Shootings and Crime Places:
An Analysis of the Determinants and Distributions of Violent Events

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ABSTRACT

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This dissertation presents a systematic approach to identify the determinants of gun shooting and forecast the distribution of gun shooting. Using frameworks of opportunities theories and social disorganization theories, this study examines the influences of urban features, including public housing, bus stops, liquor stores and bars, and schools, and neighborhood characteristics, on variations of rates of gun shooting in Newark and Irvington, NJ. A crime forecasting model is built based on the results of the determinants analyses in order to predict future shooting distributions.

This study introduces a spatial statistics method, Conditional Locational Interdependence (CLI), to identify crime generators. CLI overcomes the limitations of current common method that requires arbitrarily determining the polygon size. In addition, this study utilizes several data analyses to address the spatial interdependence of the data. Besides, to address the non-Gaussian and spatial dependence of the data, poisson regression and negative binomial regression are employed and compared by adding spatial lag as one of the predictors. Further, smoothing method is used to convert census data to smaller units. Finally, risk terrain modeling is used to build a forecasting model to predict the distributions of gun shooting.

The results show that gun shooting is not randomly distributed throughout the study area but rather is concentrated in a statistically significant way around major facilities: public housing, bus stops, liquor stores and bars, and middle and high schools. Also, shooting is clustered in poor neighborhoods with high single parents rate, low ethnic heterogeneity, and high jobless rate. This research provides another tool in establishing how risk clusters emerge and influence the distribution of crime. The clustering that takes place relates not only to the interrelationship between crime incidents but also to interdependence established between crime behavior, facilities, and neighborhoods. This study also has its implications in theory and police practice. This study supports social disorganization theory and opportunities theories. This study demonstrates a systematic method to identify the determinants and forecast the distribution of criminal events, which can help the police to allocate their limited resources more effectively and efficiently.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Chapter 1. Introduction

Places are important in crime prevention and crime control. Crime is not spread evenly across city landscapes; rather, crime clusters in very small places that generate a disproportionate amount of criminal events (Pierce et al., 1988; Sherman, Gartin, and Buerger, 1989; Weisburd et al., 1992; Braga et al. 2010). Compared to people who commit crime, places where crime occurs are far more predictable. So, if crime control policies respond to places with concentrated crime, crime can be reduced more efficiently.

This dissertation contributes to current scholarship on the role of places in the generation of violent crime. This study focuses on gun shooting and places. The purposes of this dissertation are to identify the determinants of gun shooting and to predict the distributions of shootings in urban areas.

The study areas are Newark and Irvington, New Jersey, two neighboring highly-disorganized cities. The two communities have become particular concerns for local and state police in recent years due to their serious problems with gun shootings. The local police are unable to deal with the violence problem due to their limited resources. Since 2005, a special force of state and federal agents has been assigned to the communities and the heavy lifting in law enforcement has been delivered by this special force. However, their numbers are limited. The task of managing these areas is still daunting and demands careful consideration of how to manage and distribute police effort.

Where and how to deploy limited resources to maximally control crime is an important task facing police executives. This task calls for more proactive policing strategies to identify areas of concern and develop resource allocation. Since all things cannot be protected at all times, a systematic approach should be utilized to spatially and temporally determine priorities (Van Brunschot and Kennedy, 2007). This study uses a systematic approach to identify the risk factors from both micro- and macro- levels and to predict risky areas based on the risk assessments that can be of use to police leaders in developing plans for crime control in high crime areas.

This study draws on opportunity theories and social disorganization theories in explaining and identifying the crime potential of place. Criminal opportunity theories subsume a number of perspectives that have been used to understand the distribution of crime and violence in space. The Rational choice perspective provides the basic rationale for defining place as important, since it suggests that offenders will select targets and define means to achieve their goals in a manner that can be articulated in terms of gains and losses. The routine activity perspective emerged as a vehicle to understand how the confluence of circumstances surrounding the victim, offender, and place come together to create the opportunity for crime. Environmental criminology is particularly important in developing an understanding of crime and place because it combines rational choice and routine activity theory to help explain the distribution of crime across places. Environmental criminology links places with desirable targets and the context within which they are found by focusing on how places come to the attention of potential offenders. Looked at in this way, attributes of places are the key in explaining crime concentrations (Brantingham and Brantingham, 1993).

