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THE LAW OF CRIME CONCENTRATION IN MIDSIZED CITIES: A SPATIAL ANALYSIS

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Master of Arts

By
Hannah Rebecca Ridner

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THE LAW OF CRIME CONCENTRATION IN MIDSIZED CITIES:
A SPATIAL ANALYSIS

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The geographic concentration of crime led to the proposal of the law of crime concentration in 2015 by David Weisburd. This contribution to crime and place literature needs further research to properly define, measure, and confirm this law. This study builds upon measurement techniques used in previous studies to measure crime concentration across a random sample of mid-sized cities, estimate the expected Gini coefficient in mid-sized cities, and analyze the variation in crime concentration across mid-sized cities. Determining the expected level of crime concentration and whether it varies across cities will advance the literature by providing both a benchmark for and a test of the law of crime concentration. This study brings a unique perspective on crime concentration, by having a random sample of midsized cities, representing varying regions in the United States. This filled in gaps within the literature that gravely needed to be addressed (i.e., smaller, midsized cities, larger sample size, and regionally representative.

Introduction

Evidence that crime is geographically concentrated led Weisburd (2015) to propose the law of crime concentration, which states: "for a defined measure of crime at a specific microgeographic unit, the concentration of crime will fall within a narrow bandwidth of percentages for a defined cumulative proportion of crime" (Weisburd, 2015). The law of crime concentration is an important contribution to the literature of crime and place, but more research is needed to properly define, measure, and confirm the law. Specifically, more research is needed to determine the expected level of concentration and whether concentration is invariant across cities. As currently stated, the law of crime concentration is vague which makes it difficult to know whether the law is confirmed after studies are conducted. Determining the expected level of crime concentration and whether it varies across cities will advance the literature by providing both a benchmark for and a test of the law of crime concentration.

The law of crime concentration is based on the theoretical perspectives of environmental criminology and is most often explained by routine activities theory and social disorganization theory (Jones & Pridemore, 2018). Ecological studies testing the law of crime concentration emphasize the role of criminal opportunity operating on small microgeographic units of analysis. Studies have shown microgeographic units are advantageous in studies of crime concentration because studies at higher levels of analysis mask important variation. Following the lead of prior research on the law of crime concentration, this study adopts a microgeographic approach by using street segments as the main unit of analysis. However, this study is unique because it focuses on studying the law of crime concentration across a random sample of midsized cities as opposed to the more common focus on crime concentration in a single, larger urban city.

Recently, research exploring the law of crime concentration has become the focus of environmental criminology (O'Brien, 2018; Bernasco & Steenbeek, 2017; Weisburd, 2015; Weisburd, Groff, & Yang, 2012). In particular, environmental criminology has shifted focus to street segments as the main unit of analysis (Weisburd, 2015). A street segment is a short section of a street that goes from intersection to intersection, which allows data to be aggregated to very small spatial contexts. The emphasis on small geographic units of analysis started with Sherman, Buerger, and Gartin's (1989) classic study of crime concentration that found 5% of the addresses in the city of Minneapolis accounted for 50% of the crime calls to the police. Similarly, Pierce, Spaar, and Briggs (1998) found that 3.6% of addresses in the city of Boston accounted for 50% of the crime calls to police. Following Sherman et al., later studies confirmed their results, using different methodologies and locations, showing similar levels of crime concentration in urban environments (Pierce et al., 1998; Weisburd 1992).

A key concern raised in recent criminological studies is the measurement of crime concentration for the law. For example, the use of cumulative percentages to measure crime concentration is problematic, because concentration values are inflated when there are fewer crime incidents than geographic units (Bernasco & Steenbeek, 2017; Mohler, Brantingham, Carter, & Short, 2018). Bernasco and Steenbeek (2017) address the limitations of cumulative percentages by arguing that the wording of the law should be changed to *"for a defined measure of crime at a specific micro-geographic unit, the observed concentration of crime, relative to its concentration under maximally possible* *dispersion, will fall within a narrow bandwidth of percentages for a defined cumulative percentage of crime"* (p. 464). The methods used in Bernasco and Steenbeek's (2017) study suggests that their measurement approach and definition changes the law to account for the impossibility of perfect dispersion.[1] This key amendment suggests that future analysis of crime concentration should use a method that takes into account maximal dispersion. In their study, Bernasco and Steenbeek (2017), use the generalized Gini coefficient to account for this issue of maximal dispersion.[2]

Only a couple of studies exploring crime concentration anaylzed the law with data from mulitple cities (Weisburd, 2015; Hipp & Kim, 2017). Most studies have focused on cirme concentration in a single city, which does not provide answers to questions about the variability of crime concentration in different environments (Levin, Rosenfeld, & Deckard, 2017; Carter, Mohler, & Ray, 2019; Braga, Hureau, & Papachristos, 2011). In contrast, this study is unique because it measures crime concentration across a random sample of cities. For the purpose of testing the law in smaller cities, to see if the law is consistent when measured outside of major cities.

Currently, there are unanswered questions surrounding the law of crime concentration. Questions regarding this study are: (1) what is the average Gini coefficient in midsized cities, (2) what are the confidence intervals for the mean Gini coefficient, (3) oes the generalized Gini coefficient vary by crime type, and (4) does the generalized Gini coefficient vary across cities? Hipp and Kim (2017) argue that assessment of crime concentration has challenges in terms of the variability expected to be observed, how

[1] Perfect dispersion is when all street segment in a city have the exact same number of crimes.
[2] Maximal dispersion is the maximum level of concentration possible given the ratio of crime to street segments. This replaces the line of perfect equality used to calculate Gini coefficients.

concentration should be measured, and assumptions when measuring high crime locations. Favarin (2018) mentions that knowledge on the determinants of crime concentration is lacking, especially in Europe, where Favarin's study was based.

This study follows the work of Bernasco and Steenbeek (2017) and Weisburd (2015), studies of crime concentration. The purpose of this study is to: (1) measure crime concentration across a random sample of mid-sized cities, (2) estimate the expected Gini coefficient in mid-sized cities, and (3) analyze the variation in crime concentration across mid-sized cities.

Literature Review

Environmental Criminology

Environmental criminology, as defined by Andresen (2014), is an "umbrella term [..] used to describe a number of theoretical frameworks: routine activity theory, the geometric theory of crime, rational choice theory, and pattern theory." The occurrence of crime by time and place is most prevalent in places where there are opportunities and a lack of social control (Brantingham & Brantingham, 1995). In environmental criminology, crime is explained by the coincidence of environmental conditions that facilitate and enable offenders and victims/targets to converge in time and space (Wortley & Townsley, 2016). Seeking to explain why some environments are more criminogenic than others, environmental criminology demonstrates that crime will concentrate around places that provide opportunities and lack social control (Wortley & Townsley, 2016).

The upshot of environmental criminology is crime prevention through experimental design (CPTED), which says that "the proper design and effective use of the built environment can lead to a reduction in the fear and incidence of crime" (Crowe, 2000). CPTED's focuses on conditions of the physical and social environment and the opportunities provided by these conditions (Cozens, Saville, & Hillier, 2005). CPTED is used as a way to modify environments to reduce the opportunities for crime (Cozens et al., 2005). Matthews, Yang, Hayslett, and Ruback (2010) find that the spatial structure played a significant part in property crimes in their study in Seattle. Using methods of "exploratory spatial data analysis" tools they showed that there was spatial clustering of property crime, suggesting that the built environment significantly affects crime (Matthews et al., 2010).

The Law of Crime Concentration

The literature on crime and place has been growing since the late 1980s and was recently reinvigorated by Weisburd et al.'s (2012) longitudinal study of crime and place in Seattle (Sampson, Gartin, and Buerger, 1989; Weisburd and Green, 1994). The crime and place perspective moves the focus away from traditional theories of individuals toward theories that focus on explaining crime concentration (Weisburd, 2015).

A central question that environmental criminology attempts to answer is how much crime concentration exists (Hipp & Kim, 2017; Sherman et al., 1989). Traditionally, criminology has focused on units of analyses like states, counties, zip codes, and neighborhoods, but recent research moved the focus to smaller units of analysis. Sherman, Buerger, and Gartin's (1989) study in Minneapolis showed that about 50% of the police calls for service made occurred at only 3-7% of the addresses. Following Sherman et al. (1989) Weisburd's et al. study found comparable results in Seattle, showing that about 60% of call occurred on 5% of the street segments. These studies support the emphasis on small spatial units of analyses as a key focus of studies exploring the association between crime and place.

The law of crime concentration posits that a small percentage of places can account for a majority of crime (Farrell, 2015). Instead of focusing on smaller geographic units of analysis, most studies have focused on using neighborhoods and census tracts to study crime concentration (Weisburd 2015; Weisburd, Bushway, Lum, and Yang, 2004). The law of crime concentration suggests that by using microgeographic units of analysis, the range of percentages for crime in an area would be extremely narrow (Weisburd, 2015). The use of smaller spatial units helps criminologists to understand the relationship between the crime and the elements surrounding the occurrence of the crime (McCord, Ratcliffe, Garcia, & Taylor, 2007). The importance of studying crime at lower geographic levels comes from the opportunity theories presented in criminology, and the sense that the convergence of criminals and the opportunities for crime happen in specific spaces (Weisburd et al., 2012).

In a twenty-nine-year period studying robberies in Boston, Braga et al. (2011) found robberies were concentrated at intersections and street segments. The study found that 8% of street segments and intersections in Boston account for 50% of reported robberies in the city of Boston. This trend of cumulative percentages is found in many more studies throughout crime and place literature (Weisburd, 2015; Sherman, 1989). These hot spots of crime are at microgeographic units, enforcing the growing idea that most of the crime is happening in smaller and more concentrated areas, as opposed to the crime being spread out throughout an area.

Studying the spatial concentration of crime through longitudinal studies, answers one question posed by Weisburd's (2015) study of if the concentration of crime is stable over time. Gill, Wooditch, and Weisburd (2017) found that over a period of 14 years, crime in Brooklyn Park, a suburban city in Minnesota, had high concentrations of crime. Specifically, these findings showed that 2% of street segments produced 50% of the crime (Gill et al., 2017). Similar to Weisburd's (2015) study, Levin et al. (2017) found support for crime concentration. They analyzed crime in St. Louis between 2000 and 2014 and found that more than 40% of street segments did not experience violent crime during this period (Levin et al., 2017). Carter et al. (2019) analyze the concentration of opioid deaths in Indianapolis and find support for the spatial concentration of these deaths. They find that 5% of places account for more than 50% of any opioid death (Carter et al., 2019). O'Brien (2018) used requests for government services in the city of Boston and found support for this concentration at addresses, streets, and census-tracts.

General environmental cues will show much diversity in the type of crime that will occur in an area (Brantingham, 2016). However, very specific environmental cues do not show much diversity in the types of crime generated at that place (Brantingham, 2016). Meaning, general cues allow for any crime to be possible and specific cues only allow for a few types of crime to be possible. Compared with smaller geographic spatial units, this relationship suggests that larger geographic spatial units should have more diversity of crime than smaller units (Bernasco & Block, 2011). Studies have demonstrated that a micro-level focus shows a higher percentage in crime variability at the street segment level (Jones & Pridemore, 2018; Steenbeek & Weisburd, 2016). Steenbeek and Weisburd (2016) collected police data on crime events during a 9-year period and credited 58-69%

of the variability of crime to street segments. Andresen and Malleson (2011) use a spatial point pattern test and find that when using smaller scales of analysis, significant variations are revealed. More specifically, their findings found that street segments accounted for 50% of all crime (Andresen & Malleson, 2011).

Several measurement approaches to the law of crime concentration have been introduced; however, there has not been an agreed-upon measure (Weisburd, 2015; Bernasco & Steenbeek, 2017; O'Brien, 2018; Hipp & Kim, 2018; Favarin, 2019). Weisburd's (2015) method uses the percentages of street segments and the percentages of crimes to analyze the crime concentration. O'Brien (2018) introduces the use of nested Gini coefficients to analyze the average level of concentration. Mohler, Brantingham, Cart, and Short (2019) attempted to reduce bias estimates by using negative binomial regression to compute the concentration statistic. Mohler et al. (2019) use a Poisson—Gamma coefficient to reduce the bias when there are zero-inflated counts, meaning there are zero crimes on a street segment. Most importantly for this study, the work of Bernasco and Steenbeek (2017) similarly measure crime concentration by using the method of the Gini coefficient to analyze the law of crime concentration. Their study found that using the generalized Gini coefficient, concentration was around .70 when using microgeographic units of analysis (Bernasco & Steenbeek, 2017).

Crime and Place Studies

Geography and spatial methodologies are becoming popular in many academic disciplines. Geographers studying crime often lean toward finding the causes of crime instead of controlling for crime (LeBeau & Leitner, 2011). Instead of specific crime-prevention, geographers often study why environments are more conducive to crime.

When studying communities, criminologists focus on explaining why certain communities experience more crime, or why certain crime types (i.e., violent, property) happen in specific communities (Braga & Weisburd, 2010). Place and its importance is still a variable often overlooked and not stressed by crime prevention theorists (Braga & Weisburd, 2010). Combining geography and criminology helps communities and police by addressing problems in criminal activity (LeBeau & Leitner, 2011). For example, Schmid (1960) analyzed the number of crimes and determined other social variables (e.g., low family and economic status, race, population mobility) that cause crime in communities. This study also stressed the importance of these aspects and their relation to specific areas within a larger area (Schmid, 1960).

Emerging in the 70s, theorists began to analyze why crime happens where it does (Alber, Adams, & Gould, 1971; Rose, 1978; Sherman, Gartin, & Buerger, 1989; Georges-Abeyie & Harries, 1980). They noted that crime depends on criminals and targets meeting at the same place and time (Davies & Johnson, 2015). This event occurs during normal or routine activities, when there is not a capable guardian present, forming the importance of routine activities theory in crime and place literature. Additional theorists focused on how the environment provides opportunities for crime (Timmermans 1990; Gold 1980).

Little research has been focused on environmental conditions and if environments produce general crimes or specific types of crime (Lentz, 2018). The environment can also help to explain what types of crime that could occur at a specific place (Lentz, 2018). (Brantingham, 2016; Lentz, 2018). After reexamining the results from Brantingham’s (2016) study, Lentz’s (2018) found that studying specific crime types provides stronger evidence for environmental contributions to crime than by looking at crime alone. When looking at macro and micro geographic areas, it should hold true that the larger areas will have more diverse crime types, while the smaller geographic areas should not have as much diversity (Brantingham, 2016). When looking at crime diversity, crime richness can be used to count how many unique crime types there are in the sample being looked at (Brantingham, 2016). Crime evenness is described where each crime type has an equal number of incidents associated with the specific crime type (Brantingham, 2016).

Taylor (1998) reinforces what can be learned from emphasizing place in criminological studies. Taylor’s (1998) research implies that place-based studies and viewpoints may help police succeed in crime prevention. Taken from geography, a “cone of resolution” may be used for crime rates, describing how they vary down the cone, while using smaller units of analysis (Taylor, 1998; Brantingham, Delmar, & Brantingham; 1976). According to Taylor (1998), the relationship between crime and place has been strengthened by: growing frustration, well-supported theories, and better tools. However, Taylor (1998) points out that without knowing exactly where and when crime may occur, this knowledge is not extremely effective, hence the frustration. The main tool in crime and place studies used is the development and increased use in geographic information systems and software (Taylor, 1998). Finally, the crime and place literature has grown tremendously, with numerous studies on geography and crime (Sherman, 1989; Weisburd, 2015; Weisburd, Groff, & Yang, 2012; Bernasco & Steenbeek, 2017). Crime was eventually believed to be linked to certain places based on the characteristics of places, the opportunities places may provide, environmental criminology, and social disorganization (Sampson, 2014; Weisburd et al., 2012; Davies

& Johnson, 2015; Bernasco & Block, 2011; Wortley & Townsley, 2016; Groff & Lockwood, 2014).

Theoretical Background

The theoretical framework for this study is largely based on the theories within environmental criminology. Environmental criminology focuses on the settings of where crime occurs, and the characteristics of those settings. The theories encompassed by environmental criminology are necessary to explain the spatial concentration of crime, by identifying the environmental factors that create criminal opportunities. In total, there are six theories necessary to mention that explain crime concentration, why areas are criminogenic, and criminal opportunities. This study does not test these theories, but specifically uses the theory to strengthen spatial analysis of crime.

Routine Activities Theory

Routine activities theory (RAT) posits that criminal opportunity is composed of three factors: motivated offenders, suitable targets, and the lack of capable guardians (Cohen & Felson, 1979; Wilcox, Madensen, & Tillyer, 2007). While originally proposed as a form of rational choice theory, RAT has evolved to emphasize the role of place and time in producing interactions between offenders, the target, and guardians (Ratcliffe, 2006). Though the presence of targets, offenders, and the lack of guardianship is essential to the core of RAT, accounting for what factors cause their paths to cross is equally important (Sherman, 1989).

The essence of offending is in the opportunities for crime in the routine activities of life (Ratcliffe, 2015). These criminal opportunities stem from a lack of guardianship and the presence of crime generators (i.e., bars, gas stations), which create environments where certain crime types consistently recur (Ratcliffe, 2015). Opportunities for crime are not evenly distributed across geographic space, as it has been shown that crime clusters (Weisburd, Groff, & Yang, 2012; Ratcliffe, 2006). Hawley (1950) introduced the space-time concepts of rhythm, tempo, and timing. Rhythm is how regularly events occur, tempo is the number of events per the time, and timing is the synchronization of these events (Hawley, 1950). Events occur at specific places and these events, along with the three components proposed by Hawley (1950), are essential to spatio-temporal necessities of crime (Cohen & Felson, 2016). Without the concurrence of these events, offenders and targets would not cross paths and crime would not occur (Cohen & Felson, 2016). RAT focuses on the changes of an environment from moment to moment, instead of assuming an offender's motives (Clarke, 1997).

Davies and Johnson (2015) point out that urban street networks provide the necessary context for offenders and victims to meet one another. Both criminals and non-criminals move throughout space, and the street network serves as the main pathway for this movement, which increases the probability of interaction (Davies & Johnson, 2015; Groff, 2008). In St. Jean's (2008) ethnographic study, what is called "pockets of crime" (e.g., hot spots) were said to be at micro places such as bars and pawn shops, because these places bring people who may have cash and could be targeted for crime, demonstrating how offenders and targets may cross paths to provide the opportunity for crime.

RAT compliments other criminological theories by stressing no crime can occur without opportunity, even with the element of the motivated offender (Cullen, Agnew, & Wilcox, 2018). Developing after World War II, Cohen and Felson (1979) attempted to explain the increase in crime through the development of RAT. Not in the sense of looking at the individual, but explaining how the spatiotemporal organization of activities helps crime to occur (Cohen & Felson, 1979). Brantingham and Brantingham (1981), with the development of environmental criminology, contributed the idea that offenders do not commit criminal acts at random. Instead, they proposed that offenders search for criminal opportunities within the geographic space offenders carry out their routine activities (e.g., their schools, workplaces, shopping places) (Brantingham & Brantingham, 1981). RAT falls short of explaining what makes a geographic location a good opportunity, which lead to the importance of crime pattern theory.

Crime Pattern Theory

Crime pattern theory focuses on the crime event, which explains the convergence of offenders, a target, and opportunity in space and time (Brantingham & Brantingham, 2013). Offenders will typically choose an area close by to operate in, because of its familiarity (Brantingham & Brantingham, 1981). These interactions influence crime over time and space, and this happens because offenders engage in routine activities (Eck & Weisburd, 2015). Cornish and Clarke (1986) argue that crime does not happen by pure coincidence, and that there is an intent on the criminals' behalf to commit an act. The importance of focusing on the clusters of crime as a necessity to reduce victimization is stressed by this (Farrell & Sousa, 2001). Crime generators are areas that can attract many people, such as retail stores or entertainment facilities (Kinney, Brantingham, Wuschke, & Brantingham, 2008). Crime attractors are areas known to already produce a lot of crime, or areas that are well-suited for crime (Bernasco & Block, 2011).

Crime pattern theory is composed of edges, nodes, and paths (Brantingham & Brantingham, 1995). Edges are the boundaries that separate the distinct differences of places (Brantingham, Brantingham, Vajihollahi, & Wuschke, 2009). From edges, there are nodes, which are places that offenders go to in their daily lives that draw many people (Kinney et al., 2008). Offenders typically engage in criminal opportunities in areas they are familiar with. This, in turn, makes non-offenders frequent places (i.e., school, work, or home) that are the areas they are often victimized (Brantingham & Brantingham, 1995). Crime attractors are developed from the clustering of nodes, while the paths people take in their daily lives back and forth from their nodes help to solidify their routines in how they travel back and forth from their nodes (Brantingham & Brantingham, 1995). The paths that people take come together with nodes, the places people frequent, to better predict the patterns of crime and victimization (McCord et al., 2007). Crime pattern theory combines rational choice theory and RAT together in a way that contributes to the understanding of crime concentration (Eck & Weisburd, 2015).

A study by Bernasco (2010) showed that offenders target areas they either currently live in or have previously lived near, since these areas are more familiar. Similarly, Bernasco and Block (2009) found that crime generators and crime attractors (e.g., places with drug activity) as well as retail businesses, make areas appealing to offenders. Other studies on crime pattern theory find similar results of offenders committing crimes close to their home (Townsley & Sidebottom, 2010).

Crime pattern theory stresses the importance of locations and how and why these locations are chosen by offenders (Eck & Weisburd, 2015). Crime pattern theory assumes that crime, criminal events, and criminal opportunities are structured (Cullen et al., 2018).

