0	0.15	0.54	0.06

	one year / census tract residential population				
Five-year residential mobility	Number of residential movers in last five years / census tract residential population	0	0.44	0.87	0.12
Economic Deprivation					
Low family income residents	% of residents with low income families after tax	0	14.84	56.60	8.54
Families receiving government transfer payment	% of families receiving government transfer payments	0	11.05	34.50	5.80
Unemployment rate	100 x (No. of unemployed people / labor force)	0	7.59	18.80	2.72

3.3.2 Routine activity

Routine activity variables were selected to represent land uses hypothesized to converge motivated offenders, suitable targets, and limited guardianship. Land uses were chosen to operationalize routine activity to direct applications of results to inform law enforcement planning as it relates to land use planning. Routine activity land use variables can be broken into three categories: residential land use, non-residential land use, and guardianship.

3.3.2.1 Residential land uses

Residential land use variables included dwelling density, and densities of single detached, semi-detached, row houses, duplex apartments or apartments attached to other dwellings or buildings, apartments in buildings less than five stories, apartments in buildings with five or more stories, and other single dwellings (Table 3.3.2.1). Residential variables were obtained from Statistics Canada (2006c).

Table 3.3.2.1. Descriptive statistics for residential land use routine activity variables.

	Description	Min.	Mean	Max.	Std. Dev.
Residential land use					
Dwelling density	No. of occupied dwellings / census tract area	25.86	2,836.91	29,695.65	3,091.17
Single detached	No. of single detached houses (a single dwelling not attached to any other dwelling or structure) / census tract area	0	484.61	1,956.90	361.03
Semi detached	No. of semi-detached houses / census tract area	0	189.28	1,680.00	274.60
Row house	No. of row houses (one of three or more dwellings joined side by side) / census tract area	0	139.93	1,583.33	214.49
Apartments that are a duplex or attached to other dwellings or buildings	No. of apartments (duplex or apartments attached to other dwellings or	0	95.73	628.21	99.49

	buildings) / census tract area				
Apartment buildings with five or more stories	No. of apartments in buildings with 5 or more stories / census tract area	0	1,401.31	29,173.91	2,975.18
Apartment buildings with fewer than five stories	No. of apartments in with fewer than 5 stories / census tract area	0	521.40	3,720.59	731.45
Other single dwellings	No. of other single dwellings / census tract area	0	3.65	250.00	16.10

3.3.2.2 Non-residential land uses

Non-residential land uses included neighborhood, community, and regional shopping centres, hotel, police stations, subway stops, secondary schools, primary schools, and places of worship. These non-residential land uses were analysed using binary indicator variables, where a value of one was assigned to the presence of that land use in a census tract and a value of zero was assigned when that non-residential land use was not present in a census tract. Continuous non-residential land use variables included the density of park land and roads, and the concentration of commercial, resource-industrial, government-institutional, and open area land uses. Descriptive statistics for non-residential land uses can be seen in Table 3.3.2.2.

All non-residential variables analysed as binary indicator variables were obtained from the City of Toronto Geospatial Competency Centre for the year 2010 and distributed as address point data (City of Toronto, 2010). Address points were joined to census tracts and summed using a point-in-polygon spatial join in ArcGIS 10.0. Remaining non-residential land use variables were obtained from DMTI for the year 2010 (DMTI, 2010). Distributed as polygons, these land use variables were intersected with census tract boundaries and areas summed within each census tract using Geospatial Modeling

Environment software (Beyer, 2012). Summed land use areas were divided by census tract area to account for varying census tract areas.

Table 3.3.2.2. Descriptive statistics for non-residential land use routine activity variables.

	Description	**Min.**	**Mean**	**Max.**	**Std. Dev.**
Non-residential land use					
Neighborhood shopping centre	Binary indicator	0	0.39	1.00	0.49
Community shopping centre	Binary indicator	0	0.03	1.00	0.17
Regional shopping centre	Binary indicator	0	0.01	1.00	0.10
Hotel	Binary indicator	0	0.12	1.00	0.32
Police station	Binary indicator	0	0.05	1.00	0.21
Subway stop	Binary indicator	0	0.10	1.00	0.30
Secondary school	Binary indicator	0	0.25	1.00	0.43
Primary school	Binary indicator	0	0.78	1.00	0.42
Place of worship	Binary indicator	0	0.80	1.00	0.40
Park density	Park area / census tract area	0	0.10	0.62	0.11
Road density	Length of roads in census tract (km) / census tract area	6.86	17.16	38.55	4.82
Resource-industrial land use	Area of resource-industrial land use / census tract area	0	0.14	0.90	0.18
Government-institutional land use	Area of government-institutional land	0	0.07	0.92	0.08

	use / census tract area				
Commercial land use	Area of commercial land use / census tract area	0	0.02	0.98	0.07
Open area land use	Area of open area / census tract area	0	0.04	0.75	0.07

For reference, neighborhood shopping centres are typically anchored by a supermarket and are intended to provide daily needs to shoppers, community shopping centres offer a wider range of foods than neighborhood shopping centres including apparel, home furnishings, and electronics and sporting goods (ICSC, 1999). Larger than both neighborhood and community, regional shopping centres have department or fashion stores as anchors and provide full service and variety to shoppers (ICSC, 1999).

Non-residential land use categories include resource-industrial, government-institutional, commercial and open area (DMTI, 2010). Resource-industrial land uses generally represent industrial facilities including factories and utilities. Government-institutional land uses include post offices, universities and colleges, municipal and provincial government buildings, and libraries. Commercial land uses are stores and open areas are generally fields and conservation areas.

3.3.2.3 Guardianship

Three variables were selected to represent the guardianship dimension of routine activity theory (Table 3.3.2.3). Measures of degradation of the physical environment are included as these may influence offender perception regarding local levels of guardianship. This operationalization of guardianship was proposed by Cohen and Felson (1979) when they discuss the possibility of architectural and environmental design altering capable guardianship. Similarly, operationalizing land uses as places that influence guardianship also follows the broken windows theory, which hypothesizes that minor physical deterioration of the physical environment can lead to serious crime (Wilson and Kelling, 1982; Harcourt, 1988). The broken windows theory was not explicitly included in this thesis because there is little consensus among researchers regarding the validity of broken windows in explaining small-area crime (Harcourt and Ludwig, 2006).

The three variables selected to represent the guardianship dimension of the routine activity theory were concentration of dwellings in need of major repair, concentration of dwellings constructed before 1946, and concentration of vacant land uses (Statistics Canada, 2006c) (Table 3.3.2.3). We assume, then, that these variables will have a positive relationship with acquisitive crime types such that high levels of physical deterioration result in decreased perceived guardianship among offenders and increased criminal offences.

Table 3.3.2.3. Descriptive statistics for guardianship routine activity variables.

	Description	**Min.**	**Mean**	**Max.**	**Std. Dev.**
Dwelling in need of major repair	No. of dwellings in need of major repair / census tract area	0	0.08	0.28	0.04
Dwelling constructed before 1946	No. of dwellings constructed before 1946 / census tract area	0	0.20	0.86	0.25
Vacant land uses	No. of vacant land uses / census tract area	0	7.54	247.06	14.07

Chapter 4

Exploring Hotspots of Drug Offences in Toronto, Ontario: A Comparison of Four Local Spatial Cluster Detection Methods

4.1 Introduction to Spatial Cluster Detection

Cluster analysis is a technique of exploratory spatial data analysis that identifies spatial clusters, or areas of high or low risk that are surrounded by areas of similar risk (Murray et al., 2001; Anselin et al., 2001; Besag and Newell, 1991). Spatial cluster analysis can be employed in any field where the identification of points or areas with statistically significant high or low rates is paramount to understanding the location and characteristics of a phenomenon. The use of spatial cluster analysis is widespread, including fields of archaeology, ecology, economics, and genetics, and is a useful investigative technique whenever etiology is expected to vary due to geographic attributes (Kulldorff et al., 2003; Marshall, 1991). This extends to investigations of crime in general, and drug offences in particular, as these are known to have a spatial dimension such that some areas exhibit high drug rates while other areas exhibit low drug rates (Ratcliffe and Breen, 2011; Robinson and Rengert, 2006; Rengert et al., 2000; Chakravorty, 1995).

The applications of spatial clustering for crime data are numerous from both a practical and academic perspective. In practice, the large economic and societal costs of crime make it imperative that crime prevention and enforcement are efficient and effective (Sharpe, 2000). Certainly, one way to address this is to make the role of police more place-specific (Lawton et al., 2005) through an improved understanding of the geographic distribution of high crime rates, allowing for law enforcement and prevention to be strategically tailored to neighborhood-scale characteristics (Lu, 2000; Grubesic and Murray, 2001; Brantingham and Brantingham, 2005; Braga, 2001). For example, large clusters may be used to inform law enforcement planning and crime prevention such as police patrols, as well as identify socio-economic or environmental characteristics that may be influencing cluster location. In contrast, small clusters may be more suitable to be targeted with resource-intensive policing and crime prevention initiatives not feasible on a larger scale because of high resource demands (e.g. cost and specificity of operation).

Academically, local cluster analysis is an apt starting point for systematic inquiry. It aids in identifying the presence of geographic patterns, for example spatial autocorrelation - the degree to which observations at one location are similar or dissimilar to observations nearby (Burra et al., 2002) - which can provide insight for hypothesis generation and the basis for unique statistical tests such as spatial regression models. Additionally, clusters can be investigated as to how they work within existing theoretical frameworks of environmental criminology such as the concentric zone model (Park and Burgess, 1925), as well as neighborhood-scale mechanisms thought to influence crime such as collective efficacy and institutional resources (Townsley, 2009). McCord and Ratcliffe (2007), for example, explore the interaction between social disorganization and routine activity theories and the location of drug offences in Philadelphia, Pennsylvania. Specifically, they hypothesize that areas with high social disorganization lack the resources needed to prevent the establishment of a drug market, while certain land uses, such as transit stops or cash providing businesses, attract many potential customers to neighbourhoods (McCord and Ratcliffe, 2007). In this case, local spatial cluster detection could be used prior to confirmatory analysis to locate high drug offence rate clusters and inform the research hypothesis and independent variables selected.

There are two shortcomings with respect to the use of spatial cluster detection techniques in past studies of crime that this chapter seeks to address. First, despite the numerous advantages of employing spatial cluster detection in crime analysis, no local cluster detection method has been proven preferable to others in this context. Because there are many different methods and thus many possible resulting clusters, understanding which method most suitably models the phenomena under study and best informs practical applications is important. Second, in studies of criminal geography it is not uncommon to suggest the presence of a hotspot or cluster without employing statistical spatial cluster detection methods. For example, in Charron's (2009) overview of crime in Toronto, he frequently refers to clusters (i.e. "Most of the smaller shopping centres represent secondary clusters of property crime"), but determines these on visual observation alone and cannot, therefore, infer the significance of the clusters. It is entirely possible that visual clusters are a product of map or data characteristics, for example the scale, legend, use of colour, or whether offence count or rate is measured, and not the disproportionate distribution of a crime.

In light of these two shortcomings, this chapter has two research objectives: first, to identify the locations of drug offence hotspots in Toronto, Ontario and second, to highlight the advantages and limitations of four local cluster detection methods in their application to studies of crime and practical efforts including law enforcement planning and crime prevention.

First, this chapter will provide a brief introduction to spatial cluster analysis with a specific focus on four local cluster analysis methods: 1) spatial scan statistic based on Euclidean radius (SSS), 2) spatial scan statistic based on non-Euclidean contiguity (SSS-contiguity), 3) flexibly shaped scan statistic (FSS), and 4) local Moran's I (LMI). This will be followed by a review of past literature that employs cluster methods in crime research or evaluates cluster techniques from a methodological perspective. Next will be a brief discussion of the data, including an overview of the study region, Toronto, Ontario, and the prevalence of drug offences in the city. Results of cluster analysis will follow and finally, a discussion that explores the results of the four cluster analysis methods and the potential implications of the findings on understanding the location of drug offences in Toronto and how these cluster analysis results can be used in practical and research applications.

4.2 Cluster Analysis Approaches

Cluster analysis works to "visualize spatial distributions, identify atypical locations or hotspots, and suggest spatial regimes or other forms of spatial heterogeneity (Anselin et al., 2001)." Exploratory spatial data analysis (ESDA) does not estimate relationships among dependent and independent variables, but rather visualizes trends and patterns. In this sense ESDA, and cluster analysis in particular, are valuable starting points for crime analysis.

There are two broad classes of spatial cluster detection: global and local. Global clustering methods measure the average tendency of data to disprove the null hypothesis of spatial randomness, but do not indicate the specific location or significance of individual clusters (Chakravorty, 1995; Kulldorff et al., 2003; Burra et al., 2002). A common global cluster technique is Moran's I, where results are measured on a scale of negative one to one, with zero indicating spatial randomness, negative one indicating negative spatial autocorrelation or spatial outliers, and one indicating positive spatial autocorrelation. In cases where global Moran's I is close to either negative one or one, there are substantial deviations of local values from the global mean and the dataset is suspected to exhibit clustering (Anselin, 1995). While useful to inform the use of some confirmatory techniques such as spatial regression, global spatial cluster detection methods do not allow for the identification of high and low crime rate clusters (Burra et al., 2002).

Local cluster detection methods, on the other hand, process subsets of global data to identify individual clusters, or neighboring areas that exhibit disproportionately high or low risk relative to a null hypothesis of spatial randomness (Anselin, 1995; Kulldorff et al., 2003). In general, local methods are advantageous to global methods because they identify the specific location of clusters and measure significance against the null hypothesis for all detected clusters. One notable local cluster detection method that is not examined in this chapter is Getis and Ord's G_i* statistic (Getis and Ord, 1992), which is similar to local Moran's I, but instead of comparing neighboring values with the overall mean, the G_i* statistic analyses the sum of neighbouring values.

The following sections (4.2.1 to 4.2.4) will provide an overview of four local spatial cluster detection tests. In general, local cluster analysis methods fall into one of two categories depending on how they measure spatial interaction. One is radius-based, where observations are considered to exert influence on each other if they are located within a scan window sized at a given radius. Second is contiguity-based, where areas are considered to influence each other if their location is adjacent to the target area as specified in a spatial weight matrix. Of note, the spatial scan statistic is a radius-based method while the local Moran's I is a contiguity-based method. Bridging this gap are the spatial scan statistic with non-Euclidean contiguity and the flexibly shaped scan statistic, both of which use a combination of scan window and contiguity to identify local spatial clusters.

4.2.1 Spatial Scan Statistic

The spatial scan statistic (SSS) was originally developed by Martin Kulldorff to examine incidences of breast cancer (Kulldorff, 1997; Tango and Takahashi, 2005). It has been applied in a variety of epidemiological studies including soft tissue sarcoma, non-Hodgkin's lymphoma, bovine tuberculosis, and renal syndrome (Song and Kulldorff, 2003; Fang et al., 2006). The SSS is considered "one of the most widely used statistical methods for automatic detection of clusters in spatial data (Yao et al., 2011)," and has been used in over one-hundred scholarly studies (Read et al., 2011).

The SSS imposes a circular scan window of a given radius centered on an area centroid (Kulldorff, 2010). The scan window radius increases to a specified limit, usually fifty-percent of population at risk. For each scan window, as the window both increases in size and moves across all data points, a likelihood ratio is calculated (Equation 4.2.1.1). The most likely cluster is comprised of the areas contained within the scan window that possess the greatest likelihood ratio and secondary clusters are ranked according to likelihood ratio. Significance is determined through Monte Carlo hypothesis testing, a comparison of the rank of the likelihood ratio from the real data to a likelihood ratio from randomized versions of the same dataset (Kulldorff, 2010).

$$LR(Z) = \frac{L(Z)}{L_0} = \left(\frac{c(Z)}{n(Z)}\right)^{c(Z)} \left(\frac{C - c(Z)}{C - n(Z)}\right)^{C - c(Z)} \qquad (4.2.1.1)$$

From Equation 4.2.1.1, *LR(Z)* represents the likelihood ratio statistic for scan window *Z*, which is calculated as the likelihood of the alternative hypothesis of spatial clustering (*L(Z)*), divided by the likelihood of the null hypothesis of complete spatial randomness (L_0). *c(Z)* is observed cases in scan window *Z*, *n(Z)* is the expected number of cases inside *Z*, and *C* is the number of global cases.

Advantages of the SSS over other local cluster analysis methods is that it calculates a likelihood test statistic, avoids multiple testing, and has a variable scan window which avoids pre-selection bias (Mather et al., 2006). The SSS determines statistical significance without specifying the number of areas or location of the clusters prior to calculating significance and all significant clusters must reject the null hypothesis based on their strength alone (Almeida et al., 2011; Kulldorff, 2010). Because of this, any rearrangement of cases outside of the scan window will not change cluster significance (Kulldorff et al., 2003). The SSS cluster detection method has been modified to use an ellipsoidal scan window for improved detection of non-circular clusters.

Analysis was completed in SaTScan v.9.1.1 and used a discrete Poisson model, where the expected number of cases is assumed to be proportional to census tract population at risk (sum of working and residential population). The maximum scan window size was set at 50 percent of the population at risk with circular scan windows centred on census tract centroids. Significance was calculated through Monte Carlo hypothesis testing with 999 permutations. It is possible to use covariates for SSS tests to control for the influence of characteristics, however these were not included for better comparison to other local cluster detection methods.

4.2.2 Spatial Scan Statistic with Non-Euclidean Contiguity

The SSS can be modified to include a non-Euclidean neighbor contiguity file (SSS-contiguity). In this case, the scan window centers on the target area centroid and the radius increases to include the neighboring areas specified in the contiguity matrix. This variation on the SSS limits the maximum scan window size, also limiting maximum cluster size.

Calculations for the SSS-contiguity method remain the same as Eq. 4.2.1.1, but since Z is constrained to the areas defined in the contiguity matrix, the test calculates $LR(Z)$ for groups with fewer areas than the SSS. This results in substantially fewer calculations than the SSS (i.e. no variable scan window size). As with the SSS method, the most likely cluster is the group of areas with the highest likelihood ratio and each cluster must be significant on its own power.

Most commonly, contiguity is specified through queen relationships including all neighbouring areas that share a border or vertex. The construction of the contiguity matrix is paramount to the accuracy and relevance of cluster detection since it is a "theoretical decision regarding the processes being discussed and one that has implications for the statistical estimates generated (Tita and Radil, 2010: 111)." SSS-contiguity analysis was conducted in SaTScan v.9.1.1 using first-order queen contiguity. First-order queen contiguity was chosen because it was found that with increased order of contiguity, spatial autocorrelation decreased suggesting diminished clustering when more neighbors were included in analysis.

4.2.3 Flexibly Shaped Scan Statistic

The flexibly shaped scan statistic (FSS) was developed by Tango and Takahashi (2005) and allows for irregularly shaped clusters to be detected (Torabi and Royschuk, 2011; Huang et al., 2008). As Tango and Takahashi (2005, p.2) state, "for any given region i, the [SSS] considers K concentric circles, whereas the [FSS] considers K concentric circles plus all sets of connected regions whose centroids are located within the K-th largest concentric circle." So, the FSS centres an irregularly shaped scanning window at an area centroid and the window expands to a given radius to include the contiguous area centroids, searching for nearest maximums and high rates similar to the observed rate of the target area (Yao et al., 2011; Tango and Takahashi, 2005). FSS still calculates a most likely cluster based on the greatest likelihood function (Equation 4.2.1.1) (Tango and Takahashi, 2005) and just like SSS and SSS-contiguity, clusters must disprove the null hypothesis of spatial randomness on their own power (Tango and Takahashi, 2005).

Broadly, the FSS is similar to the SSS-contiguity because it is a method that uses both a scan window and contiguity matrix. However, where the SSS-contiguity uses a circular scan window and all areas within the scan window are considered to be part of the cluster, the FSS has an irregularly shaped scan window where it selects some, but not all, of the areas that would be included in a circular scan window. Because of the large number of calculations (i.e. many combinations of irregular scan windows at one area centroid) it is recommended that the FSS be limited to measuring a maximum of 30 observations, therefore detecting clusters that are 30 census tracts or fewer (Tango and Takahashi, 2005).

For this research, the FSS analysis was completed in FlexScan v.3.1 and was conducted using a Poisson model with first-order queen-contiguity matrix. Maximum spatial cluster size was set to 20 census tracts and significance determined using 999 Monte Carlo replications. After testing at a number of maximum cluster size limits, 20 was chosen because calculations were completed in a reasonable amount of time (approximately 30 minutes or so compared to a number of hours at cluster size limits larger than 20 census tracts).

4.2.4 Local Moran's I

Local Moran's I (LMI) was developed by Anselin (1995) to identify areas of non-stationarity, or areas where global methods cannot explain local variations in phenomena (Hanson and Wieczorek, 2002; Brunsdon et al., 1996). LMI is a local indicator of spatial association, or LISA, which possess two characteristics: 1) the LISA for each area provides a measure of spatial clustering of surrounding values, and 2) the sum of all LISA observations is proportional to a global indicator (Anselin, 1995). In this research the sum of all LMI observations is proportional to global Moran's I.

Often with small-area analysis, LMI relies on a contiguity matrix to define and interpret spatial relationships, so only the areas that are contiguous to the target area and the target area itself are considered (Cohen and Tita, 1999). The calculation for LMI can be seen in Eq. 4.2.4.1, where I_i is the local Moran's I value at area i, x_i is the value of variable x at area i (drug offence rate), $\bar{x}$ is the global mean of x, n is the number of areal units, and w_{ij} represents contiguity as per the first-order queen contiguity matrix (Anselin, 1995).

$$I_i = \frac{(x_i - \bar{x})\sum_j w_{ij}(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2 / n} \qquad (4.2.4.1)$$

LMI analysis results in five output classes (for one percent significance, for example): insignificant clustering ($p>0.01$), high values surrounded by high values (HH; $I_i>0$, $p<0.01$), low surrounded by low (LL; $I_i>0$, $p<0.01$), high surrounded by low (HL; $I_i<0$, $p<0.01$), and low surrounded by high (LH; $I_i<0$, $p<0.01$). Areas that are surrounded by similar values (HH and LL) are indicative of spatial clustering and have positive LMI values. Only HH clusters will be considered in this research. LMI analysis was completed in OpenGeoDa v.0.9.8.14.

These four local spatial cluster detection methods were chosen because the LMI method is relatively common in crime research (e.g. Baller et al., 2001; Messner and Anselin, 2004; Messner et al., 1999; Mencken and Barnett, 1999; Cohen and Tita, 1999; Murray et al., 2001) but has never been compared to other cluster methods in the context of crime at the small-area scale. As remarked, the SSS was chosen for its radius-based interpretation of spatial relationships, which contrasts LMI's contiguity-based method (Hanson and Wieczorek, 2002). SSS-contiguity and FSS methods were included because they incorporate both radius- and contiguity-based interpretations of spatial data, effectively bridging the gap between LMI and SSS.