Environmental criminologists divide locations into two types: crime generators and crime attractors. Crime generators produce crime by creating particular times and places that provide appropriate concentrations of people and other targets in settings that are conducive to particular types of criminal acts. Crime attractors are places that bring people to come to commit crime. Both crime generators and crime attractors are spread across the environmental backcloth of cities (Brantingham and Brantingham 1995).

In identifying crime generators, this study introduces a method called Conditional Locational Interdependence (CLI). CLI overcomes the limitations in traditional methods in two ways: Firstly, CLI does not require creating any quadrat. The traditional method relies on quadrats creation and regression analysis. A region is divided into a number of quadrats, and the number of crime points in each quadrat is regressed on variables related to infrastructural elements. However, this method suffers from the problem of size: the result may dramatically change according to the size of a quadrat. Secondly, CLI does not aggregate data. Spatial relations between crime points and infrastructural elements become ambiguous because the configuration of crime points in each quadrat is neglected by aggregation. CLI, on the other hand, is based on nearest neighbor analysis to test whether the mean minimal distance from the hypothetically crime distribution to the infrastructural distribution is significantly less than that from a spatially random pattern of crime.

Social disorganization theory, which we consider along with opportunity theory, suggests that communities characterized by weak interpersonal networks (both ties between persons and ties between persons and institutions) are less able to regulate the behavior of their residents through the communication of shared values and standards for behavior (Shaw and McKay 1942). Three structural factors, low economic status, ethnic heterogeneity, and residential mobility, lead to the disruption of community social organization, which, in turn, account for variations in crime and delinquency (Shaw and McKay 1942; Sampson and Groves 1989; Veysey and Messner 1999).

The study of crime generators and the neighborhood analyses provide the foundation for crime forecasting. The underlying factors of violence are embedded in certain features of the environment. When the environmental conditions become ripe, violence occurs. The results of crime generators analysis and neighborhood analysis help to predict future violence distribution.

This study builds a forecasting model of violence based on the results from crime generators and neighborhood analyses. Crime forecasting did not become relevant until two things occurred. First, the importance of place was established based on theories such as rational choice theory, routine activity theory, environmental criminology, and hot spots of crime. Second, in the past decade, police began regularly mapping crimes using geographic information systems. The focus of crime prevention and law enforcement is on places where crime is most likely to take place. The use of Geographic Information Systems in law enforcement has increased significantly. However, most applications are retrospective - that is, they examine criminal phenomena and related factors that have already occurred. While such retrospective mapping efforts are useful, the true promise of crime mapping lies in its ability to identify early warning signs in places and inform a proactive approach to police problem solving and crime prevention.

This study has three parts. The first part is designed to identify crime generators for shooting. The second part examines neighborhood influence on shooting. The third part builds a forecasting model to predict shooting distribution. The first two parts will look for underlying risk factors that generate violence. The third part will use the risk factors found in the first two parts to forecasting future violence. Also, in order to test the predictability of this model, a logistic regression will be conducted to test how well this model can predict subsequent time period shooting locations.

The literature reviews are covered from Chapter 2 to Chapter 5. Chapter 2 presents an overview of the theoretical framework on crime and place. Chapter 3 goes through social ecology theories about crime and the proactive policing in response to social disorganization. Chapter 4 focuses specially on shootings and place. Chapter 5 reviews intelligence-led policing and place risk assessment. Chapter 6 introduces the design of this study.

Understanding the spatial effects of certain factors on crime is the key to assessing and valuing crime risk. Chapter 7 examines whether certain factors are crime generators of shootings. Chapter 8 tests whether the predictability of forecasting models varies by using different factors with different levels of crime generating effects. These two chapters belong to the first part.

Chapter 9 examines the neighborhood influences on shootings. Based on social disorganization theory, concentrated disadvantage, ethnic heterogeneity, and residential instability are the three structural factors that account for the variations of crime. This chapter looks to the effects of these three structural factors on shootings. Also, the results give the most important neighborhood factors that influence shooting rates.

Based on the results from crime generator analysis and neighborhood analysis, chapter 10 builds a forecasting model using risk factors that have been identified in the first two parts. The approach of building this model is Risk Terrain Modeling (RTM) (Caplan, Kenndy and Miller 2010). Before building the RTM model, the units of all the risk factors are standardized. To disaggregate census data, smoothing methods in GIS are used. The result of this chapter is a composite map that contains all the information of all the risk factors. This composite map shows places with different risk values. The places with higher risk values are the most dangerous places that the police should deploy more resources in. Finally, statistical tests are conducted to test the validity of this forecasting method. Chapter 11 presents the conclusions, discussions, and implications of this study.