Routine activities are tied to around activity nodes, which are determined by the built environment, causing the nodes and paths of people to be similar (Cullen et al., 2018). Crime generators and crime attractors both become hot spots of crime, because they are either known for crime or they are locations that attract many people (e.g., crime generators) (Brantingham & Brantingham, 1995).

Situational Crime Prevention

Situational crime prevention (SCP) focuses on the nature of an environment and its conductivity for criminal acts to occur (Clarke, 1997). This theory focuses on the settings where crime happens and seeks to make the crime look risky, unappealing, or not rewarding (Clarke, 1997). As an environment changes, assessments are made by offenders about the benefits and risks of committing a crime (Clarke, 1997).

This theoretical perspective furthers the importance of looking at more situational factors of crime (Clarke, 1983). Considering that motivated offenders, lack of capable guardians, and a suitable target are the three key elements needed for a crime to occur, the capability of the guardian to deter crime is essential to the situational crime prevention model (Clarke, 1997). Situational crime prevention factors into the physical environment and how this is essentially favorable to crime (Clarke, 1997). The concept of defensible space, originally posed by Oscar Newman (1972), describes how architectural structure, like fences and walls provide a barrier in environments. This idea led to the hypothesis that housing without such barriers could provide more social opportunities, which could lessen criminal opportunities (Newman & Franck, 1982). Some studies have shown that a reduction in crime and an increase in social control and cohesion have been related to defensible space and crime (Perkins, Wandersman, Rich, & Taylor, 1993).

In a study on crime in bars, Graham (2009) found that having sufficient staff, intervention to reduce intoxication, and knowledge of potential aggression, can help reduce violence and crime at these establishments. For example, Graham (2009) notes that treating aggression as unacceptable and having staff and clear policies to increase the risk of being caught and/or punished, can make crime feel less rewarding. Another study found that with the use of video surveillance, crime was reduced by 13% in target areas (Ratcliffe, Taniguchi, & Taylor, 2009). This made the crime seem too risky, by implying there was an increased risk in the potential to be caught for crimes (Ratcliffe et al., 2009). Huisman and Erp (2013) found that SCP helps explain environmental crime when offenses do not take much effort and when the risk of being caught is low. In those cases, rationalizing criminal activity is easy. Their study from the Netherlands of 23 criminal investigations showed that most environmental crimes are crimes of omission, meaning crimes of doing nothing (Huisman & Erp, 2013). Farrington and Welsh (2002) studied the effects of street lighting on crime, and found four studies that showed a decrease in crime in areas with improved street lighting. Shane, Piza, and Mandala (2015) used SCP to compare successful and unsuccessful piracy attacks. Their results showed that there was an association with unsuccessful piracy attacks on a global level when SCP techniques (i.e., measures of increased risk and effort) were instilled (Shane et al., 2015).

Environmental data (i.e., roads or land use) and environmental characteristics can aid in understanding an area known for crime, as well as preventing crime (Andresen & Jenion, 2008). This knowledge can be used for primary prevention, secondary prevention, and tertiary prevention to reduce criminal opportunity. Primary prevention is the alteration of the physical environment, secondary prevention assesses the risk of an environment for becoming hot spots, and tertiary prevention identifies where crime prevention efforts should happen (Andresen & Jenion, 2008).

Systemic Model of Social Disorganization

Social disorganization theory posits three main foundational factors for a crime: low economic status, residential mobility, and ethnic heterogeneity (Sampson & Groves, 1989). These structural characteristics inhibit a neighborhood from maintaining informal social control (i.e., neighborhood watches) (Sampson & Groves, 1989). Sampson, Raudenbush, and Earls (1997) based their research on uncovering why poor structural characteristics in neighborhoods caused crime to occur. This research implicated the inability of a neighborhood maintaining social control as a main contributor to offenders committing crime (Sampson et al., 1997). Without these social control, the people who inhabit neighborhoods become less likely to be capable guardians and are not able to establish control over the behavior of the local population (Shaw & McKay, 1942). A lack of cohesion in neighborhoods is what causes the stability of neighborhoods to disappear (Fagan, 1987).

Sampson et al. (1997) argues that a lack of collective efficacy in a neighborhood not only causes violence but leads to the variation in violence in a neighborhood. Collective efficacy connects social ties and social control (Kubrin & Weitzer, 2003). Sampson (1986) defines collective efficacy as “the process of activating or converting social ties among neighborhood residents to achieve collective goals, such as public order or the control of crime.” Social control can also be applied to issues of well-being within neighborhoods (Sampson et al., 1997).

Researchers have argued that racial segregation leads to a concentration of black poverty and that racial segregation continues across educational and economic levels (Massey & Eggers, 1990). Studies on concentrated disadvantage mostly focuses on economic disadvantage and racial exclusion (Sampson, Morenoff, & Earls, 1999). Income, education, and race are not evenly distributed across neighborhoods (Sampson et al., 1999). Weisburd's et al. (2015) study argues for police efforts to increase collective efficacy in crime hot spots to reduce crime. Furthering the importance of micro-units, St. Jean (2008) tested collective efficacy and broken windows theory and found that the concentration of crime does not usually go beyond a street segment. Sampson's et al. (1997) study tested collective efficacy in neighborhoods in Chicago, Illinois, showing that concentrated disadvantage and residential instability associated with violence can be lessened with collective efficacy.

Fagan's (1997) study showed that the main problem in neighborhood disorganization was a lack of social services for the residents, which lead to these areas being overall worse economically. Low socioeconomic status contributes to the weakening of social cohesion and control in neighborhoods (Steenbeek & Hipp, 2011). The weaknesses of neighborhoods with low socioeconomic status and lack of social cohesion are known to experience higher levels of crime and disorder (Steenbeek & Hipp, 2011). Shaw and McKay's (1942) findings from neighborhoods in Chicago led to the conclusion that the environmental conditions of a neighborhood are essential to the crime rates, even over the characteristics of the residents. This finding gave roots to social disorganization theory and helped advance this theory forward (Kubrin & Weitzer, 2003). Cancino, Martinez, and Stowell's (2009) study analyzed tract-level data to understand how social structure influences crime, and mainly found support for social disorganization. Hipp (2010) analyzed the structural characteristics of neighborhoods and crime, finding that crime increased residential instability, had more impoverished residents, and more heterogeneity than neighborhoods without as much crime. Weisburd et al. (2012) studied social disorganization on the street segment level be using a variety of measures for the city of Seattle (e.g., registered voters, property values, distance from the city center, etc.). Both studies demonstrated the concentration of social disorganization geographically, and they showed crime's effects on neighborhoods. The focus of social disorganization at micro geographic units has reinvigorated the focus on the integration of routine activities theory and social disorganization.

Integration of Routine Activities and Social Disorganization

RAT and social disorganization theory are the most common theories used to explain geographic variability in crime. Spatial factors demonstrate the role that geographic location plays in the chances of criminal activity occurring, such as the neighborhood and its characteristics (Smith, Frazee, & Davison, 2000). Criminologists believe that the integration of RAT and social disorganization theory may strengthen knowledge on crime and the use of spatial analysis in crime analysis (Smith et al., 2000; Miethe & Meier, 1990; Miethe & McDowall, 1993; Jones & Pridemore, 2018).

The integration of these theories comes from the interactions of the three elements of RAT and the type of neighborhood (Smith et al., 2000). Acknowledgment of this overlap in key assumptions and concepts has led environmental criminologists to propose theoretical integration between the two theories (Jones & Pridemore, 2018; Rountree, Land, & Miethe, 1994; Rice & Smith, 2002; Smith et al., 2000; Weisburd et al., 2012;

Wilcox, Land, & Hunt, 2003). Researchers have argued integrating routine activities theory and social disorganization theory will provide a richer understanding of crime concentration. The three main components of RAT (suitable target, lack of a capable guardian, and a motivated offender) may be largely reliant on the occurrence of these mechanisms regarding their social contexts (Rice & Smith, 2002). Wilcox, Land, and Hunt (2003) provide a model for the integration of these two theories, and Jones and Pridemore (2018), adopt this model and modify it to improve the explanation of crime concentration.

To integrate these theories together, relating aspects from one and explain how these aspects are dependent on the aspects of the other theory is important (Smith et al., 2000). Smith et al. (2000) says that the individual aspects from routine activities theory may change depending on how a neighborhood changes, which comes from social disorganization theory. Wilcox's et al. (2003) study primarily focuses on the risk of victimization in a neighborhood context, while the Jones and Pridemore (2018) model combines social disorganization and criminal opportunity into one model to specifically explain spatial variability in crime. Wilcox's et al. (2010) approach did not use social disorganization at the micro-level, since this model approach focused on individuals, and not solely on places. However, Jones and Pridemore's (2018) findings support both Weisburd et al.'s (2012) approach and Wilcox's et al. (2003) approach. Moreover, Jones and Pridemore (2018) find support for the impact of micro-level analysis of crime on street segments is greater than of a macro approach. This provides an important result for research that focuses on micro geographic units of analysis for criminological research (Steenbeek & Weisburd, 2016).

Smith's et al. (2000) study focused on the integration of routine activities and social disorganization by measuring opportunity and informal social control on face blocks. Smith, Frazee, and Davison (2000) find interaction effects between variables used in social disorganization and RAT, providing a path for future research to integrate the two. Weisburd et al. (2012) studied crime at the street-segment level and found support for social disorganization and routine activities operating at this micro-geographic level. Both Smith's et al. (2000) study and Weisburd's et al. (2012) study proposed single level models, and Wilcox's et al. (2003) study and Jones and Pridemore's (2018) study used multilevel models for this theory integration.

Miethe and Meier (1994) recognize the limitations of RAT and create a model for integrated theory to explain offender motivation and the opportunities for crime. Criminologists suggest that opportunity theories and social disorganization theory be integrated to study crime at the place (Wilcox et al., 2007; Jones & Pridemore, 2018). Weisburd et al. (2012) suggest that if street segments are considered a "micro-community," then social disorganization would be beneficial to the criminology of place.

Summation of the Theoretical Background

The introduction of the law of crime concentration was produced after years of studies showing that crime is concentrated at only a few places within cities (Weisburd, 2015; Weisburd, 2018; Weisburd et al., 2012). Research stemming from analyzing crime concentration demonstrates that hot spots of crime should be the focus of police efforts (Weisburd, 2018). Crime concentration results are strengthened when specific crime types are analyzed, instead of crime as a whole (Sherman et al., 1989; O'Brien, 2018; Pierce et al., 1988).

The crime and place literature stems from environmental criminology, which encompasses routine activities theory and crime pattern theory (Andresen, 2014). The opportunities for crime stem from the convergence of paths between offenders and targets (Ratcliffe, 2015). Situational crime prevention factors in the environment, specifically guardianship, and its conductivity of crime (Clarke, 1997). Social disorganization plays its role in the crime and place literature through the study of neighborhoods and crime at the street segment level (Groff & Lockwood, 2014). The integration of RAT and social disorganization stems from limitations of criminological theories and helps to explain opportunities for crime to strengthen place-based criminology.

Research Questions

The current study focuses on exploring the law of crime concentration, by measuring the concentration of crime across a random sample of mid-sized cities. The purpose of this is to estimate the population mean for mid-size cities and to determine whether there is a significant variation in crime concentration across the cities. This is not done by testing theory, but by measuring crime concentration, so that future studies have a baseline to compare the results to. The goal of this study is to define unknown parameters of crime concentration, as well as provide evidence for the law of crime concentration**.** This study seeks to determine the mean Gini coefficients will be in all cities, what the confidence intervals are for the Gini coefficients, and if the mean and confidence intervals will vary by crime types.

This study looks at crime types as a whole (i.e., property crime and violent crime combined) and crime types separately to be able to answer if these measurement techniques will differ when looking at all crimes and when looking at individual crime types. If specific crime types do not follow similar levels of concentration, then those results could imply that the parameters for crime concentration are different by crime type. The expectations of this study are as follows:

Question 1: What is the average Gini coefficient in midsized cities?

Since this study is an exploratory study, the study estimates the mean and standard error of crime concentration to be used in future studies. The gaps in Weisburd's (2015) study did not answer many questions regarding the standardization of crime concentration. This study, following Bernasco and Steenbeek (2017), hopes to be able to fill these gaps and gain a deeper understanding of the estimations of crime concentration. Using a generalized Gini coefficient helps to produce a more useful number for measuring crime concentration because it allows for the comparison of multiple types of crime and areas (Bernasco & Steenbeek, 2017). A Gini coefficient of 1 would mean complete crime concentration, while a value of 0 would mean complete lack of concentration. In short, this means that values closer to 1 imply higher levels of crime concentration and values closer to 0 imply less crime concentration. Using midsized cities is important as most studies in the crime and place literature does not focus on smaller cities (Weisburd 2015; Bernasco & Steenbeek, 2017; Bernasco & Block, 2009; Braga, Hureau, & Papachristos, 2011).

Question 2: What are the confidence intervals for the mean Gini coefficient?

After the Gini coefficients were found, the confidence interval associated with these coefficients were also analyzed to see if these intervals were small ranges. By doing this, it can be shown whether the Gini coefficients can be consistent across all areas and all cities, and that they will fall within a narrow confidence interval. A narrow confidence interval will help to bring more assurance to the validity of the law of crime concentration.

Question 3: Does the generalized Gini coefficient vary by crime type?

The range statistic for the generalized Gini coefficients reveals that the bandwidth of concentration is wider than what would be tolerated by the broader scientific community and violates both Weisburd’s (2015) and Bernasco and Steenbeek’s (2017) definition of the law of crime concentration. Being able to use these results as generalizable across all cities is important. Doing this will help to enrich the law of crime concentration and help to provide a standardized way of measuring crime concentration. The overarching goal of this study is to be able to use this method of measurement and apply it to all cities and expect that the results are similar.

Question 4: Does the generalized Gini coefficient vary across cities?

Hipp and Kim (2017) measure crime concentration across cities and seek to answer the question: does crime concentration vary over cities? In their study, Hipp and Kim (2017) mention a few challenges in answering this: (1) the bandwidth for the level of crime is not specified or agreed upon as to how similar it should be across cities, (2) by random chance there will be an amount of crime concentration, (3) should crime concentration be compared across cities of different sizes or not, and (4) how should the concentration of crime be measured. These are issues that studies have sought to answer in recent years (Weisburd, 2015; Bernasco & Steenbeek, 2017; Lentz, 2018). Hipp and Kim’s (2017) results raised more questions on if crime concentration should be similar across a range of cities. They found that certain cities consistently had high concentrations of crime, and others consistently had low concentrations of crime (Hipp & Kim, 2017).

Data

Sample

This study includes a sample of 21 randomly selected midsized cities. The cities came from a Census-designated places file, containing a list of counties. Using Excel, a random number was assigned to each county. Then, the numbers were sorted and the first 21 were chosen. The cities were selected from the county seat of the random sample created in Excel. A midsized city is based on a population of at least 50,000 people, but less than 250,000. This size of city is often overlooked in spatial research, because of the attention put on larger populations in cities.

Unit of Analysis

The unit of analysis for this study begins on a microgeographic level at the street segment. Then, a single value (Gini coefficient) is produced for each city representing its degree of crime concentration at the street segment level. The final analysis shifts the unit of analysis to the city level, where the mean, confidence intervals, and range of the Gini coefficients are compared across the cities. Table 1 shows all of the cities and their populations in the sample.

Crime Data

The crime data were requested from the cities' police departments and consisted of: (1) latitude and longitude coordinates, (2) addresses, (3) crime type, and (4) the incident description. This cross-sectional study uses data from the year 2016. The crime data were requested either by emailing the police department directly, or submitting a freedom of information request, depending on the rules of the police department. Most of the cities were contacted via email, where a formal letter was sent. If there was not an email to send this letter to, a public records request was submitted containing the contents for this email. A couple of the cities had portals where requests could be submitted, and when answered, the data were uploaded online. One city (Asheville) had an open data portal, where the needed information was downloaded and cleaned from there. Table 1 shows all of the cities and their populations in the sample.

Table 1: Cities and Population

City	State	Population
Albany	New York	98,111
Asheville	North Carolina	89,121
Beaumont	Texas	118,296
Boulder	Colorado	101,125
Ellicott	Maryland	65,834
Elyria	Ohio	53,715
Erie	Pennsylvania	101,786
Fayetteville	North Carolina	204,759
Fort Collins	Colorado	164,207
Gainesville	Florida	131, 591
Galveston	Texas	50,550
Green Bay	Wisconsin	105,139
Kalamazoo	Michigan	75,984
Merced	California	82,594
Murfreesboro	Tennessee	108,755
Norman	Oklahoma	122,180
Olympia	Washington	51,609
Portland	Maine	66,937
Richmond	Virginia	220,289
Savannah	Georgia	146,763
Tallahassee	Florida	101,735

For the purposes of this study, violent crime, property crime, and all crime types will be factored into the results. This way, the consistency across the three types can be measured. The distinctions of violent crime and property crime come from the Uniform Crime Report, developed by the Federal Bureau of Investigation. The type of crime is being requested as data from the 21 cities, and the measures of violent crime and property crime will be used to fit the crime types in their respective categories. The only crimes that are included in the crime counts are the ones that fall under either violent or property crime, the other crimes given by the police departments were excluded from this study.

Violent Crime. Violent crime is composed of: murder and manslaughter, robbery, and aggravated assault (UCR, 2016). Rape was excluded from this study because some police departments redacted the addresses due to the sensitivity of this crime, which was a necessary component. Therefore, to be consistent across all cities, all rape was excluded from the analysis.

Property Crime. Property crime includes: burglary, larceny-theft, and motor vehicle theft (UCR, 2016).

All Crime. All crime is operationalized by looking at all types of crime, instead of specific types of crime.

Methods

Geoprocessing

Geoprocessing is used to organize and manipulate the spatial data and used to replicate the analysis procedures of the study. More specifically, the geoprocessing steps in this study are used to select specific cities, select specific streets, geocode the data, and obtain the crime counts for each street segment. Models were created to automate the geoprocessing steps, so that the same rules apply to every city and therefore; the data is treated consistently across each city in the study.

This study uses the geographic information system software package, ArcGIS 10, to run the analyses. All of the shapefiles used in ArcGIS were TIGER files downloaded from the Census Bureau's website (Census Bureau, 2019). These files include: a "places" shapefile and an "all lines" file. These files were then narrowed down to include just the information for the cities in the sample. The crime data were obtained through open data portals or from the police departments directly.

Step 1: City Selection

Before the geoprocessing selection, it is important to note that the cities in this study were randomly sampled. The places file is used to determine the precise geographic boundary for each city included in the study. The Census Bureau defines places as "a concentration of population: a place may or may not have legally prescribed limits, powers functions. This concentration of population must have a name, be locally recognized, and not be part of any other place" (Census Bureau, 2018). The places file is an ideal choice for identifying the geographic boundaries of the cities because police jurisdictions generally correspond to the city-limits identified in the places file. This is advantageous because the data used to measure crime concentration are geographically consistent with the boundaries in the places file, which improves the validity of the measurement of crime concentration. Figure 1 shows a map of an example of what the places file contains, and what needs to be selected.

Figure 1: Map of City Extraction

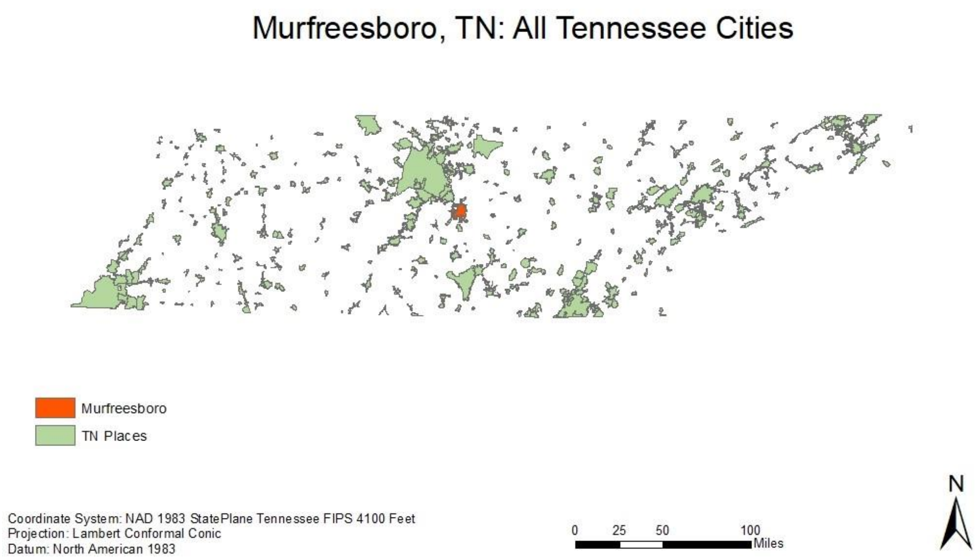


Table 2 shows the projections used for each city. A projection uses the "project" tool in ArcMap to convert the data into the most applicable coordinate system. The coordinate system allows files to be correctly analyzed. Otherwise, an unprojected coordinate system is assigned to each file. Selecting the proper coordinate system, based on the locations of the cities, creates a more standardized and correct way of analyzing spatial data.