4.3 Review of Spatial Cluster Analysis Approaches

4.3.1 Past crime research

Although local spatial cluster detection methods are used in many fields including crime and epidemiology, these literatures are largely distinct with infrequent cross-references (Waller, 2009). And while much epidemiological research uses SSS or FSS methods, crime related cluster analysis predominantly uses LISA statistics, LMI in particular. One such study examined the occurrence of homicide in the United States at the county scale using LMI, finding significant spatial autocorrelation (Baller et al., 2001). Mencken and Barnett (1999) also employ LMI in their study of murder and manslaughter in mid-south United States counties. Other studies using LMI include Messner and Anselin's (2004) investigation of homicide rates in St. Louis, a study of property crime in Brisbane, Australia (Murray et al., 2001), and violent gang activity in Pittsburgh (Cohen and Tita, 1999).

4.3.2 Past methodological research

Past methodological research articles have examined the processes of spatial clustering methods, yet there has been no comprehensive comparison of spatial clustering methods focused on urban crime at the small-area scale. A number of studies have tested the power of cluster detection tests to reject the null hypothesis of complete spatial randomness. For example, Kulldorff et al. (2003) found that the SSS has good power for urban, mixed, and rural clusters and that generally, the power of the SSS increases when population increases. These findings were also noted by Song and Kulldorff (2003). Tango and Takahashi (2005) propose that the SSS is the most powerful cluster detection test for detecting localized clusters but has substantially less power in detecting non-circular clusters.

Power to reject the null hypothesis, however, does not necessarily mean that clusters are correctly identified (Tango and Takahashi, 2005). It has been suggested that the SSS detects more clusters, larger clusters, and more partial clusters than other methods and that the SSS has a high error rate for cluster identification (Wan et al., 2012; Tango and Takahashi, 2005; Takahashi and Tango, 2006). Also, Wan et al. (2012), Yao et al. (2011) and Duczmal et al. (2006) argue that the SSS fails to give the exact shape of clusters, generally detecting clusters of similar shape as the scanning window (i.e. circular scan window results in a relatively circular cluster).

Kulldorff and Tango (2003) take a more nuanced perspective, proposing that the power of the SSS depends on the compactness of the cluster shape, not the scan window shape. That is, the closer similar values are located to each other, the better power for the SSS. They also suggest that clusters can be non-circular and the SSS will have accurate detection as long as high values are compact (Kulldorff and Tango, 2003). Yao et al. (2011) concur, noting that the performance of the SSS is unsatisfactory when clusters become less compact. In some cases, particularly when clusters are larger than expected, it is possible that non-high risk areas are included in SSS clusters due to the boundary effect, whereby observations on the edge of the scan window do not affect the likelihood calculations to a significant degree and are included, despite not truly being part of the cluster (Hanson and Wieczorek, 2002; Rogerson and Yamada, 2009)

In testing the FSS, Wan et al. (2012) and Huang et al. (2008) observe that it does not produce false positive errors to the same degree as SSS, but that the FSS usually divides large clusters into a number of pieces. This becomes problematic when parts of the cluster are determined to be insignificant and could be overlooked (Wan et al., 2012). In general, the FSS method has been found to have poor performance when clusters are ring-shaped or when there are weak links (i.e. areas with rates unlike the cluster values) within clusters (Yao et al., 2011). Whereas other clustering methods will include non-high values in clusters if surrounded by many high values, the FSS has a tendency to fragment clusters if there is a discontinuation in high values within the scan window.

In a study comparing five cluster detection methods for the identification of childhood cancer clusters in Alberta, Canada, Torabi and Royschuk (2011) find that FSS and SSS identified similar regions, with SSS identifying mostly circular and FSS identifying circular and irregularly shaped clusters. Interestingly, the SSS identified fewer significant clusters than the FSS, which the authors attribute to the fact that some true clusters were irregular in shape and therefore not detected by a circular scan window (Torabi and Royschuk, 2011). Additionally, FSS and SSS were found to have similar power in identifying cancer clusters among a comparison of six local cluster detection methods (Huang et al., 2008).

Comparing nine cluster detection methods for colorectal cancer in the United States, LMI was found to have a good chance of detecting parts of larger clusters with a low false-positive rate compared to other methods including SSS and FSS (Huang et al., 2008). Also, Hanson and Wieczorek (2002) examined SSS and LMI clustering methods with respect to alcohol mortalities at the county level in New York. It was found that the most likely cluster in SSS was also detected in LMI, however secondary clusters were not. The authors posit that this is because significance values of secondary clusters in SSS are conservatively calculated and it is possible for groups of a few counties to be undetected if they are included in larger clusters during simulations (Hanson and Wieczorek, 2002).

4.4 Cluster Analysis Results

Global Moran's I was calculated to determine the average level of spatial autocorrelation throughout the dataset. Global Moran's I indicates that there is significant spatial autocorrelation (I=0.2913, p=0.001). So, clustering of drug offences is present and will potentially be identified by local methods. Fig. 4.2.4.1 displays drug offence rates per 1,000 people, where visually observed clustering of high rates can be seen in the downtown and along the west of Toronto and clustering of low rates can be seen north of downtown, in the northeast above highway 401, and in the west in Etobicoke.

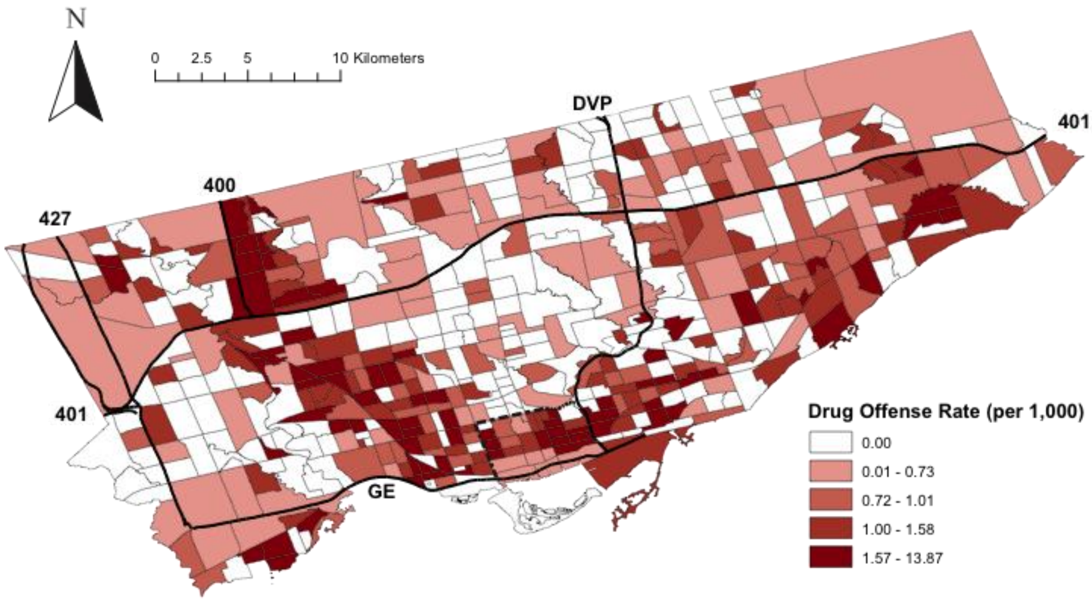

Figure 4.3.2.1. Quantile map of 2006 drug offence rates per 1,000 people in Toronto, Ontario by census tract. Generally high drug offence rates are located in the downtown and northwest while low drug offence rates are located in the north and central areas.

The SSS detected six significant clusters (p<0.01) ranging in size from two census tracts to 40 census tracts (Table 4.2.4.1, Fig. 4.2.4.2). Because of the considerable variation in geographic cluster size there was also a large variation in the observed and expected number of cases. The most likely cluster (MLC) has the greatest observed/expected ratio (O/E) and log likelihood ratio (LLR). O/E is calculated as the observed drug offence rate in a cluster divided by the expected drug offence rate in the cluster where the expected value is the global average drug offence rate. Secondary clusters have smaller O/E, and LLR compared to the MLC.

Clusters were detected in the south-central, or downtown, of Toronto and along the west-side of the city. In the west, clusters were at Highways 401 and 400, in Rexdale and Eglinton and Dundas West, generally following the greenbelt of parks that runs to the south-east along the Humber River. One large cluster was found on the east-side of the city in Scarborough. As seen in Fig. 4.2.4.2, clusters were generally circular in shape.

Table 4.3.2.1. SSS output. All clusters are significant at one percent significance level.

Cluster Rank	**Cluster Size (No. of census tracts)**	**Observed / Expected (O, E)**	**LLR**
MLC	2	16.47 (177, 10.74)	334.47
2	40	2.35 (429, 182.44)	131.64
3	19	2.44 (181, 74.22)	56.59
4	22	1.97 (196, 99.65)	37.89
5	34	1.46 (219, 149.89)	14.79
6	2	2.92 (29, 9.93)	12.07

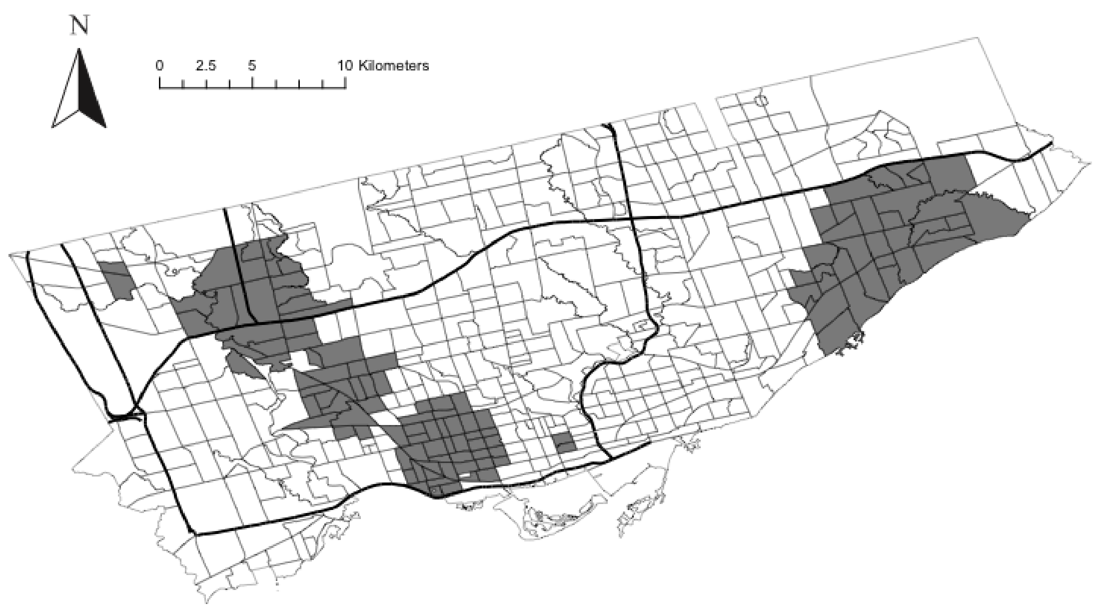

Figure 4.3.2.2. SSS cluster output map. High drug offence rate clusters are located in downtown and the northwest, west, and east areas of Toronto.

SSS-contiguity with first-order queen contiguity resulted in 22 significant clusters (p<0.01) (Table 4.2.4.2, Fig. 4.2.4.3). Most of these clusters were small, ranging in size between two and ten census tracts, suggesting that the clusters detected in the SSS method were broken up into a number of smaller clusters in the SSS-contiguity method. Clusters were found in the downtown and west side at the intersection of Highway 401 and 400 (north on Highway 400), Eglinton West, and oriented east-west in downtown. Smaller clusters were found in the east in Scarborough (Fig. 4.2.4.3).

Table 4.3.2.2. SSS-contiguity output (top 6 LLR clusters). All clusters are significant at one percent significance level.

Cluster Rank	Cluster Size (No. of census tracts)	Observed / Expected (O, E)	LLR
MLC	4	11.33 (229, 20.21)	354.79
2	9	3.04 (125, 41.09)	56.38
3	3	5.11 (61, 11.94)	50.86
4	1	8.91 (35, 3.93)	45.64
5	5	3.13 (81, 25.82)	37.96
6	8	3.18 (78, 24.49)	37.34

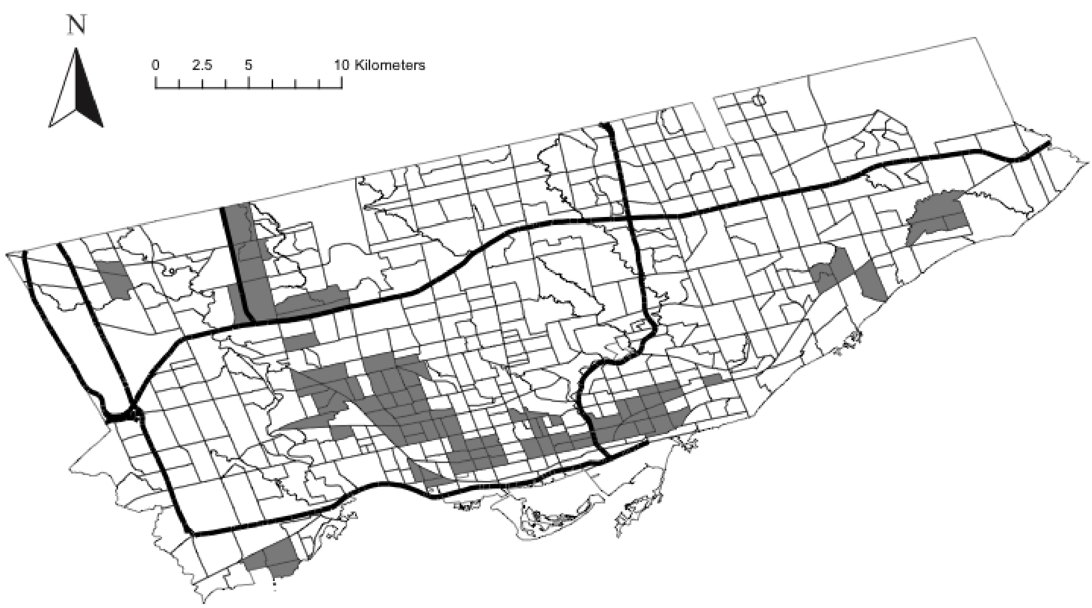

Figure 4.3.2.3. SSS-contiguity output map. High drug offence rate clusters are located in the downtown, west and northwest areas of Toronto.

The FSS detected 12 significant clusters (p<0.01) (Table 4.2.4.3, Fig. 4.2.4.4). All of the clusters detected were of similar size, ranging between four and 12 census tracts. FSS clusters were detected in similar locations to the SSS-contiguity clusters in the downtown and west-side with smaller, fragmented clusters on the east-side of Toronto. Specifically, clusters were found at Highway 400 and 401, along the Humber River oriented northwest-southeast, an east-west oriented clusters in the downtown, a number of clusters in Scarborough close to Lake Ontario, and a few smaller clusters in Etobicoke.

Table 4.3.2.3. FSS output (top 6 LLR clusters). All are significant at one percent significance level.

Cluster Rank	Cluster Size (No. of census tracts)	Observed / Expected (O, E)	LLR
MLC	4	11.30 (229, 20.26)	354.27
2	11	3.60 (189, 52.56)	108.721
3	8	2.43 (268, 110.17)	84.89
4	11	3.21 (135, 42.0296)	66.07
5	11	2. 69 (140, 52.05)	51.93
6	8	2.51 (137, 54.54)	44.92

Figure 4.3.2.4. FSS cluster output map. High drug offence rate clusters are located in the downtown, west, northwest and east areas of Toronto.

Table 4.2.4.4 and Fig. 4.2.4.5 show LMI cluster detection results. As shown in Table 4.2.4.4, HH and LL clusters indicate positive local Moran's I values, confirming that they identify areas with drug offence rates that are surrounded by similar areas. The majority of Toronto census tracts show insignificant LMI clustering and because of the large number of census tracts the insignificant category also contains the most drug offences and population at risk. HH clusters demonstrate the second most number of drug offences and highest drug offence rate. Of note, the average local Moran's I for HH clusters is 8.76, the largest of all cluster types and indicating that HH clusters are more spatially grouped than LL, HL, or LH clusters. Observed from the map in Fig. 4.2.4.5, HH clusters were only located in downtown Toronto close to the south terminus of the Don Valley Parkway along the Don River.

Table 4.3.2.4. LMI output for first order queen contiguity. All clusters are significant at one percent significance level.

	Cluster size (No. of census tracts)	Population in census tracts	Summed Count Drug Offences (min, max)	Cluster Drug Offence Rate	Avg. I for all included CT
HH	9	94, 520	346 (5, 108)	0.0037	8.76
LL	10	102, 315	27 (0, 7)	0.00026	0.29
LH	1	1, 435	0	0	0
HL	8	40, 965	48 (5, 9)	0.0012	-0.25

Figure 4.3.2.5. LMI HH cluster output map. One high drug offence cluster is identified in the downtown of Toronto.

For a more direct comparison of the location of clusters detected by the four methods, Fig. 4.2.4.6 shows the number of methods that identified each census tract as being part of a cluster. The most identified census tracts (e.g. by four cluster detection methods) were in downtown. Less identified census tracts were on the east edge of Toronto. No drug offence clusters were detected in the north-east and north-central areas of Toronto.

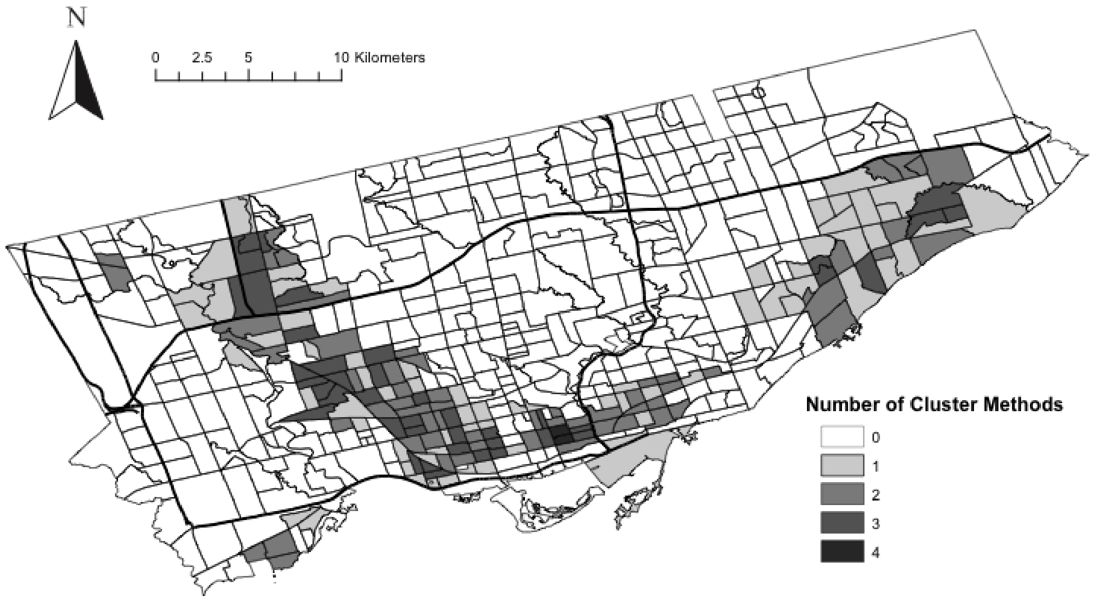

Figure 4.3.2.6. Map showing the number of cluster tests that identified each census tract as part of a significant drug offence rate cluster. Only one area in the downtown was identified by four methods, while the west, northwest and east had areas identified by two and three methods.

4.5 Cluster Analysis Discussion

Consistent across all cluster detection methods, drug offence clusters were detected in downtown Toronto (Fig. 4.2.4.6). While LMI only identified high drug offence clusters in the downtown, SSS, SSS-contiguity, and FSS methods detected primary clusters in the downtown and secondary clusters in the west along the greenbelt of parks running north-south along the Humber River (near Eglinton and Dundas West), and east in Scarborough (Figs 4.2.4.2-4.2.4.5). No methods detected clusters in the north-central (North York) and north-east areas (close to Highways 400 and 404) of Toronto.

4.5.1 Informing law enforcement planning

Without conducting confirmatory analyses, it is not possible to identify socio-economic or land use characteristics related to drug offence rate, however based on visual observation of the cluster maps a few possible explanations focused on the geographic locations of high drug offence clusters can be proposed to inform law enforcement planning. First is the presence of clusters in downtown Toronto.

Specifically, these clusters were located close to Regent Park and the Don River and Don Valley Parkway. This is possibly due to the large number of potential customers in the downtown, including those most likely to engage in drug activity such as the young, unemployed, and individuals with less than a high school education (Rengert et al., 2000). Under the assumption that drug markets are established in areas where profits are maximized (Robinson and Rengert, 2006), it is logical that areas with more potential customers (e.g. large populations and with populations more prone to drug activity) are the location of drug offence clusters (McCord and Ratcliffe, 2007).

Second is the location of secondary clusters near major highways that transect Toronto, specifically along the Gardiner Expressway in the south and at the intersection of Highway 401 and Highway 400 in the north. One possible explanation for this could be that close proximity to a highway in these areas provides easy accessibility to drug markets from non-local drug users, an important factor in the formation and sustainability of drug markets (Robinson and Rengert, 2006). This has been supported by Rengert et al., (2000), who observe that proximity to highways and highway interchanges create advantageous environments where drug markets can be established. Also, it could be that a substantial portion of drug offences are incurred as a result of traffic stops on the high traffic highways located in these areas.

Interestingly, the general location of clusters in the downtown and west of Toronto mirroring the variety of parks bordering the Humber River are visually similar to the distribution of possibly related socio-economic characteristics. For example, low income neighborhoods mapped by Hulchanski (2010, p.16) in his report on 2006 income polarization in Toronto are located in similar areas as drug clusters. Further, the observed pattern of drug offence clusters is the inverse of high income neighborhoods mapped by Charron (2009, p.8). So beyond the possible environmental correlates observed from inspection of drug offence clusters and features of the physical environment, it is possible that socio-economic characteristics such as income are associated with the location of high drug offence rate clusters.