Chapter 2 Places are important

1. The Concentration of Crimes

Crimes are highly concentrated. A few offenders commit a great many crimes; those who have been victims once are more likely to be victims again than are nonvictims likely to be first-time victims; and many crimes occur in a few locations—“hot spots”. Many crime problems can be reduced more efficiently if crime control policy responds to these concentrations of criminal offending. John Eck (2001) observes that 10% of the offenders committing the most crimes are involved in about 50% of the offenses; that 10% of the most victimized people are involved in about 40% of the crimes; and that 10% of the places with the most crime accounts for about 60% of crime. As a result, repeat address incidents dominate police work.

A relatively small number of offenders commit most crimes. Sherman (1992) found that only 2.7% of the estimated 500000 individuals in Kansas city were arrested twice or more in 1990. They produced over 60% of all arrests that year. The most frequently arrested 642 persons produced over 10% of all 71461 “body arrests”, defined as each event of taking a person into custody regardless of the number of charges, victims, or co-offenders. One hundred persons were arrested fifteen or more times that year, and ten persons were arrested thirty-two times or more.

Repeat victimization is the recurrence of crime in the same places and/or against the same people. A major finding of the research on repeat victimization is that people and places that have been victimized in the past have a higher likelihood of being victimized again than do people and places that have never been victimized (Farrell and Pease 1993, Pease and Laycock 1996). The phenomenon of repeat victimization facilitates the identification of patterns of opportunities and provides a focus for prevention, in that those who have been victimized in the past should be at the top of the list for the targeting of prevention measures.

Not only offenders and victims are highly clustered, but the time of criminal events is highly concentrated. Even within hot crime locations, of all the crimes, fully half or about one-third of the total violent crimes were reported to have occurred between midnight and 3:00am (Sherman 1992). A one-year analysis of all calls for service in 100 Minneapolis hot spot address clusters found that they were all quite inactive between 3:00am and 11:00am(Sherman 1992).

Wolfgang (1958) in his classic work in Phladelphia demonstrated that offending clustered in a small portion of the general youth population. Six percent of the 1945 cohort he studied had committed five or more offenses and accounted for more than half of all offenses committed by the cohort. Similarly, Sherman showed that over 60% of crimes are committed at only 3% of the places within communities (Sherman 1987). Only 5% of 115000 street addresses and intersections in the city produced 100% of the calls for those usually stranger offenses in Minneapolis. These findings have subsequently been replicated in Kansas City (Sherman et al. 1991). Analyses of taverns and surrounding areas in Milwaukee and Kansas City shows that 4% of homicides, 5% of aggravated assaults, 3% of robberies, and 3% of all serious violent offenses combined occurred in taverns constituted only 0.5% of all places in the city (Sherman et al. 1991). Even within the worst neighborhoods, crime clusters at a few locations (Sherman et al. 1989; Weisburd et al. 1992). Certain areas are more likely to attract crime than are others (Eck et al. 2005).

2. The Criminology of Places

1) Hot Spots Perspective

In the recent decades, there has been a renewed theoretical interest in the correlation between crime and place; in particular, in explaining differential rates across areas. In this domain, a series of perspectives and theories related to crime and place have been developed, tested, and applied. Crime is not randomly distributed in space; rather, it is concentrated in relatively small places. Over half of all crimes in a city are committed at a few discrete locations and other areas are relatively crime free (Sherman et al 1989). Even within the most crime-ridden neighborhoods, crime clusters at a few discrete locations and other areas are relatively crime free (Sherman et al 1989). In Minneapolis, only 3 percent of the city’s addresses accounted for 50 percent of calls for service to the police (Sherman, Gartin, and Buerger, 1989). In Jersey City, about 4 percent of streets and intersection areas generated nearly half of the city's narcotics arrests and almost 42 percent of the disorder arrests (Weisburd and Green Mazerolle, 2000). In Seattle, only 4.5 percent of street segments accounted for 50 percent of crime in 14 years (Weisburd et al. 2004). In Boston, only 5 percent of street segments and intersections are responsible for 74 percent of serious gun assault incidents even when controlling for prior levels of gun violence and existing linear and nonlinear trends (Braga et.al. 2010). Even in the most crime-ridden neighborhoods, crime clusters in a few discrete locations, while other areas are relatively crime free (Sherman, Gartin, and Buerger, 1989).