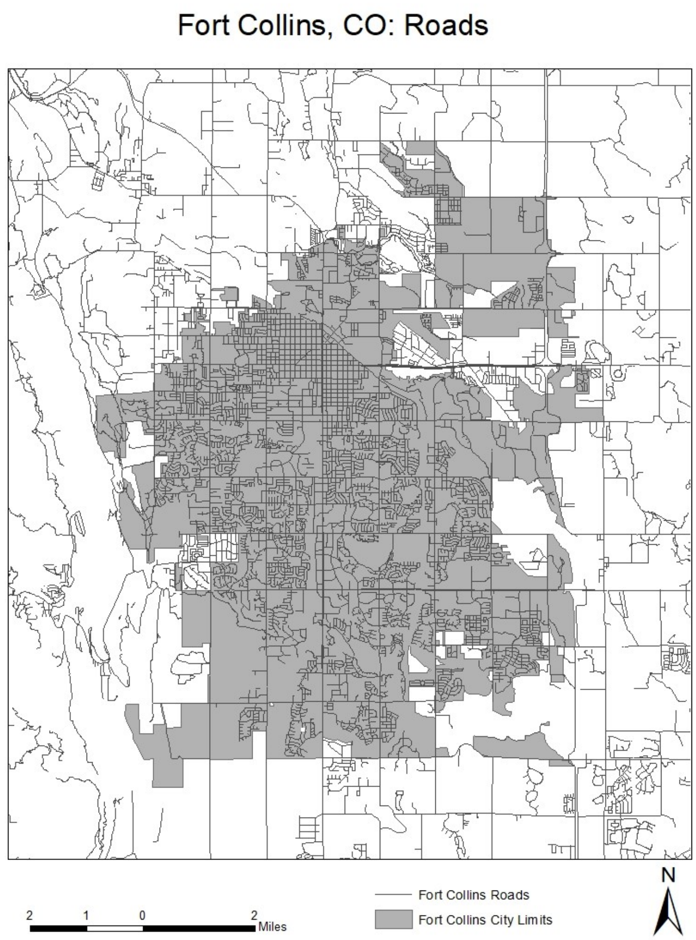
Table 2: List of Cities and Their Projection

City	Projection
Albany	New York East State Plane
Asheville	North Carolina State Plane
Beaumont	Texas South Central State Plane
Boulder	Colorado North
Elyria	Ohio North State Plane
Erie	Pennsylvania North State Plane
Fayetteville	North Carolina State Plane
Fort Collins	Colorado North State Plane
Gainesville	Florida North State Plane
Galveston	Texas South Central State Plane
Green Bay	Wisconsin Central State Plane
Kalamazoo	Michigan South State Plane
Merced	California Zone 3 State Plane
Noblesville	Indiana East State Plane
Norman	Oklahoma South State Plane
Olympia	Washington South State Plane
Portland	Maine West State Plane
Richmond	Virginia South State Plane
Rockford	Illinois West State Plane
Santa Cruz	California Zone 3 State Plane
Savannah	Georgia East State Plane
Tallahassee	Florida North State Plane

Step 2: Street Segment Selection/Clip

The second step in the geoprocessing process was to select the streets within the city limits, and only the road types that were necessary. The data from the Census is an "all lines" file that contains all of the streets for the entire county. Two types of roads were extracted using a feature in ArcMap called "select by attribute." This method selects out only the types of roads needed. These roads are the "MTFCC S1200," which are secondary roads, and the "MTFCC S1400," which are local neighborhood roads, rural roads, and city streets. In ArcMap, a model was designed to extract the necessary road types, as well as the roads within the city limits, this created a new shapefile for the needed roads. The last stage in the model projects these streets in the correct projection for the city that they are in, and this creates the final shapefile for this model that will be used in the study. Figure 2 shows a map of the streets that are outside of the city limits, to display why the streets needed to be clipped.

Figure 2: Map of the Street Segments Outside City Limits



Step 3: Address Locator

Before generating the crime location shapefiles, an address locator needed to be created first. In this model, the projected roads file, containing only the MTFCC codes was used to create an address locator. This file was joined to the address locator tool, which generates a database with addresses on the streets. Figure 3 shows the model built to create the address locator.

Figure 3: Address Locator Model

Step 4: Geocoding Crime Location Points

The address locator from step 3 (“Address_Locator”) was used, along with the Excel spreadsheet (“Crime_Table.csv”) containing the crime data to geocode the crime locations. Geocoding is a way to create actual points (e.g., latitude and longitude coordinates) for the crime locations. This is used to get the crime counts on each street segment (“Geocode_Results”). Figure 4 shows the geocoding model created for this process.

Figure 4: Geocoding Model

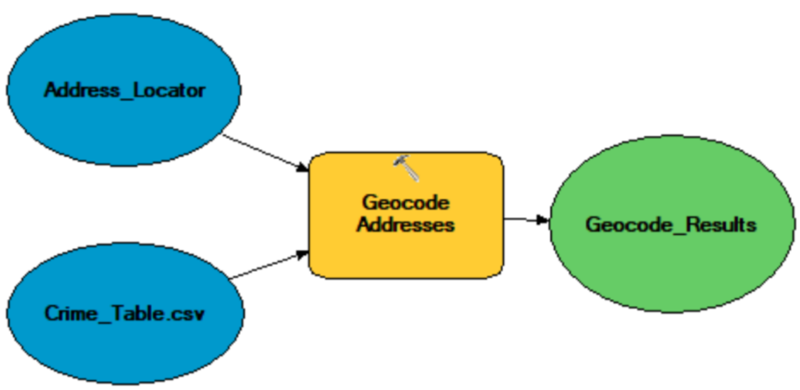


Table 3 shows the results from the geocoding process. ArcGIS assigns a match number, ranging from 0-99, to show how closely the addresses from the data provided by the police departments are to the streets from the Census. To make the addresses usable in ArcGIS, the addresses needed to be cleaned within Excel first. This was done with a few steps: removing all apartment numbers, removing all secondary information (i.e., basement floor, other specific locations), and changing "/" to "&" for intersection addresses. These steps were repeated for each of the cities, to make sure that everything was consistent. The lowest match score and spelling sensitivity were set to 75, to mirror the minimum requirement for the geocode percent match.

Table 3: Geocode Matches for Cities

City	Geocode Match Percent	Match Score
Albany	78	75
Asheville	70	75
Beaumont	67	75
Boulder	88	75
Elyria		75
Erie	86	75
Fayetteville	87	75
Fort Collins	84	75
Gainesville	79	75
Galveston	73	75
Green Bay	94	75
Kalamazoo	90	75
Merced	93	75
Murfreesboro	81	75
Norman	78	75
Olympia	85	75
Portland	93	75
Richmond	95	75
Rockford	92	75
Savannah	76	75
Tallahassee	84	75

Step 5: Crime Data Selection

In the final model, an attribute query was created to include only certain crime types. In Excel, a number was assigned to each of the crime types to put into the query. This was done since not all of the police departments gave the crime types the exact same names. Homicide was coded as “1,” robbery as “3,” aggravated assault as “4,” burglary as “5,” theft as “6,” motor vehicle theft as “7,” and assault as “10.” Then, this model spatially joined the crime points to the street segments, which generates the counts of crime on the segments. The end result of this process is shown by this map in figure 5, displaying the crime counts on the street segments for all crime in Albany, NY.

Figure 5: Final Results: Crime Counts

Crime Data Aggregation

Also in the final model, the aggregations for crime go as follows: violent crime, property crime, and a file was created for all crimes, which includes both violent and property crimes together. In this step, the crime events are being aggregated in each city to the street segment level.

Measures

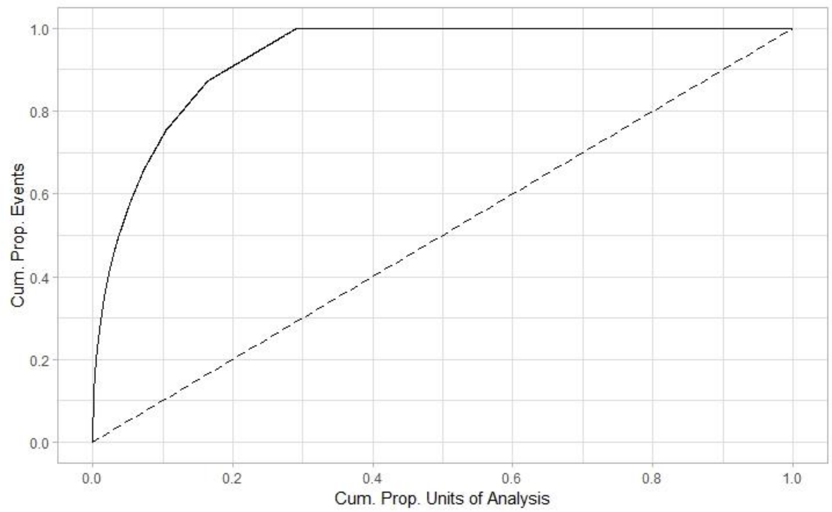
Lorenz Curve. For this study, the Lorenz curve serves as a way to visualize and link the number of crimes and the number of places (Bernasco & Steenbeek, 2017). In the case where the number of places is greater than the number of crimes, the line of perfect equality would never exist (Bernasco & Steenbeek, 2017). Instead of using this, Bernasco and Steenbeek (2017) use the line of maximal equality in place of the line of perfect equality.

The equation for the line of maximal equality is:

$$\frac{n}{\min(c, n)} = \max(\frac{n}{c}, 1)$$

Figure 6 shows the Lorenz curve, which is a way to visualize the percentage of crimes and the percentage of places. The Lorenz curve also visually represents the line of maximal equality, which is what the generalized Gini is based on.

Figure 6: Lorenz Curve Example for Albany, NY



Gini Coefficient and Generalized Gini. Crime concentration is measured using a Gini coefficient, which is a single number ranging from 0 to 1. One Gini coefficient will be produced for violent crime and one for property crime. The concentration of crime will be analyzed by obtaining the Gini coefficient, while the generalized Gini coefficient will be used to account for the crime types that might be sparse, meaning that there are more places than crime.

The equation used for the Gini coefficient is:

$$G = \left(\frac{1}{n}\right) \left(2\sum_{i=1}^{n} iy_i - n - 1\right)$$

The Gini coefficient and the generalized Gini coefficient are similar in definition to one another. This Gini references the line of perfect equality, which for the generalized Gini coefficient, does not exist (Bernasco & Steenbeek, 2017). The generalized Gini coefficient refers to the Gini coefficient, but this equation inflates the concentration of crimes, and the generalized Gini corrects this inflation (Bernasco & Steenbeek, 2017).

The generalized Gini coefficient uses this formula:

$$G' = \max\left(\frac{n}{c}, 1\right)(G - 1) + 1$$

The generalized Gini coefficient factors in the fact that perfect equality is not attainable, meaning that there are an equal number of places and crimes (Bernasco & Steenbeek, 2017). This is achieved by using the line of maximal equality (Bernasco & Steenbeek, 2017).

Poisson—Gamma. The Poisson—Gamma coefficient is similar to the Gini coefficient, and also uses a resampling method to generate the coefficient. Mohler et al. (2019) introduced this method to help reduce the bias from the generalized Gini coefficient, which underestimates the concentration of crime. This method is useful when there is a smaller sample size, implying there are zero-inflated counts (e.g., times when there are zero crimes on a street segment). The Poisson—Gamma coefficient differs from non-parametric approaches by running simulations repeatedly on synthetic data to estimate the level of crime concentration.

Analytic Strategy

Bootstrapping. The method of bootstrapping is a way of resampling with replacement, to see if findings will repeat across other samples (Higgins, 2005). Bootstrapping creates random samples repeatedly to find the estimated mean and confidence intervals for the Gini coefficients (Dixon, Weiner, Mitchell-Olds, & Woodley, 1987). One goal of this study is to answer what the unknown parameters are for the law of crime concentration. The bootstrapping method is typically a good answer to the accuracy of the estimates and results of this study (Efron & Tibshirani, 1986). Through resampling, bootstrapping can help to see if the parameters found will be consistent and repeat across the sample of cities, which will then be used for other studies of the law of crime concentration. This feature is an important component of this study, because if the estimates of the confidence intervals are mean are not as expected, then the law of crime concentration may not be supported by this study's results.

Results

All Crime

RStudio, or simply, R, is a free and open-source statistics software. Most of the programming language for R is written in Java, though some is partly written in C++. RStudio was used to calculate the Gini coefficients, Lorenz curves, and Poisson—Gamma coefficients. Table 4 shows the Gini coefficients for all crime in each city, as well as the total crime counts and total street segments in each city. Overall, there are 154,977 crimes throughout the 21 cities, and 164,306 street segments. The Gini coefficients range from 0.83 to 0.96, while the generalized Gini coefficients range from 0.74-0.96. The larger range for the generalized Gini is largely due to the correction the generalized Gini equation makes. Mohler et al. (2019) similarly found a large range for the generalized Gini coefficients. The Gini neglects when there are more street segments than there are crime locations, which overestimates the crime concentration. These results indicate that crime is concentrated, as the generalized Gini is above this number.

Table 4: All Crime Concentration Results for Sample of Mid-Sized Cities

City	Crime Count	Street Segments		Gini	Gini'
Albany	3,783	4,003		0.88	0.86
Asheville	35,516	7,430		0.96	0.96
Beaumont	7,862	9,502		0.94	0.85
Boulder	2,251	5,897		0.82	0.74
Elyria	1,075	3,135		0.91	0.74
Erie	3,404	4,865		0.93	0.91
Fayetteville	10,675	12,941		0.93	0.87
Fort Collins	4,964	9,334		0.94	0.89
Gainesville	5,349	9,816		0.93	0.79
Galveston	2,116	6,497		0.88	0.83
Green Bay	3,854	5,343		0.83	0.83
Kalamazoo	6,386	4,232		0.83	0.83
Merced	7,078	4,282		0.92	0.91
Murfreesboro	5,521	6,426		0.94	0.84
Norman	4,571	12,739		0.91	0.83
Olympia	2,572	3,891		0.91	0.87
Portland	2,482	4,727		0.90	0.90
Richmond	21,957	14,081		0.89	0.76
Rockford	6,087	13,125		0.84	0.83
Savannah	10,025	10,777		0.93	0.89
Tallahassee	7,449	11,263		0.88	0.86
Total	154,977	164,306	Range	0.83-0.96	0.74-0.96

Property Crime

Table 5 shows the Gini coefficients for all property crime throughout the cities. There are a total of 128,498 property crimes in this sample. The range for the Gini coefficients is 0.83 to 0.96, while the generalized Gini range goes from 0.73 to 0.96. This is similar to the findings for all crime, since the majority of the 154,977 crimes are property crimes. Property Crimes make up 82% (0.829) of all total crimes.

Table 5: Property Crime Concentration Results for Sample of Mid-Sized Cities

City	Crime Count	Street Segments		Gini	Gini'
Albany	3,212	4,003		0.85	0.82
Asheville	28,078	7,430		0.96	0.96
Beaumont	4,593	9,502		0.95	0.84
Boulder	1,895	5,897		0.82	0.73
Elyria	3,228	4,865		0.96	0.93
Erie	7,600	12,941		0.94	0.85
Fayetteville	4,054	9,334		0.94	0.89
Fort Collins	5,151	9,816		0.95	0.75
Gainesville	1,421	6,497		0.89	0.80
Galveston	2,815	5,343		0.84	0.80
Green Bay	3,377	4,232		0.84	0.84
Kalamazoo	5,775	4,282		0.94	0.89
Merced	3,704	6,426		0.94	0.81
Murfreesboro	3,798	12,739		0.92	0.81
Norman	2,106	3,891		0.92	0.85
Olympia	1,927	4,727		0.90	0.90
Portland	20,537	14,081		0.89	0.75
Richmond	5,768	13,125		0.85	0.82
Rockford	9,196	10,777		0.93	0.89
Savannah	7,051	11,263		0.85	0.82
Tallahassee	3,212	4,003		0.85	0.82
Total	128,498	164,306	Range	0.83-0.96	0.73-0.96

Violent Crime

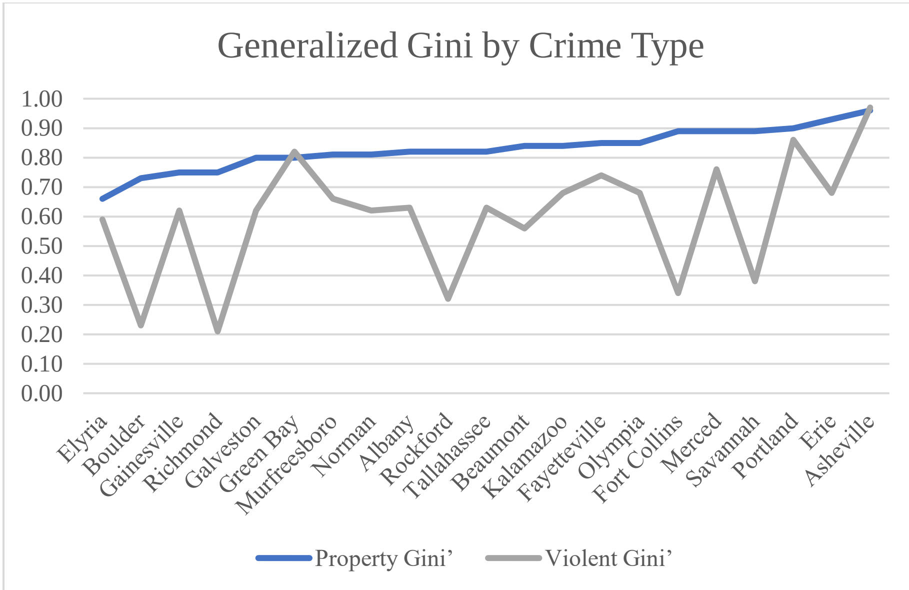
Table 6 shows the Gini coefficients for all violent crimes across the cities. The Gini coefficients for violent crime are much lower than the coefficients for violent crime and property crime. When comparing violent crime to property crime, violent crime is only 18 (0.188) of all total crime, while property crime makes up the other 82% (0.829). The range for the Gini coefficients is .90-0.99, while the range for the generalized Gini coefficients is 0.21-0.97.

Table 6: Violent Crime Concentration Results for Sample of Mid-Sized Cities

City	Crime Count	Street Segments		Gini	Gini'
Albany	575	4,003		0.95	0.63
Asheville	7,438	7,430		0.97	0.97
Beaumont	3,269	9,502		0.97	0.56
Boulder	356	5,897		0.97	0.23
Elyria	176	4,865		0.92	0.68
Erie	3,075	12,941		0.97	0.74
Fayetteville	910	9,334		0.99	0.34
Fort Collins	198	9,816		0.96	0.62
Gainesville	695	6,497		0.93	0.62
Galveston	1,039	5,343		0.87	0.82
Green Bay	3,009	4,232		0.90	0.68
Kalamazoo	1,303	4,282		0.93	0.76
Merced	1,817	6,426		0.98	0.66
Murfreesboro	773	12,739		0.96	0.62
Norman	466	3,891		0.96	0.68
Olympia	555	4,727		0.99	0.86
Portland	1,420	14,081		0.98	0.21
Richmond	319	13,125		0.95	0.32
Rockford	829	10,777		0.98	0.38
Savannah	398	11,263		0.95	0.63
Tallahassee	575	4,003		0.95	0.63
Total	29,195	164,306	Range	0.90-0.99	0.21-0.97

Figure 7 shows the distribution of the generalized Gini coefficients by crime type (e.g., property and violent crime), sorted from smallest to largest. The Gini coefficients for property crime are more consistent, and also higher than the estimates for violent crime. Property crime makes up most of the overall crime total, leading to the lower Gini coefficients represented in this line graph.

Figure 7: Generalized Gini Coefficients by Crime Type



Bootstrapping

The bootstrapping method resamples with replacement the Gini coefficients from the cities 1,000 times in this analysis. Table 7 shows the 95% confidence intervals for the Gini and generalized Gini, as well as the mean Gini for all crime. For the Gini, one can be 95% confident that the true average Gini in midsized cities for all crime is between 0.88 and 0.92. For the generalized Gini, one can be 95% confident that the true average generalized Gini is between 0.82 and 0.87. The average Gini coefficient for this sample of midsized cities for all crime is 0.90, indicating a high level of concentration of crime. The average generalized Gini coefficient is 0.85, which adjusts for the times where there are more places than crime. This also indicates a high level of concentration of crime.

Table 7 shows the 95% confidence intervals for the Gini and generalized Gini, as well as the mean Gini for property crime. For the Gini, one can be 95% confident that the true average Gini in midsized cities for property crime is between 0.89 and 0.92. For the generalized Gini, one can be 95% confident that the true average generalized Gini is between 0.80 and 0.86. The average Gini coefficient for this sample of midsized cities for property crime is 0.90, indicating a high level of concentration of crime. The average generalized Gini coefficient is 0.83, which adjust for the times where there are more places than crime. This also indicates a high level of concentration of crime.

Table 7 shows the confidence intervals for the Gini and generalized Gini, as well as the mean Gini for violent crime. For the Gini, one can be 95% confident that the true average Gini in midsized cities for violent crime is between 0.94 and 0.97. For the generalized Gini, we can have 95% confident that the true mean Gini is between 0.51 and 0.68. The average Gini coefficient for this sample of midsized cities for violent crime is 0.94, indicating a high level of concentration of crime. The average generalized Gini coefficient is 0.60, which adjust for the times where there are more places than crime. This also indicates a low level of concentration of crime. This lower coefficient is most likely due to violent crime being sparse within most cities.

Table 7: Average Gini Coefficients with Confidence Intervals for All Crime Types

All Crime			
Gini 95% C.I.	Gini' 95% C.I.	Mean Gini	Mean Gini'
0.88-0.92	0.82-0.87	0.90	0.85
Property Crime			
Gini 95% C.I.	Gini' 95% C.I.	Mean Gini	Mean Gini'
0.89-0.92	0.80-0.86	0.90	0.83
Violent Crime			
Gini 95% C.I.	Gini' 95% C.I.	Mean Gini	Mean Gini'
0.94-0.97	0.51-0.68	0.95	0.60
Range of Mean Gini	0.90-0.95		
Range of Mean Gini'	0.60-0.85		

Summary

Table 8 shows a summary of the Gini coefficients and generalized Gini coefficients of each city in the sample, by crime type (property, violent, and all). This table also displays the difference between the generalized Gini coefficients for property crime and violent crime. The mean, standard deviation, and range are also calculated for this table.