Recognizing that cluster detection conducted by police may use address point data and focus on areal units smaller than the census tract (e.g. street corners as in Weisburd et al. (2006) and Lawton et al. (2005)), there are still practical benefits to understanding the pattern of drug offences at the census tract scale. One, the results of cluster analysis at this spatial scale can be employed in both academic and police-based studies using socio-economic data from the Canadian census distributed at the census tract scale. Because researchers do not often have access to address data for confidentiality reasons, the use of aggregated crime data at the census tract scale aligns the spatial scales of academic and police-based research. Two, identifying clusters based on point data does not take into account underlying variation in population size. Rather, clusters are based on the location of individual drug offence incidents, which introduces the possibility that locations of these clusters could be influenced by large population counts rather than high drug offence rates. Three, broader patterns of crime may not be recognized in studies focusing on smaller spatial scales. For example, the possible relationship between drug clusters and highways discussed above may not be revealed at smaller scales such as the street corner because they are located at a distance from the highways. In the following, we suggest some possible applications of the cluster detection methods examined in this research.

4.5.2 Applications for cluster detection techniques

Compared to other cluster analysis methods, the SSS had the largest and, noticeably, the most circular clusters (Fig. 4.2.4.2). This can be attributed to the use of a circular scan window, which has been shown to influence cluster shapes (Tango and Takahashi, 2005; Kulldoff et al., 2003), and a maximum cluster size of 50 percent population at risk, which is relatively large compared to other methods tested in this research. The larger clusters could also be attributed to the possibility that the scan window absorbed surrounding regions that do not have as high offence rates compared to the census tracts at the centre of the clusters, yet these low rate areas do not decrease the likelihood ration and stop scan window expansion. The most eastern cluster identified by SSS suggests that this is a possibility because in other methods (Figs 4.2.4.3 and 4.2.4.4) this cluster has been fragmented into a number of clusters (Yao et al., 2011). It is possible that with larger orders of contiguity, that contiguity-based methods could detect larger clusters.

From this, the SSS can be considered the most suitable for large scale observations. The larger SSS clusters allow for broad insight for law enforcement planning and a starting point for further inquiry into the patterns of drug offences in Toronto. From a policy perspective, SSS would be useful to identify areas where patrols and general police interventions can be targeted to alter drug market operations (Gruenewald et al., 2010). Because the output of SSS highlights larger clusters than those of other methods and the relatively high false-positive rate of SSS clusters found in past research

(Wan et al., 2012; Huang et al., 2008), these areas should be interpreted as a general indicator of high drug activity rather than the focus of resource-intensive policing strategies.

In general, SSS-contiguity results are less circular than the SSS clusters, but share many of the same locations (Fig. 4.2.4.3). Specifically, clusters are located in the east and in the very north-west part of the map, which are not detected in other methods (LMI and FSS in particular). Compared to SSS, SSS-contiguity clusters are more rectangular or linear in shape, which can be attributed to the use of a contiguity matrix rather than a circular scan window. FSS clusters are noticeably more fragmented than SSS and SSS-contiguity clusters. This has been highlighted in past research, which notes the tendency for FSS to break up clusters when low rates are present (Yao et al., 2011). At the same time, the FSS appears to be more sensitive to cluster location than SSS-contiguity as observed on the east side of Toronto (Fig. 4.2.4.4), where more significant clusters were identified, possibly because these are non-circular in shape.

SSS-contiguity and FSS, then, can be considered the most suitable cluster detection methods for framing hypotheses into ecological dimensions of crime. By combining a scan window with contiguity, both of these methods detect smaller and non-circular clusters compared to SSS while also highlighting larger-scale cluster patterns that may be indicative of environmental correlates not observable through inspection of the smaller clusters identified by LMI. For example, both SSS-contiguity and FSS observe clusters oriented in the east-west direction in downtown (Figs 4.2.4.3 and 4.2.4.4) and north-south oriented clusters at the intersection of Highways 401 and 400.

One possible theory from which to interpret the results of SSS-contiguity and FSS is the concentric zone model, which hypothesizes that cities are arranged in concentric circles where the central business district is at the centre and grows towards the periphery. In second-most central zone, termed the transition zone, there is high invasion and conflict resulting in the breakdown of social control (Roh and Choo, 2008). From these cluster results, it can be seen that in the centre of downtown there are few clusters but clusters are identified on the periphery of this inner zone on the east close to Regent Park and the Don River and in the west close to Dundas, Bloor, and Eglinton West. Considering the visual similarities between drug offence hotspots and what is hypothesized by the concentric zone model, this may be a useful lens for confirmatory analysis.

LMI detected the fewest census tracts as part of high drug offence clusters as well as the smallest, most compact clusters (Fig. 4.2.4.5). Significant LMI clusters ($p<0.01$) were only detected in the downtown of Toronto, with no clusters identified in the east and west of the city. From this, it is reasoned that LMI is most appropriate for identifying compact clusters that can be targeted with resource intensive police interventions and law enforcement initiatives not implementable at a larger scale. Some policing approaches such as crackdowns, which are abrupt increases in proactive police enforcement (Robinson and Rengert, 2006), problem-oriented policing, where police and policy makers attempt to remedy the underlying problems that create crime (Lawton et al., 2005), or 'weed and seed' techniques, where police action against drug dealers and community empowerment are combined to resist drug dealers, are not feasible on a large scale (i.e. at the scale of SSS clusters) because these interventions need to be designed to address specific situations (Braga, 2001; Rengert et al., 2000). The benefits of these situational and resource intensive crime prevention strategies have been proven to expand beyond the immediately targeted areas to nearby neighborhoods (Weisburd et al., 2006), so it is possible that by targeting census tracts identified by LMI, areas included in larger clusters will also experience reduced drug offences.

4.5.3 Cluster detection limitations

There were a number of limitations to this research. As in most research that employs spatial data, the modifiable areal unit problem (MAUP) should be acknowledged. The MAUP recognizes that varying scales of spatial aggregation will alter analysis results (Openshaw, 1984; Fotheringham and Wong, 1991; Yao et al., 2011; Tu et al., 2012). That is, distinctly different cluster patterns will emerge if analysis is conducted at different areal scales, for instance the census dissemination area (smaller) or census metropolitan area (larger). Crime data was only available to researchers at the census tract scale, so this was chosen as the scale of analysis.

Second, clusters are measured against a null hypothesis of spatial randomness, which is inherently unrealistic considering the non-random distribution of both crime and population. We attempt to account for some degree of population clustering through analysing drug offence rate rather than drug offence count, yet ideally clusters would be measured against the underlying risk of the phenomena (Weisburd et al., 2006) rather than spatial randomness. Third, FSS clusters were limited in size to 20 or fewer census tracts because of computational inefficiencies, so larger potential clusters (e.g. SSS identified a cluster with 40 census tracts) could not be identified.

4.6 Cluster Analysis Conclusions

Spatial cluster analysis methods identify areas and groups of areas with disproportionately high drug offence rates using statistical methods and hypothesis testing. A variety of cluster analysis methods have been developed, and thus a number of possible clustering outcomes are possible, yet none have been compared as to their utility in spatial studies of crime.

This chapter explores the SSS, SSS-contiguity, FSS, and LMI methods, finding that all methods identify similar cluster locations of high drug offences in downtown Toronto, with fewer methods identifying clusters in the west and east. It is observed that the SSS, a method using a circular scanning window, identifies large circular clusters and should be used for insight into possible variables to be included in confirmatory analysis and broad trends of drug offences, perhaps informing large scale policing issues such as patrol location. Second, the combination of scan window and contiguity as used in SSS-contiguity and FSS is advantageous because it overcomes the influence of scan window shape on cluster shape and incorporates contiguity, which allows these methods to highlight linear clusters that may follow environmental features such as highways or coastlines. Third, the LMI method, using only contiguity, identifies compact clusters that are appropriate for targeting resource intensive and highly specific law enforcement efforts such as crackdowns or problem-oriented policing that are not feasible for larger clusters.

Future research should look to add a temporal lens to the purely-spatial scans conducted in this article with the goal of identifying significant geographic clusters over a number of years. For example, researchers could flag the census tracts identified as high drug offence rate clusters in 2006 and compare these to clusters generated from crime data from future years with the intent of identifying the changing locations of drug offence clusters as cities, policing, and crime policies evolve. Additionally, various parameters for the contiguity matrix should be employed to examine the influence of, for example, differing adjacency definitions (e.g. inverse distance) on high crime clusters. Lastly, cluster results could be employed in confirmatory analysis (e.g. Andresen, 2011), where clusters are specified as the dependent variable in logistic regression models and significant covariates identified.

Chapter 5
Spatial Regression Modeling

5.1 Introduction

Crime is not uniformly distributed through geographic space. Instead, and as observed in Chapter 4, crime rates generally exhibit spatial patterning, where some areas have high rates of crime and other areas have low rates of crime (Wikstrom and Dolmen, 1990). Recognizing the non-random spatial distribution of crime has tremendous methodological and theoretical implications for spatial studies of crime.

Methodologically, spatial dependence among the dependent variable (i.e. crime rate) violates assumptions of linear regression models such as ordinary least squares (OLS). When analysing a spatially structured dataset with OLS, where location helps to explain the occurrence or value of a phenomenon, regression residuals often exhibit spatial autocorrelation. This can lead to incorrect estimation of regression coefficients and Type 1 errors, or false positives (Ward and Gleditsch, 2008; Tita and Radil, 2010; LeSage, 1997; Baller et al., 2001).

Theoretically, spatial models should reflect the spatial context of crime and provide insight into the spatial distribution of crime, enhancing the explanation of confirmatory crime analysis (Smith et al., 2000). That is, spatial regression methods allow researchers to recognize the influence of geographically proximate values and inform hypotheses and research findings. For example, when accounting for the influence of nearby dependent variables in regression models, as done in a spatial lag dependent regression, the model implicitly makes an assumption regarding the spatial relationships among the dependent. These assumptions inform our understanding of the spatial processes influencing crime, in this case indicating that crime rates are spatially clustered and incidents of tend to occur in close proximity.

The intent of this chapter is to provide an overview of spatial regression modeling beginning with non-spatial ordinary least squares regression and progressing to spatial error, spatial lag dependent, and spatial lag independent regression models. Modeling approaches, or the process of choosing the best fitting spatial regression model and selecting and eliminating explanatory variables, are detailed in Chapters 6 and 7.

5.2 Ordinary Least Squares Linear Regression

Ordinary least squares (OLS) regressions estimate a linear relationship between explanatory, or independent, and outcome, or dependent, variables. In the crime context a univariate OLS takes the form shown in Equation 5.2.1, where y is crime rate, β_0 is the regression constant, β_1 is the regression coefficient for explanatory variable x_1, and ε represents regression error.

$$y = \beta_0 + \beta_1 x_1 + \varepsilon \tag{5.2.1}$$

Equation 5.2.1 can be expanded to account for many explanatory variables through a multivariate OLS regression model as shown in Equation 5.2.2, where the terms $\beta_2 x_2 + \ldots + \beta_n x_n$ are added to demonstrate additional explanatory variables and estimated regression coefficients. If we use a univariate regression (Eq. 5.2.1) to model the relationship between crime rate and poverty, a multivariate regression (Eq. 5.2.2) can be used to model the relationship between crime rate and poverty, ethnicity, and residential mobility.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \varepsilon \tag{5.2.2}$$

5.3 Spatial Regression Models

Much past crime research has employed spatial regression methods. Three commonly used methods, spatial error, spatial lag dependent, and spatial lag independent (Fowler, 2011), are examined in Sections 5.3.1, 5.3.2, and 5.3.3 respectively. For all spatial regression methods, we incorporate spatial effects through a first-order row-standardized queen contiguity matrix.

5.3.1 Spatial Error Regression Model

The spatial error regression adds a spatially lagged error term, calculated as the mean regression error from adjacent census tracts, to a linear regression model. A multivariate spatial error regression model can be seen in Equation 5.3.1.1, where y_i is crime rate for area i, β_0 is the regression constant, and $\beta_1 x_{1i} + \ldots + \beta_n x_{ni}$ represent regression coefficients and explanatory variables for area i. Encompassing the spatial error term, ρ is a measure of the strength of spatial association, w_{ij} refers to the existence of spatial association between location i and location j, and ε_j is error terms for j neighboring areas. Error of the regression model is represented by u (Ward and Gleditsch, 2008).

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + ... + \beta_n x_{ni} + \rho w_{ij} \varepsilon_j + u \qquad (5.3.1.1.)$$

The spatial error regression model considers spatial effects as a nuisance by accounting for them through adding a spatially structured error term rather than adding an explanatory variable that would suggest spatial patterning of the independent or dependent variable (Anselin et al., 2001). Further, the spatial error model addresses omitted variable bias, or the presence of an unspecified explanatory variable (Zhukov, 2010). The spatial error model can also be used when spatial heterogeneity is suspected, or when the similarity of nearby observations is thought to be due to similar stimuli acting on a scale larger than the unit of analysis (Fowler, 2011).

In past research, the spatial error regression model has been employed by Andresen (2006) to study automotive theft, break and enter, and violent crime in Vancouver, British Columbia. Deane et al. (2008) test both spatial lag and spatial error models in the context of city-level robbery rates and find that the spatial error model best accounts for spatial dependence. Messner and Anselin (2004), in their study of homicide rates in the United States, find that the spatial error model exhibits superior fit compared to other models tested and Ceccato (2009), who tested both spatial lag (dependent) and spatial error regression models in her study of crime in Estonia, found that assault and robbery are best modeled through spatial error regression.

5.3.2 Spatial Lag Dependent Regression Model

The spatial lag dependent regression model, also known as the spatial autoregressive model (Anselin et al., 2001), adds a spatially lagged dependent variable as an explanatory term to a linear regression. A multivariate spatial regression model can be seen in Equation 5.3.2.1, where y_i is crime rate, β_0 is the regression constant, $\beta_n x_{ni}$ is regression coefficient and explanatory variable and ε is error. The spatially lagged crime rate term is indicated by $\rho w_{ij} y_j$, where ρ is the strength of spatial association, w_{ij} is the presence of a spatial association (as specified in the spatial weights matrix), and y_j is the crime rate of adjacent census tracts.

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_2 i + ... + \beta_n x_{ni} + \rho w_{ij} y_j + \varepsilon \qquad (5.3.2.1)$$

In contrast to the spatial error model which deals with spatial structure through an error term and treats spatial structure as nuisance, the spatial lag dependent regression model adds an explanatory term that provides additional insight into the spatial patterning of crime. Specifically this model recognizes the spatial dependence of observations, assuming that census tract crime rates are influenced by neighboring census tract crime rates (Zhukov, 2010).

The spatial lag dependent regression model has been employed in past research including Kubrin and Herting's (2003) investigation into neighborhood structure and homicide rates in St. Louis, and Smith et al.'s (2000) study focusing on robbery diffusion in the context of social disorganization and routine activities theories. Noting the theoretical assumptions of the spatial lag dependent model, Smith et al. (2000) remark that "proximate face blocks are likely to have similar robbery rates because they are part of the same awareness space of motivated robbers, because robbers' pattern of movement (work, play, home) is systematic rather than random." Similarly, Rosenfeld et al. (1999) add a spatially lagged crime rate term in their research into gang-motivated, gang-affiliated, and non-gang youth homicides, finding that the spatial lag coefficient is only significant in the gang-motivated category. This is theoretically justified, as they posit that the spatial clustering of gang-motivated homicides is due to the intrinsic, perhaps retaliatory, nature of this criminal act (Rosenfeld et al., 1999).

5.3.3 Spatial Lag Independent Regression Model

The spatial lag independent regression model adds a spatially lagged explanatory variable to a linear regression model. Like the spatial lag dependent model, the spatial lag independent regression model has theoretical implications of its use, specifically that rates of nearby explanatory variables, for instance poverty (Anselin, 2003) or resource deprivation (Mears and Bhati, 2006), influence census tract crime rates.

Spatial lag independent regression model can be seen in Equation 5.3.3.1, where y_i is crime rate, β_0 is the regression constant, $\beta_n x_{ni}$ is regression coefficient and explanatory variable and ε is error. The spatial lag independent term is represented by $\beta_n(\rho w_{ij} x_\mathrm{n})$, where ρ is the strength of spatial association, w_{ij} denotes the presence of spatial association, and x_{nj} is the spatially lagged explanatory variable x for neighboring areas j.

$$y_i = \beta_0 + \beta_1 x_{1i} + ... + \beta_n x_{ni} + \beta_1(\rho w_{ij} x_{1j}) + ... + \beta_n(\rho w_{ij} x_{nj}) + \varepsilon \qquad (5.3.3.1)$$

Hipp et al. (2009) employ the spatially lagged independent regression model in their study focusing on the role of neighborhood-level racial and ethnic change on intragroup and intergroup crime. Importantly they note that the spatially lagged dependent variable is not theoretically suitable because intergroup or intragroup crime are not suspected to exhibit a contagion effect where nearby crime rates influence crime rate observations. Rather, they include lagged explanatory variables such as racial/ethnic composition, income level, and economic inequality (Hipp et al., 2009).

5.3.4 Combining spatial lag dependent and independent regression models

A number of studies combine spatially lagged independent and dependent variables, also known as a spatial durbin model (Fowler, 2011), including Mears and Bhati's (2006) examination of resource deprivation on violence. Here, a lagged violent crime rate term is included to account for possible diffusion of crime and spatially lagged explanatory variables are added to account for the influence of nearby resource deprivation (Mears and Bhati, 2006). In Rosenfeld et al.'s (2007) research on the impact of order-maintenance policing on New York City homicide and robbery rates, both spatially lagged order-maintenance policing term (independent) and lagged crime rates (dependent) are included. Gorman et al. (2001) investigate the relationship between alcohol availability, neighborhood structure, and violent crime in Camden and Newark, New Jersey through testing two models, one with a spatially lagged crime rate and one with both spatially lagged crime and explanatory variables including welfare rate, population moved, and alcohol outlet density.

Chapter 6

The Influence of Land Use and Social Disorganization on Health: Insight from Geographic Analysis of Expressive Crimes

6.1 Introduction

Crime is recognized as an issue not only relevant to law enforcement and criminologists, but also one that is important to the public health field and public health professionals (Winett, 1998; Perdue et al., 2003; Kawachi, et al., 1999). The interwoven factors driving small-area expressive crime and community health (Sparks, 2011) has prompted the notion that the priorities of the public health perspective –notably community health over law enforcement and complex systems of causality over a simplistic intent and behavior rationale – can contribute to understanding, reducing, and preventing violent crime (McDonald, 2000). Indeed, because high crime detracts from quality of life, a comprehensively healthy community is one that is not only absent of disease, but one that is also absent of crime and fear of crime (Wilcox et al., 2003; Kawachi et al., 1999).

Expressive crimes, or crimes that involve aggression and violence and are not directed towards the acquisition of anything tangible, are the source of both direct and indirect negative community health outcomes (Hayward, 2007; Burek, 2006; Cohn and Rotton, 2003). Directly, victims of violent crimes incur increased physical injuries, disability, and medical costs, have a higher than normal risk of psychological trauma and emotional distress, and reduced quality of life (Lorenc et al., 2012; Robinson and Keithley, 2000; Miller et al., 1993; Winett, 1998). Indirectly related to crime, areas with high violent crime rates and fear of crime have poorer self-reported health, increased all-cause mortality, and a higher rate of low birth weight children, among other deleterious outcomes (Lorenc et al., 2012; Chandola, 2001). So, expressive crimes do not reflect only on the criminogenic characteristics of a community but to some degree can also be considered a "social mirror", or a small-area outcome indicative general community health and well-being (Kawachi et al., 1999, p. 719; Robinson and Keithley, 2000).

Interestingly, the ecological determinants of crime and community health are very closely related, if not the same (Sparks, 2011). One theory that contributes to understanding both small-area health and crime is the social disorganization theory, which was originally developed in the context of juvenile delinquency but has been applied in the health context (Sampson, 2003). Broadly, the social disorganization theory hypothesizes that community-scale social disorganization impedes the realization of common values and the maintenance of effective social control, limiting community capacity to control group-level dynamics and creating neighborhood social conditions that do not inhibit the occurrence of negative social outcomes (Sampson and Groves, 1989). For a more detailed review of social disorganization, refer to Section 2.1.

This chapter, investigating the relationship between expressive crime rates and non-residential land use and social disorganization, is motivated by two research shortcomings. First, although past literature provides general support for social disorganization in the context of expressive crimes, specific land uses and features of the built environment, which contribute to processes related to social disorganization such as quality of life and social interactions (Diez Roux, 2001; Roncek, 1981; McCord et al., 2007; Cohen et al., 2008) are rarely included in analysis (Stucky and Ottensman, 2009). Since research investigating the relationship between land uses and expressive crimes is underdeveloped (Section 2.1.1), it is possible that dimensions of the built environment interact with social disorganization and contribute to neighborhood conditions conducive to high expressive crime rates. Second, when more detailed built environment variables are included in analysis, non-residential land uses in particular, studies generally use perceived rather than official crime rate (e.g. Wilcox et al., 2004; Wilcox et al., 2003; McCord et al., 2007; Sampson and Raudenbush, 2004). This chapter seeks to complement these studies by analysing official crime incident rate.

The goal of this chapter is to investigate the relationship between land use and social disorganization and five expressive crimes in Toronto, Ontario at the census tract scale using officially-recorded criminal incident data. We hypothesize that in addition to traditional measures of social disorganization, concentrations of non-residential land uses will be related to high levels of expressive crimes. We posit that the presence of non-residential land uses, for instance industrial and commercial lands, will attract large numbers of non-residents, increasing anonymity among residents and non-residents and impeding the establishment and realization of common values and norms, thereby contributing to census tract social disorganization.

First, we will discuss the utility of employing the social disorganization theory in the public health context. Next, the regression modeling approach used in this chapter will be detailed. Results will highlight the findings of spatial regression models and we will discuss the results focusing on how built environment variables may influence expressive crime rates from a social disorganization perspective. Finally, the practical implications of these findings as they can be applied in law enforcement planning, public health, and land use planning fields are discussed.

6.2 Social disorganization as a lens for public health research

While social disorganization theory was originally developed to explain geographic differences in crime, it can also contribute to understanding small-area or community health outcomes. In fact, Shaw and McKay (1942) hypothesized that small-area structural factors influence neighborhood social conditions including both crime and health. Specifically, they hypothesized that neighborhoods with high levels of economic deprivation, ethnic heterogeneity, and population turnover, were home to more young offenders as well as elevated rates of deleterious health outcomes including infant mortality, low birth weight, and tuberculosis (Sampson, 2003).