Studies on crime clustering have confirmed that places are important in the distribution of violent street crime across the city landscape. In the well-known Minneapolis hot spots research, all robbery calls for service were concentrated at only 2.2% of all places and all assault calls were concentrated in 7% of all places (Sherman et al 1989). The clustering of violent crime at places suggests that there are important features or dynamics at these locations that give rise to violent situations; focused crime prevention efforts could modify these criminogenic conditions and reduce violence.

Scholars have argued that many crime problems can be reduced more efficiently if officers systematically focus their attentions on these deviant places (Sherman and Weisburd 1995; Weisburd and Green 1995)

2) Rational Choice Perspective

In making sense of this crime concentration, we draw on theories that address how people operate in space. The rational choice perspective draws heavily on classical theory and economic theories of crime, and argues that crimes are broadly the result of rational choices based on analyses of anticipated costs and benefits (Cornish and Clarke 1986). Individuals choose to engage in crime in an effort to maximize their benefits and minimize their costs.

This choice process occurs in two stages: first, individuals decide whether they are willing to become involved in crime to satisfy their needs. Whether they decide to engage in crime is heavily influenced by their previous learning and experience, including their moral code, view of themselves, personal experience of crime, and the degree to which they can plan and exercise foresight. In turn, the previous learning and experience are heavily influenced by a range of background factors, including individual traits, their upbringing, and their social and demographic characteristics such as sex and class.

Second, once individuals decide to engage in crime, they must decide to commit a particular offense. This decision is heavily influenced by the immediate situation of the individual. The individual may have a desperate need for money or may be out with friends who suggest engaging in crime. The individual then selects a target for the offense based on a consideration of costs and benefits. For example, the individual selects a home to burglarize based on considerations of whether the home is occupied, whether the home is easily accessible, or whether there is reason to believe that it contains valuable items. The factors that individuals consider may differ dramatically from one type of crime to another, which is why rational choice theorists argue that crime-specific models must be employed. Different models of decision making are necessary for different types of crime. This is one of the leading contributions of rational choice theory.

This perspective is often combined with routine activity theory to explain criminal behavior during the criminal event (Clarke and Felson 1993). The theoretical focus of rational choice theory has important policy implications on how best to reduce crime: situational crime prevention.

3) Routine Activity Perspective

According to Cohen and Felson (1979), a crime can occur only if there is someone who intends to commit a crime (motivated offender), something or someone to be victimized (a suitable target), and no other person present to prevent or observe the crime (the absence of a capable guardian). When a suitable target that is unguarded comes together in time and space with a motivated offender, the potential for a crime is there.

Routine-activities theories are mainly based on two central assumptions (Miethe and Meier 1990). First, patterns of routine activities and lifestyles are assumed to create a criminal-opportunity structure by enhancing the contact between potential offenders and victims. Second, the subjective value of a target and its level of guardianship are assumed to determine the choice of the particular crime victim.

Routine-activities theories generally acknowledge four risk factors in explaining the individual's risk of falling victim to crime: proximity to high crime areas, exposure to criminal opportunities, target attractiveness, and guardianship (Meier and Miethe 1993). Physical proximity to high crime areas is a major factor that increases victim risk. Living in or near an area with large populations of potential offenders increases the likelihood of frequent contacts with these offenders and thus increases the risks of victimization. Relatively high rates of crime should occur in larger cities. Exposure to criminal opportunities is an additional factor that increases the risk of victimization. Visiting certain places, using public transportation, and interacting with a large number of persons may be assumed to increase the frequency with which a person comes into the vicinity of potential offenders and consequentially increases one's risk of falling victim. Besides, engaging in delinquent conduct can be viewed as an important feature of a specific lifestyle that greatly enlarges the risk of being a victim. People who engage in offending more frequently put themselves into high-risk situations and associate with other offenders, thus enlarging their own risk of victimization.

An individual's risk of victimization is also assumed to be affected by the target attractiveness of that individual and/or his or her belongings. The higher the economic or symbolic value is, the more attractive the target, and thus the higher the risk of victimization. Therefore, persons with higher income, status, and education, who probably own more valuable properties, are more attractive to criminals. They are assumed, therefore, to have a higher risk of victimization, especially of property crimes. Finally, the risk of victimization is presumed to be related to the availability of capable guardians. Leaving one's house unattended more often and getting into situations where help is unavailable decrease the level of guardianship and consequentially increase the victimization risk.