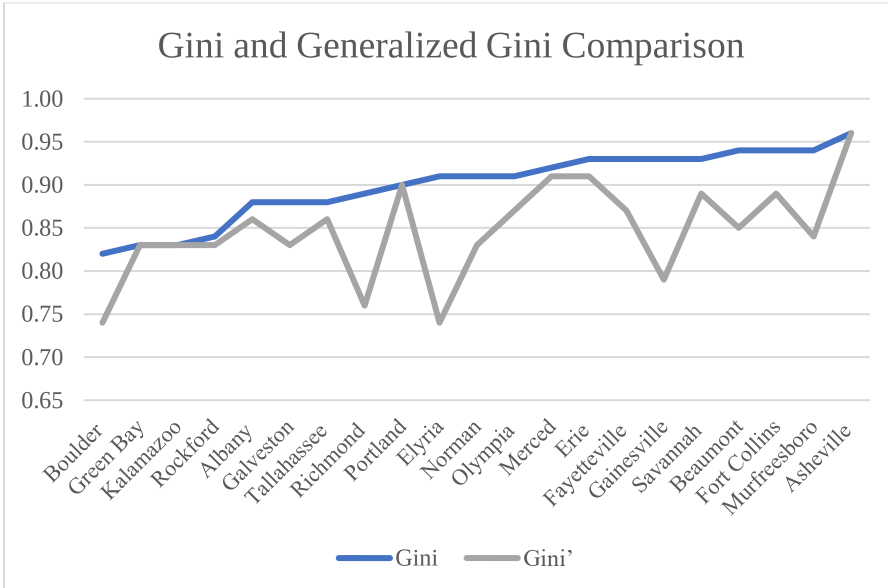
The differences between the violent Gini coefficient and the property Gini coefficient range from -0.01 to 0.15. The differences between the violent crime generalized Gini coefficients and the property crime generalized Gini coefficients show range from -0.02 to 0.54. This is a huge range, showing the difference between the concentrations of the two crime types. The range of the Gini coefficients are much smaller than those for the generalized Gini coefficients. This difference gives a representation of how the Gini coefficients overestimate crime concentration, and how the generalized Gini underestimates concentration. These ranges also help to see the differences of concentration between violent crime and property crime, as property crime is shown to concentrate at higher levels than violent crime.

Table 8: Summary of All Crime and Differences between Property and Violent

	All Crime		Property Crime		Violent Crime		Difference Violent and Property	
City	Gini	Gini'	Gini	Gini'	Gini	Gini'	Gini	Gini'
Albany	0.88	0.86	0.85	0.82	0.95	0.63	-0.10	0.19
Asheville	0.96	0.96	0.96	0.96	0.97	0.97	-0.01	-0.01
Beaumont	0.94	0.85	0.95	0.84	0.97	0.56	-0.02	0.28
Boulder	0.82	0.74	0.82	0.73	0.97	0.23	-0.15	0.50
Elyria	0.91	0.74	0.91	0.66	0.96	0.59	-0.05	0.07
Erie	0.93	0.91	0.96	0.93	0.92	0.68	0.04	0.25
Fayetteville	0.93	0.87	0.94	0.85	0.97	0.74	-0.03	0.11
Fort Collins	0.94	0.89	0.94	0.89	0.99	0.34	-0.05	0.55
Gainesville	0.93	0.79	0.95	0.75	0.96	0.62	-0.01	0.13
Galveston	0.88	0.83	0.89	0.80	0.93	0.62	-0.04	0.18
Green Bay	0.83	0.83	0.84	0.80	0.87	0.82	-0.03	-0.02
Kalamazoo	0.83	0.83	0.84	0.84	0.90	0.68	-0.06	0.16
Merced	0.92	0.91	0.94	0.89	0.93	0.76	0.01	0.13
Murfreesboro	0.94	0.84	0.94	0.81	0.98	0.66	-0.04	0.15
Norman	0.91	0.83	0.92	0.81	0.96	0.62	-0.04	0.19
Olympia	0.91	0.87	0.92	0.85	0.96	0.68	-0.04	0.17
Portland	0.90	0.90	0.90	0.90	0.99	0.86	-0.09	0.04
Richmond	0.89	0.76	0.89	0.75	0.98	0.21	-0.09	0.54
Rockford	0.84	0.83	0.85	0.82	0.95	0.32	-0.10	0.50
Savannah	0.93	0.89	0.93	0.89	0.98	0.38	-0.05	0.51
Tallahassee	0.88	0.86	0.85	0.82	0.95	0.63	-0.10	0.19
Mean	0.90	0.85	0.90	0.83	0.95	0.60	-0.05	0.23
SD	0.04	0.06	0.05	0.07	0.03	0.20	0.04	0.18
Range	0.82-0.96	0.74-0.96	0.82-0.96	0.66-0.96	0.87-0.99	0.21-0.97	-0.01-0.15	-0.02-0.54

Figure 8 shows a line graph of the Gini and generalized Gini coefficients for all crime, sorted from smallest to largest. The blue line represents the Gini coefficient, and shows higher levels of concentration than the generalized Gini coefficient line. Based on previous research, these results echo Bernasco and Steenbeek (2017), who noted that the Gini coefficient overestimated crime concentration. Without the application of this generalized Gini method, crime concentration would be highly overestimated.

Figure 8: Comparison of the Gini and the Generalized Gini



The Poisson methods runs a simulation, repeated 250 times in this analysis. Table 9 shows the Poisson coefficients, along with their ranges for all crime. The range for the Poisson—Gamma is 0.77 to 0.96, while the range for the generalized Gini coefficient 0.74 to 0.96. There is a larger range with the generalized Gini coefficient compared to the Poisson—Gamma coefficients. In general, the Poisson—Gamma coefficients are higher in concentration than the generalized Gini coefficients for all crime.

Table 9: Poisson—Gamma and Generalized Gini Coefficients for All Crime

City	Poisson	Gini'
Albany	0.83	0.86
Asheville	0.96	0.96
Beaumont	0.89	0.85
Boulder	0.96	0.74
Elyria	0.86	0.74
Erie	0.86	0.91
Fayetteville	0.86	0.87
Fort Collins	0.89	0.89
Gainesville	0.90	0.79
Galveston	0.89	0.83
Green Bay	0.82	0.83
Kalamazoo	0.82	0.83
Merced	0.77	0.91
Murfreesboro	0.87	0.84
Norman	0.91	0.83
Olympia	0.83	0.87
Portland	0.91	0.90
Richmond	0.91	0.76
Rockford	0.91	0.83
Savannah	0.77	0.89
Tallahassee	0.89	0.86
Range	0.77-0.96	0.74-0.96

Figure 9 shows the comparison of the generalized Gini and Poisson coefficients, sorted from smallest to largest. The Poisson—Gamma coefficients are shown in grey, and the generalized Gini coefficients are in blue. This line graph shows the distribution of the coefficients, and that overall, the Poisson—Gamma's are higher than the generalized Gini's.

Figure 9: Comparison of Poisson and Generalized Gini for All Crime

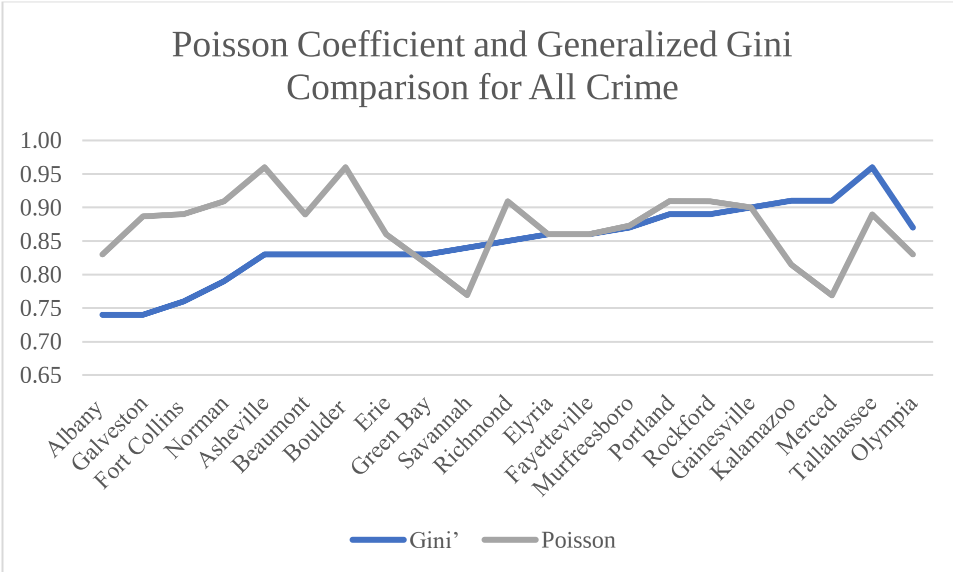


Table 10 shows the Poisson coefficients, along with their ranges for all crime. The range for the Poisson—Gamma is 0.78 to 0.96, while the range for the generalized Gini coefficient 0.66 to 0.96. There is a larger range with the generalized Gini coefficient compared to the Poisson—Gamma coefficients. In general, the Poisson—Gamma coefficients are higher in concentration than the generalized Gini coefficients for all crime.

Table 10: Poisson—Gamma and Generalized Gini Coefficients for Property Crime

City	Poisson	Gini'
Albany	0.83	0.82
Asheville	0.96	0.96
Beaumont	0.89	0.84
Boulder	0.96	0.73
Elyria	0.85	0.66
Erie	0.85	0.93
Fayetteville	0.85	0.85
Fort Collins	0.90	0.89
Gainesville	0.91	0.75
Galveston	0.90	0.80
Green Bay	0.83	0.80
Kalamazoo	0.82	0.84
Merced	0.78	0.89
Murfreesboro	0.90	0.81
Norman	0.91	0.81
Olympia	0.83	0.85
Portland	0.91	0.90
Richmond	0.91	0.75
Rockford	0.91	0.82
Savannah	0.78	0.89
Tallahassee	0.89	0.82
Range	0.78-0.96	0.66-0.96

Figure 10 shows the comparison of the generalized Gini and Poisson coefficients for property crime, sorted from smallest to largest. The Poisson—Gamma coefficients are shown in grey, and the generalized Gini coefficients are in blue. This line graph shows the distribution of the coefficients, and that overall, the Poisson—Gamma's are higher than the generalized Gini's.

Figure 10: Comparison of Poisson and Generalized Gini for Property Crime

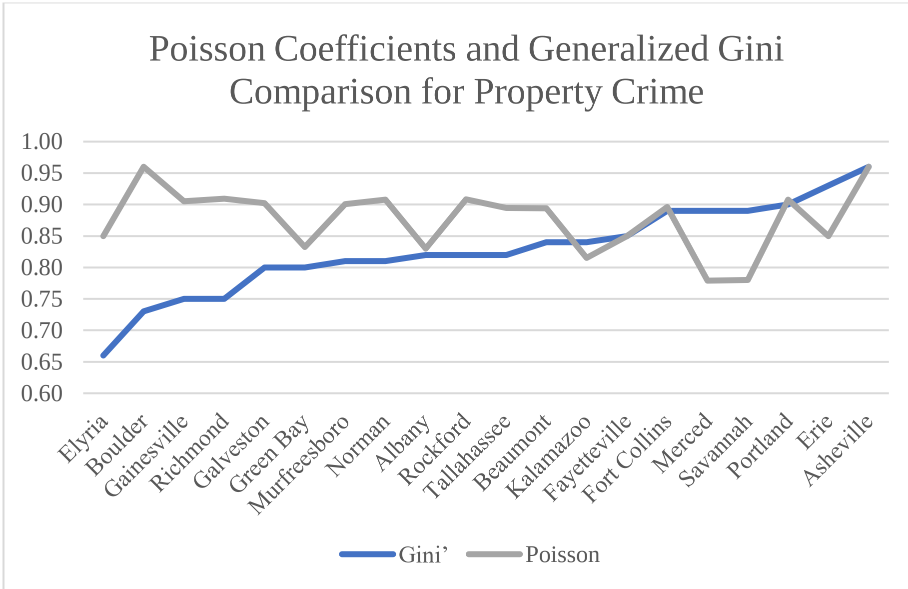


Table 11 shows the Poisson coefficients, along with their ranges for all crime. The range for the Poisson—Gamma is 0.81 to 0.96, while the range for the generalized Gini coefficient 0.21 to 0.97. There is a larger range with the generalized Gini coefficient compared to the Poisson—Gamma coefficients. In general, the Poisson—Gamma coefficients are higher in concentration than the generalized Gini coefficients for all crime.

Table 11: Poisson—Gamma and Generalized Gini Coefficients for Violent Crime

City	Poisson	Gini'
Albany	0.83	0.63
Asheville	0.96	0.97
Beaumont	0.93	0.56
Boulder	0.97	0.23
Elyria	0.93	0.59
Erie	0.92	0.68
Fayetteville	0.92	0.74
Fort Collins	0.95	0.34
Gainesville	0.95	0.62
Galveston	0.92	0.62
Green Bay	0.85	0.82
Kalamazoo	0.85	0.68
Merced	0.84	0.76
Murfreesboro	0.88	0.66
Norman	0.96	0.62
Olympia	0.83	0.68
Portland	0.96	0.86
Richmond	0.96	0.21
Rockford	0.96	0.32
Savannah	0.81	0.38
Tallahassee	0.93	0.63
Range	0.81-0.96	0.21-0.97

Figure 11 shows the comparison of the generalized Gini and Poisson coefficients for violent crime, sorted from smallest to largest. The Poisson—Gamma coefficients are shown in grey, and the generalized Gini coefficients are in blue. This line graph shows the distribution of the coefficients, and that overall, the Poisson—Gamma's are higher than the generalized Gini's.

Figure 11: Comparison of Poisson and Generalized Gini for Violent Crime

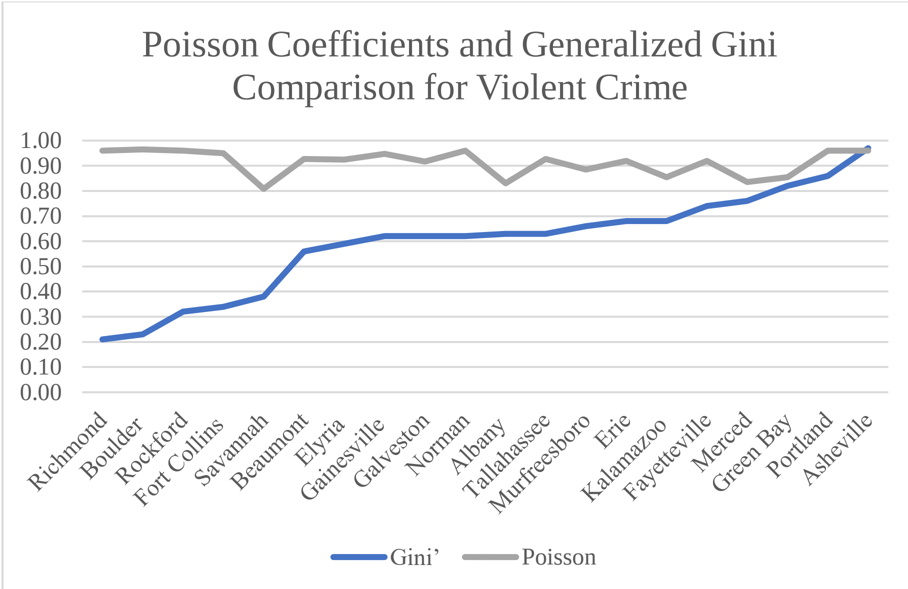


Table 12 shows the confidence intervals for the Poisson coefficients across all crime types, as well as the mean. For all crime, one can be 95% confident that the true mean falls between 0.85 and 0.89. For property crime, one can be 95% confident that the true mean falls between 0.85 and 0.90. Finally, for violent crime, one can be 95% confident that the true mean falls between 0.89 and 0.93. The average Poisson coefficients for all crime and property crime is 0.87, and the average for violent crime is 0.97. These are all shown to concentrate higher than the means for the Gini and generalized Gini.

Table 12: Poisson—Gamma Coefficients with Confidence Intervals for All Crime Types

All Crime	Mean
Poisson 95% C.I.	0.87
0.85-0.89	
Property Crime	Mean
Poisson 95% C.I.	0.87
0.85-0.90	
Violent Crime	Mean
Poisson 95% C.I.	0.97
0.89-0.93	
Range of Mean Poisson	0.87-0.97

Table 13 shows the generalized Gini coefficient range, percent, and the Poisson—Gamma range and percent for all crime types (violent, property, and all). The generalized Gini coefficients range from 0.22 to 0.76 across the three crime types. The Poisson—Gamma coefficients range from 0.19 to 0.15. The range for the Poisson coefficients is much tighter than the range for the generalized Gini coefficients.

Table 13: Generalized Gini and Poisson by Crime Types, Range and Percent

Crime Type	Gini' Range	Gini' Percent	Poisson Range	Poisson Percent
All	0.22	22%	0.19	19%
Property	0.30	30%	0.18	18%
Violent	0.76	76%	0.15	15%

Discussion

The results of this study come from a random sample of 21 midsized cities selected from a Census Designated Places file. These cities were randomly selected and their police departments for each city were contacted to get the crime data. Previous studies on the law of crime concentration have not measured concentration in smaller cities (Weisburd, 2015; Bernasco & Steenbeek, 2017) nor have many focused on multiple cities (Gill, Wooditch, & Weisburd, 2017; Levin et al., 2017; Carter et al., 2019). This study fills gaps within the literature on crime concentration by placing a focus on smaller cities, a component often overlooked in spatial research, as well as looking at multiple cities to analyze the variation in their results.

Crime was shown to be concentrated, when looking at all the generalized Gini coefficients for all crime (i.e., 0.74-0.96 for the range). However, when breaking crime down by type (e.g., violent and property), violent crime was shown to be far less concentrated than property crime. Violent crime ranged from 0.21-0.97, and property crime had a more narrow range 0.73-0.96. With property crime making up over half of the crimes in this study, the argument of whether or not it is necessary to look at crime by types or simply all crime takes shape (Lentz, 2018; Brantingham, 2016). Previous research suggests that larger geographic units will have more diversity of crime, than the smaller units used in this study (Brantingham, 2016). The larger cities in population hosted an overall greater amount of crime counts, and a greater number of both property and violent crime, with property crimes being the most prevalent. This study looked at smaller, mid-sized cities, and had fewer violent crimes than larger cities. It would be useful for future research to compare the number of violent and property crimes from larger cities and smaller cities to help see if this is the case. This also helps to see if crime concentration is invariant across cities. However, with characteristics of larger cities versus smaller cities being different, the way crime concentration is measured may not fall under the same requirements for all sizes of cities.

With the average generalized Gini coefficients being high and close to a value of 1, these results suggest that the cities in this sample have a high concentration of crime in certain areas, as opposed to being equally spread. However, it is unclear if the confidence intervals are tight enough to be considered narrow enough fall within the definition of the law of crime concentration. The confidence intervals for the mean Gini coefficient for all crime were consistent with the expectation of a narrow confidence interval from the second research question (0.88—0.92). This expectation was also consistent for property crime (0.81—0.87). However, contrary to the expectation, the confidence interval was not narrow for violent crime (0.50—0.69). Again, with fewer violent crimes, the concentration of them may be harder to find. This could also change from year-to-year, and may be different based on city size.

The use of the generalized Gini coefficients, compared to the Gini coefficients, are consistent with Bernasco and Steenbeek's (2017) suggestion of the overestimation of that Gini coefficients. All Gini coefficients compared to generalized Gini coefficients were shown to be much higher. Overall, the results from this study matched the expectations of the research questions were.

Consistent with the expectations for the first research question, the average Gini coefficient was at least 0.70 (0.95). The average generalized Gini coefficient was 0.85, for all crime. For property crime, this was also consistent with the expectations, with a Gini of 0.91 and a generalized Gini of 0.84. For violent crime, the average Gini was 0.94, and the average generalized Gini was 0.59. This was not consistent with the expectations of the second research question. This is most likely due to crime counts for violent crimes being sparse, especially when compared to the counts for violent crime.

Consistent with the expectations for the third research question, the generalized Gini's vary by crime type. For all crime, the generalized Gini's range from 0.74 to 0.96. Property crime ranges from 0.73 to 0.96, while violent crime ranges from 0.21 to 0.97. However, the difference between the ranges for property crime and all crime are extremely similar. This is most likely due to the majority of crimes being classified as property crimes, with a low number of crimes being classified as violent. As violent crime only makes up about 19% of all crime (.1860), property crime makes up 81% of all crime (0.8140). From the fourth research question, for all crime, the generalized Gini coefficients varied somewhat across the cities. The mode for the generalized Gini's is 0.83, with a range of 22. Property crime's mode is 0.82, with a range of 23. Violent crime showed a large range of 76, with a mode of 0.62, indicating low crime concentration.

The Poisson--Gamma range for all three crime types is between 0.15 and 0.19. Although this is a tight range, it is unlikely this range meets the requirement for invariance. Invariance of this concentration would mean that these ranges would not change, regardless of conditions of cities or changing much across cities. These results imply that more research is needed for the law of crime concentration. Consistently, violent crime was shown to not be as high in concentration as property crime or all crime. Since most of the crime for this study is property crime, it could be argued that is mainly what the all crime calculations are studying. This needs to be studied across more cities and other sizes of cities to see if this varies across cities or not. From these results, the levels of concentration vary too much to fit within the current definition of the law. The generalized Gini coefficients are still bias in the direction of underestimating crime concentration, so further research should test other measurement techniques and further test the Poisson—Gamma to determine the best way to measure the concentration of crime.