Further research has supported the notion that social disorganization, or in some cases the variables operationalized to measure social disorganization, has a negative impact on small-area health. For example, studies have found that social disorganization is related to increased rates of tuberculosis, suicide, murder, and mental illness (Yen and Syme, 1999; Faris and Dunham, 1939), self-rated physical health (Browning and Cagney, 2002), stroke mortality (Neser et al., 1971), and poorer dietary habits (Lee and Cubbin, 2002). Further, social disorganization has been useful in explaining high levels of smoking, morbidity, and coronary risk factors at the community scale (Sampson, 2003).

As noted in Section 3.2, criminal offence data is analysed for this thesis which constrains the interpretation of results, particularly regarding the influence of crime on health. That is, because offence data measures the location of offence, the criminal victim may not live in the same census tract as where offence was located, so the negative health effects assumed to result from expressive crimes, often on the victim, may not be attributable to the offence census tract. Certainly, complementing offence data with victimization data (as used in Wilsem (2003) and Levitt (1999)) would provide a more intuitive interpretation of results and comprehensive analysis of the influence of non-residential land use and social disorganization on both crime and health. The presence of many expressive crimes, however, may still influence fear of crime and have simultaneous deleterious health effects and is worthy of further research.

Social disorganization was chosen as the lens for investigating expressive crimes from a public health perspective because of the concomitant influence of neighborhood structural factors on crime and health (Sparks, 2011). So, factors previously overlooked when studied from a public health perspective could be highlighted when analysing violent crimes from a criminological perspective, including the possible influence of land uses. Findings then, can be used to inform public health, law enforcement, and land use planning strategies to reduce expressive crime with simultaneously benefits to related public health problems.

6.3 Regression Modeling Approach

Testing the hypothesis that social disorganization and non-residential land use variables are associated with expressive crime rates in Toronto at the census tract scale, we first conducted ordinary least squares (OLS) linear regressions between expressive crime rates and each explanatory variable representing social disorganization (Section 3.3.1) and non-residential land use (Section 3.3.2.2). Recalling that expressive crime rates were calculated using residential population as the denominator, a sum of residential and working populations was also included in regression analyses as a proxy measurement for the total number of people travelling through the area in a given time period, or an indicator of relative anonymity among residents and non-residents.

Significant variables were identified from univariate OLS regressions and investigated for multicollinearity. When highly correlated explanatory variables ($r>0.5$) measured variables in the same social disorganization dimension (e.g. low family income and government transfer payment, $r=0.709$) the explanatory variable that exhibited inferior model fit as indicated by a larger residual sum of squares was removed from analysis and the better fitting explanatory variable (i.e. smaller residual sum of squares) was kept. In the presence of highly correlated explanatory variables measuring different dimensions (e.g. government transfer payment and immigration, $r=0.672$), both were kept for multivariate analysis. A bivariate correlation matrix can be found in Appendix A.

Significant explanatory variables from univariate regressions were included in multivariate OLS regression models, creating one multivariate regression model for each expressive crime type. Attention was paid to previously identified highly correlated explanatory variables that could influence regression results, notably variables that had coefficients switching from positive to negative or vice versa between univariate and multivariate regressions. If a change in coefficient sign was observed, the correlated variable with best univariate model fit (as indicated through univariate OLS regression residual sum of squares) was retained. Insignificant explanatory variables were removed from analysis until a final OLS multivariate regression model contained all significantly related explanatory variables.

We theorized that spatial error regressions were most suitable for modeling expressive crimes because expressive crimes are relatively infrequent compared to acquisitive crime types, so we did not expect adjacent expressive crime rates to influence each other. Additionally, violent crimes generally occur close to offenders residences (Morenoff et al., 2001), so the movement offenders to adjacent census tracts, resulting in clustering of offences modeled through spatial lag dependent, was unlikely. It was more likely, we felt, for an unspecified explanatory variable to be influencing expressive crime rates than adjacent crime rate or adjacent explanatory variables. Regardless, spatial error, spatial lag dependent, and spatial lag independent regression models were tested. A row-standardized first-order queen contiguity spatial weights matrix was used to model spatial structure and was created in OpenGeoDa v.1.01. All OLS and spatial regressions were completed in the statistical software R. Spatial regressions in R used the spdep package (Bivand, 2012).

6.4 Results

All five expressive crime rates exhibited positive global spatial autocorrelation measured through global Moran's I at the five percent significance level. Minor assault was the most spatially autocorrelated expressive crime (I=0.2594) followed by violent crime (I=0.2488), major assault (I=0.2404), uttering threats (I=0.2287), and sexual assault (I=0.1228).

Multivariate OLS regression residuals displayed significant spatial autocorrelation ($p<0.05$) as measured through Moran's I. Specifically, minor assault had the greatest Moran's I of regression residuals (I=0.128), followed by violent crime (I=0.127), uttering threats (I=0.098), major assault (I=0.095), and sexual assault (I=0.037).

The best fitting regression model for each expressive crime type was determined using largest log likelihood. Spatial error was the best fitting model for all five expressive crime types (Table 5.3.4.1).

Table 5.3.4.1. Log likelihood values for OLS and spatial regression models. All models contained the same explanatory variables.

	OLS Log Likelihood	Spatial Lag Dependent Log Likelihood	Spatial Error Log Likelihood
Major Assault	2534.37	2540.56	2541.58
Minor Assault	2078.24	2082.63	2092.41
Sexual Assault	3061.41	3069.97	3070.30
Uttering Threats	2501.25	2503.27	2504.93
Violent Crime	1637.201	1640.21	1651.88

Final multivariate spatial error model results containing all diagnostics including regression coefficients, standard error, Z-values, and p-values are shown in Table 5.3.4.2 to 5.3.4.6. A table featuring final spatial error regression results with only significant explanatory variables and coefficients can be seen in Table 5.3.4.7.

Table 5.3.4.2. Multivariate spatial error regression results for major assault.

	β	Std. error	Z-value	Pr.
Demography				
Working and residential population	4.28e-08	6.22e-09	6.87	6.23e-12
Economic deprivation				
Unemployment	8.39e-05	3.84e-05	2.19	0.029
Ethnic heterogeneity				
Aboriginal residents	3.40e-02	1.54e-02	2.21	0.028
Immigrant residents	-3.82e-03	8.19e-04	-4.67	3.06e-06
Index of ethnic heterogeneity	2.59e-03	8.44e-04	3.07	0.0022
Non-residential land use				
Commercial	2.41e-03	1.23e-03	1.96	0.049
Government institutional	3.30e-03	1.03e-03	3.19	0.0014
Resource industrial	2.79e-03	5.07e-04	5.50	3.79e-08
Spatial error	0.28			0.0001

Table 5.3.4.3. Multivariate spatial error regression results for minor assault.

	B	Std. error	Z-value	Pr.
Demography				
Working and residential population	2.23e-07	1.51e-08	14.76	2.20e-16
Ethnic heterogeneity				
Aboriginal	9.69e-02	3.61e-02	2.68	0.0073
Immigration	-1.04e-02	1.87e-03	-5.56	2.68e-08
Index of ethnic heterogeneity	6.11e-03	2.04e-03	2.99	0.0028
Non-residential land use				
Government institutional	1.02e-02	2.42e-03	4.21	2.54e-05
Resource industrial	5.88e-03	1.21e-03	4.86	1.18e-06
Open area	1.30e-02	3.13e-03	4.15	3.34e-05
Spatial error	0.41			1.01e-07

Table 5.3.4.4. Multivariate spatial error regression results for sexual assault.

	B	Std. error	Z-value	Pr.
Demography				
Working and residential population	2.05e-08	2.09e-09	9.81	2.00e-16
Ethnic heterogeneity				
Index of ethnic heterogeneity	5.92e-04	2.44e-04	2.42	0.016
Non-residential land use				
Resource industrial	3.94e-04	1.75e-04	2.24	0.025
Spatial error	0.12			0.04

Table 5.3.4.5. Multivariate spatial error regression results for uttering threats.

	B	Std. error	Z-value	Pr.
Demography				
Working and residential population	1.08e-07	6.82e-09	15.87	2.20e-16
Ethnic heterogeneity				

Aboriginal	5.30e-02	1.61e-02	3.28	0.0010
Index of ethnic heterogeneity	2.10e-03	8.20e-04	2.56	0.010
Non-residential land use				
Hotel	6.77e-04	2.91e-04	2.33	0.021
Government institutional	3.15e-03	1.10e-03	2.85	0.0043
Open area	4.16e-03	1.43e-03	2.91	0.0036
Resource industrial	2.19e-03	5.56e-04	3.94	8.17e-05
Spatial error	0.36			7.26e-07

Table 5.3.4.6. Multivariate spatial error regression results for violent crime.

	B	**Std. error**	**Z-value**	**Pr.**
Demography				
Working and residential population	5.49e-07	3.56e-08	15.42	2.20e-16
Ethnic heterogeneity				
Aboriginal	2.40e-01	8.38e-02	2.86	0.0042
Immigration	-2.51e-02	4.40e-03	-5.69	1.25e-08
Index of ethnic heterogeneity	1.08e-02	4.78e-03	2.26	0.024
Non-residential land use				
Commercial	1.44e-02	6.61e-03	2.18	0.029
Government institutional	2.34e-02	5.62e-03	4.16	3.22e-05
Open area	3.39e-02	7.25e-03	4.68	2.90e-06
Resource-industrial	1.29e-02	2.83e-03	4.56	5.13e-06
Spatial error	0.43			6.05e-08

Table 5.3.4.7. Multivariate spatial error regression results for all expressive crime types.

	Major Assault	**Minor Assault**	**Sexual Assault**	**Uttering Threats**	**Violent Crime**
Demography					
Working and	4.28e-08***	2.23e-07 ***	2.05e-08 ***	1.08e-07***	5.49e-07***

residential population					
Social disorganization					
Economic deprivation					
Unemployment	8.39e-05*				
Ethnic heterogeneity					
Index of ethnic heterogeneity	3.40e-03**	6.11e-03**	5.92e-04*	2.10e-03*	1.08e-02*
Immigrant residents	-3.82e-03 ***	-1.04e-02***			-2.51e-02***
Aboriginal residents	3.40e-02*	9.69e-02**		5.30e-02**	2.40e-01**
Non-residential land use					
Hotel				2.91e-04*	
Resource industrial	2.79e-03***	5.88e-03***	3.94e-04*	5.56e-04***	1.29e-02***
Government institutional	3.30e-03**	1.02e-02***		3.15e-03**	2.34e-02***
Commercial land use	2.41e-03*				1.44e-02*
Open area		1.30e-02***		4.116e-03**	3.39e-02***
Spatial error	0.28***	0.41***	0.12*	0.36***	0.43***

***p<0.001

** p<0.01

*p<0.05

6.5 Discussion

Results indicate that both social disorganization and non-residential land uses are associated with census tract expressive crime rates in Toronto, Ontario. Of the four dimensions of social disorganization, measures of ethnic heterogeneity were most prominently represented in regression results with index of ethnic heterogeneity and the proportion of aboriginal residents being positively related to five and four expressive crime types, respectively. Proportion of immigrant residents was negatively associated with three expressive crime types. The only other social disorganization variable significantly related to expressive crimes was unemployment rate, which was positively associated with major assault rates.

Significant non-residential land use variables positively related to expressive crimes included densities of resource-industrial land uses (5 crime types), government-institutional land use (4), and open area land use (3). Commercial land use density and the presence of a hotel were positively associated with two and one expressive crime type, respectively. The sum of working and residential populations, a proxy measurement for the total number of people occupying a census tract and providing insight into relative census tract anonymity, exhibited a positive relationship with all five expressive crime types.

6.5.1 Influence of social disorganization

Overwhelmingly, the ethnic heterogeneity dimension of social disorganization was found to play an important role in the location of high expressive crime census tracts. Specifically, the index of ethnic heterogeneity, measuring the ethnic mix of a census tract, exhibited a positive relationship with expressive crime rates while proportion of immigrant residents exhibited a negative relationship. Both of these findings have support in the literature, as high ethnic heterogeneity is thought to fragment communities along ethnic lines and limit the ability of residents to achieve consensus through impeding communication and interaction (Veysey and Messner, 1999; Sampson and Groves, 1989). The negative association of immigrant residents, on the other hand, may be a recent phenomenon not reflected in past interpretations of social disorganization (Kubrin, 2009; Browning et al., 2010). Rather than compromising community social control as ethnic heterogeneity is generally suspected to, immigration could strengthen control "due to strong familial and neighborhood institutions and enhanced job opportunities associated with enclave economies – the result being less crime (Kubrin, 2009, p.234)." Past research finding negative or no relationship between immigration and expressive crimes include studies focused on homicide in Miami, El Paso, and San Diego in the United States (Lee et al., 2001; Lee and Martinez, 2006).

With the exception of major assault, where unemployment rate was positively related to crime rate, variables representing the economic deprivation of social disorganization were insignificant in multivariate regressions. Interestingly, these variables were positively related in univariate regression models but were insignificant when included in multivariate models with other measures of social disorganization and non-residential land use. This has some support in past research, for example Kawachi et al. (1999), who found that poverty and unemployment were weakly or inconsistently related to violent crimes when accounting for other measures of social disorganization.

6.5.2 Influence of non-residential land use

Results indicate that non-residential land use variables, even after accounting for dimensions of social disorganization, are associated with expressive crime rates. Unlike the routine activity framework, which would interpret non-residential land uses as locations that bring together offenders, targets, and limited guardianship, understanding the role of non-residential land uses from a social disorganization perspective considers how these land uses influence small-area social dynamics. In particular, we posit that the effects of non-residential land uses can be explained by two hypotheses. First, non-residential land uses bring together many residents and non-residents, increasing anonymity and contributing to an inability for residents and non-residents common values and norms and leading to social disorganization. Second, non-residential land uses are specific locations in the urban fabric where little resident-based informal control is exerted, reducing small-area social control and increasing census tract social disorganization.

Census tracts with high densities of resource-industrial, government-institutional, and commercial land uses attract many non-residents to work, visit, and shop, among other activities. This mixing of large numbers of non-residents with residents limits the familiarity of faces and increases anonymity (Wilcox et al., 2004; Kurtz et al., 1998), reducing social control (Osgood and Chambers, 2000). In addition, the significant positive association between expressive crime rates and sum of working and residential population, a proxy measurement for census tract anonymity, suggests that anonymity could be playing a role in criminogenic creating neighborhood conditions. So, the mixing of large numbers of non-residents and residents, likely through non-residential land uses attracting non-residents, contributes to census tract social disorganization and influences expressive crime rates.

Further, when large number of residents and non-residents mix, common values are difficult to realize because residents and non-residents have contrasting notions of the local environment. For example, residents of a census tract may prioritize safety in the local environment and hold this as a common value, and is expected among residents. In contrast, non-residents may not value safety, as they do not live in the census tract in which they work. Implicit differences in expectations between residents and non-residents such as this could result in value and norm conflicts contributing to social disorganization.

It is important to note that the hypothesis that value conflicts arise out of resident – non-resident mixing contributes to the processes driving expressive crimes is only intended to apply to non-residential land uses that regularly attract large numbers of non-residents. For instance, these include resource-industrial, government-institutional, and commercial land uses. All three of these land uses attract many non-residents who work, visit, or fulfill daily activities at these land uses relative to census tracts with predominantly residential land uses, will not attract large numbers of non-residents. Likewise, land uses that will infrequently attract smaller numbers of non-residents such as police stations, places of worship, or parks are not considered in this reasoning.

In addition to anonymity and value conflicts between residents and non-residents, the presence of non-residential land uses have been shown to alter residential dynamics and discourage the use and management of public space by residents (McCord et al., 2007). That is, non-residential land uses act as holes in the resident-based urban fabric, where residents exhibit little informal social control (Taylor et al., 1995). Non-residential land uses in particular are parcels of land within neighborhoods where residents exhibit a reduced sense of ownership and are unlikely to exert the same amount of social control that they would in a census tracts comprised entirely of residential land uses (Kurtz, 1998).

Specifically, we posit that hotels and open area land uses are non-residential land uses that act as holes in the urban fabric and decrease informal social control. That is, hotels and open areas are land uses which are generally not part of the daily routine of residents or non-residents, and are not meaningful parts of the urban fabric, so both residents and non-residents exhibit reduced ownership when in the presence of these land uses. In contrast, non-residential land uses such as subway stations may frequently bring together large numbers of residents and non-residents, but are parts of the urban fabric that residents interact with and exert ownership. It is reasoned, then, that hotels and open areas are land uses where informal social control is not exerted to the same extent as other residential and non-residential land uses, contributing to a reduction in census tract-scale social control and increased social disorganization.

In addition to significantly related explanatory variables, insight can be gained from the use of the spatial error regression model. Rather than assuming that expressive crimes are influenced by adjacent crime rates or adjacent explanatory variables, which has been found in past research (Rosenfeld et al., 1999), the spatial error model suggests that expressive crime rates at the census tract scale in Toronto are influenced by unmeasured explanatory variables. These could include social cohesion or, since these are official crime rates, the prevalence of police patrols or locations of targeted police operations (e.g. Rosenfeld et al., 2007), and should be examined in future research.

6.5.3 Practical applications

From a practical perspective, these results have relevance to police, land use planners, and public health professionals.

6.5.3.1 Law enforcement planning

Police should be aware of the relationships between non-residential land uses and expressive crimes and take this into account when developing law enforcement planning strategies and crime prevention initiatives. For example, in areas where there are high densities of resource-industrial land uses, it may be useful to initiate campaigns that target value and norm conflicts between residents and non-residents. Additionally, law enforcement agencies should look to partner with non-residential businesses or institutions and inform them of how social dynamics may be contributing to expressive crimes and provide methods of overcoming the negative effects of resident – non-resident mixing.

Additionally, the importance of ethnic heterogeneity on expressive crimes should not be overlooked when allocating police resources, targeting areas where there is high ethnic heterogeneity. Practically, law enforcement planning should design crime prevention initiatives for many ethnicities, for example translating posters and brochures into many languages and ensuring that presentations are appropriately translated. Further, outreach should consider a variety of cultural values of violence and social control when constructing crime prevention initiatives.

6.5.3.2 Land use planning

Land use planners should consider the relationships uncovered in this research and attempt to incorporate crime preventative design at the building scale in high crime areas. For example, planners should look to building scale defensible space (Newman, 1972), where features of individual buildings are adapted to facilitate increased surveillance, ownership or territoriality, and ultimately increase crime deterrence (Lorenc et al., 2012). Practically this could take the form of crime prevention through environmental design features such as improved lighting, increased visibility, and a reduction in the number spaces where people loiter (CMHC, 1998).

Also, land use planners can look to address a lack of resident control through advocating a sense of ownership and belonging to neighborhoods. This could take the form of installing public recreational or leisure spaces such as parks, which have been shown to have a positive effect on neighborhood social cohesion and increase sense of ownership among residents (Cohen et al., 2008; Peterson et al., 2000). Additionally, residents and non-residents should be considered in the public engagement process to incorporate the values and norms of both groups, perhaps overcoming the limited ownership felt by non-residents.

6.5.3.3 Public health professionals

Recalling that expressive crimes have both direct (e.g. increased injuries and health costs) and indirect community health impacts (e.g. increased neighborhood mental disorder and prevalence of low birth weight children), the findings in this research are relevant to public health professionals. In an effort to address expressive crimes, public health professionals should identify high risk populations and neighborhoods through targeting areas where there is a mix of ethnicities and concentrations of non-residential land uses. Similar to crime prevention initiatives through law enforcement planning, public health agencies could outreach efforts on areas where large numbers of residents and non-residents frequently mix.

Importantly, addressing expressive crimes could have public health benefits including the reduction of deleterious small-area health outcomes. Indeed, since small-area health and crime are influenced by similar processes of social disorganization, concentrating on the reduction of expressive crimes through public health initiatives could result in, for instance, decreased mental illness and fewer low birth weight children.

6.5.4 Research limitations

Limitations of this research include the possibility that the presence of non-residential land uses influences crime reporting rates, differing years of data availability, and the lack of a direct measurement of social disorganization. First, past research has suggested that residents in areas with non-residential land uses have higher than average crime reporting rates (McCord et al., 2007; Kurtz et al., 1998). This could be playing a role in the spatial distribution of official crime data, whereby neighborhoods with many non-residential land uses have elevated officially reported crime rates compared to areas with mostly residential land uses. Second, crime and socio-economic data was extracted from the 2006 Uniform Crime Reporting Survey and Canadian Census, respectively, while non-residential land use variables were only available for 2010. While it is unlikely that land use had substantial change over four years, this should be acknowledged and addressed in future research. Third, there is no direct measure of social disorganization. The small-area structural factors used to measure social disorganization in this research are generally agreed upon in the literature, however it is possible that other variables influence census tract social disorganization in Toronto.

6.6 Conclusion

Exploring small-area health through analysing expressive crimes is beneficial because expressive crime rates are directly and indirectly related to negative small-area health outcomes. Interestingly, the small-area determinants of expressive crime and negative health are similar and have both been explained using the social disorganization theory. So, the potential reduction of expressive crimes through addressing significantly associated social disorganization and land use determinants may also reduce deleterious small-area community health outcomes such as the prevalence of mental illness and children born with low birth weight.

Census tract scale social disorganization variables found to be related to expressive crimes are mainly represented by the ethnic heterogeneity dimension, with index of ethnic heterogeneity and proportion of aboriginal residents being positively related to five and four expressive crimes respectively, and proportion of immigrant residents negatively related to three expressive crimes. Areas with high ethnic heterogeneity are thought to fragment along ethnic lines contributing to social disorganization, and communities with high immigrant concentrations are posited to possess strong familial bonds and community institutions, resulting in reduced social disorganization and fewer expressive crimes.

Non-residential land uses found to be positively related to expressive crimes at the census tract scale include resource-industrial, government-institutional, and commercial land uses. Concurrently with large population at risks, it is hypothesized that these land uses regularly attract many non-residents to census tracts, which increases anonymity among residents and non-residents and impedes the formation of common values and norms. Additionally, open area land uses and hotels were positively associated to expressive crime types. These areas are hypothesized to act as holes in the residential fabric where residents exhibit limited social control, contributing to an overall reduction in informal social control and an increase in small-area social disorganization. These results have numerous practical application to police, land use planners, and public health professionals, with the intent to address the influence of social disorganization and non-residential land uses on expressive crimes. Further benefits, specifically the reduction of negative community health outcomes, are also possible.

Future research should focus on investigating the relationship between expressive crimes and land use at a finer areal scale (e.g. census dissemination area), employ statistical methods that overcome limitations of frequentist spatial linear regressions when data is scarce in small areas, for example Bayesian spatial methods, and approach this research from a qualitative perspective looking to incorporate neighborhood perceptions of non-residential land uses to inform the potential processes by which land use and social disorganization are related. Additionally, analysing victimization data rather than offence data may provide a unique perspective on the small-area risk factors contributing to expressive and crimes.