4) Environmental Criminology

Environmental criminology's basic contribution lies in its call for a change in the unit of analysis from persons to places. The attributes of a place are viewed as key in explaining clusters of criminal events.

Environmental criminology, also known as crime pattern theory, explores the distribution and interaction of targets, offenders, and opportunities across time and space (Brantingham and Brantingham 1991). Brantingham and Brantingham suggest that the criminal event is comprised of four elements: the law, offender, target, and place. Their Environmental Criminology proposes the following (Brantingham and Brantingham 1978, 1993):

• Individuals exist who are motivated to commit specific offenses;

• Given criminal motivation, the actual commission of an offense is the end result of a multistage decision process in which an offender seeks out and identifies a target within the general environment.

• The "activity spaces" and "awareness spaces" that comprise the environment emit cues about its physical, spatial, cultural, legal and psychological characteristics.

• The motivated individual uses cues from the environment to locate and identify targets or victims.

Thus, the environment, or place, provides the structural backcloth against which criminal events may be played out. But place may similarly establish what has been dubbed an "activity backcloth" as well.

According to Eck and Weisburd (1995), it does so because offenders engage in routine activities. Just like other, non-offending individuals, offenders move between home, school, work, shopping, and recreation. As they conduct their normal legitimate activities, they become aware of criminal opportunities. Thus, criminal opportunities that are not near areas offenders routinely move through are unlikely to come to the attention of offenders. Criminal opportunities found at places that come to the attention of offenders have an increased risk of becoming targets.

5) Crime Attractors and Crime Generators

As crimes are clustered in a few locations, the locations where offenders commit crimes are one of the focal interests for researchers. Brantingham and Brantingham (1995) divided the locations into two groups: crime generators and crime attractors. Crime generators are places to which large numbers of people are attracted for reasons unrelated to criminal motivation. Providing large numbers of opportunities for offenders and targets to come together in time and place produces crime or disorder. Examples of generators include shopping areas, transportation hubs, festivals, and sporting events. The large number of crime or disorder events in these locations is due principally to the large number of place users and targets. Crime attractors are places affording many criminal opportunities that are well known to offenders. People with criminal motivation are drawn to such locales. In the short run, offenders may come from outside the area, but over longer time periods, and under some circumstances, offenders may relocate to these areas. Prostitution and drug areas are examples. Some entertainment spots are also well known for allowing deviant activity. Such places might start off being known only to locals, but as their reputation spreads increasing numbers of offenders are drawn in, thus increasing the number of crime and disorder events (Clarke and Eck 2005)

6) Characteristics of Places

Taylor and Gottfredson (1986) suggest characteristics of neighborhood, street blocks and specific sites determine whether an offense will be committed. For potential offenders, the first level of at which physical environment comes into play is the selection of a neighborhood where an offense may be carried out. Five classes of factors are likely to influence the content and clarity of the neighborhood image held by an offender: physical environment features, resident sociodemographic characteristics and behavior patterns, policing patterns, offenders' collective social knowledge of locale and the knowledge and disposition of the individual offender (Taylor and Gottfredson 1986).

The physical characteristics of the locale can influence neighborhood images by shaping offenders' perceptions of the characteristics of residents, by influencing the characteristics of the resident population, and by setting the salient features of the crime activity space (Taylor and Gottfredson 1986). A neighborhood with more streets leading into it, adjoining a main artery, close to an exit off a major highway, adjacent to a commercial center, having many vacant houses, littered playgrounds, abandoned cars, graffiti, etc, is more likely to be targeted by potential offenders (Taylor and Gottfredson 1986).

Wilson and Kelling (1982) suggested that offenders from adjoining areas will move into a neighborhood if they see physical cues suggesting residents' lack of caring for their environment, co-residents, and street activities. Physical incivilities act as such cues. Skogan (1990) argued that disorder, both social and physical, acts as an instrument of destabilization and decline. Disorder initiates an iterative process that results in community change and spiral decay. Ultimately, disorder adversely affects a community's ability to exercise effective control. Disorder breeds fear and demoralization, and, more importantly, have the further contagious effect of breeding more and more serious crime.

Physical and social characteristics of particular blocks are the second level consideration by potential offenders. A range of factors determines block images:

housing quality, routine activity patterns of residents, the degree of observable social cohesion among neighbors, and physical characteristics of the street (Taylor and Gottfredson 1986).