The theoretical background for this study largely comes from the environmental criminology framework. Environmental criminology focuses on the characteristics of where crime occurs, a notion that is extremely important to this study. The invariance of the measurement technique is a key component to these results. However, the characteristics of cities are a major element of the variance in concentration across cities. RAT and CPT explain that crime cannot occur without opportunities, with CPT explaining how specific areas within cities may generate opportunities. This comes from the activities of people, and their similar paths around activity nodes (Cullen et al., 2018). Also within cities, there are areas that attract crime and attract large numbers of people, which help to facilitate crime (Brantingham & Brantingham, 1995). The environmental characteristics of cities explain why an area is known for crime, as well as help to prevent crime (Andresen & Jenion, 2008). SDT breaks down the characteristics of neighborhoods and what factors (e.g., low economic status, residential mobility, and ethnic heterogeneity) facilitate crime (Sampson & Groves, 1989). These theories explain how the opportunities, given both by people and the environment, give way for crime to occur. These characteristics, applied to microgeographic units of analysis, are important in understanding the variance of crime concentration levels across cities because these opportunities are different in different environments.

Limitations

Since the sample size of this study is relatively small, it is unclear on whether or not this sample of cities is enough to represent all midsized cities. This is a cross-sectional study, only looking at the year 2016, for all 21 cities, which could be a limiting factor as hotspots may move. Previous longitudinal studies have found that crime concentrates in cities, and answer if the concentration of crime is stable overtime, which this study lacks (Gill et al., 2017). Reporting difference between police departments did occur, as not police department recorded or reported their crimes the same way. This led to issue when processing the data, in terms of what crime types were counted in the study. If it was unclear what the crime type was, it was not included in the final count. The addresses from the police departments were not all exact addresses, as some included intersections, and block ranges instead of exact street numbers. This could slightly skew the exact locations of the crimes. This study looked at only two crime types, violent and property, and then those crime types combined. Future research may still be needed to experiment on if crime types need to be broken down even more, or if all crime is enough (O'Brien, 2018).

Recently, there have been a couple of studies showing the limitations of the Gini coefficients (Mohler, Brantingham, Carter, & Short, 2019; Carter et al., 2019). The argument is that the Gini coefficient overestimates the concentration of crime, while the generalized Gini underestimates the concentration of crime. Carter et al. (2019) propose "using leading indicator hotspots with high volume of events as a proxy" to address when there are few incidents and the bias that stems from the Gini when this occurs.

Conclusion

The literature on crime and place has been growing since the late 1980s (Sampson & Groves, 1989). After the importance of smaller geographic units of analysis came into play, crime could be looked at in ways that could have overlooked important aspects of crime prevention (Sampson & Groves, 1989). In recent years, only 6% of articles on the criminology of place literature use microgeographic units of analysis (Weisburd, 2015). This indicates that the literature is growing, but still occupies a small portion of the field. Most literature that does exist is heavily skewed toward larger cities. This study uses smaller geographic units of analysis to look at smaller cities, to add to the literature that is so far scarce.

Criminological theory has often studied why people commit crimes, and not placed a focus on why certain areas are hot spots for crime (Weisburd, 2015). The purpose of this study was to explore the law of crime concentration and build the literature on providing a standard measure to explore crime concentration. This study followed the work of Bernasco and Steenbeek (2017) and Weisburd (2015). This exploratory research intended to establish the unknown parameters and help develop the best methods for crime concentration, so future studies have a baseline to compare their results to. Future research is needed for this topic, to stress the importance of focusing on smaller geographic units when looking at crime. With more research on the crime concentration, better strides to help monitor and prevent crime can be made.

This study used microgeographic units of analysis, by looking at street-level segments within neighborhoods to better understand crime concentration, along with exploring the law of crime concentration. Further research on crime concentration will help grow the generalizability of the law (Weisburd, 2015). Although there have been studies on crime using micro levels of analysis (Weisburd et al., 2004), the full use of geographic tools was not used (Weisburd, Groff, & Yang, 2010). This study also contributes to crime prevention, reinforcing the need for hot-spot policing. The effectiveness of policing hot spots has been studied often, and continues to grow in support (Weisburd & Green, 1995; Braga, 2001; Weisburd & Eck, 2004; Rosenfield, Deckard, & Blackburn, 2014).

The purpose of this study was to (1) measure crime concentration within the boundaries of the law of crime concentration, (2) estimate what the expected Gini coefficient should be in midsized cities, and (3) analyze the variation in crime concentration across midsized cities. This study built upon a measurement technique used in previous research to measure crime concentration, but still has limitations in the technique used. The Gini coefficients between all crime and property crime were similar, but the Gini coefficients between all crime and violent crime varied greatly in range. Therefore, further research is needed before an expected Gini coefficient can be determined.

Although more research is needed to better create a standard measurement technique, the high crime concentration coefficients from smaller cities bodes well for the future of this law. This study brought a unique perspective on crime concentration, by having a random sample of midsized cities, representing varying regions in the United States. This filled in gaps within the literature that gravely needed to be addressed (i.e., smaller, midsized cities, larger sample size, and regionally representative). Further research is still needed to define the law of crime concentration and develop an infallible measurement technique.

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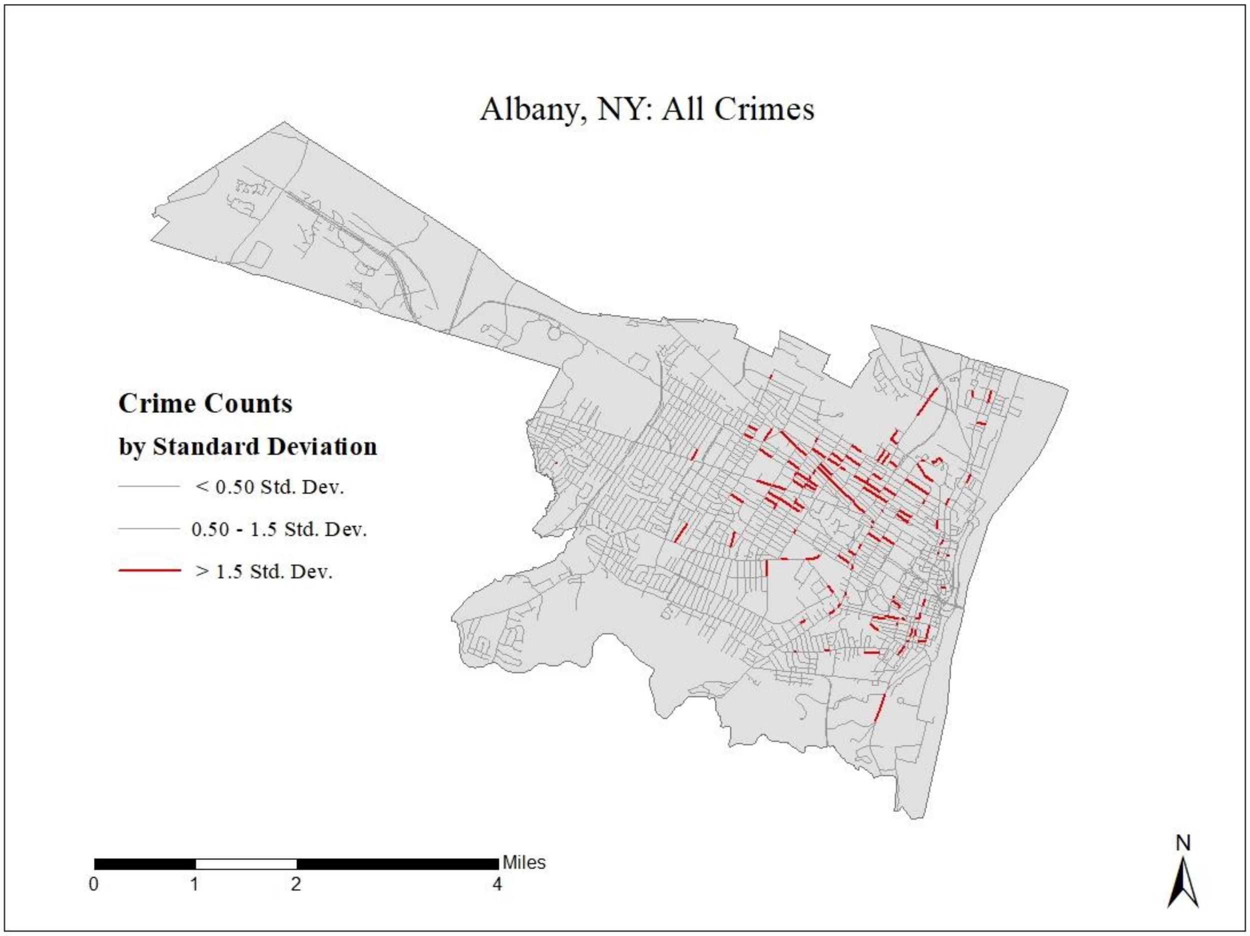
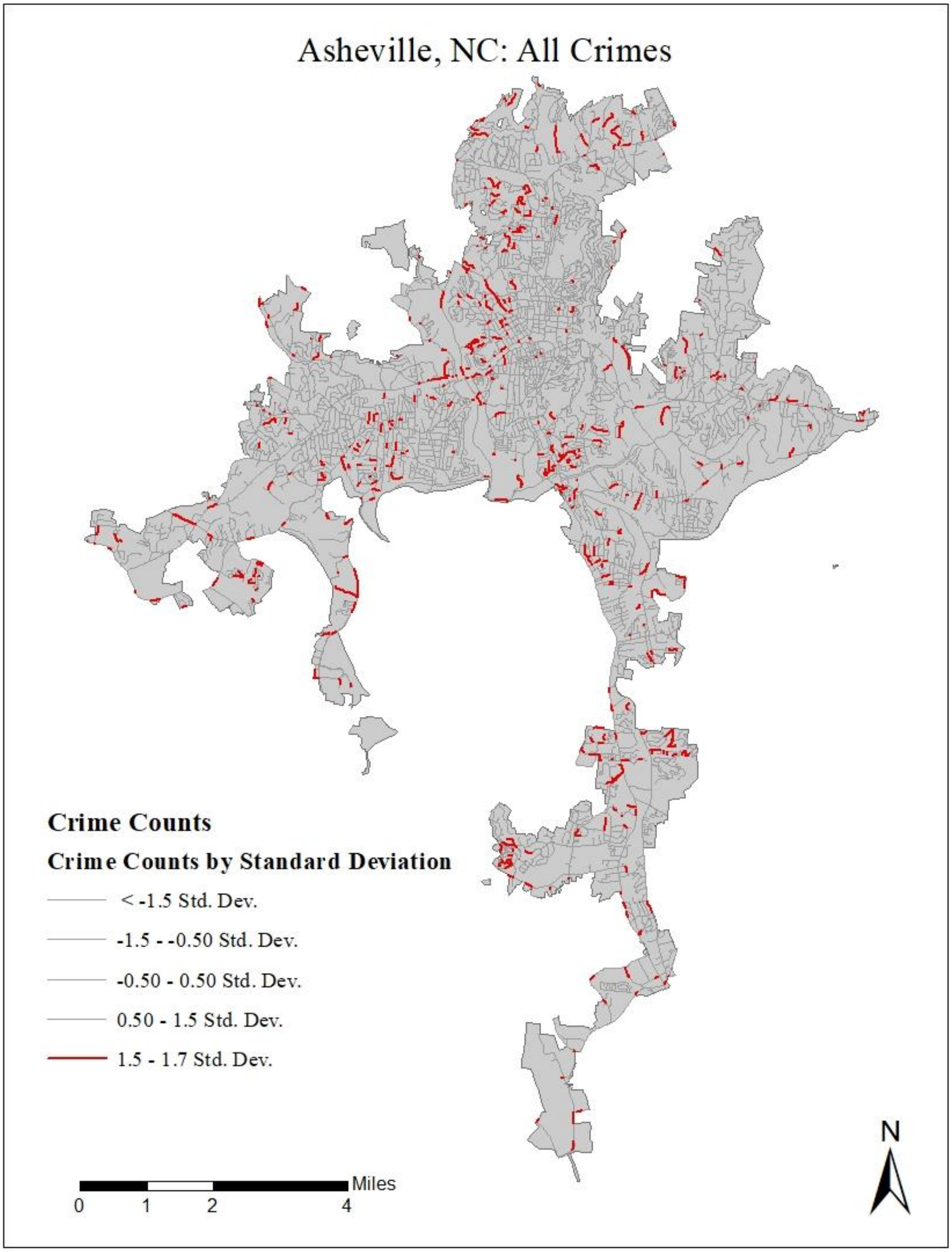
Appendix A