Chapter 7

Investigating acquisitive crime types in Toronto, Ontario: Integrating social disorganization and routine activity theories

This chapter reviews ten crime types in Toronto. Eight are categorized as acquisitive crimes, or those driven by the intent to obtain a tangible good, and are detailed in Section 7.2. Two crime types, criminal harassment and drug offences, are not considered to be expressive or acquisitive, and are explored separately in Section 7.3.

In contrast to Chapter 6, which investigated the role of social disorganization and non-residential land use in the context of expressive crimes, this chapter approaches the study of acquisitive crimes through a theoretical lens that integrates social disorganization and routine activity theories. The integrative approach, as detailed in Section 2.3, has been employed in past research on acquisitive crimes such as robbery (Smith et al., 2000), break and enter, and automotive theft (Andresen, 2006).

Briefly, integrating social disorganization and routine activity theories attempts to understand acquisitive crimes as they are influenced by characteristics of both social and physical environments (Rountree et al., 1994; Smith et al., 2000). One way to consider this integration is for social disorganization variables to measure baseline crime risk, with routine activity variables measuring characteristics of the physical environment, in this case operationalized through land uses, that alter the opportunity structure of criminal events. Land uses, then, are considered to how they increase the likelihood that offender and target interact or increase or decrease guardianship (Sampson and Wooldredge, 1987; Smith et al., 2000).

7.1 Regression modeling approach for acquisitive crimes

First, univariate OLS regressions were run between each explanatory variable, including social disorganization, residential, non-residential, and guardianship land use categories, and crime rates. Significant explanatory variables were identified ($p<0.05$) and included in multivariate OLS regressions.

Addressing potential multicollinearity among explanatory variables, highly correlated variables ($r>0.5$) were identified. When highly correlated variables measured the same dimension of social disorganization (e.g. low family income and government transfer payment, $r=0.71$) or closely related land use measures (dwelling density and density of apartments in buildings with five or more stories, $r=0.90$), the explanatory variable with inferior univariate model fit as determined through larger residual sum of squares was removed from analysis. Occasionally there were highly correlated variables that did not measure similar dimensions (e.g. road density and apartments with five or fewer stories, $r=0.57$), and in these instances, both were retained for OLS multivariate regressions. If a change in coefficient sign was observed when both of these correlated variables were included in multivariate regressions, univariate model fit between both variables was considered and the variable with inferior model fit, was removed.

From OLS regression models containing significant explanatory terms, spatial error, spatial lag dependent, and spatial lag independent regression models were tested. We hypothesized that the spatial lag dependent regression model would best model acquisitive crimes because risk factors, specifically land uses, could span a number of census tracts, increasing the likelihood that proximal crime rates are similar.

Multivariate spatial regression model fit was evaluated based on log likelihood, with higher log likelihood indicating superior fit. Generally, spatial lag independent regression models demonstrated high multicollinearity among explanatory and lagged explanatory variables (e.g. government transfer payment and lagged government transfer payment, $r=0.78$; density of single detached dwellings and lagged density of single detached dwellings, $r=0.66$) and unpredictable significance, which made results difficult to interpret. Spatial regression modeling for acquisitive crimes was conducted in R using the spdep package (Bivand, 2012). A first-order queen-contiguity row-standardized spatial weight matrix created in Open GeoDa v.1.0.1 was used to incorporate spatial effects for spatial regression models.

7.2 Acquisitive Crime Results

In the following eight sections, results of exploratory and confirmatory spatial analyses are presented for acquisitive crime types. Discussion of each crime type begins with a brief explanation of the crime for context, followed by exploratory local cluster detection using the flexibly shaped scan statistic with a maximum cluster size of twenty census tracts. Confirmatory spatial regression results follow and each crime type concludes with a discussion of the findings with reference to both social disorganization and routine activity theories.

7.2.1 Property Crime

Property crime represents a number of crimes against property, where outcome of criminal offences are property-based. Property crimes include the acquisitive crimes detailed in Section 7.2.2 to 7.2.6 (break and enter, mischief, shoplifting, theft of a motor vehicle, and theft from a motor vehicle) as well as arson, fraud, and identity theft (Charron, 2009).

To be clear, while property crimes are acquisitive crimes, there is distinction between the two categorizations. Property crimes concern the outcome of the crime, where the result is property-based such as theft or vandalism, while acquisitive crimes concern criminal motivation directed towards the acquisition of tangible goods including property (Cohn and Rotton, 2003).

7.2.1.1 Exploratory spatial data analysis – Property Crime

Property crime rates exhibited significant positive global spatial autocorrelation ($I=0.38$, $p<0.05$). Local clusters were detected predominantly in the downtown and southwest of Toronto. Smaller, more isolated clusters were found in the east in Scarborough, in the west in Etobicoke, and in northwest areas close to Rexdale. In total, the flexibly shaped scan statistic detected twenty-five clusters ($p<0.05$) ranging in size from one to fifteen census tracts (Figure 7.2.1.1). The most likely property crime cluster was located west of downtown.

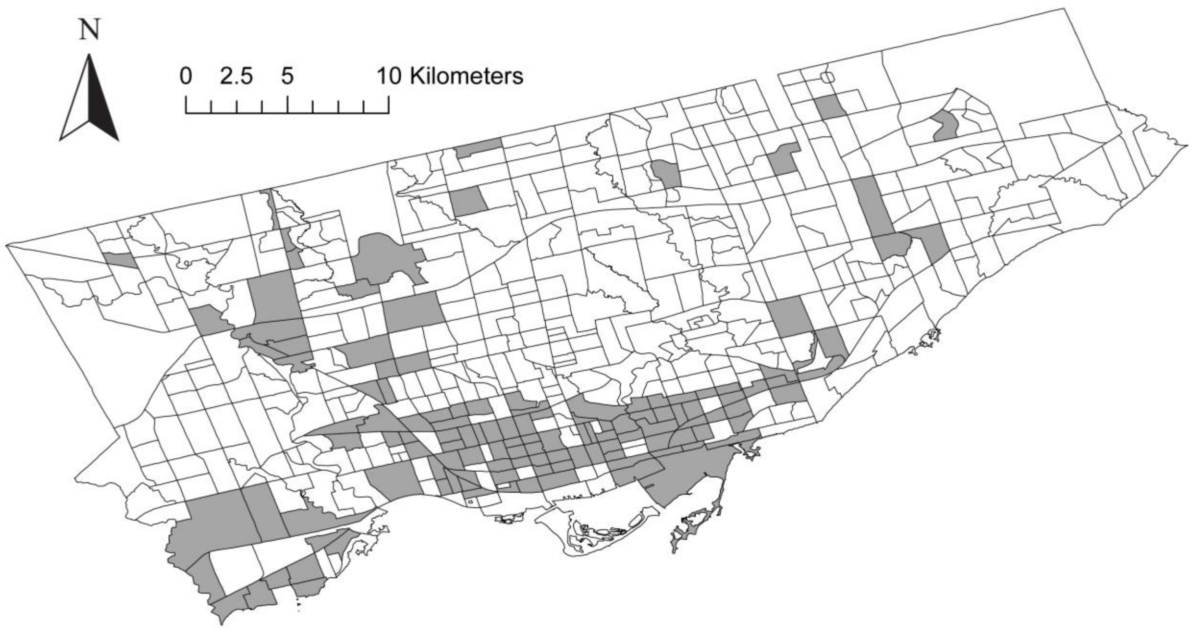

Figure 7.2.1.1. High property crime rate clusters (p<0.05). Property crime clusters were generally located in the downtown and west of Toronto with smaller clusters in the north and east areas.

7.2.1.2 Confirmatory spatial data analysis – Property Crime

OLS regression residuals demonstrated significant positive spatial autocorrelation ($I=0.12$, $p<0.05$). The spatial lag dependent regression model had the highest log likelihood of the regression models tested and results can be seen in Table 7.2.1.1.

Table 7.2.1.1. Property crime multivariate spatial lag dependent regression results.

	β	Std. Error	Z-value	Pr.
Social Disorganization				
Aboriginal residents	2.20e-01	5.39e-02	4.08	4.60e-05
Immigrant residents	-6.67e-03	2.51e-03	-2.65	0.0079
Routine Activity				
Dwellings in need of major repair	3.10e-02	8.97e-03	3.45	0.00056
Commercial land use	2.23e-02	4.55e-03	4.89	1.00e-06
Community shopping centre	1.56e-02	1.78e-03	8.73	2.2e-16

Regional shopping centre	1.49e-02	3.03e-03	4.91	9.16e-07
Dwelling built before 1946	5.56e-03	1.91e-03	2.91	0.0036
Place of worship	2.17e-03	7.58e-04	2.86	0.0043
Road density	1.89e-04	7.28e-05	2.59	0.0096
Single detached dwellings	-3.60e-06	8.97e-07	-4.02	5.94e-05
Spatially lagged crime rate	0.37			4.17e-12

Eleven explanatory variables were found to be associated with property crime rate representing both social disorganization and routine activity theories as well as spatially lagged property crime rate. Social disorganization was shown through measures of ethnic heterogeneity, with proportion of aboriginal residents being positively related and proportion of immigrant residents being negatively related to property crime. Significantly associated routine activity theory variables included one negatively associated residential land use variable, single detached dwellings, as well as five positively related non-residential land use variables: road density, concentration of commercial land, and the presence of community and regional shopping centres, and places of worship. The guardianship dimension of routine activity theory was represented by two positively associated variables, concentration of dwellings in need of major repair and concentration of dwellings built before 1946.

From a social disorganization perspective, the negative association between proportion of immigrant residents and property crime rates is contradictory to traditional understandings of social disorganization but has found support in recent interpretations. Generally, large groups of immigrants is thought to result in higher crime rates because immigration increases residential instability and ethnic heterogeneity, both contributing to the processes driving social disorganization (Kubrin, 2009). More recently, however, empirical evidence has supported immigration as being negatively related to crime, perhaps because immigrant communities contribute to social organization and mediate the effects of other dimensions of social disorganization (Lee and Martinez, 2006). Specifically, Kubrin (2009) posits that the strong familial bonds and neighborhood institutions formed by newly arrived immigrants, often located in ethnic enclaves, are social and physical manifestations of a socially organized, rather than socially disorganized, immigrant community.

Focusing on variables representing routine activities, density of single detached dwellings was found to be negatively associated with property crime rates. Intuitively, census tracts with many single detached dwellings have fewer suitable targets for property crimes compared to areas with large concentrations of commercial land use, which was found to be positively related to property crime rates. These areas could include land uses such as shopping centres, which have a variety of potential targets and target sites for acquisitive crimes such as thefts and mischief. Additionally, census tracts with large concentrations of single detached dwellings likely have smaller working and transient populations compared to census tracts with many different land uses. In this sense, it is possible that there are fewer total offenders in areas comprised of single detached dwellings, which would be related to fewer property crimes.

Census tracts with high densities of commercial land and the presence of a community and/or regional shopping centre were shown to be positively associated with property crime rates. Commercial areas in general, and shopping malls in particular, contain a large number and diverse range of suitable targets for offenders, for example stores and vehicles for thefts and vandalism, as well as large populations, which increases the number of potential offenders. Large populations are also thought to decrease guardianship by increasing perceived anonymity among census tract occupants (LaGrange, 1999). It is likely then, that commercial lands and shopping centres are land uses where the three criminal elements of the routine activity theory frequently converge.

The positive relationship between dwellings in need of major repair and dwellings built before 1946 with property crime rate suggests that physical deterioration of the built environment influences property crime rates. This follows in line with the broken windows theory, where deterioration of the physical environment is interpreted by offenders as a signal that no one cares, so further damage to the physical environment is considered more acceptable than in an area with little deterioration (Wilson and Kelling, 1982). In the context of this research, we posit that deterioration of the physical environment through the presence of many old dwellings and dwellings in need of repair is perceived by offenders as an area where crimes are less likely to be reported by attentive citizens, decreasing guardianship and contributing to an increase in property crimes.

Interestingly, the presence of a place of worship is also positively related to property crime rates. From a routine activity perspective, it is difficult to interpret places of worship as locations where motivated offenders and targets converge with limited guardianship, however it is possible that census tracts containing places of worship have higher crime reporting rates for property crimes. Perhaps communities with places of worship such as churches and related community or church groups, are more active in reporting crime, leading to a positive relationships between the presence of a place of worship and official incident-based crime rates. In this sense, it is possible that the presence of a place of worship contributes to increased guardianship, contrasting the influence of physical deterioration.

7.2.2 Break and Enter

Break and enter is one of the most common and serious property offences and is defined as the breaking and entering of residences, commercial institutions, and other buildings such as detached garages and tool-sheds (Fedorowycz, 2004; Kowalski, 2000). Property is frequently stolen during a break and enter, most commonly audio/video equipment in residences and money and office equipment in commercial buildings (Fedorowycz, 2004). While violence does occur in approximately one percent of break and enters, it is considered an acquisitive crime because we assume the intent of this crime is to obtain goods rather than exert violence (Kowalski, 2000).

7.2.2.1 Exploratory spatial data analysis – Break and Enter

Break and enter rate in Toronto exhibited significant positive global spatial autocorrelation ($I=0.29$, $p<0.05$). In total, sixteen significant break and enter clusters were detected ($p<0.05$) and are shown in Fig. 7.2.2.1. Cluster size ranged from three to seventeen census tracts, with the largest and most likely cluster (as determined by highest log likelihood ratio) located in the east of downtown near the Regent Park neighbourhood. Secondary high break and enter rate clusters were located in the downtown, west in Etobicoke, north-west near York University and southeast areas of Toronto near Scarborough. Unlike other crime types, substantial break and enter clustering was detected in areas north of downtown Toronto in neighbourhoods such as North York and Lawrence Heights.

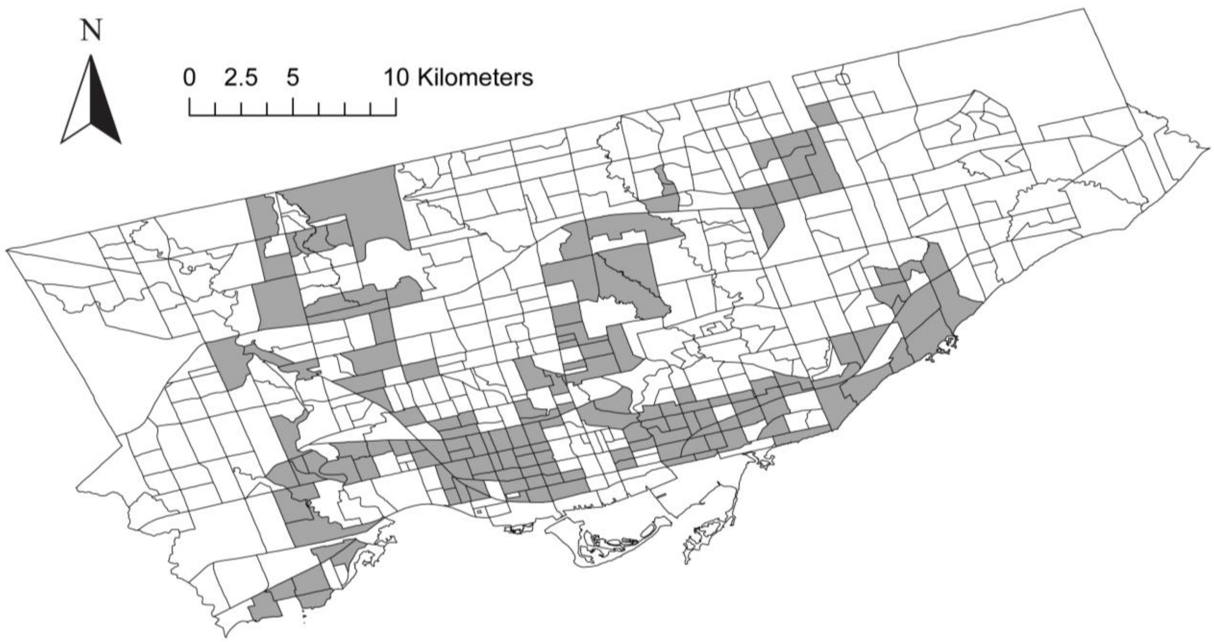

Figure 7.2.2.1. High break and enter rate clusters (p<0.05). High break and enter clusters were located in the downtown, west, east, and northwest areas of Toronto.

7.2.2.2 Confirmatory spatial data analysis – Break and Enter

OLS regression residuals exhibited significant positive global spatial autocorrelation (I=0.09, p<0.05). Spatial lag dependent regression was found to have best model fit and results can be seen in Table 7.2.2.1.

Table 7.2.2.1. Break and enter multivariate spatial lag dependent regression results.

	β	**Std. Error**	**Z-value**	**Pr.**
Social Disorganization				
Aboriginal residents	3.67e-02	1.12e-02	3.26	0.0011
Routine Activity				
Dwelling built before 1946	1.88e-03	3.08e-04	6.11	9.54e-10
Park density	-1.24e-03	5.81e-04	-2.14	0.032
Place of worship	4.22e-04	1.65e-04	2.55	0.011
Row house	1.18e-06	2.97e-07	3.95	7.72e-05
Spatially lagged crime rate	0.28			6.25e-06

Six explanatory variables were found to be significantly related to break and enter rates in Toronto. Social disorganization was only represented through the ethnic heterogeneity dimension, as proportion of aboriginal residents exhibited a positive association with break and enter rate. From a routine activity perspective, positive relationships were found with the proportion of row houses and the presence of a place of worship, while park density was negatively associated with break and enter rate. The concentration of dwellings built before 1946, a measure of census tract guardianship, demonstrated a positive relationship with break and enter rate.

The proportion of aboriginal residents was positively associated with break and enter rates, suggesting that the ethnic heterogeneity dimension of social disorganization contributes to break and enter rate. This concurs with past interpretations of social disorganization theory, as it is believed that communities with diverse ethnicities living in close proximity will have few social interactions, undermining the establishment of common goals and social norms and contributing to an elevated baseline risk of crime compared to communities with fewer ethnicities (Kubrin, 2009).

Examining routine activity variables, the concentration of row houses and the presence of a place of worship were positively associated with break and enter rate while density of park land exhibited a negative relationship. Typically, row houses are very densely located, so from an offenders perspective, areas with high concentrations of row houses have many potential target residences for break and enters. In contrast to apartment buildings, which are also densely distributed, row houses often have street-facing entrances and fewer barriers to entry such as security guards (i.e. apartment building and apartment unit).

As with property crime rate, the presence of a place of worship is positively associated with break and enters, perhaps because of higher crime reporting rates as remarked earlier. It is also possible, however, that many churches and places of worship are located in older residential neighborhoods with many row houses and older dwellings. If this is the case, the association between places of worship and break and enter rate characterizes high risk environments for break and enters, but may not represent a determinant of break and enters.

The density of park land in a census tract was found to be negatively related to break and enter rate. So when a census tract has large amounts of park land, fewer break and enter crimes occur. This could be because there are fewer locations, such as residential dwellings and businesses, in census tracts that have high concentrations of park land. Compared to census tracts with many row houses, the census tract with more potential targets would generally be more attractive to potential break and enter offenders.

The density of dwellings built before 1946 was also positively related to break and enter rate. The possible implications of older dwellings from a guardianship perspective have been explored in Section 7.2.1 – that old dwellings exhibit physical deterioration and contribute to decreased perceived guardianship among offenders, increasing the likelihood of a criminal acting in these environments – however it is also possible that older dwellings have inferior building-level security measures compared to newer buildings, making them more suitable targets. Moreover, the positive relationship between older dwellings and break and enter rate, just like the positive association exhibited by places of worship, could possibly characterize older and dense residential urban neighborhoods where break and enter crimes are likely to occur, rather than provide insight into the factors driving break and enters.

7.2.3 Mischief

Mischief is the destruction or damaging of property, rendering the property useless, inoperative or ineffective (Department of Justice, 2012a). A charge of mischief is applied to specific offences such as vandalism and graffiti.

7.2.3.1 Exploratory spatial data analysis – Mischief

Globally, mischief rate exhibited significant positive spatial autocorrelation ($I=0.48$, $p<0.05$). Locally, the flexibly shaped scan statistic detected fourteen clusters ($p<0.05$), generally located in the downtown, in the southeast in Scarborough close to Lake Ontario, and along the Humber River in the west of the city (Figure 7.2.3.1). Cluster size ranged from three to sixteen census tracts with the most likely cluster located in the downtown. No high mischief rate clusters were found in midtown, north, or north-east areas of the city.

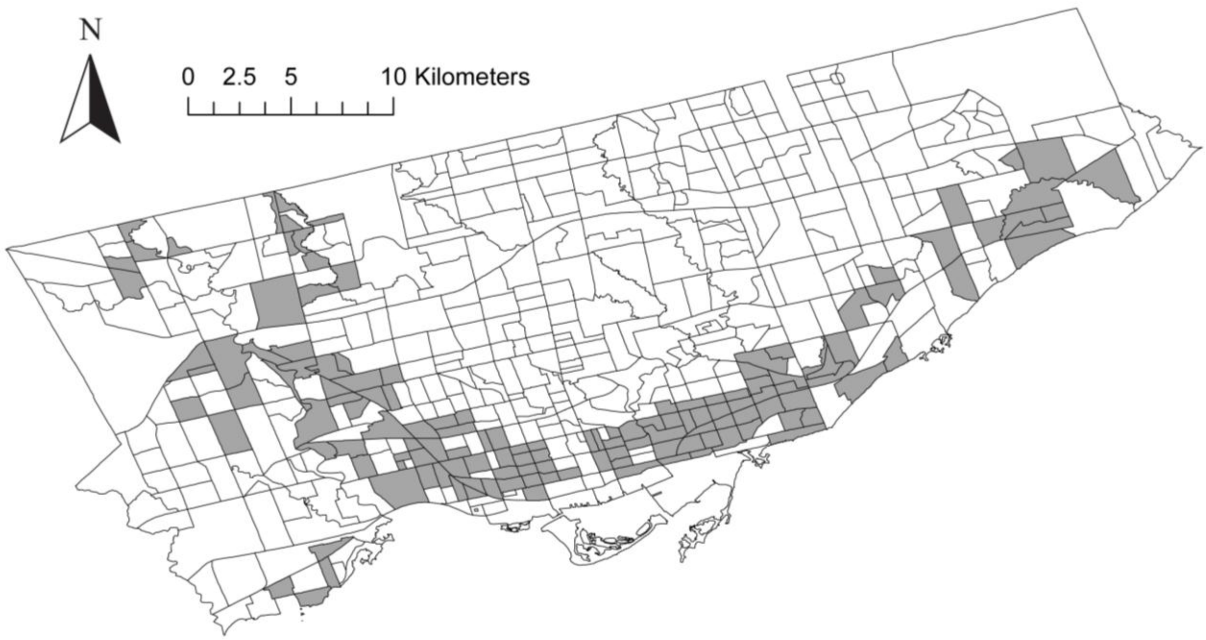

Figure 7.2.3.1. High mischief rate clusters (p<0.05). Mischief clusters were generally in the downtown, south, southwest of Toronto with no clusters in the north, northeast, and central areas.