Also, potential offenders' personal preferences, levels of familiarity, and experience with similar types of blocks play a role in shaping target-block images (Taylor and Gottfredson 1986).

7) Facilities

Extensive research has shown that crime tends to cluster in certain areas. Some facilities may have inherent characteristics that generate or attract certain types of crime.

Understanding the characteristics of places, such as facilities, is important because these attributes give rise to the opportunities that rational offenders will encounter during their routine activities.

Facilities, such as bars, churches, and apartment buildings, have been found to affect crime rates in their immediate environment depending on the type of people attracted, the way the space is managed, or the possible crime controllers present, such as owners, security, or police. Spelman (1993) found the presence of unsecured, abandoned buildings on city blocks was positively associated with criminal activity. Much research points to the relationship between bars and crime in proximate areas (Block and Block 1995; Roncek and Meier 1991).

The variety of physical and social characteristics known as site features can enhance or diminish the attractiveness of a place to offenders (Taylor 1997). Eck (1994) revealed evidence suggesting that cocaine sellers favor small apartment buildings because they tend to be owned by people who cannot afford to control drug selling and because dealers also tend to prefer housing complexes that have secure access points. Likewise, the presence of attendants (Laycock and Austin 1992) and closed-circuit television (Poyner 1991) have been found to reduce the number of auto thefts in parking lots. In short, features such as easy access, lack of guardians, inept or improper management, and the presence of valuable items influence the decisions offenders make about the places they choose to commit their crimes (Eck and Weisburd 1995).

A specific location or an area may be a preferred target for potential offenders. Some sorts of place may have inherent characteristics that generate or attract certain types of crime, for example, bus stops (Newton 2004; Loukaitou-Siderisa 1999), an abandoned building (Spelman, 1993), public housing (Roncek etal., 1981), or a public school (Roncek and Lobosco, 1983; Roncek and Faggiani, 1985).

3. Controlling Violence at Problem Places

1) Situational Crime Prevention

Situational crime prevention measures seek to reduce opportunities for specific categories of crime by increasing the associated risks and difficulties and reducing the rewards (Clarke 1992). Different from traditional criminology in its orientation, situational crime prevention introduces environmental change to reduce the opportunity for crimes to occur. Crime is prevented not by changing offenders but rather by changing aspects of the situations in which offenses occur. The focus is on making crime more difficult to commit or less profitable so that it becomes a less attractive choice. It is difficult to rehabilitate offenders or eliminate the root causes of crime. However, the components of situations are easier to manipulate. The key in doing this situational intervention effectively is to make the choice of crime more difficult or less appealing.

Clarke (1992) provided a useful way of understanding how crime opportunities can be blocked or made less attractive. First, there are strategies that seek to increase the effort needed to commit a crime. These might include using more effective physical barriers to crime. Second, there are strategies to increase the risks of attempting to commit a crime. These might include ways of increasing the chances of detection. Third, there are strategies to reduce the rewards of crime. These might include limiting the cash kept in a store. Fourth, there are strategies to reduce excuses such as set rules, signs.

2) Broken Windows

Research suggests that the best way to prevent violent crimes such as robbery and stranger assault may be to prevent disorder (Wikstrom 1995). In their seminal "broken windows" article, Wilson and Kelling (1982) argue that social incivilities (loitering, public drinking, prostitution) and physical incivilities (vacant lots, trash, and abandoned buildings) cause residents and workers in a neighborhood to be fearful. Fear causes many stable families to move out of the neighborhood and the remaining residents isolate themselves and avoid others. Anonymity increases and the level of informal social control decreases. The lack of control and the escalating disorder attract more potential offenders to the area and this increases serious criminal behavior.

Although some have criticized the "broken windows" hypothesis (Greene and Taylor 1988), Skogan's (1990) survey research found disorder to be significantly correlated with perceived crime problems in a neighborhood even after controlling for the population's poverty, stability, and racial composition. Further, Skogan's (1990) analysis of robbery victimization data from 30 neighborhoods found that the links between economic and social factors and crime were indirect and mediated through disorder. In their closer look at crime in Minneapolis hot spots, Weisburd and his colleagues (1992) reported that calls for service for assault and for robbery of persons were significantly correlated with "drunken person" calls for service at .46 and .50, respectively.