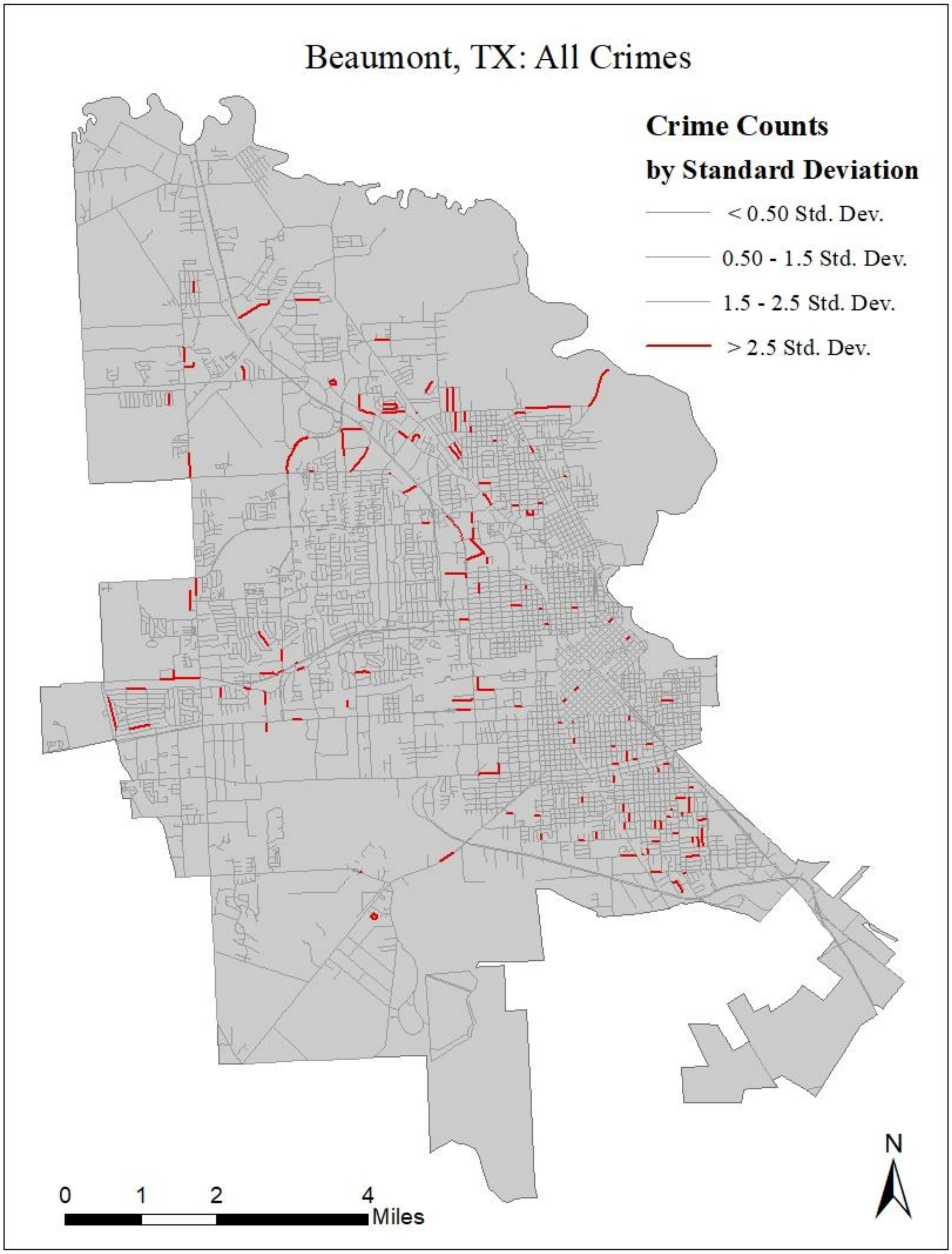
Albany, NY Crime Counts Map



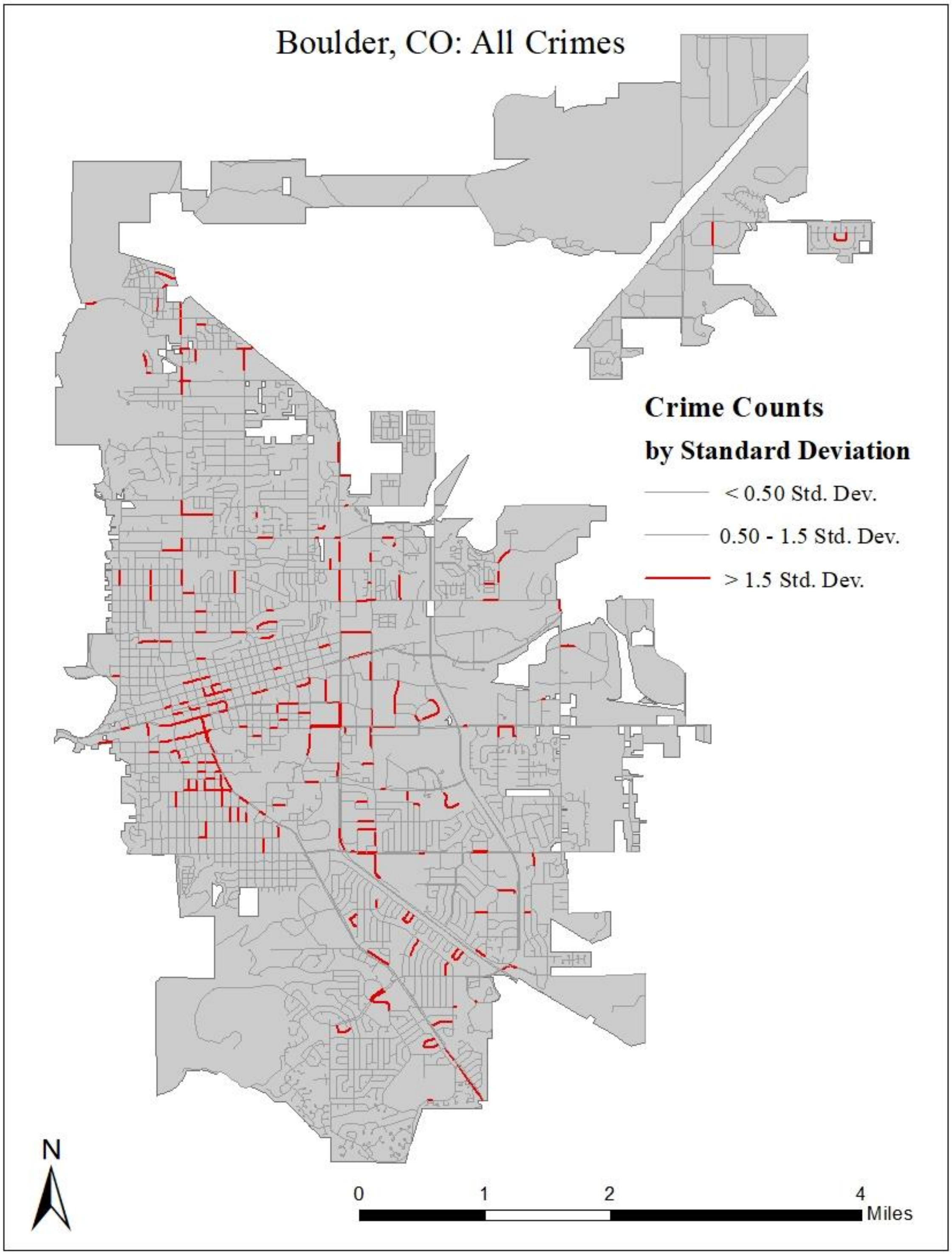
Asheville, NC Crime Counts Map



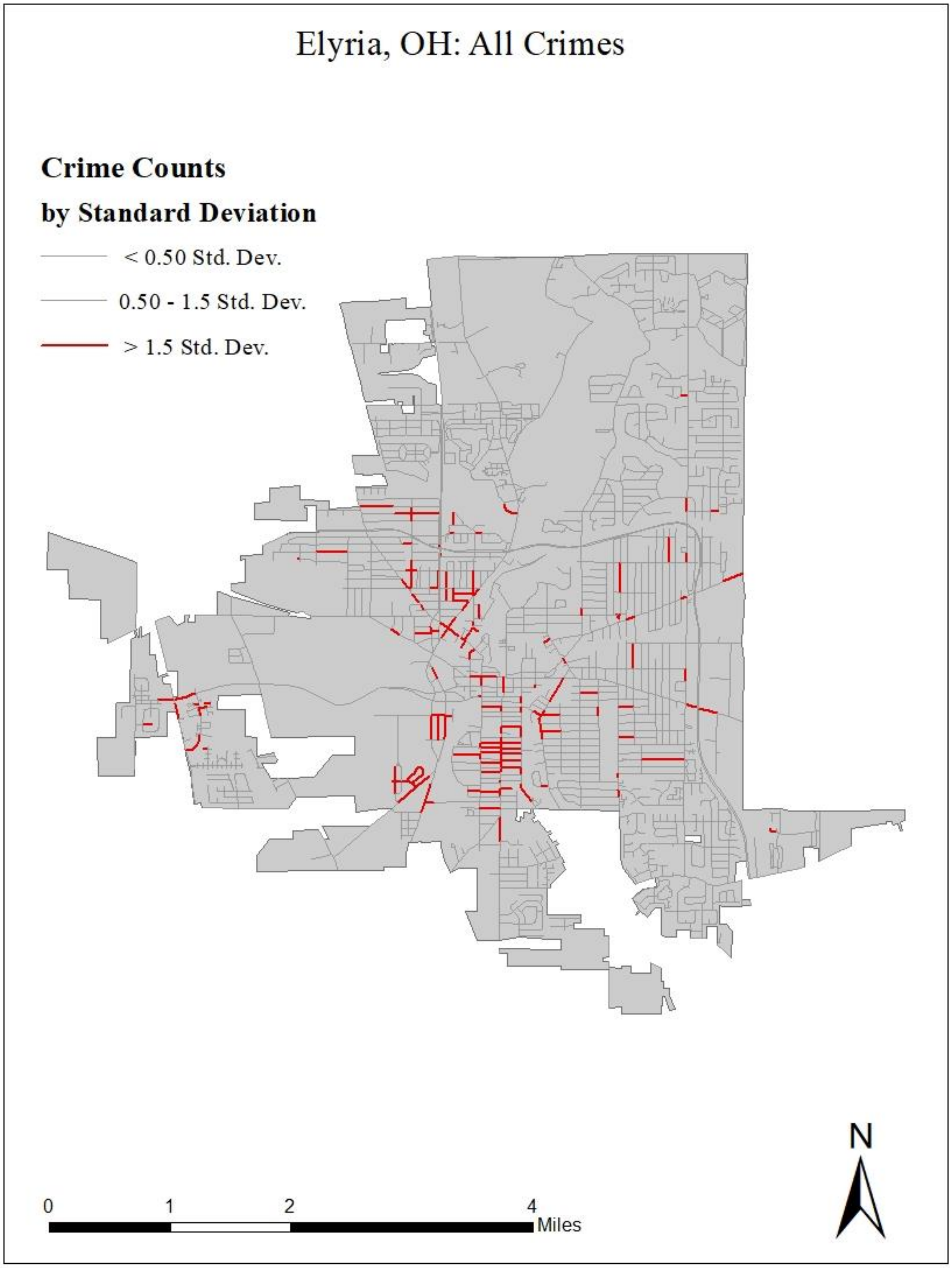
Beaumont, TX: Crime Counts Map



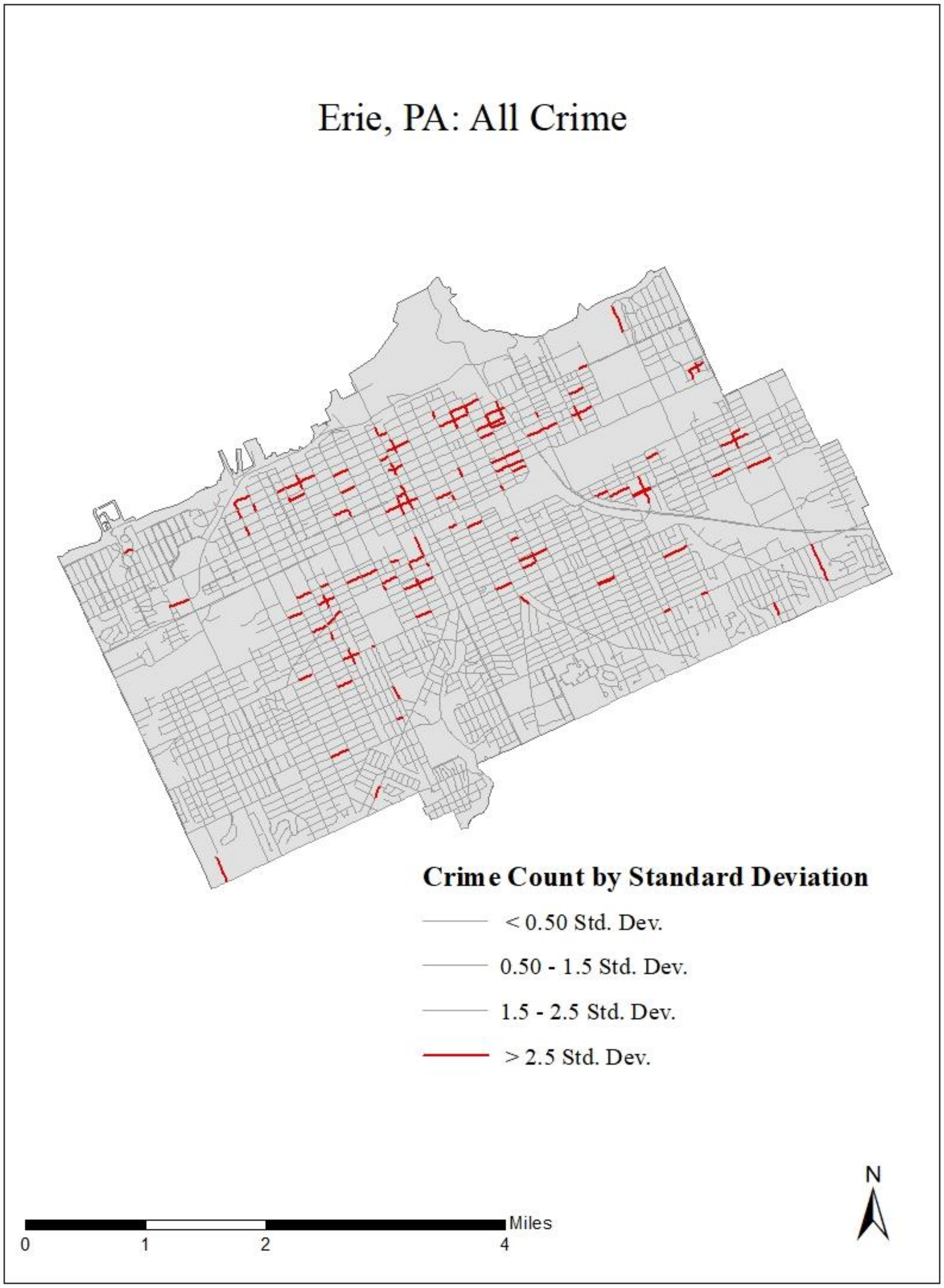
Boulder, CO: Crime Counts Map



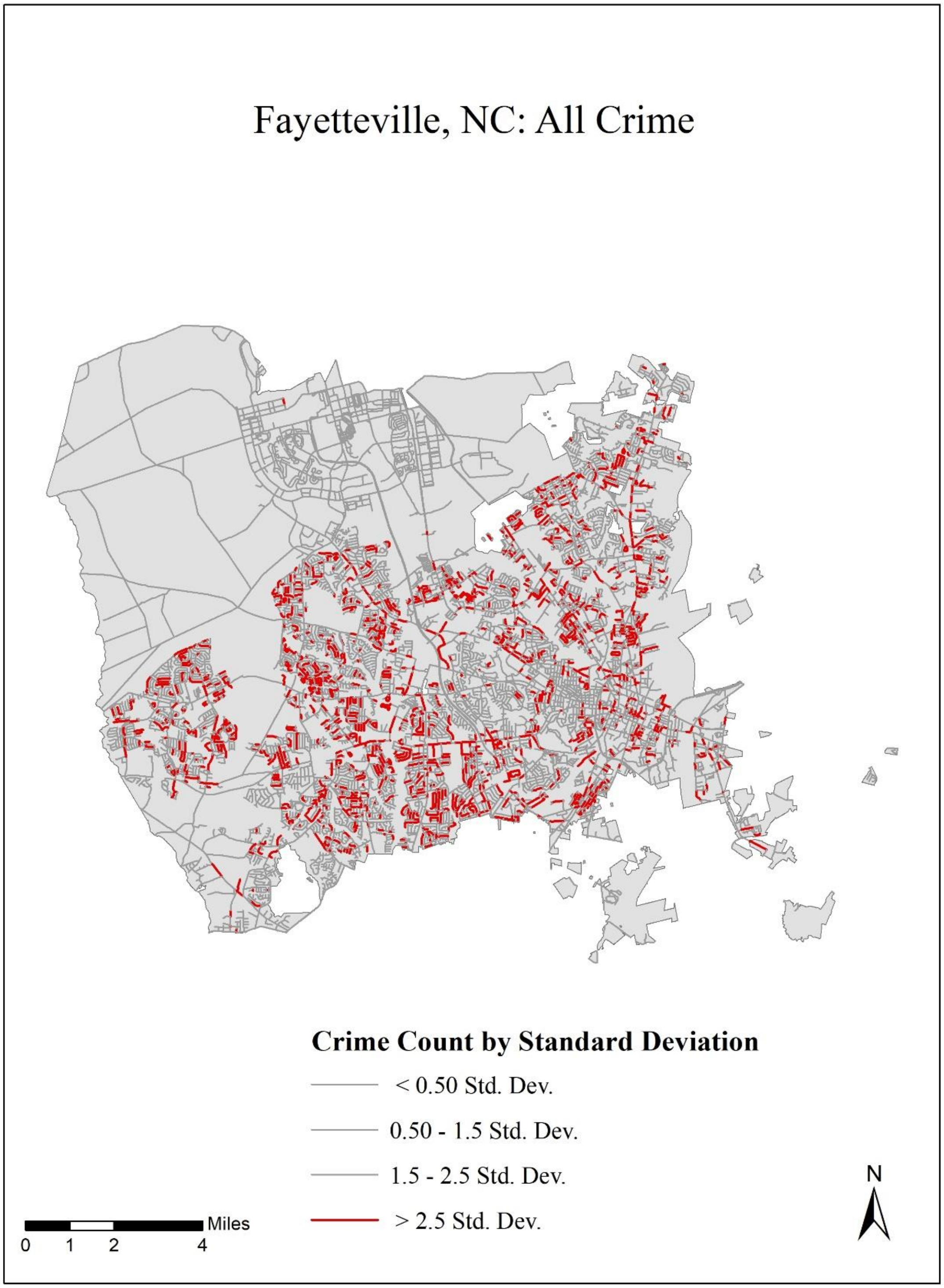
Elyria, OH: Crime Counts Map



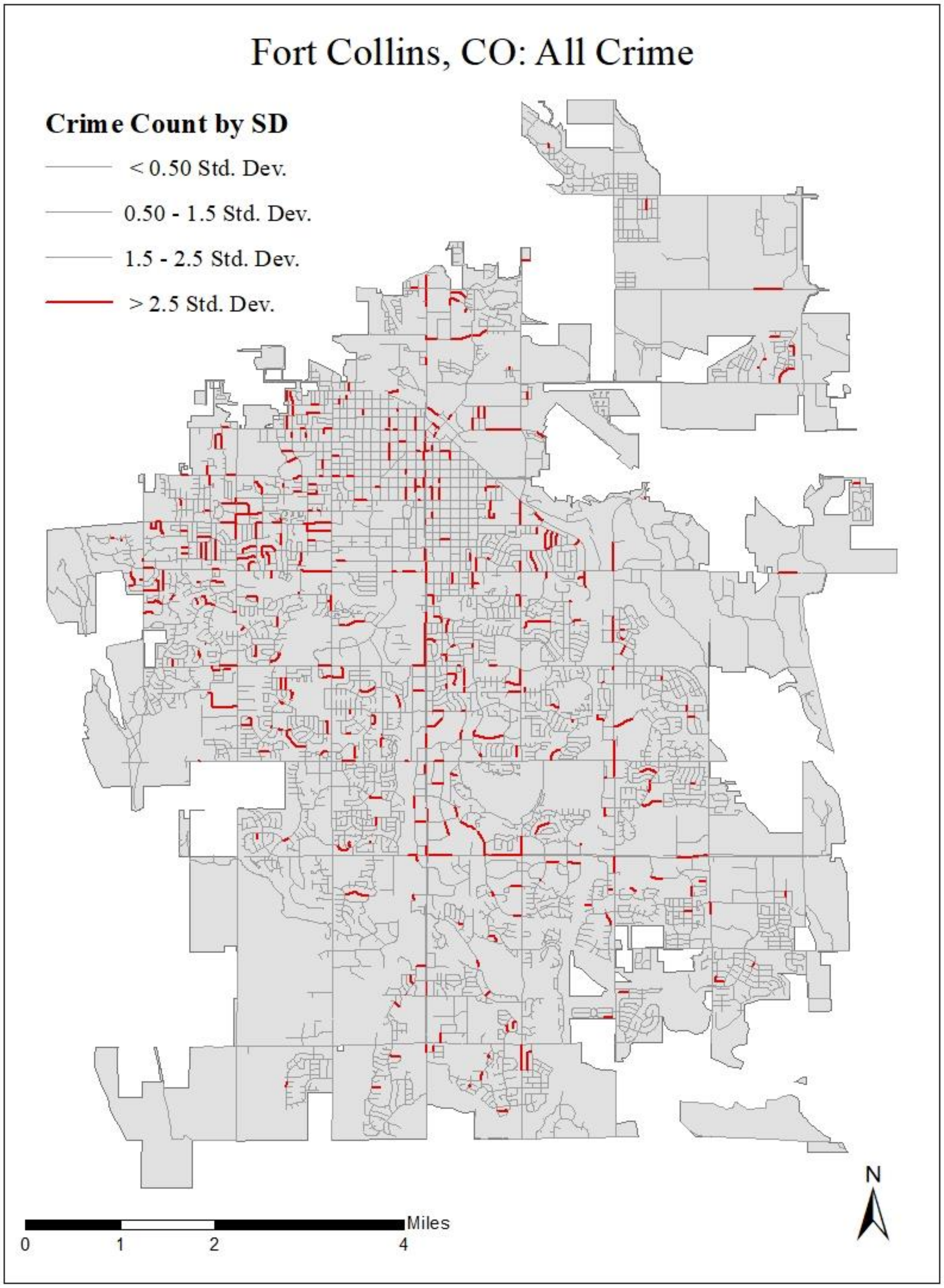
Erie, PA: Crime Counts Map



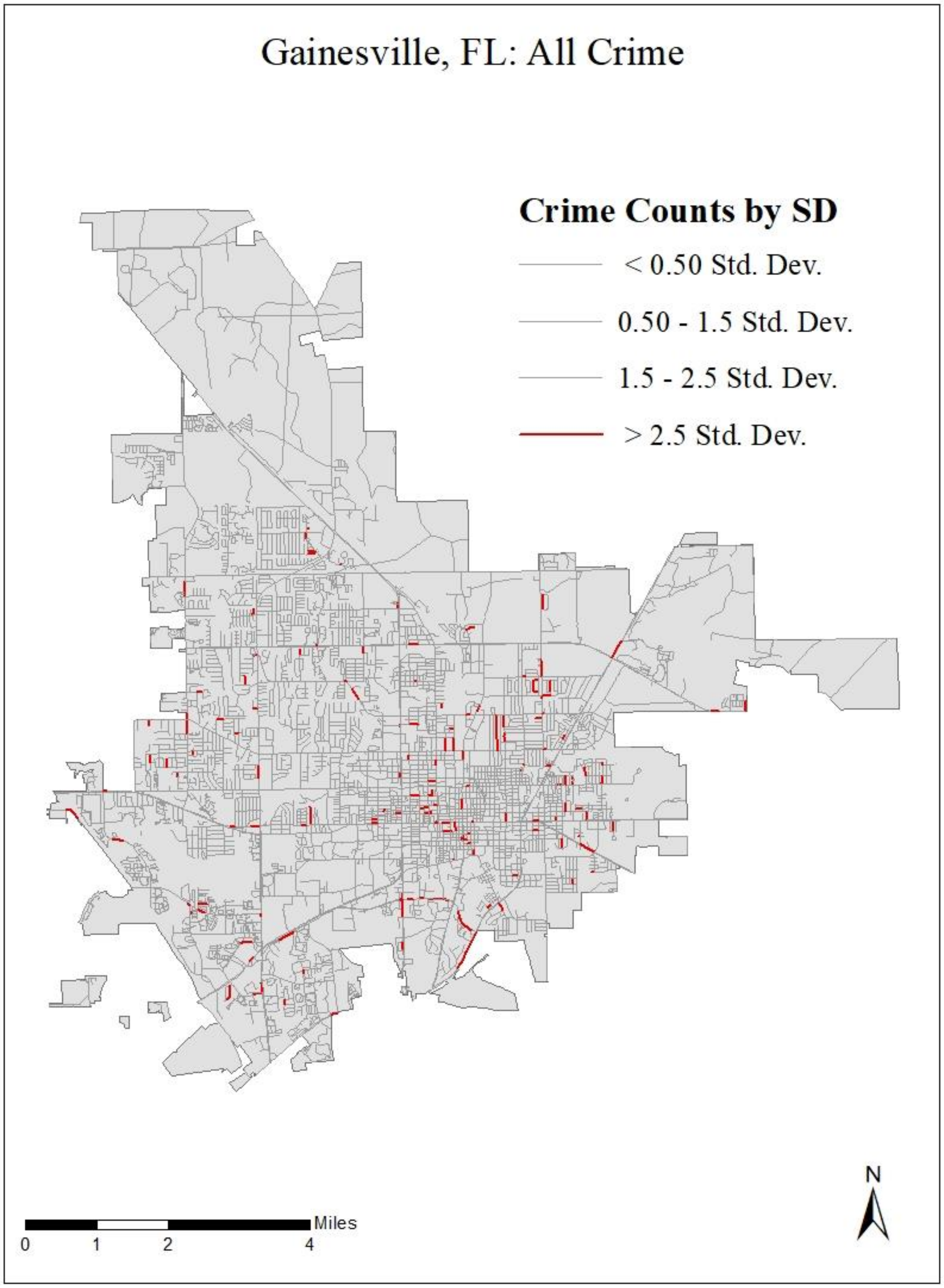
Fayetteville, NC: Crime Counts Map



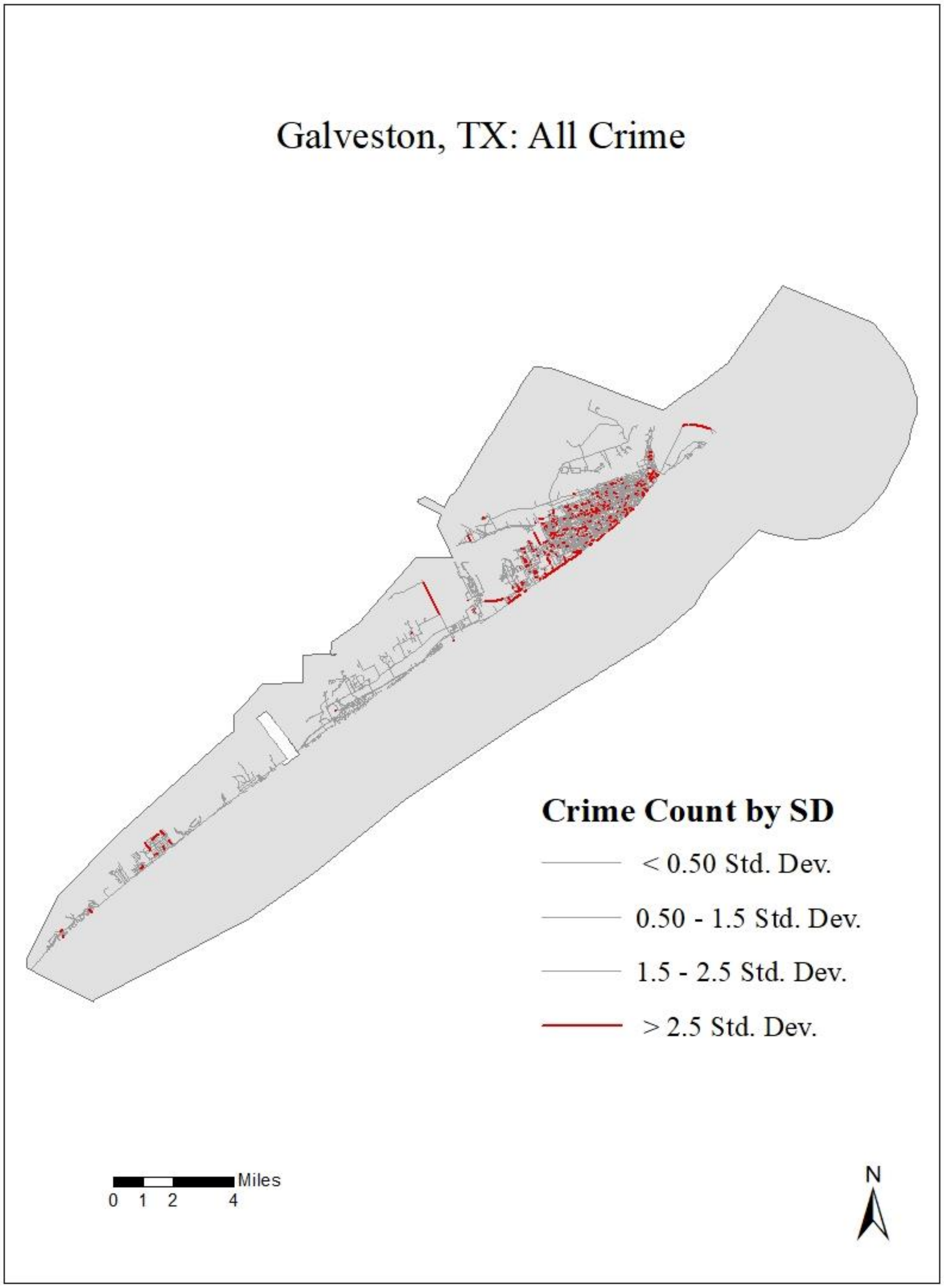
Fort Collins, CO: Crime Counts Map



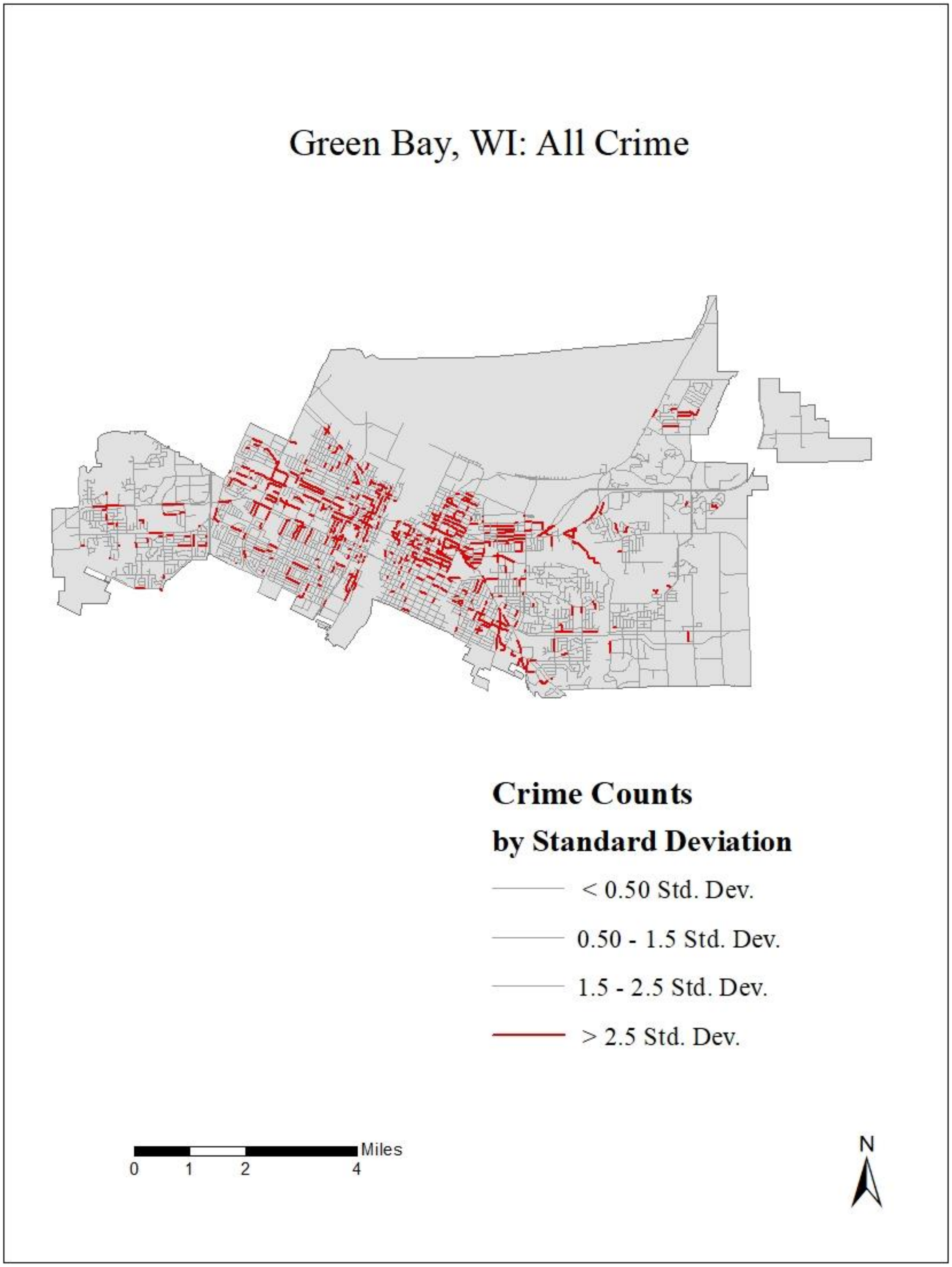
Gainesville, FL: Crime Counts Map



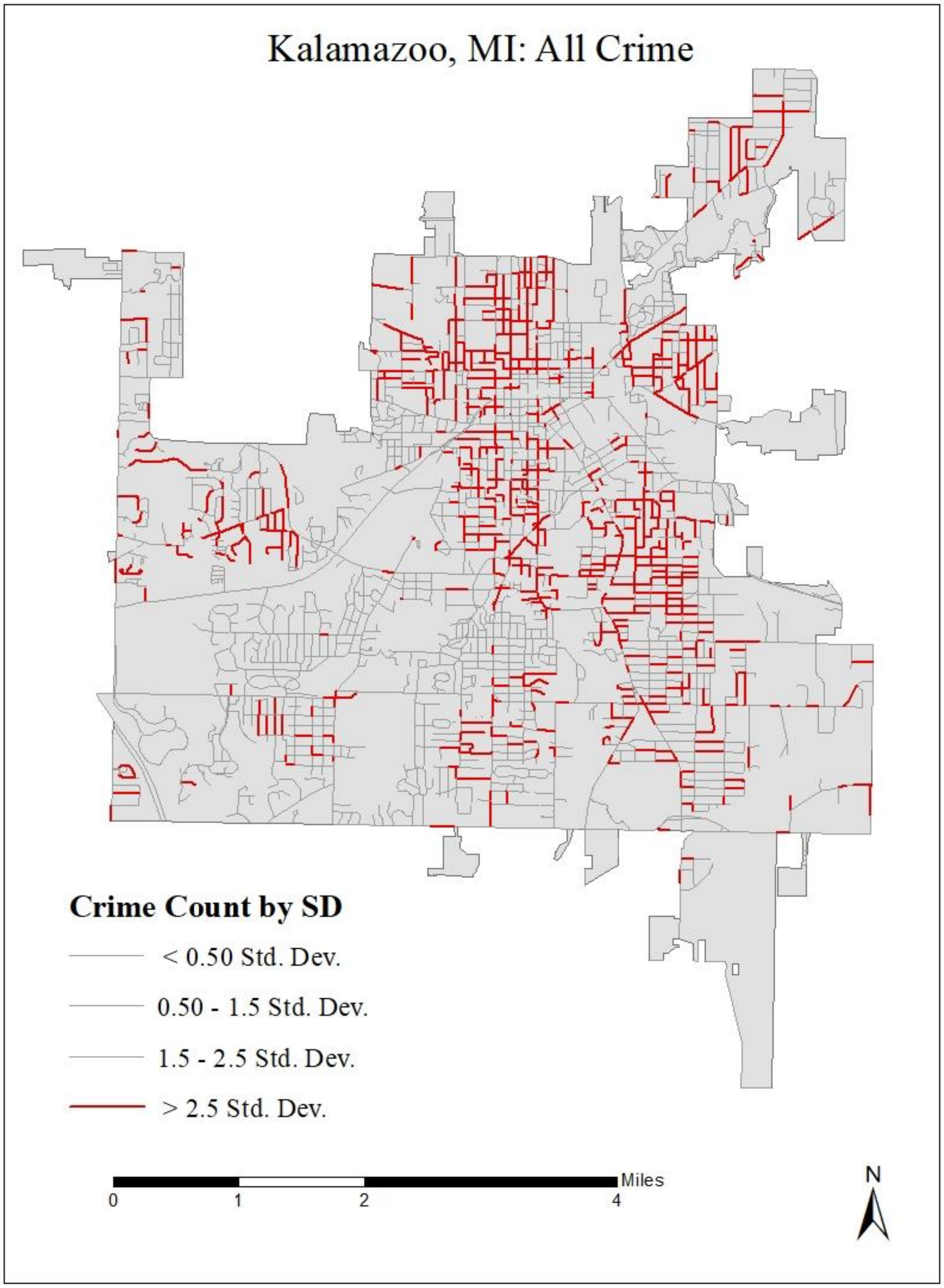
Galveston, TX: Crime Counts Map



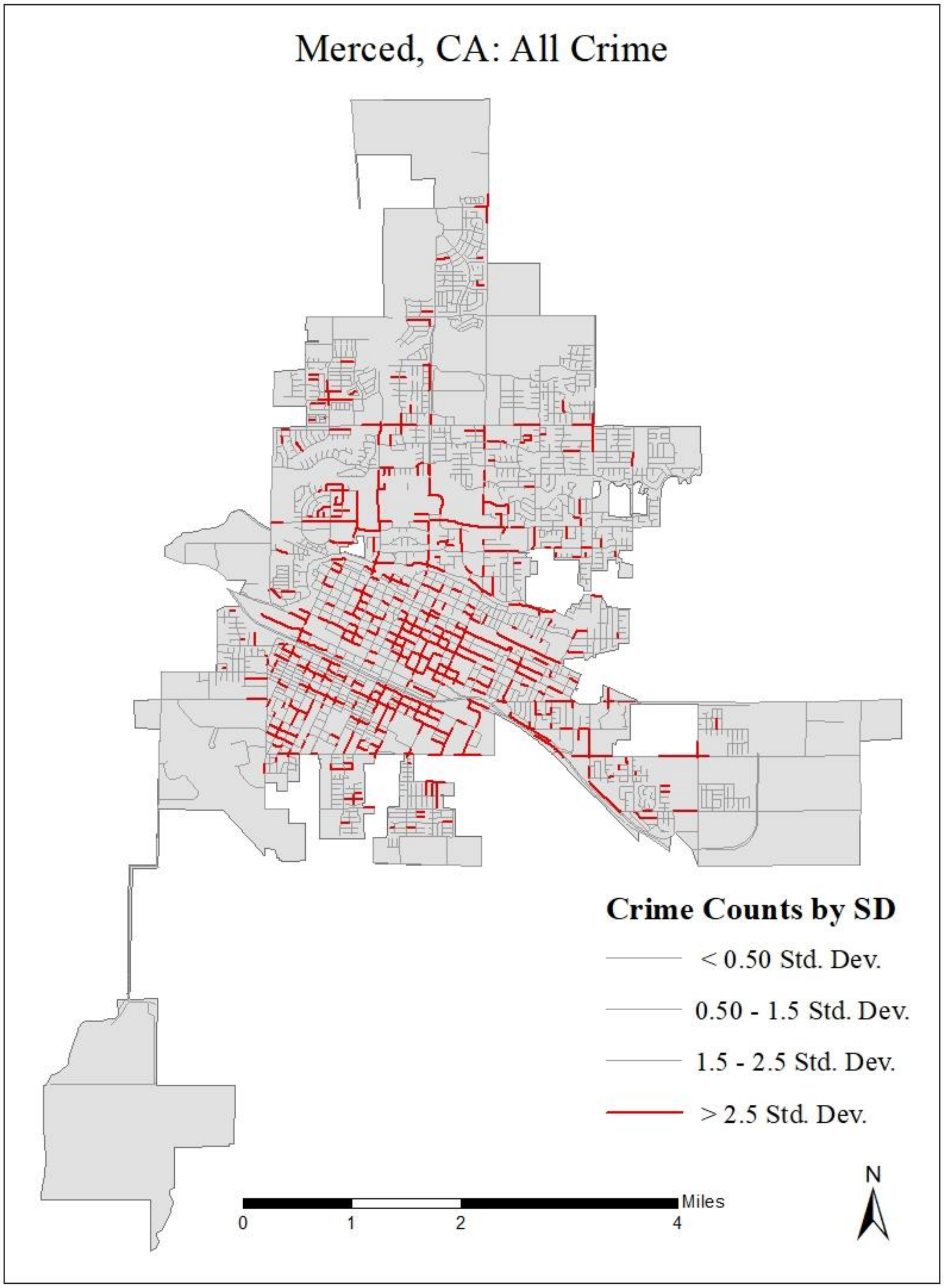
Green Bay, WI: Crime Counts Map



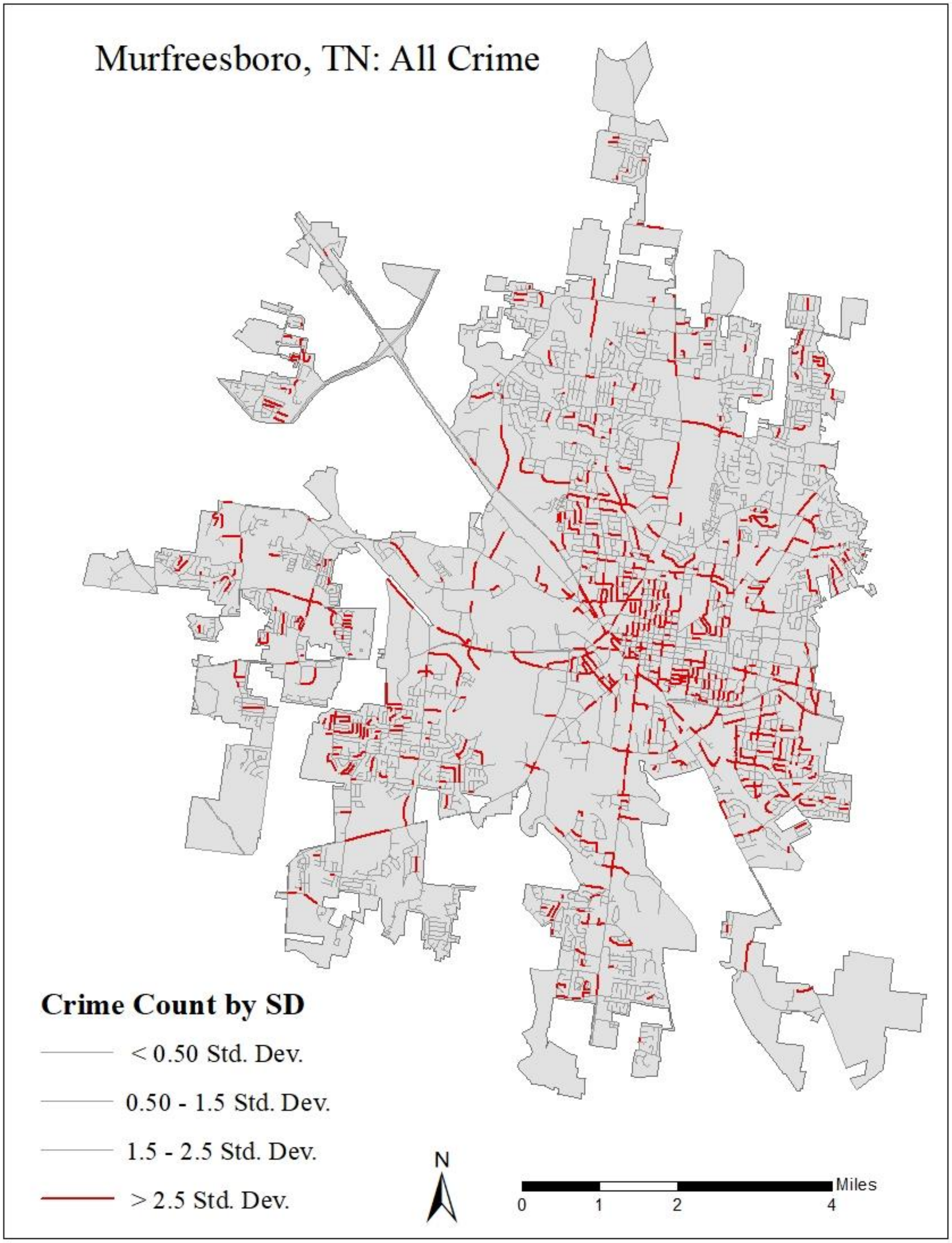
Kalamazoo, MI: Crime Counts Map



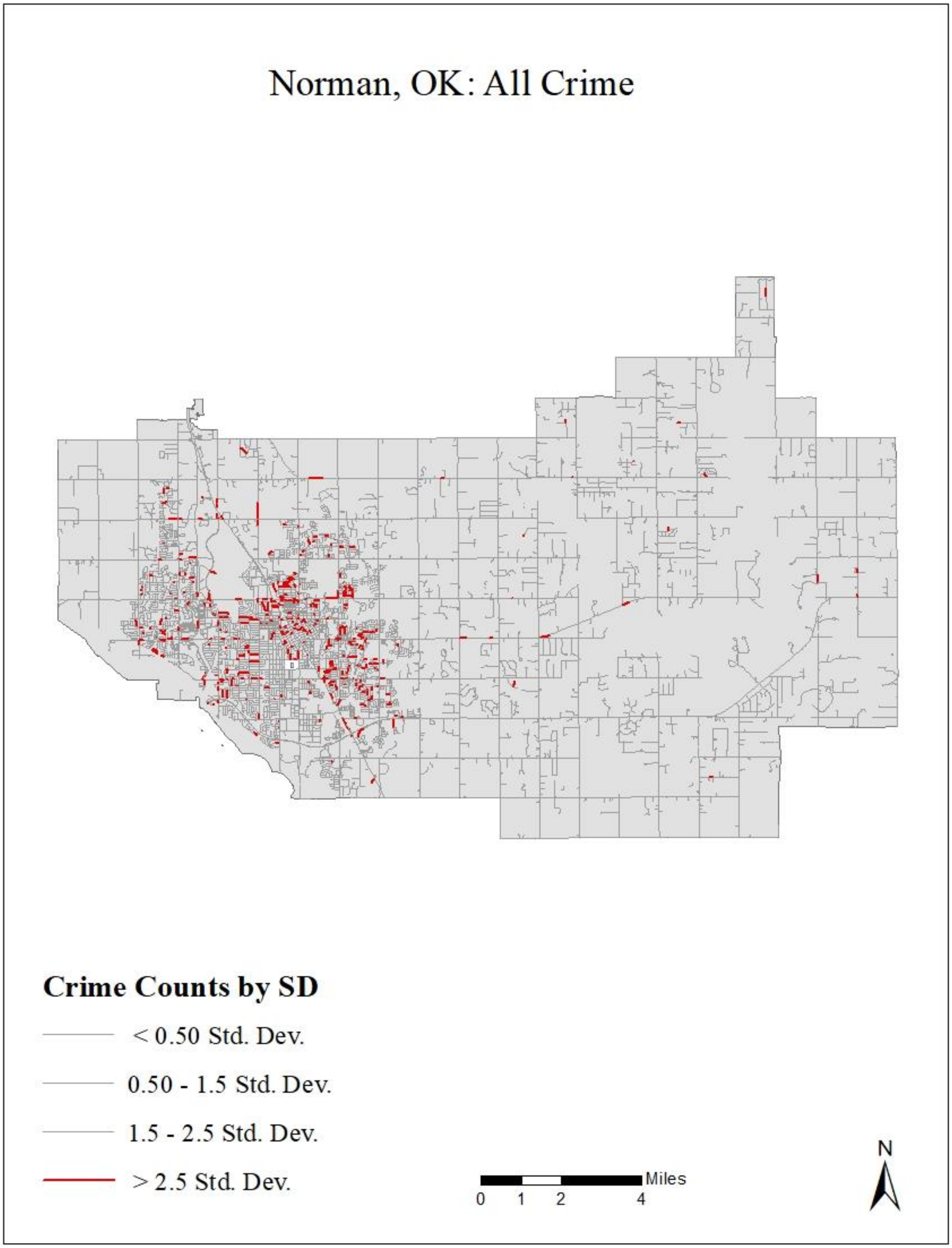
Merced, CA: Crime Counts Map



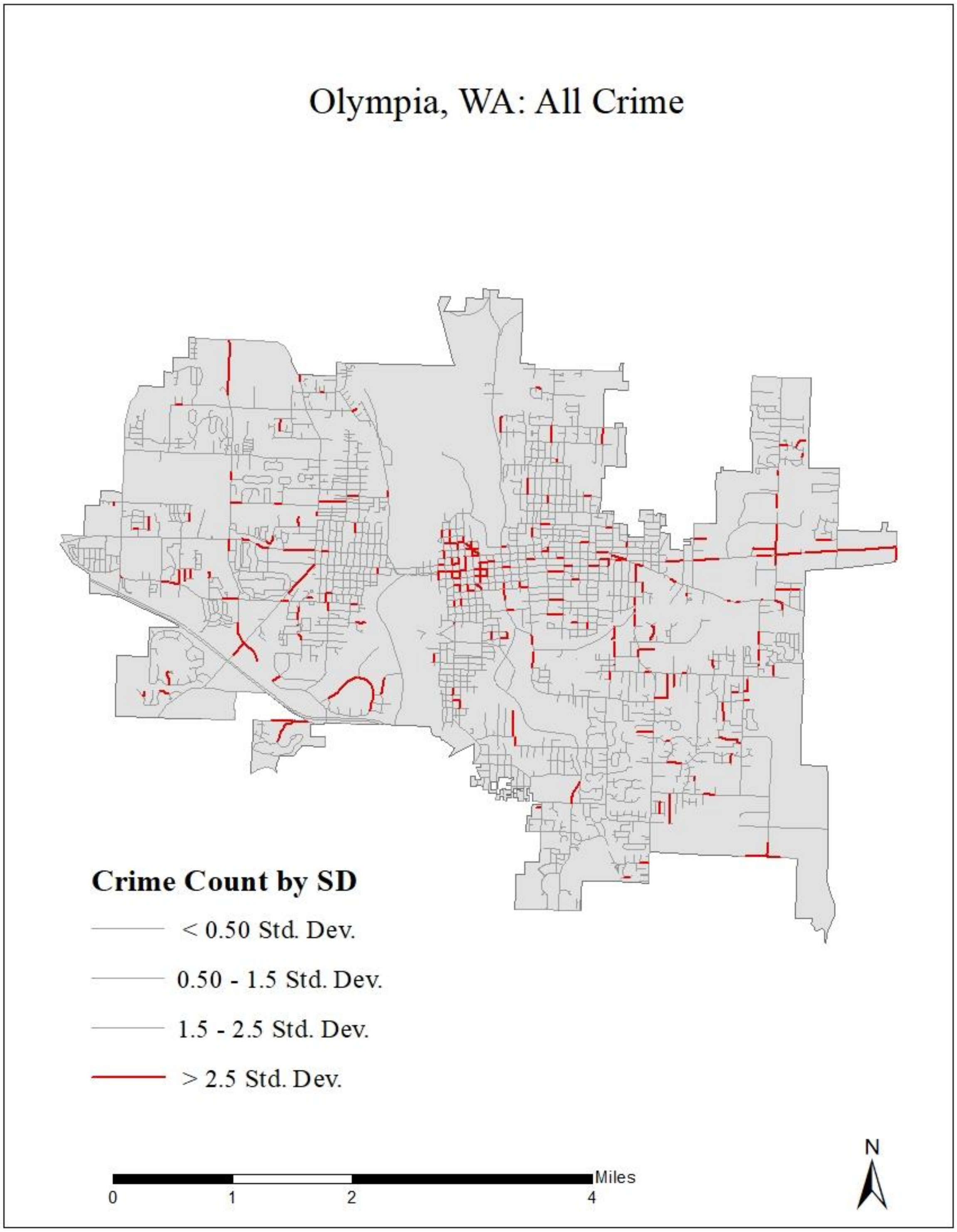
Murfreesboro, TN: Crime Counts Map



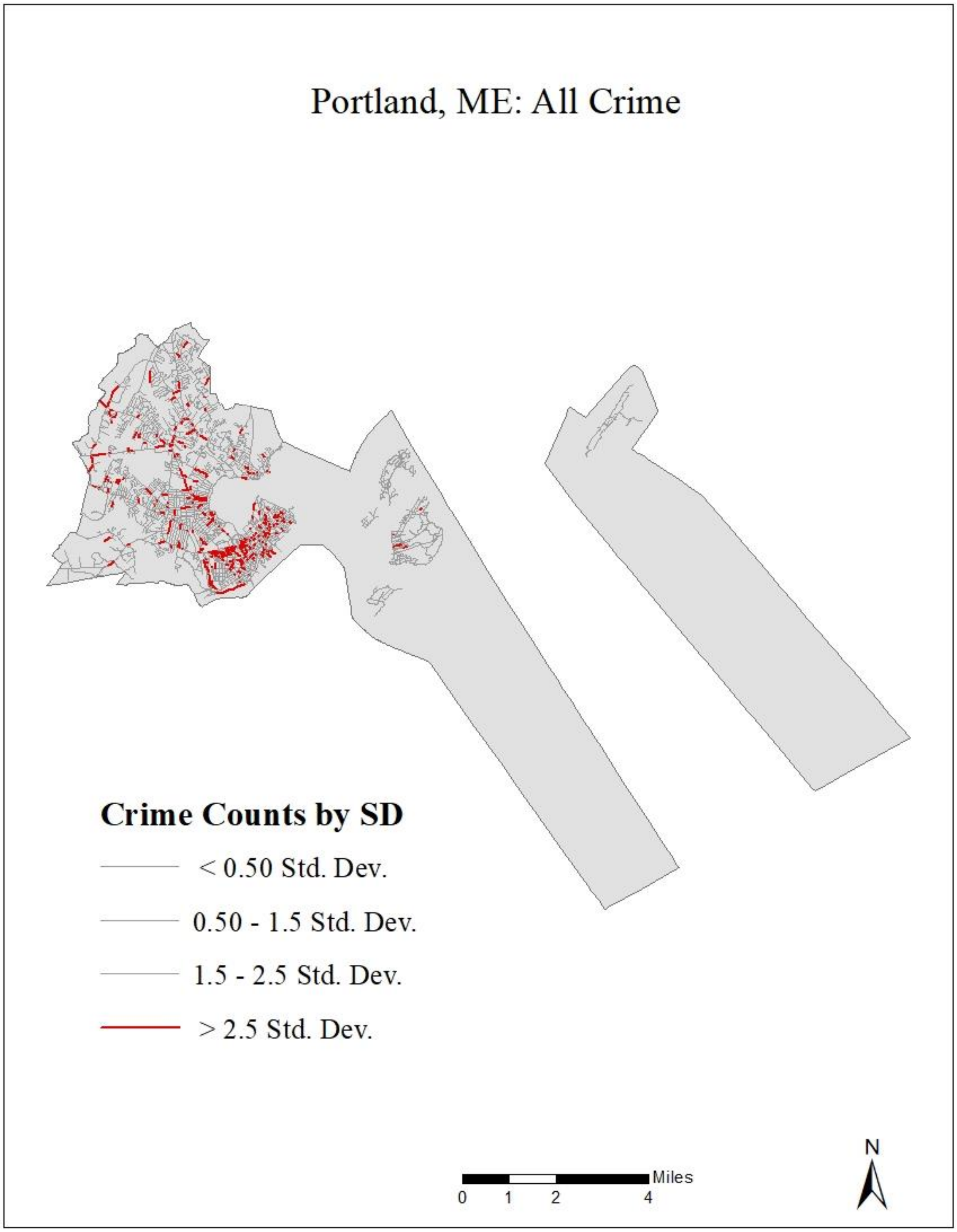
Norman, OK: Crime Counts Map