7.2.3.2 Confirmatory spatial data analysis – Mischief

Testing multivariate OLS regression residuals for global spatial autocorrelation, it was observed that Moran's I was significantly different from zero ($I=0.18$, $p<0.05$). Spatial lag dependent was the best fitting regression model as it had the highest log likelihood of the models tested. Final multivariate spatial lag dependent regression results can be seen in Table 7.2.3.1.

Table 7.2.3.1. Mischief multivariate spatial lag dependent regression results.

	β	**Std. Error**	**Z-value**	**Pr.**
Social Disorganization				
Aboriginal residents	0.043	0.014	3.08	0.0021
Lone parent families	0.0051	0.0014	3.73	0.00019
Immigrant residents	-0.0051	0.00077	-6.63	3.27e-11
Routine Activity Theory				
Dwelling in need of major repair	0.0081	0.0023	3.48	0.00051

Spatially lagged crime rate	0.60			2.22e-16

Five explanatory variables were found to be associated with mischief. Three variables represented social disorganization, while only one variable, density of dwellings in need of major repair, is derived from the routine activity theory.

Proportion of aboriginal residents and proportion of immigrant residents, measuring the ethnic heterogeneity dimension of social disorganization, were found to be positively and negatively related to mischief rate, respectively. This concurs with many other crime types evaluated, including expressive crimes (Chapter 6), and property crimes (Section 7.2.1), and suggests that census tract ethnic heterogeneity is an important characteristic influencing mischief rates.

Also representing social disorganization, percentage of lone parent families was found to be positively associated with mischief rate. Family disruption, the dimension of social disorganization represented by lone parent families, could be influencing mischief rates because one-parent households do not provide the same level of informal social control as two-parent households. This social control has been posited to extend over the immediate household as well as over the entire neighborhood (Sampson and Groves, 1989). Considering that mischief offences such as vandalism are most frequently committed by male juveniles under eighteen years of age (Whittingham, 1981), it is possible that a high percentage of lone parent families in a census tract could result in decreased social control over youth in the neighborhood.

From a guardianship perspective, regression results indicate that areas with high concentrations of dwellings in need of major repair are positively related to mischief rates. Vandalism, one possible mischief offence, is explicitly mentioned in Wilson and Kelling's (1982) formative discussion on the broken windows theory, which hypothesizes that when there is physical deterioration of the built environment, as inferred in this research through dwellings in need of repair, vandals feel that no one cares and are more likely to act. We posit that the feeling of little caring from the community translates into reduced perceived guardianship and an increase in the possibility of offenders committing mischief offences.

Unlike many acquisitive crime types which are well represented by routine activity variables, mischief is only significantly related to one guardianship dimension. For the specific criminal offences charged as mischief, there is no shortage of possible crime locations (LaGrange, 1999), so it is not unreasonable for there to be no residential or non-residential land use routine activity variables related to mischief rate. In contrast to break and enter, for instance, whereby offenders commit crimes at desirable residential or commercial locations, mischief acts such as vandalism can be located in most urban locations, ranging from destruction of a bench in a park to graffiti of a transit vehicle or commercial building. The lack of significant relationships between land use variables and mischief rate suggests that it is primarily social disorganization that contributes to crime risk and land use dimensions of routine activity theory do not substantially modify census tract mischief risk.

Past research provides support for the notion that social disorganization plays an important role in estimating mischief risk. For instance, Ceccato and Haining (2005), in their study of vandalism in Stockholm, Sweden at the census district scale, observe the importance of social disorder in explaining the locations of vandalism, even after accounting for routine activity variables.

7.2.4 Other Thefts

Other thefts encompass thefts not charged as shoplifting, theft from a motor vehicle, or theft of a motor vehicle (Charron, 2009). Because other thefts can include many different types of theft, it is difficult to infer possible social disorganization or routine activity land use variables that could be associated.

7.2.4.1 Exploratory spatial data analysis – Other thefts

Globally, other thefts exhibited significant spatial autocorrelation ($I=0.50$, $p<0.05$). The flexibly shaped scan statistic detected 14 other theft clusters ($p<0.05$), generally located in the downtown and southern areas of the Toronto close to the University of Toronto and east of downtown near the Portlands and West Don Lands. Clusters were also located in the west in Etobicoke the and in the northwest near Highways 400 and 401 (Figure 7.2.4.1). Significant clusters ranged in size between one and sixteen census tracts and the most likely cluster was located in the downtown.

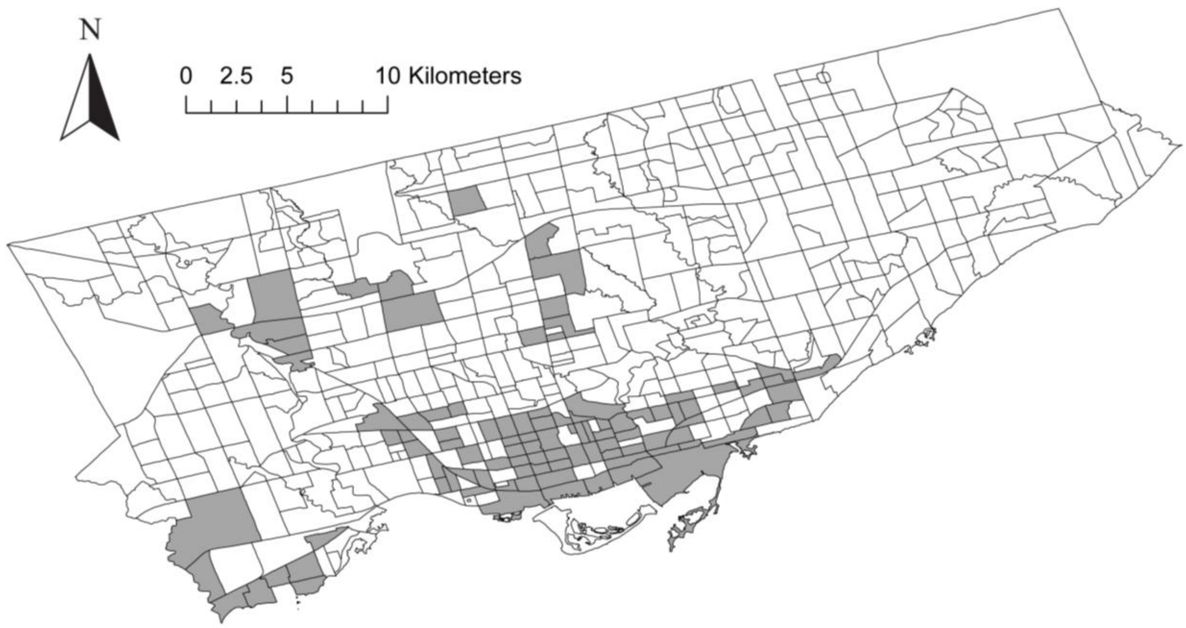

Figure 7.2.4.1. High other theft rate clusters (p<0.05). Other theft clusters were generally located in the downtown and southwest areas of Toronto.

7.2.4.2 Confirmatory spatial data analysis – Other thefts

OLS regression residuals demonstrated positive spatial autocorrelation significantly different from zero (I=0.10, p<0.05). Spatial lag dependent regression model exhibited the best model fit and results can be seen in Table 7.2.4.1.

Table 7.2.4.1. Other theft multivariate spatial lag dependent regression results.

	β	**Std. Error**	**Z-value**	**Pr.**
Social Disorganization				
Aboriginal residents	5.05e-02	1.73e-02	2.92	0.0035
Immigrant residents	-4.93e-03	7.74e-04	-6.37	1.90e-10
Routine Activity				
Commercial land use	7.21e-03	1.42e-03	5.10	3.44e-07
Government-institutional land use	5.77e-03	1.16e-03	4.98	6.53e-07
Road density	8.24e-05	2.32e-05	3.56	0.00038
Vacant land use	1.45e-05	6.93e-06	2.09	0.037
Single detached dwellings	-1.85e-06	3.53e-07	-5.23	1.67e-07

Apartments, duplex or attached to other dwelling or building	4.05e-06	1.22e-06	3.33	0.00088
Spatially lagged crime rate	0.40			6.53e-07

Nine explanatory variables were found to be significantly associated with other thefts, representing both social disorganization and routine activity theories (Table 7.2.4.1). Like many expressive and acquisitive crime types in Toronto, social disorganization is related predominantly through the dimension of ethnic heterogeneity, with the proportion of aboriginal residents and concentration of immigrants exhibiting positive and negative associations, respectively. Past chapters elaborate on this relationship, as ethnic heterogeneity is theorized to fragment social bonds and contribute to social disorganization, whereas a high concentration of immigrant residents may strengthen social networks and lead to lower crime rates.

Focusing on the routine activity perspective, a negative association was found between the density of single detached dwellings and other theft rate. Simply, single detached dwellings are generally not located in areas with many suitable targets for thefts such as a mixed-used downtown, so census tracts with many single detached dwellings do not provide the potential opportunities that would attract other theft offenders.

Positive associations were found between other theft rate and the density of apartments, roads, government-institutional, commercial, and vacant land uses. The combination of these variables suggests that other thefts occur in census tracts with high traffic and mixed land use. For example, areas that exhibit high other theft rates could be characterized by many apartments located above non-residential land uses including commercial and government-institutional uses. Additionally, because other theft encompasses a number of possible theft offences, it does not necessitate a distinct type of land use as shoplifting would (i.e. commercial), so it is plausible that suitable targets for other theft offences include apartments, commercial, and government-institutional land uses.

From a routine activity guardianship perspective, other theft rates are positively associated with the density of vacant land uses. Specifically, when there are many vacant land uses offenders may feel like there are fewer guardians than in areas without vacant land uses, increasing the likelihood of offenders acting in high vacancy areas census tracts.

7.2.5 Robbery

Robbery is legislated as a criminal offence under Section 343 of the Canadian Criminal Code and is defined as theft while using violence directed towards person or property, or the assault of a person with the intent to steal (Department of Justice, 2012b). Despite Statistics Canada considering robbery a violent offence (Charron, 2009), for this research it is considered an acquisitive crime because the primary motivation of robbery is to acquire property rather than express emotion or aggression.

7.2.5.1 Exploratory spatial data analysis – Robbery

Robbery rates exhibit significant positive global spatial autocorrelation ($I=0.31$, $p<0.05$). Eleven significant local robbery rate clusters ($p<0.05$) were identified in the west along the Humber River close to the greenbelt of parks and in east of Toronto in Scarborough, particularly Malvern and Scarborough Village with smaller clusters located in the downtown and north in the Willowdale neighbourhood (Figure 7.2.5.1). Cluster size ranged between seven and sixteen census tracts, with the largest and most likely cluster located in the north-west.

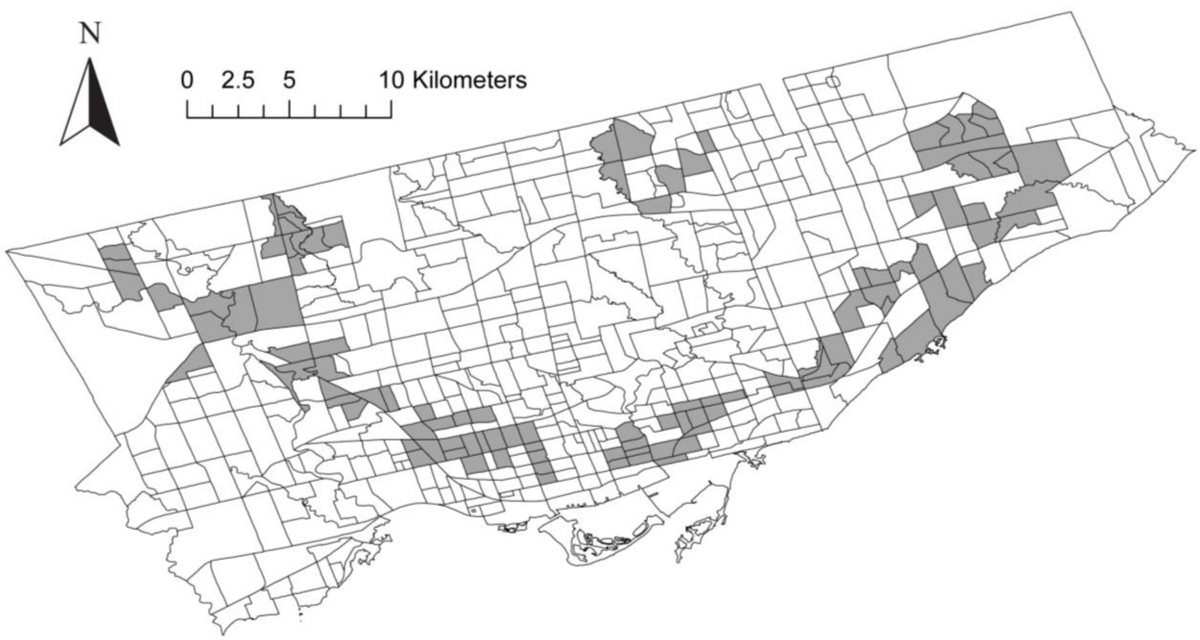

Figure 7.2.5.1. High robbery rate clusters ($p<0.05$). Clusters were located in the downtown, northwest, and southeast areas of Toronto.

7.2.5.2 Confirmatory spatial data analysis – Robbery

OLS regression model residuals exhibited significant positive spatial autocorrelation (I=0.11, $p<0.05$). Spatial lag dependent regression model had best model fit and results can be seen in Table 7.2.5.1.

Table 7.2.5.1. Robbery multivariate spatial lag dependent regression results.

	β	Std. Error	Z-value	Pr.
Social Disorganization				
Lone parent families	1.90e-03	7.08e-04	2.69	0.0072
Immigrant residents	-1.50e-03	3.20e-04	-4.69	2.67e-06
Unemployment rate	7.13e-05	1.70e-05	4.19	2.79e-05
Government transfer payment	3.21e-05	1.14e-05	2.82	0.0048
Routine Activity				
Commercial land use	1.99e-03	5.04e-04	3.97	7.26e-05
Secondary school	2.68e-04	7.97e-05	3.36	0.00077
Apartments, duplex or attached to other dwelling or building	1.46e-06	3.63e-07	4.03	5.50e-05
Row house	8.78e-07	1.69e-07	5.20	2.04e-07
Spatially lagged crime rate	0.34			3.30e-09

Nine explanatory variables were found to be significantly related to robbery. Three dimensions of social disorganization were represented across four variables: economic deprivation through percentage of residents receiving government transfer payments and unemployment rate, ethnic heterogeneity through proportion of immigrant residents, and family disruption through proportion of lone parent families.

Unlike other crime types which are generally only related to the ethnic heterogeneity dimension, robbery is associated with three dimensions of social disorganization. The relationship between robbery and many measures of social disorganization has been supported by Smith et al. (2000) at the street block level, who find that measures of ethnic heterogeneity, single parent families, and average dwelling value (operationalizing economic deprivation) are significantly associated with robbery. So social disorganization in general, rather than just the ethnic heterogeneity dimension, helps to explain the risk of small-area robbery victimization (Smith et al., 2000).

Moderating risk of robbery victimization estimated by social disorganization, routine activity land use variables related to robbery rate include two measures of housing type, densities of apartments that are a duplex or attached to other dwellings or buildings and row houses, and two non-residential land use variables, the density of commercial land and the presence of a secondary school.

Residentially, apartments and row houses are densely located dwellings, which can be seen from an offender's perspective as having a large number of potential targets in a small geographic space. Non-residentially, census tracts with many commercial land uses and secondary schools bring together many offenders and targets, increasing the likelihood of a robbery act to take place (LaGrange, 1999; Roncek and Lobosco, 1983). Both of these non-residential land uses are frequented by many people, including students, shoppers, and employees, so many offenders and targets are brought together increasing the likelihood of a robbery offence.

7.2.6 Shoplifting

Shoplifting involves the theft of goods from a commercial location.

7.2.6.1 Exploratory spatial data analysis – Shoplifting

Global spatial autocorrelation of shoplifting rates was insignificantly different from zero using global Moran's I ($I=-0.0222$, $p>0.05$). Despite insignificant average spatial autocorrelation throughout the dataset, the flexibly shaped scan statistic detected twenty-seven significant shoplifting clusters ($p<0.05$) (Figure 7.2.6.1). All clusters were small, ranging in size between one and five census tracts with the most likely cluster was located on the east side of Toronto. The largest cluster of five census tracts were located in the downtown, a location with many commercial targets for shoplifting offenders.

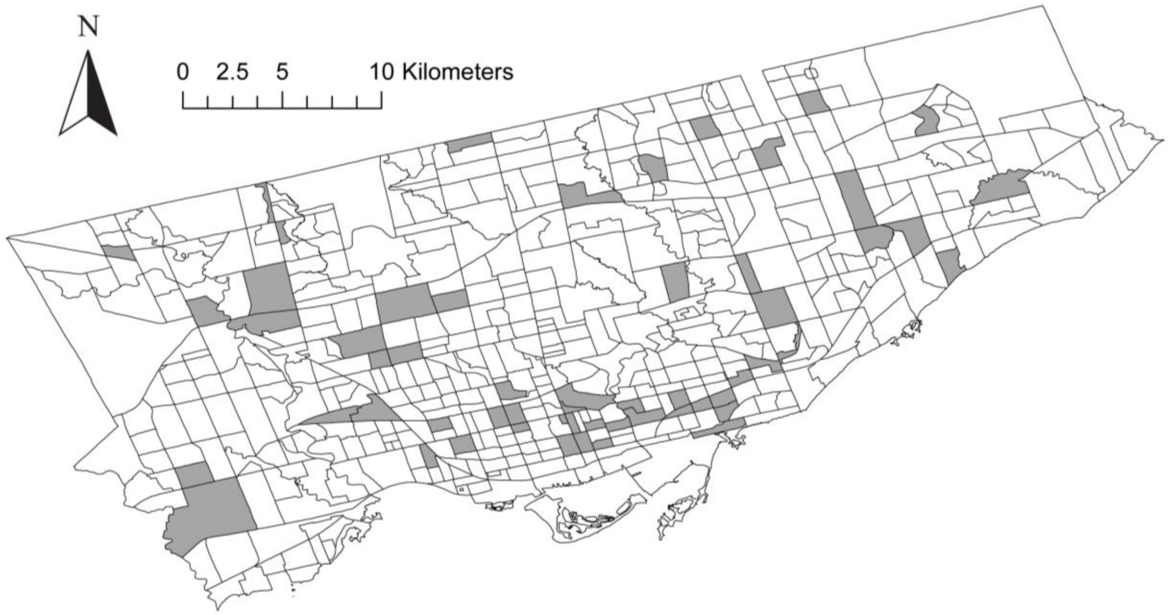

Figure 7.2.6.1. High shoplifting rate clusters (p<0.05). Shoplifting clusters were generally small in size and distributed throughout Toronto in the downtown, north, northeast, and west areas.

7.2.6.2 Confirmatory spatial data analysis - Shoplifting

Testing OLS regression residuals for spatial autocorrelation, global Moran's I was insignificantly different from 0 (I=0.001, p>0.05), suggesting that local variation in explanatory variables included in the OLS model accounted for any possible spatial patterning in shoplifting offence rate. Comparing regression models, log likelihood between OLS and spatial regression models differed by less than one unit, with both spatial regression models containing insignificant spatial terms (i.e. lagged dependent term, spatial error term). OLS regression results can be seen in Table 7.2.6.1.

Table 7.2.6.1. Ordinary least squares regression results for shoplifting rate.

	β	**Std. Error**	**T-value**	**Pr.**
Routine Activity				
Commercial land use	0.014	0.0024	5.86	8.37e-09
Community shopping centre	0.012	0.00093	13.14	2.00e-16
Regional shopping centre	0.0081	0.0016	5.11	4.58e-07
Subway stop	0.0011	0.00050	2.19	0.029

Four explanatory variables were found to be positively related to shoplifting rate: concentration of commercial land use, the presence of community and regional shopping centres, and the presence of a subway station. All variables can be explained from a routine activity theory perspective as they bring together offenders and targets, increasing the opportunities for shoplifting incidents.

High concentrations of commercial land and the presence of regional and/or community shopping centres are desirable locations for offenders because there are many suitable targets. For example, census tracts containing these land uses will likely have a variety of retail stores including department and clothing stores, grocery stores, variety stores, and pharmacies, making these areas more attractive to offenders than census tracts that are predominantly comprised of residential land uses. Shoplifting is defined as the theft from these types of land uses, so it is intuitive that areas with many commercial land uses and shopping centres are positively associated with shoplifting rate. The infrequent distribution of shopping centres could also be considered for its influence on the cluster results, as these small clusters could mirror where shopping centres are located (Figure 7.2.6.1).

In addition to census tracts with many commercial outlets having a variety of suitable targets, the presence of a subway station provides convenient access to large numbers of motivated offenders. Subway lines are routed and stations are located to provide transportation to some of the busiest commercial areas in Toronto, namely downtown, so it is not unexpected that high rates of shoplifting, which requires commercial land uses, occur in areas where a subway station is present. Also, shoplifting offenders are generally young people between the age of ten and eighteen (Gibbens, 1981), making it unlikely that they can drive a car to commercial locations, instead relying on public transit including subways.

7.2.7 Theft From a Motor Vehicle

Theft from motor vehicle consists of the theft of a good from a motor vehicle, where a motor vehicle is defined as a vehicle that is driven by any means other than muscular power excluding railway equipment (Department of Justice, 2012c). Examples of theft from a motor vehicle include stealing recently purchased clothes out of a car trunk or theft of a global positioning system from the front seat of a car.

7.2.7.1 Exploratory spatial data analysis – Theft From a Motor Vehicle

Theft from a motor vehicle rates exhibited positive global spatial autocorrelation (I=0.426, $p<0.05$). Thirteen significant theft from motor vehicle clusters were identified ($p<0.05$), predominantly located in the downtown and west of Toronto close to Dundas and Eglinton West (Figure 7.2.7.1). Additonal clusters were found in the north near York University and the Rexdale neighbourhood and in the northwest close to Pearson International Airport. Clusters ranged in size from one to fifteen census tracts, with the most likely cluster located in the downtown.