Experimentation with policing tactics has further illuminated the connection between crime and disorder. Research evidence from numerous community policing projects suggests that serious crime and fear can be affected by reducing disorder (Pate et al 1986; Police Foundation 1981; Reiss 1985; Skogan 1990; Trojanowicz). An analysis of robbery rates in 156 American cities revealed that aggressive policing of disorderly conduct and driving under the influence reduces robbery (Sampson and Cohen 1988). Sherman and Weisburd (1995) found that substantial increases in police patrol in hot spots can cause modest reductions in crime and impressive reductions in disorder. Further, a traditional crackdown on a disorderly street-level heroin market in Lynn, Massachusetts, not only reduced drug sales, but also reduced violent crimes and property crimes and improved the quality of life in the area (Kleiman 1988).

4. Summary

Places have recently gained new prominence by criminologists. Scholars are attempting to develop appropriate theoretical and methodological tools for understanding spatial and temporal distributions of crime. Hot spots perspective has generated not only scholarly interest in crime at place but also strong policy and practitioner interest.

Opportunity theories are important in providing a theoretical framework for why examining crime at places is critical to furthering our understanding of crime events. Rational choice theory and routine activity theory suggest that offenders are influenced by situational and environmental features that provide desirable offending opportunities. Thus Clarke (1992) suggests using situational crime prevention methods to change the environment to reduce the opportunities for crime to occur. Environmental criminology emphasizes how micro level places can play different roles in stimulating crime. This theory maintains that criminal events occur in persistent, identifiable patterns in time and space. These patterns are temporally structured by routine human social and economic activities and are spatially structured by physical and social nodes, paths, and edges that constrain physical activity. They are shaped more deeply by the cultural, social, economic, and physical backcloth that underlies any place of human habitation (Brantingham and Brantingham 1993).

Characteristics of places have their effects on crime and violence. Three levels of characteristics of places determine whether an offense will be committed or not, in particular, the characteristics of neighborhood, street blocks and specific sites. The physical and social disorder results in community decay and thus attracts serious crime. Therefore, a good way to prevent violent crime is to control disorder.

In sum, places of concentrated crime are predictable, which helps formulating crime prevention strategies. The environmental conditions play a key role in the variations of crime rates.

Chapter 3. Social Ecology of Crime

1. Social Disorganization Theory

Social disorganization theory grew out of the research conducted in the early 1930s in Chicago by Shaw and McKay (1942). Upon studying Chicago's juvenile court records over a period of several decades, Shaw and McKay noted that rates of crime were not evenly dispersed across time and space in the city. Rather, crime tended to be concentrated in particular areas of the city –namely, slum neighborhoods. Further, crime rates were highest in these neighborhoods regardless of which racial or ethnic group happened to reside there at any particular time; and, as the previously crime-prone groups moved to other lower-crime areas of the city, their rate of criminal activity decreased accordingly. These observations led Shaw and McKay to the conclusion that crime was likely a function of neighborhood dynamics and not necessarily a function of the individuals within such neighborhoods. To identify the characteristics of the high-crime neighborhoods that set them apart from low-income neighborhoods, Shaw and McKay focused on the urban areas experiencing rapid changes in their social and economic structure, called "zone of transition". These are neighborhoods that were characterized by low socioeconomic status, high rates of residential mobility, and high degrees of racial heterogeneity. These structural factors were held to produce neighborhoods that were socially disorganized.

In sum, social disorganization theory argues that communities characterized by weak interpersonal networks (both ties between persons and ties between persons and institutions) are less able to regulate the behavior of their residents through the communication of shared values and standards for behavior (Bursik and Grasmick 1993; Shaw and McKay 1942). This lack of shared behavioral standards results in an environment of disorder in which traditional social repressors of criminal behavior do not function. An excess of disorder results in an increased likelihood of criminal events. Socioeconomic disadvantage, residential instability, and ethnic heterogeneity, factors often cited in disorganization research, are not specified to be directly related to rates of crime. Instead they are thought to be factors that affect the prevalence of networks among community members, which provide the framework for communication of common values and standards for behavior.

The social environment and its influence on human behavior has been the primary focus of criminology since the early twentieth century, when sociologists Robert E. Park and Earnest W. Burgess (1925) developed models that could be superimposed o social behavior. The most important of the applications focused on the development of what the ecologists referred to as "natural areas", locations where people drawn from similar backgrounds congregated and pursued common interests. These natural areas were defined by boundaries that changed over time and developed as a function of competition that led to selection processes that sorted groups from one another and allowed certain communities to win over others in the control of urban space.