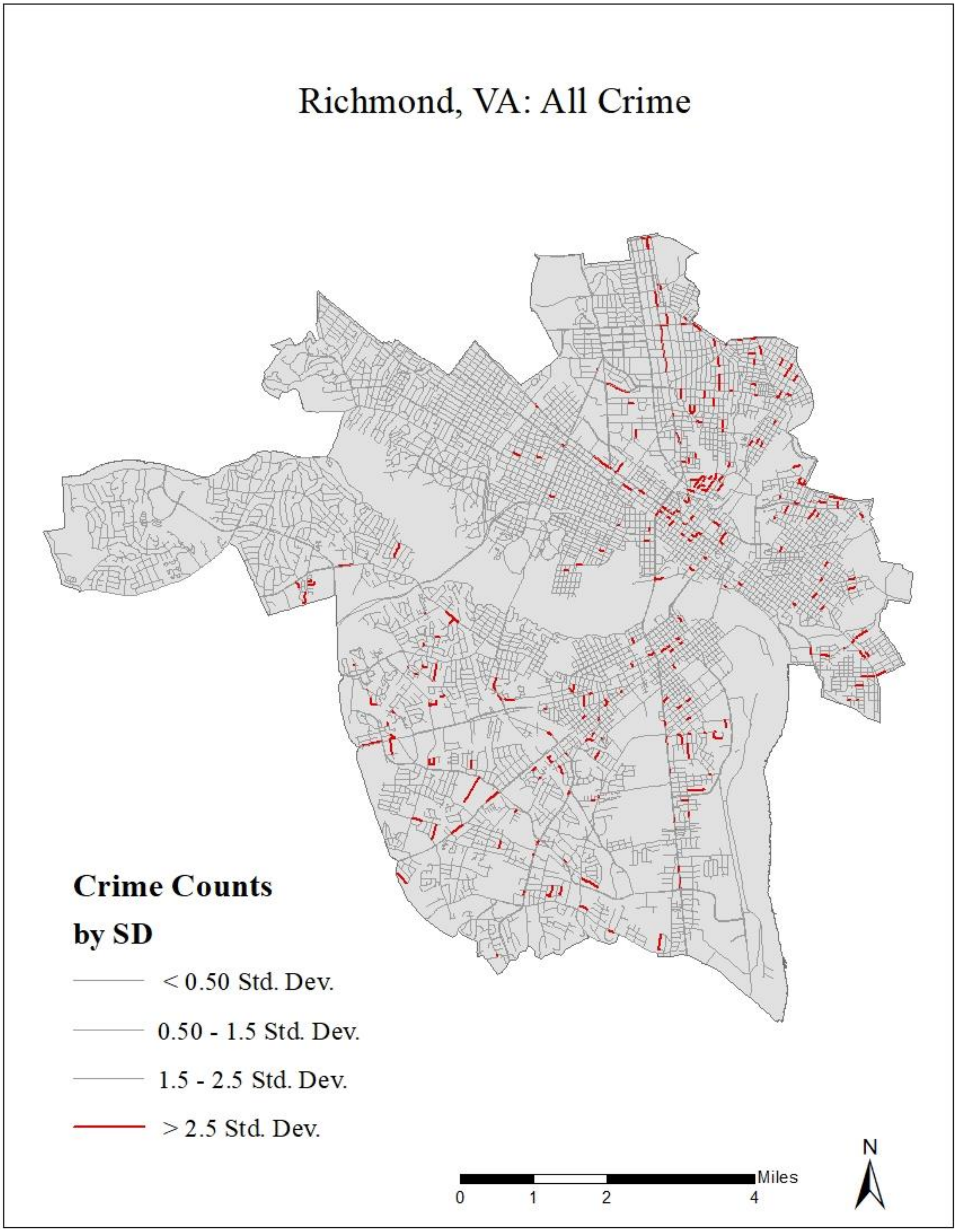
Olympia, WA: Crime Counts Map



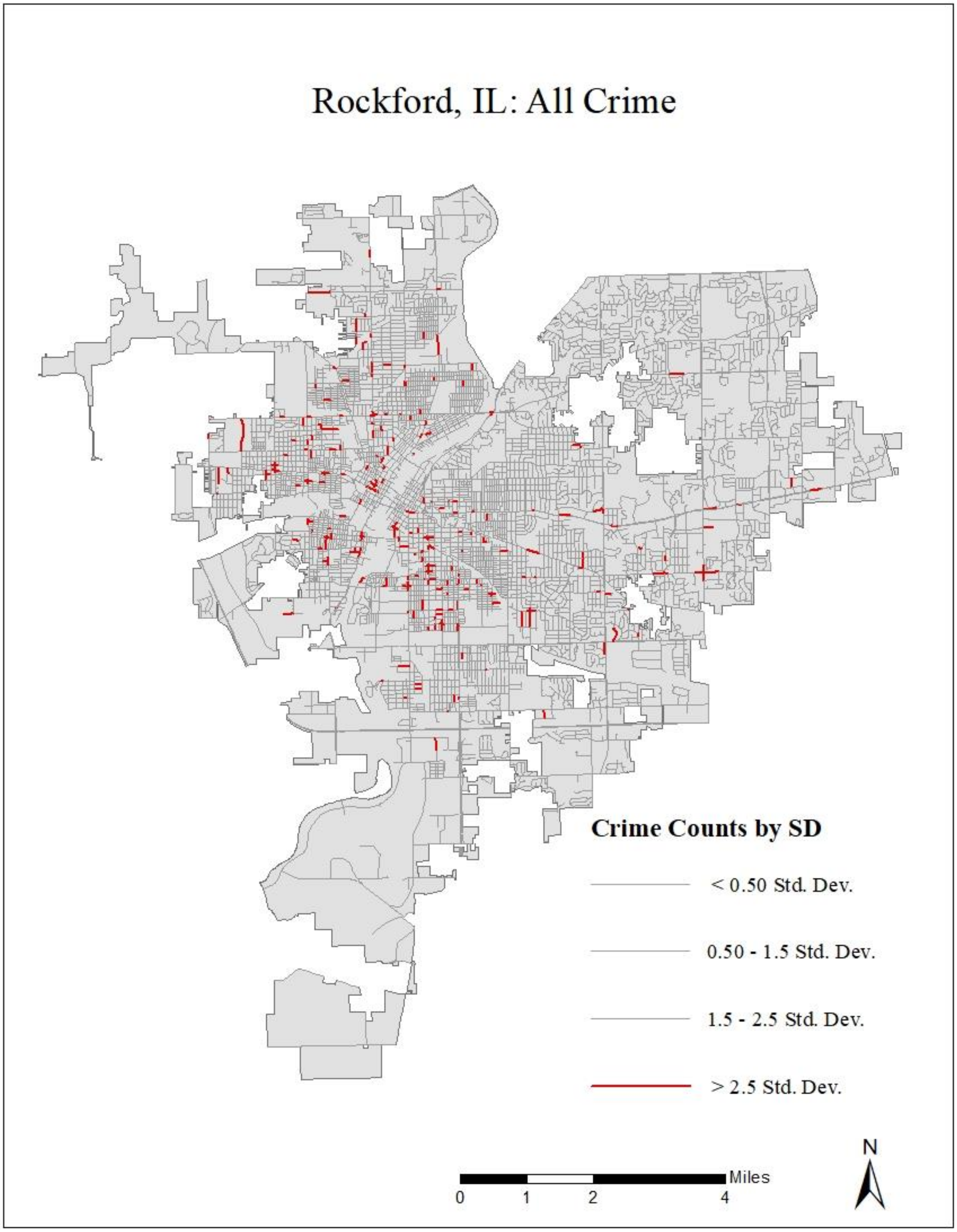
Portland, ME: Crime Counts Map



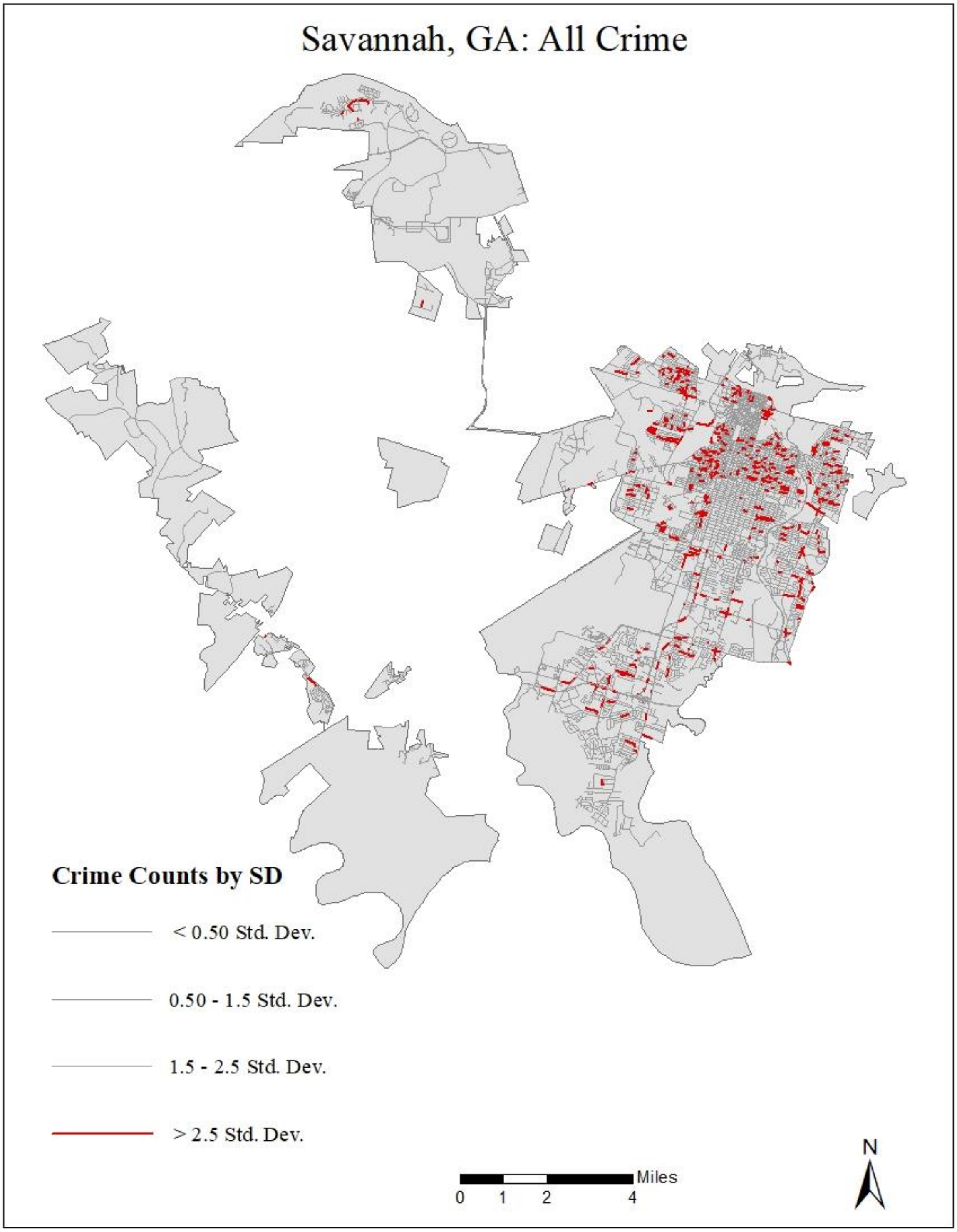
Richmond, VA: Crime Counts Map



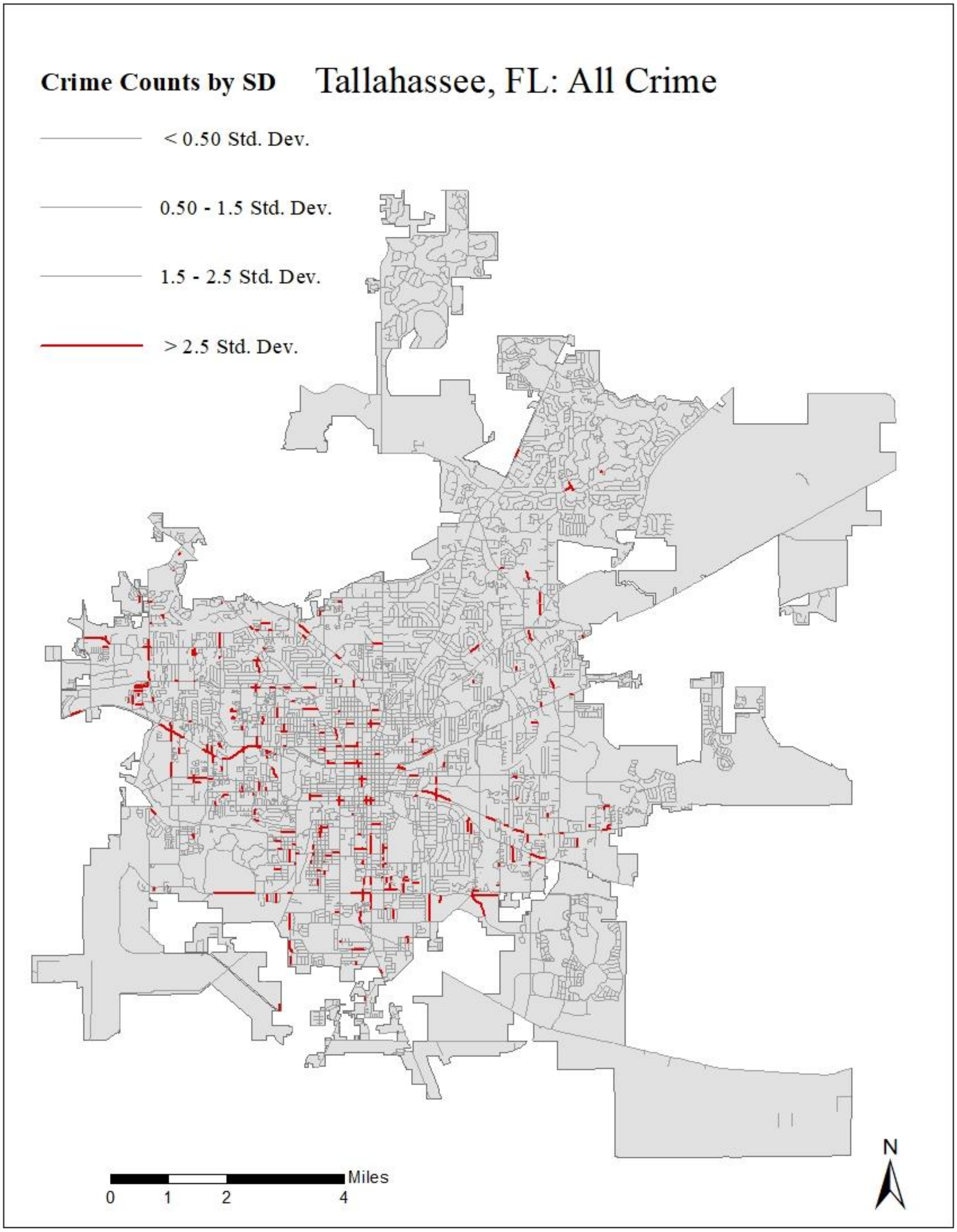
Rockford, IL: Crime Counts Map



Savannah, GA: Crime Counts Map



Tallahassee, FL: Crime Counts Map



Appendix B

Copy of Formal Letter Sent to Police Departments

WKU

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DEPARTMENT OF SOCIOLOGY

To whom this may concern,

My name is Hannah Ridner and I am a graduate student at Western Kentucky University in the Sociology Department.

The purpose of this letter is to formally request access to crime incident data for the year 2016.

I am doing research for my Master's thesis, where I will be exploring crime concentration across a sample of 25 mid-sized cities throughout the United States. The purpose of this study is to measure the concentration of crime to determine the level of consistency across American cities.

This is measured by using a Gini coefficient, which is a single number ranging from 0 to 1, where the values closer to 1 indicate more concentration. From this study, two Gini coefficients will be produced, one for violent crime and one for property crime. The findings of this study will greatly contribute to our understanding of crime concentration, and help establish an idea of what to expect as we continue to look at crime concentration.

Regarding the data, I am requesting the following fields: (1) Addresses, (2) X-Y coordinates, (3) Crime type, and (4) Incident description. Due to differences in how various police agencies record crime incidents, I am requesting access to all crime incidents for the year of 2016, so that I can ensure violent and property crime measures are as consistent as possible across the 25 cities.

If possible, the delivery of the data in Excel format is preferable. If you need any more information about me or my study, please do not hesitate to contact me.

E-mail: Hannah.ridner154@topper.wku.edu
Phone: (865) 235-5023

Thank you for your time and help,
Hannah Ridner
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Western Kentucky University

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