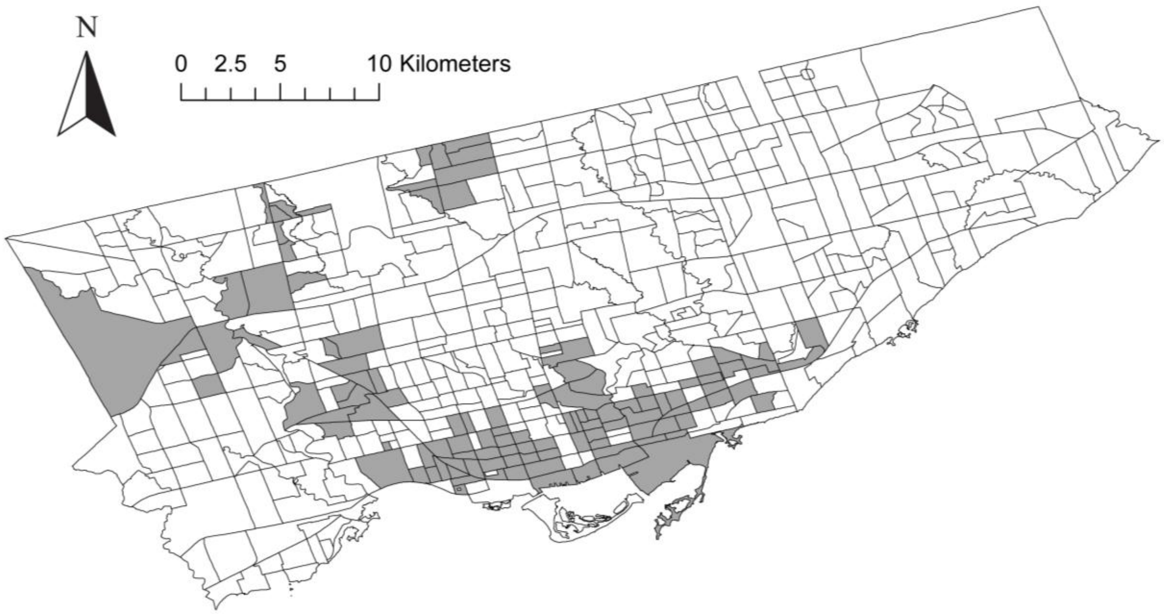

Figure 7.2.7.1. High theft from motor vehicle rate clusters ($p<0.05$). Theft from motor vehicle clusters were located in the downtown and south as well as west areas.

7.2.7.2 Confirmatory spatial data analysis – Theft From a Motor Vehicle

OLS regression residuals exhibited significant positive spatial autocorrelation (I=0.181, $p<0.05$). Spatial lag dependent was the best fitting regression model as determined by highest log likelihood. Multivariate spatial lag dependent regression results can be seen in Table 7.2.7.1.

Table 7.2.7.1. Theft from motor vehicle rate multivariate spatial lag dependent regression results.

	β	Std. Error	Z-value	Pr.
Routine Activity				

Dwellings in need of major repair	8.46e-03	2.40e-03	3.53	0.00042
Road density	6.53e-05	2.0041e-05	3.26	0.0011
Vacant land use	1.55e-05	6.52e-06	2.38	0.017
Single detached dwellings	-8.14e-07	2.5379e-07	-3.21	0.0013
Spatially lagged crime rate	0.54			2.22e-16

Five significant variables were identified through the spatial lag dependent regression model representing the routine activity theory and the spatially lagged crime rate. The density of single detached dwellings was found to be negatively associated with theft from motor vehicles. Many single detached homes have garages or parking beside their homes, reducing the visibility and accessibility of targets (i.e. property goods in motor vehicles) as well as the attractiveness of these areas to potential offenders. Also, census tracts largely comprised of single detached homes will likely have fewer non-residents over a given time period (e.g. shopping, working, etc.), which could act to reduce the total number of potential offenders and the number of thefts from motor vehicles.

Road density was found to be positively related, so the more roads in a census tract, the higher the rate of theft from a motor vehicle. With large densities of road in a census tract, it is probable that there are a variety of different types of roads, including those that allow on-street parking or have municipal parking lots or parking garages, or are publically visible. In contrast to cars parked in a dwelling's garage or behind a single detached home, motor vehicles parked in public locations are visible to offenders and are more likely to be considered for the theft of goods. Additionally, areas with high road density can be expected to contain more cars, or potential targets, than areas with fewer roads.

Incorporating the guardianship dimension of routine activity theory, positive relationships are observed between theft from a motor vehicle rate and dwellings in need of major repair and concentration of vacant land uses. Considering that theft from a motor vehicle is a crime that often occurs in public locations and in the presence of onlookers such as in parking lots or streets, it is plausible that physical deterioration of the built environment could decrease perceived guardianship and increase the likelihood of an offender acting.

7.2.8 Theft of Motor Vehicle

Theft of a motor vehicle involves the theft of a motor vehicle, where a motor vehicle is a vehicle that is driven by any means other than muscular power excluding railway equipment (Department of Justice, 2012c).

7.2.8.1 Exploratory spatial data analysis – Theft of a Motor Vehicle

Theft of a motor vehicle rates exhibited significant positive spatial autocorrelation (I=0.28, p<0.05). The flexibly shaped scan statistic indicated twelve significant theft of motor vehicle clusters (p<0.05), predominantly located in northwest Toronto near York University and Pearson International Airport (Figure 7.2.8.1.). Hotspots in the east were located in the Morningside Heights and Malvern neighbourhoods of Scarborough. Clusters ranged in size from one to thirteen census tracts, with the most likely cluster located along the east side of the northwest clusters.

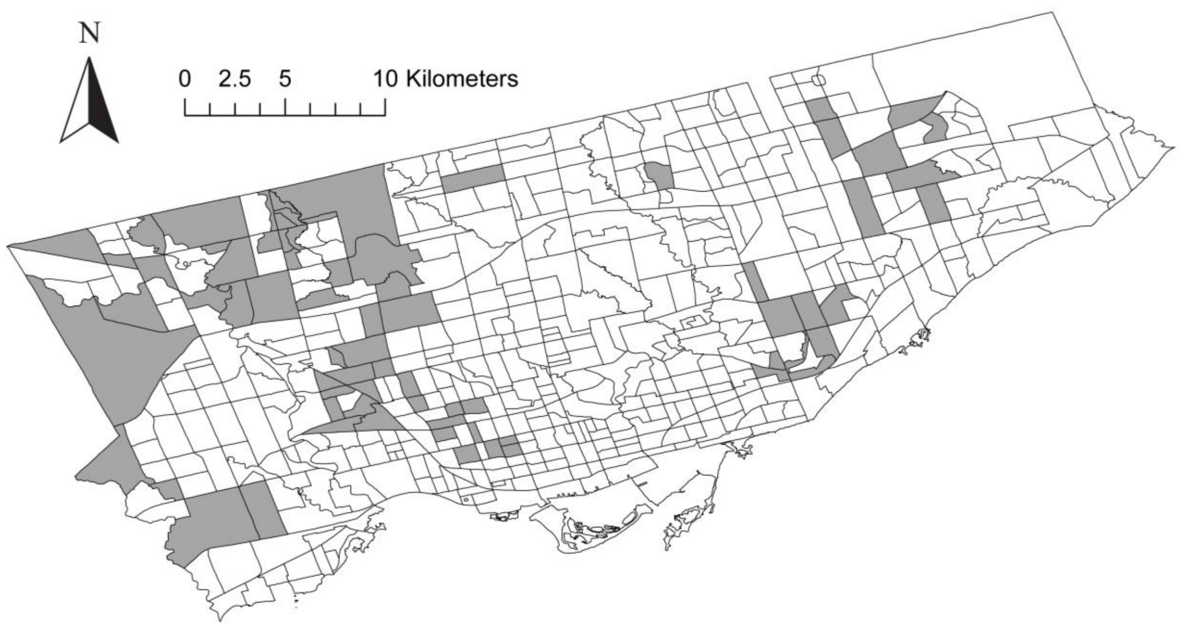

Figure 7.2.8.1. High theft of motor vehicle clusters (p<0.05). Theft of motor vehicle clusters were found in the northwest and east areas of Toronto.

7.2.8.2 Confirmatory spatial data analysis – Theft of a Motor Vehicle

OLS regression residuals exhibited significant spatial autocorrelation (I=0.28, p<0.05). The spatial lag regression model demonstrated superior model fit and results can be seen in Table 7.2.8.1.

Table 7.2.8.1. Theft of motor vehicle multivariate spatial lag dependent regression results.

	β	Std. Error	Z-value	Pr.
Social Disorganization				
Aboriginal residents	2.91e-02	6.90e-03	4.21	2.54e-05
Government transfer payment	3.69e-05	7.35e-06	5.02	5.25e-07
Routine Activity				
Regional shopping centre	2.71e-03	4.10e-04	6.60	4.10e-11
Community shopping centre	1.03e-03	2.33e-04	4.42	1.00e-05
Road density	2.21e-05	8.65e-06	2.55	0.011
Spatially lagged crime rate	0.39			5.82e-11

Six explanatory variables were found to be significantly associated with theft of a motor vehicle rate. Representing social disorganization was percentage of residents receiving government transfer payments and proportion of aboriginal residents. Both ethnic heterogeneity and economic deprivation dimensions of social disorganization are related to theft of a motor vehicle rate in Toronto.

From a routine activity perspective, community and regional shopping centers are land uses that attract large numbers of potential offenders and have large parking lots which contain a large number of potential targets (i.e. motor vehicles). While we cannot attribute the precise location of motor vehicle theft to these shopping malls, it is reasonable to expect that the presence of these land uses in census tracts will increase the rate of motor vehicle thefts enough to show a relationship at the census tract scale.

Additionally, road density, which can be interpreted as being a measurement of the total number of cars in an area, was also positively related to theft of a motor vehicle rate. High census tract road density can be interpreted, like our explanation of theft from a motor vehicle, as having a variety of roads, which likely includes visible parking and attractive targets. Many roads in a census tract may also suggest that there are many motor vehicles, increasing the number of potential targets for offenders.

7.3 Other crime types

Some crime types cannot be categorized as acquisitive or expressive because they are not motivated towards obtaining a tangible good or expressing aggression or violence. Of the fifteen crime types included in the 2006 UCR, only criminal harassment and drug offences are not considered acquisitive or expressive and are reviewed in Sections 7.3.1. and 7.3.2, respectively.

7.3.1 Criminal Harassment

Criminal harassment is repeated conduct carried over a period of time that causes victims to fear for their safety (Milligan, 2011). For example, offenders charged with criminal harassment are typically obsessed with a stranger or someone they know and have likely stalked or repeatedly watched a victims house or workplace causing the victim to fear for their safety (Family Violence Initiative, 2012). Aggression and violence is extremely rare among reported criminal harassment cases, with approximately 2% of victims experiencing injury (Milligan, 2011). Criminal harassment is not an acquisitive crime as there is no intent to obtain tangible goods, nor is it an expressive crime as there is no explicit intent to express aggression.

7.3.1.1 Exploratory spatial data analysis – Criminal Harassment

Criminal harassment rates exhibited slight positive global spatial autocorrelation ($I=0.04$, $p<0.05$). Using the flexibly shaped scan statistic, ten significant local criminal harassment clusters were identified ($p<0.05$), ranging in size between eight and fourteen census tracts. Generally they were located in the west of Toronto close to the Humber River and in Etobicoke, with smaller clusters located in the central midtown areas, while the most likely cluster was located in east downtown close to the south terminus of the Don Valley Parkway. (Figure 7.3.1.1).

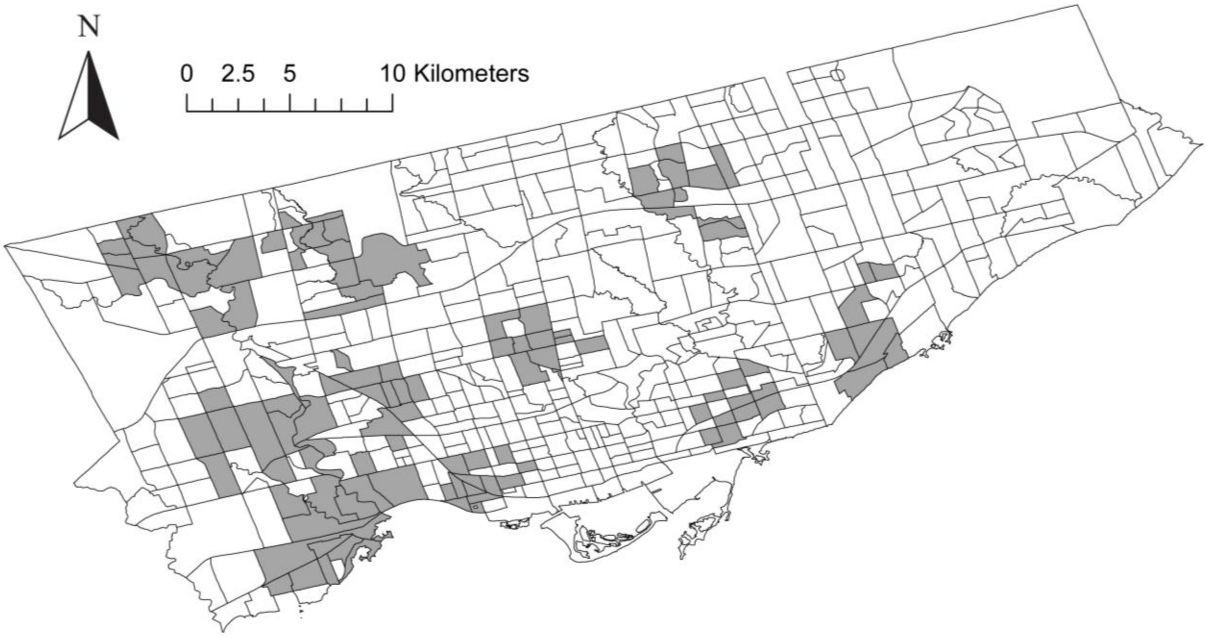

Figure 7.3.1.1. High criminal harassment rate clusters (p<0.05). Clusters were located in the west and central areas of Toronto.

7.3.1.2 Confirmatory spatial data analysis – Criminal Harassment

Non-spatial OLS regressions indicated that only two land use variables, park density and the concentration of dwellings in need of major repair, were significantly related to criminal harassment rates. Testing for spatial autocorrelation among OLS regression residuals, Moran's I was insignificant ($I=-0.03$, $p>0.05$). Multivariate OLS regression results can be seen in Table 7.3.1.1.

Table 7.3.1.1. Criminal harassment multivariate ordinary least squares regression results.

	β	Std. Error	T-value	Pr.
Routine Activity				
Dwellings in need of major repair	1.94e-03	5.77e-04	3.36	0.000084
Park density	7.40e-04	1.99e-04	3.72	0.00022

Two explanatory variables, park density and concentration of dwellings in need of major repair, were associated with criminal harassment rates in Toronto. No social disorganization variables remained significant in multivariate regressions, despite percentage of lone parent families and unemployment rate being positively associated in univariate regression models. This suggests that criminal harassment is not related to the dimensions of social disorganization after accounting for land use or routine activity variables.

While criminal harassment has been found to generally take place in a residence, Milligan (2011) notes that over ten percent of incidents take place in public spaces including parks. In Toronto, high rates of criminal harassments are associated with park densities, so it is possible that parks provide a location for offenders to observe victims. Alternatively, victims may only notice an offender stalking them when they are in public spaces such as parks and are more aware of their surroundings and their safety than when at home.

Percentage of dwellings in need of major repair, as a measure of the guardianship dimension of routine activity theory, may reduce offender perceptions of guardianship, increasing the likelihood that criminal harassment offenders act in areas with physical deterioration. In areas with many houses in disrepair it is possible that an offender feels unnoticed by the victim or other community members and is therefore more willing to act than in areas where there is little physical deterioration and perceived guardianship is high.

7.3.2 Drug Offences

A general overview of drug offences and detailed exploratory local cluster analyses can be seen in Chapter 4.

7.3.2.1 Confirmatory spatial data analysis – Drug Offences

After fitting a multivariate OLS regression model containing all significantly related explanatory variables, regression residuals were tested for spatial autocorrelation using Moran's I. Significant positive spatial autocorrelation was observed ($I=0.14$, $p<0.05$). Spatial lag dependent was the best fitting multivariate regression model by log likelihood and results can be seen in Table 7.3.2.1.

Table 7.3.2.1. Drug offence rate multivariate spatial lag regression results.

	β	Std. Error	Z-value	Pr.
Social Disorganization				
Lone parent families	2.13e-03	6.76e-04	3.15	0.0016
Index of ethnic heterogeneity	1.32e-03	3.79e-04	3.47	0.00052

Routine Activity				
Hotel	3.52e-04	1.33e-04	2.66	0.0079
Apartments in buildings with more than five stories	1.05e-06	4.67e-07	2.24	0.025
Row house	5.88e-07	2.16e-07	2.73	0.0064
Apartments in buildings building with fewer than five stories	3.02e-07	6.63e-08	4.56	5.23e-06
Spatially lagged crime rate	0.37			2.69e-09

Seven variables were found to be related to drug offence rate with two representing social disorganization, four representing routine activity theory, and the spatially lagged drug offence rate. Drug offence rates are explained by two social disorganization variables, specifically percentage of lone parent families and index of ethnic heterogeneity. It is possible that census tracts exhibiting social disorganization through these variables do not have the social control to resist the formation of a drug market and are more likely to take part in illegal activities including drug dealing and drug use (McCord and Ratcliffe, 2007). Census tract drug offence risk is modeled through family disruption and ethnic heterogeneity dimensions of social disorganization.

Routine activity theory is represented by densities of row houses, apartment buildings with fewer than five stories, and apartment buildings with five or more stories, and the presence of a hotel. Generally, all of these land use variables are dense forms of housing, suggesting that perhaps the proximity to many people in their residences contributes to census tract drug offence rate. For instance, it is possible that residents living close to each other more frequently observe drug use, and thus more frequently report it to police, through odour or waste that would otherwise not be detected if living in less dense housing such as single detached dwellings.

Additionally, it could be that many drug arrests are made in open spaces, parks, or parking lots close to high density residential areas or hotels, as these are located nearby to both drug buyers and sellers. So these locations are advantageous for drug sellers as they are close to many possible customers.

7.4 Summary of Acquisitive and Other Crime Type Results

Visualizing significant acquisitive crime spatial clusters, there was a general pattern of clusters located in the downtown and west of Toronto. Clusters were less frequently located in the east parts of the city, with few crime types exhibiting significant clustering in the middle and north areas of Toronto. This persisted across most acquisitive crime types, with only break and enter and other theft demonstrating high crime rate clusters in the middle and north areas.

Generally, multivariate spatial regression results for acquisitive crime types indicate that both social disorganization and routine activity theories are related to acquisitive crime rate. This justifies the use of a theoretical approach integrating both social disorganization and routine activity theories, where social disorganization estimates census tract crime victimization risk and routine activity theory land use variables modifying this baseline risk. Two crime types, shoplifting and theft from a motor vehicle, were not associated with variables from both theories as they were both represented only by routine activity land use variables.

From confirmatory spatial lag dependent regressions of acquisitive crimes, the most commonly related social disorganization variables were the proportion of aboriginal residents (6 crime types), proportion of immigrant residents (4), percentage of lone parent families (2), percentage of residents receiving government transfer payments (2), index of ethnic heterogeneity (1), and unemployment rate (1). The ethnic heterogeneity dimension was prominently represented through three variables, with economic deprivation represented through two variables and family disruption represented through one variable.

From a routine activity perspective, land uses were observed as being significantly related to each acquisitive crime type, suggesting that land use patterns at the census tract scale play an important role in the occurrence of acquisitive crimes, even after accounting for measures of social disorganization. Across all acquisitive crime types, the most frequently associated land use variables were single detached dwellings (4 crime types), road density (4), commercial land uses (4), community shopping centre (3), regional shopping centre (3), dwellings in need of major repair (3), and proportion of dwellings built before 1946 (3). Related to two acquisitive crime types were place of worship, density of vacant land uses, and apartments attached to non-residential land use. Concentration of apartment buildings with fewer than five stories, density of row houses, park density, concentration of government-institutional land uses, and the presence of a secondary school were all related to one acquisitive crime.

From this, it can be observed that both non-residential and residential land use patterns contribute to acquisitive crime rates. Generally, high density residential land uses were positively related to acquisitive crime rates while single detached dwellings exhibited negative relationships. Non-residential land use variables were usually positively associated with acquisitive crime rates.

The best fitting spatial regression model, spatial lag dependent, also provides insight into the spatial structure of acquisitive crime rates. Adding spatially lagged crime rate as an explanatory variable, the spatial lag dependent regression model demonstrated best model fit for seven of eight acquisitive crimes. Only shoplifting, which did not exhibit spatial clustering, was better modeled through a non-spatial ordinary least squares regression. Interpreting this from a theoretical perspective, we can infer that high acquisitive crime rate in one census tract increases the likelihood of high acquisitive crime rate in adjacent census tracts. One possible practical implication of this finding is the movement of criminal offenders throughout adjacent census tracts, whereby offenders commit acquisitive crimes in one census tract and may move to proximal census tracts for repeat offences. Alternatively, it could be that police focus on clusters of census tracts, perhaps targeting their patrols and operations in areas known to have high acquisitive crime rates.

Other crime types, including criminal harassment and drug offences, had very different clustering patterns and confirmatory regression results. Criminal harassment exhibited insignificant clustering while drug offences had many significant local clusters as detailed in Chapter 4. Drug offences were related to variables representing both social disorganization and routine activity theories while criminal harassment was only represented by routine activity land use variables.

7.5 Applications to Law Enforcement Planning

Recognizing the influence of social disorganization and routine activity theory stresses the complex nature of acquisitive crimes and has implications for law enforcement planning.

Addressing social disorganization, law enforcement agencies should target census tracts that exhibit high ethnic heterogeneity, economic deprivation, and family disruption. Since these areas have high offence rates and have reduced informal social control, census tracts exhibiting these characteristics should be the focus of increased frequency and specificity of police patrols to increase formal social control. In lieu of informal social control, the presence of formal agents of control such as police may address the processes contributing to social disorganization and high baseline crime risks. Additionally, these areas should be highlighted for crime prevention initiatives. These initiatives could be culturally and language specific to encompass as many ethnic and cultural groups as possible, and focus on building informal social control to overcome social disorganization.

From a land use planning perspective, perhaps areas with high acquisitive crime rates that are related to social disorganization would be suitable for targeted development. For instance, community or youth centres could be developed, seeking to establish supervision over youth and address the effects of family disruption caused by high rates of lone parent families. Further, land uses such as libraries or parks could have a positive effect on communities, establishing common values and norms among residents and non-residents and reducing the effect of social disorganization.

Operationalizing land use as the locations where motivated offenders, suitable targets, and limited guardianship converge to increase the likelihood of criminal events, suggests that dense residential and non-residential land uses are positively associated with acquisitive crime rates. One potential way of addressing land use risk factors is through implementing building-scale crime prevention strategies such as crime prevention through environmental design (CPTED). Briefly, CPTED advocates that design and use of the built environment can lead to a reduction in the opportunity for crime (CMHC, 1998). In areas where there is high property crime, it could be established that shopping centres and commercial land uses, both of which were found to be positively related to property crime rates, could be targeted for crime prevention improvements such as appropriate street lighting and reducing the number of places where loitering is problematic (CMHC, 1998). Incorporating CPTED into the design of non-residential and dense residential land uses, result in a decrease in property crime offences at the building-scale, which could extend to a reduction in census tract crime rates.

Another way to address crime risk hypothesized by the routine activity theory is to consider ideal land use placement and incorporate this in municipal zoning codes and by-laws. For example, given an area that has high property crime, which is significantly related to the presence of commercial and shopping centre land uses, it may be possible to target residential and industrial development to these areas. Reducing the relative concentration of commercial land uses in areas where there is high property crime could reduce the attractiveness of these areas to property crime offenders and result in a reduction of property crime offences at the census tract scale.

7.6 Limitations of Acquisitive and Other Crime Type Analysis

There are two limitations to the analysis presented in Section 7.2 and 7.3 on acquisitive and other crime types. First, the land use types used in analysis is certainly not exhaustive, so it is possible that some land uses not included in this analysis are influencing the geographic distribution of these crime types. Similarly, land use data was included based on the categories defined in datasets available to the researchers, so any misclassification of this data from the source would have implications in confirmatory results. Some land uses found to be related to acquisitive crime types in past research and not analysed in this research include bars (Roncek and Maier, 1991), restaurants and gas stations (Smith et al., 2000), and the frequency that people attend movie theatres and bingo halls (Kennedy and Forde, 1990), and should be investigated in future research.

Second, we assume that deterioration of the physical environment influences offender perceptions of guardianship. Specifically, we posit that census tracts with high levels of physical deterioration decrease guardianship and increase the likelihood of offenders committing crime offences. While this may certainly not be the case in all census tracts in Toronto, this assumption aligns with broken windows theory interpretations of guardianship and has been included in an effort to examine how characteristics of the built environment, rather than strictly land use, can influence crime at the census tract scale.

Chapter 8
Discussion

8.1 Research limitations

Beyond the limitations explored in each of the three research sections (Chapters 4, 6, and 7), there are three research limitations that apply to this thesis in general. First is the modifiable areal unit problem, which recognizes that results found using one areal unit may not apply to other areal units; second is the ecological fallacy, which reminds us that the relationships uncovered at the small-area scale are not necessarily representative of the constituents of the small-area units; and three, the use of official crime incident data.

8.1.1 Modifiable Areal Unit Problem

When analysing point data aggregated to small-area units to examine the influence of small-area or neighborhood characteristics, the modifiable areal unit problem (MAUP) should be recognized. The MAUP is "a problem arising from the imposition of artificial units of spatial reporting on continuous geographical phenomenon resulting in the generation of artificial spatial patterns (Oliver, 2001)." Often the MAUP is considered a nuisance, especially when point data is aggregated to areas (as in this research), however it can dramatically alter results and question the validity of analysis (Openshaw, 1984).

The MAUP has two components: the scale effect and the zoning effect (Oliver, 2001). The scale effect, also termed aggregation effect, is when the number of spatial units used in analysis effects results. For example, analysis at the city ward scale differ from results obtained from analysis at the census tract scale, despite being relatively similar in size. In comparison, the zoning effect is when small areal units are grouped into larger areal units. In the context of this thesis, results from analysis at the city scale and census tract scale would be different.

For this research, the census tract was chosen as the unit of analysis because of data availability as well as the practical benefits of implementing results at the small-area census tract scale (refer to Section 3.1.1). All data was aggregated to the census tract, so there were no assumptions made about varying spatial scales of data. If point data had been available, level of spatial aggregation would have been an important consideration.

8.1.2 Ecological Fallacy

The ecological fallacy is a logical fallacy whereby causal inferences from group data are applied to individual behaviours or characteristics (Schwartz, 1994). In the context of this research, it is important to recognize that the patterns or relationships observed at the census tract scale are representative of those census tracts as spatial units, not for individual people living or working, or land parcels contained within census tracts. To this, it should be noted that the findings of this thesis can only be applied to understand crime in Toronto at the census tract scale and should not be interpreted as providing insight into crime tendencies of individual people or at individual land parcels.

For example, given the negative relationship between immigrant residents and expressive crime rates at the census tract scale discussed in Chapter 6, it would be fallacious to conclude that all immigrant residents do not commit expressive crimes. Rather, for census tracts throughout Toronto, high concentrations of immigrant residents tend to be located in areas where there are few expressive crimes. Indeed, this could be because immigrant residents are less likely to commit expressive crimes, but it could also be due to broader social or cultural factors such as strong familial bonds that are exercised at the census tract scale (Kubrin, 2009). Likewise, particular locations of resource-industrial land use or hotels are not necessarily the locations where expressive crimes are committed, but rather census tracts with high concentrations of these land uses tend to have higher expressive crime rates throughout Toronto.

8.1.3 Official Crime Incident Data

As noted, the UCR is an official crime survey and includes only criminal incidents that are reported to police. It is possible then, that some crimes go unreported to police and official incident data only records a small portion of total crimes (Skogan, 1974). Additionally, since the UCR only records the most punishable criminal offence involved, criminal incidents involving both a violent and property offence could potentially be only recorded as a violent offence, underestimating the number of property offences.

Further, and relevant to the structure of this thesis, is the possibility that categorization of crimes does not accurately reflect offender motivation. This is especially problematic when determining crime rate denominator on offender motivations. For example, analysis of expressive crimes using a rate calculated with residential and working population as the denominator would result in very different regression results, altering the interpretation of related social disorganization and non-residential land use variables.

8.2 Research challenges

During the research process, there were two research challenges that should be noted: data reliability for non-residential land uses and deriving offender motivation based on crime type categories.

Most non-residential land use data was retrieved from the City of Toronto Geospatial Competency Centre and distributed as address points categorized into different land use types. Because this dataset contained over 500, 000 address points including residential and non-residential land uses (residential land uses from this source were not used as Statistics Canada also provides this data), it is likely that there are some incorrectly categorized or located addresses. For verification, some locations were checked through site visits and Google Maps, however on large we assume that land uses classifications in the dataset are representative of their true land use. This assumption, that datasets contain correct information and location of land uses, also pertains to land use classifications in polygonal land use data distributed by DMTI (e.g. commercial, resource-industrial).

A second research challenge was deriving offender motivation based on crime type categories. Generally, we attempted to characterize each crime based on documents from Statistics Canada (e.g. Charron, 2009), however these were only available for a few crimes. In the absence of documents detailing crime types, we referred to the definitions of acquisitive and expressive crimes and assumed that all instances of each crime type fit their definition. It is possible for some crime types to be both expressive and acquisitive, for instance some robberies classified in this thesis as an acquisitive crime, to be acted with aggression in revenge or to inflict personal harm and not primarily to obtain property goods.

8.3 Future research directions

There are a number of future research directions that can be extended from this thesis. First is examining these findings at a more precise spatial scale such as the census dissemination area. Analysis at a finer spatial scale will allow for the identification of smaller high crime risk neighborhoods and increase the specificity of intervention efforts. Additionally, it may highlight different relationships between crime rates and explanatory variables, complementing the findings of the research presented in this thesis. Similarly, analysis using small spatial units lends itself to including more detailed land use variables that may be related to crime rate at a more local level.

Second is to compliment this research using crime incident data with similar research using criminal offender data and victimization data. A comprehensive understanding of the spatial distribution of crime and its determinants requires that offender data and victimization data also be studied as incident and offender locations as well as underreporting of official crime data play important roles in analysis results and applications.

Third is to continue these themes from a qualitative perspective, querying residents and non-residents on their perceptions of the built environment and the role it could play in crime. Specifically, this could be applied to investigate the role of non-residential land uses and expressive crime rate. Perhaps future research can look to identify census tracts with a high concentrations of non-residential land uses and create a survey or conduct interviews focused on the relationship between the presence of these land uses the perception of neighborhood social cohesion, ownership, and informal social control.

Fourth is to employ Bayesian spatial methods, which are advantageous in small-area studies of crime because they borrow strength from nearby spatial units to stabilize risk estimates. In contrast to analysis using crime rates, which are problematic when crime counts or populations are low, Bayesian spatial methods have parameters that are probabilities and combine prior knowledge, such as neighborhood structure and data such as crime incident or offender data.

Chapter 9
Conclusion

This thesis explores crime hotspots and identifies risk factors of expressive and acquisitive crimes in Toronto, Ontario using officially recorded incident data for 2006. While comprised of relatively distinct research chapters, the research questions driving this thesis can be considered as such: Where are the locations of crime hotspots, and what are risk factors for high crime areas in Toronto? How can these findings be applied to inform practical efforts such as law enforcement planning? Conceptually, this thesis is linked through three themes: to recognize crime as an inherently geographic phenomenon, to contribute to understanding the processes and associated risk factors of crime, and to inform efficient and effective law enforcement planning. In concluding this thesis, we provide an overview of each research chapter and clarify how the themes linking this thesis were exhibited in each research section.

First, we take a methodological approach to investigate the location of drug offence hotspots and the utility of four local spatial cluster detection methods as they can be applied to practical and academic initiatives including law enforcement planning and hypothesis generation. Identifying the largest clusters, it is argued that the spatial scan statistic is most suitable for informing broad-scale policing initiatives. In contrast, local Moran's I identifies the smallest clusters, which is the most appropriate method for locating high risk areas that can be targeted with tailored resource-intensive crime prevention and policing operations. The spatial scan statistic with contiguity and the flexibly shaped scan statistic identify a number of medium-sized clusters and are the most applicable methods to inform confirmatory research hypotheses.

Second, we investigate the influence of social disorganization and non-residential land uses on expressive crime rates. Interpreting expressive crime as an outcome relevant to both small-area crime and community-level public health, it is found that non-residential land use and ethnic heterogeneity are both associated with census tract expressive crime rates. It is hypothesized that in addition to the effects of ethnic heterogeneity, the mixing of non-residents and residents introduced by the presence of non-residential land uses impedes the formation of common values and norms, contributing to social disorganization and high expressive crime rates. Further, some land uses such as hotels and open areas may be locations where there is reduced informal social control. Applications of these findings include identifying areas with concentrations of non-residential land use for building-scale crime prevention through environmental design and targeting the development of land uses that increase sense of ownership, such as parks and recreational leisure spaces, to high risk areas.

Third, we examine acquisitive and other crime types from a theoretical perspective that integrates both social disorganization and routine activity theories. It is found that both social disorganization, which we assume to estimate baseline victimization risk, and routine activity land use variables, which modify this baseline risk, are significantly related to most acquisitive crime types. Recognizing the influence of land use on crime highlights the need to incorporate these findings into land use planning and policy making. For instance, land use planners should consider the deleterious effect of some land uses and target development of these land uses to areas where there is low crime or where the police can simultaneously implement crime prevention initiatives.

The first theme uniting these research chapters is the recognition of crime as a geographic phenomenon. In each section, the spatial distribution of crime is described and methods incorporating spatial autocorrelation or spatial structure are employed. Exploratory spatial cluster detection understands crime as an inherently spatial phenomenon through identifying areas or groups of areas that exhibit significantly disproportionately high crime rates. Theories used to structure empirical inquiry into the risk factors of crime are also inherently spatial. Both social disorganization and routine activity lenses focus on where crime occurs, generally investigating locations in the urban environment that possess certain criminal characteristics. Methodologically, spatial regression techniques used in Chapters 6 and 7, which were shown to have superior model fit to non-spatial models, recognize that adjacent expressive and acquisitive crimes are influenced by spatially unmeasured processes, as in the case of expressive crimes, or adjacent crime rates in the case of acquisitive crimes.

Regarding the second theme, each research chapter contributes to understanding processes and associated risk factors of crime in Toronto, Ontario. High crime clusters indicate where high risk areas are located, providing insight into possible explanations underlying the location of criminal areas. Drug offence clusters located near highways, for instance, suggest that accessibility and movement of large numbers of people shape the location of drug markets. Confirmatory analysis of expressive and acquisitive crime types identifies both socio-economic and built environment risk factors related to crime rates. For instance, positioning non-residential land use as a factor contributing to social disorganization, which has been proposed in past research using perception of victimization data (e.g., Wilcox et al., 2004; Sampson and Raudenbush, 1999), was supported in this research using official incident data, providing insight into the social processes influencing crime. Further, operationalizing routine activity locations through land uses develops understanding of how and where people come together to create criminal opportunities.

The third theme linking research chapters is for results to inform effective and efficient law enforcement planning. Identifying high crime rate clusters and understanding which cluster detection methods are most suitable for practical applications, cluster output provides insight into the geographical targeting of law enforcement planning, police patrols, and crime prevention initiatives as well as research hypothesis generation. Uncovering associated socio-economic and built environment variables conceptualizes the types of urban environments related to expressive and acquisitive crimes and allows law enforcement planners to direct operations to these areas of Toronto that exhibit these characteristics. For land use planners, these areas are sites where the development of criminogenic land uses should be considered, perhaps locating them in areas with little crime or where simultaneous crime prevention initiatives can be enacted. Environmental design guidelines featuring crime preventative measures should also be considered by practitioners in areas exhibiting many crime risk factors.

In addition to the limitations outlined in each research section, the modifiable areal unit problem, ecological fallacy, and the use of official criminal incident data are limitations that apply to all research in this thesis. Future research should look to examine the relationships uncovered at a smaller areal scale, incorporate additional land use variables suspected to contribute to crime, employ offender data, investigate these findings from a qualitative perspective, and use Bayesian spatial methods for improved analysis when data is scarce.

Appendix A

Bivariate Correlation Matrix of Explanatory Variables

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9
X_1	1.00								
X_2	.709	1.00							
X_3	.753	.619	1.00						
X_4	.685	.725	.560	1.00					
X_5	.346	.006	.248	.031	1.00				
X_6	.420	.047	.293	.090	.858	1.00			
X_7	.593	.672	.543	.389	.135	.241	1.00		
X_8	.090	.064	.056	.231	.062	.016	-.239	1.00	
X_9	.501	.557	.453	.503	.156	.218	.486	.008	1.00
X_{10}	.248	-.012	.118	.023	.507	.498	-.001	.135	.048
X_{11}	-.366	-.223	-.279	-.180	-.407	-.478	-.261	.050	-.383
X_{12}	-.072	.037	-.063	.086	-.045	-.099	-.117	.286	-.126
X_{13}	.332	.232	.212	.283	.133	.176	.184	.030	.192
X_{14}	-.076	.079	-.077	.073	-.120	-.172	-.070	.233	-.095
X_{15}	.280	.013	.174	014	.505	.531	.099	.014	.133
X_{16}	.032	-.083	-.098	.005	.281	.186	-.277	.339	-.144

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9
X_{17}	-.003	-.002	-.041	.035	.039	.051	-.040	.087	-.018
X_{18}	.087	.142	.114	.089	-.066	-.042	.125	-.081	.226
X_{19}	.018	.022	.024	.033	.008	.034	.056	-.081	.049
X_{20}	.030	.075	.023	.027	.089	.071	.092	-.045	.089
X_{21}	-.023	-.079	-.039	-.033	.141	.136	-.119	.059	.030
X_{22}	-.040	-.008	-.027	.012	.092	.076	-.019	.008	.044
X_{23}	-.035	-.195	-.072	-.141	.235	.175	-.129	.026	-.064
X_{24}	.022	.053	-.018	.071	-.060	-.034	-.003	.026	.041
X_{25}	-.052	0.76	.025	.037	-.221	-.248	.071	-.031	.034
X_{26}	-.149	-.101	-.155	-.052	-.079	-.124	-.242	.087	-.106
X_{27}	.094	.081	.132	.120	-.099	-.043	.083	-.052	.053
X_{28}	-.057	-.156	-.138	-.011	.192	.124	-.272	.204	-.179
X_{29}	.112	.156	.099	.113	.188	.240	.135	-.004	.183
X_{30}	.072	.008	.014	-.013	.066	.029	-.029	-.077	.101
X_{31}	.115	.109	.100	.068	.179	.195	.148	-.064	.126
X_{32}	.050	-.010	.028	-.014	.055	.111	.060	-.043	.106
X_{33}	.420	.417	.351	.506	.120	.094	.062	.315	.101
X_{34}	-.284	-.321	-.284	-.129	-.031	-.123	-.587	.334	-.514
X_{35}	-.031	-.134	-.090	-.084	.059	-.003	-.073	.075	-.166

	X_{10}	**X_{11}**	**X_{12}**	**X_{13}**	**X_{14}**	**X_{15}**	**X_{16}**	**X_{17}**	**X_{18}**
X_{10}	1.00								
X_{11}	-.260	1.00							
X_{12}	.072	.024	1.00						
X_{13}	.192	-.328	.117	1.00					
X_{14}	-.012	.482	.320	-.111	1.00				
X_{15}	.945	-.355	-.148	.113	-.204	1.00			
X_{16}	.429	-.129	.437	.191	.311	.150	1.00		
X_{17}	.063	.023	.194	.063	.104	-.003	.138	1.00	
X_{18}	-.187	-.057	-.186	-.071	-.046	-.113	-.208	.009	1.00
X_{19}	-.068	-.091	-.043	-.019	-.058	-.037	-.061	-.020	.042
X_{20}	-.058	-.081	-.045	-.026	-.035	-.026	-.068	-.032	.040
X_{21}	.014	-.183	-.050	.026	-.103	,028	.064	-.017	.094
X_{22}	-.055	-.131	-.073	-.025	-.031	-.035	.015	-.031	-.007
X_{23}	.139	-.078	.041	-.070	-.011	.130	.103	-.017	-.002
X_{24}	-.053	-.022	-.033	.013	-.062	-.050	.006	.069	.065
X_{25}	-.233	.094	.022	.032	.003	-.242	-.063	-.090	.157

	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}	X_{17}	X_{18}
X_{26}	-.061	.163	.091	-.122	1.54	-.127	.157	.096	.124
X_{27}	-.164	-.222	-.156	-.057	-.258	-.059	-.231	-.085	.002
X_{28}	.385	.036	.394	.250	.269	.189	.580	.134	-.247
X_{29}	-.022	-.351	-.042	.000	-.124	.031	-.017	.061	.060
X_{30}	.028	-.148	.002	.050	-.046	.029	.065	-.027	-.010
X_{31}	.060	-.177	-.084	.046	-.078	.114	-.091	-.046	.141
X_{32}	-.100	-.245	-.154	-.068	-.212	-.014	-.139	-.038	.058
X_{33}	.161	-.072	.239	.239	.253	.038	.362	.117	-.028
X_{34}	.066	.283	.539	.007	.424	-.174	.584	.127	-.247
X_{35}	.149	.108	.053	.057	.068	.098	.129	.041	-.107

	X_{19}	X_{20}	X_{21}	X_{22}	X_{23}	X_{24}	X_{25}	X_{26}	X_{27}
X_{19}	1.00								
X_{20}	-.017	1.00							
X_{21}	.146	-.031	1.00						
X_{22}	.072	.014	.202	1.00					
X_{23}	.096	.086	.109	.016	1.00				
X_{24}	.035	.026	.036	.022	.081	1.00			
X_{25}	-.042	.042	-.016	.008	-.014	.106	1.00		

	X_{19}	X_{20}	X_{21}	X_{22}	X_{23}	X_{24}	X_{25}	X_{26}	X_{27}
X_{26}	.049	.033	.123	.040	.121	.075	.078	1.00	
X_{27}	-.048	-.033	-.017	-.046	-.045	-.038	-.045	-.212	1.00
X_{28}	-.079	-.129	.108	-.066	.116	-.050	-.132	.087	-.176
X_{29}	.148	.008	.165	.225	-.035	-.009	-.071	.080	-.112
X_{30}	-.036	-.006	.041	-.024	.096	.273	.118	-.043	-.024
X_{31}	.151	.314	.006	.091	.018	-.013	-.120	-.066	-.111
X_{32}	.117	.036	.133	.070	.024	.008	-.016	-.010	.017
X_{33}	-.043	-.030	-.057	.005	-.024	.022	-.016	.047	.050
X_{34}	-.044	-.085	.003	-.015	.113	.002	-.078	.13	-.172
X_{35}	-.027	-.055	.080	.021	.046	-.049	.034	.067	-.123

	X_{28}	X_{29}	X_{30}	X_{31}	X_{32}	X_{33}	X_{34}	X_{35}
X_{28}	1.00							
X_{29}	-.056	1.00						
X_{30}	-.059	-.175	1.00					
X_{31}	-.058	-.006	-.037	1.00				
X_{32}	-.063	.077	-.024	-.011	1.00			
X_{33}	.198	.042	.055	-.071	-.154	1.00		
X_{34}	.518	-.075	.011	-.139	-.170	.348	1.00	

X_{35}	.158	-.011	-.002	-.066	-.070	-.033	.100	1.00

Social Disorganization			
X_1	Low family income	X_2	Government transfer payment
X_3	Unemployment rate	X_4	Lone parent families
X_5	One year residential mobility	X_6	Five year residential mobility
X_7	Immigrant residents	X_8	Aboriginal residents
X_9	Index of ethnic heterogeneity		
Routine Activity Theory			
X_{10}	Dwelling density	X_{11}	Single detached dwellings
X_{12}	Semi Detached	X_{13}	Row Houses
X_{14}	Apartment	X_{15}	Apartment 1
X_{16}	Apartment 2	X_{17}	Other single dwellings
X_{18}	Neighborhood shopping centre	X_{19}	Regional shopping centre
X_{20}	Community shopping centre	X_{21}	Hotel
X_{22}	Police Station	X_{23}	Subway Station
X_{24}	Secondary School	X_{25}	Primary School
X_{26}	Place of Worship	X_{27}	Park Density
X_{28}	Road Density	X_{29}	Resource-industrial land use
X_{30}	Government-institutional land use	X_{31}	Commercial land use

X_{32}	Open area land use		

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