While human ecologists outlined the first piece of the social disorganization perspective's path toward crime "how communities become disorganized", the work of Shaw and McKay (1942) laid the framework for painting the second half "what happens once communities are disorganized?" Shaw and McKay examined the city's zones for differences in rates of juvenile crime. Shaw and McKay (1942) discovered that high delinquency rates persisted in certain Chicago neighborhoods for long periods of time despite changes in the racial and ethnic composition of these communities and concluded that neighborhood ecological conditions shape crime rates over and above the characteristics of individual residents. They found that the highest rates of delinquency were concentrated in the zone of transition. This finding held regardless of which first-generation immigrants were residing in the zone. Three structural factors – low economic status, ethnic heterogeneity, and residential mobility – led to the disruption of community social organization, which, in turn, accounted for variations in crime and delinquency (Shaw and McKay 1942; Sampson and Groves 1989; Veysey and Messner 1999).

2. Criticisms to social disorganization theory

Shaw and McKay's social disorganization theory has not been without criticism. Bursik (1988) outlined and addressed five general criticisms leveled against the theory. First, social disorganization theory's findings do not lead to any predictions concerning individual behavior. Bursik (1988) countered the claim that the perspective is therefore meaningless, offering that individual-level and community-level perspectives provide the two pieces that comprise the whole puzzle. Although they constitute explanations at different levels of aggregation, they are integral to the full explanation of crime. While individual theories may focus on individual motivation or inhibition, community-level perspectives offer the other side of the story, providing insight into the manner in which a community's processes and characteristics mitigate or aggravate an individual's decision. Recent research is beginning to combine individual and contextual perspectives. These recent multilevel analyses posit that individual risks of victimization are determined to some extent by social forces in their wider environment, and the social disorganization theory provides a basis for identifying these criminogenic conditions (Rountree, Land, and Meithe, 1994). Rountee et al. (1994), in an analysis of Seattle victimization data that placed victims in their sociological context, found support for the independent effects of social disorganization factors, controlling for individual crime opportunity measures.

The second criticism is that social disorganization theory has a hazy definition of neighborhood and there is no direct measure of disadvantage. While Bursik does not clarify the definition of neighborhood in this article, he offers that population variables now collected through the census do offer some insight into the many indicators of disadvantage.

The third criticism of social disorganization theory addressed by Bursik (1988) concerned Shaw and McKay's reliance on official measures of delinquency, that is, official measures may reflect policing practice more than actual juvenile behavior.

A fourth criticism stated by Bursik (1988) is that social disorganization perspectives assume stability in ecological structures, an assumption that might not be as tenable now as when the theory was developed. Bursik asserts that as longitudinal studies are more widely employed in community-level research, the degree to which ecological instability affects research findings will become clearer.

A final criticism of social disorganization theory leveled by some scholars that there is an assumption of value consensus at the community level that may not be accurate, brought about by the natural groupings of people hypothesized by Burgess (1925). Bursik (1988) responds by asserting that only one consensus is truly necessary. The only necessary consensus is that the community values an existence free of serious predatory crime.

3. Systemic model of social disorganization

Bursik and Grasmick (1993, 1995) further extended the social disorganization theory and built their theory: the systemic model of social disorganization. The theory emphasizes ongoing patterns of information exchange, similar to the ties and networks of a system that provide the vehicles and pathways over which the control and regulation take place. Bursik and Grasmick's approach expands "neighborhoods" into the notion of networks, beyond the flat single layer of contiguous areas specified by Shaw and McKay (1942).

In this hierarchical conception of networks, Bursik and Grasmick (1993) envision three levels of social control. As the most basic level, communities control the behavior of their residents through a system of private controls based on the close interpersonal relationships between families and intimates. Beyond this private level of control are parochial controls, the influences exercised by the institutions and organizations of a community (schools, churches, storekeepers, and the like). The third level of controls is where Bursik and Grasmick bring the most new material to the original theory of social disorganization. Because their notions of neighborhood and community are network-based, their third level of control capitalizes on the interplay between levels of aggregation. Roughly, they define a neighborhood as a small physical area embedded within a larger area. This third level of controls – the public controls – reflects the community's ability to secure goods and services allocated by agencies outside the community. These goods and services are of two types. First is a general ability to secure financial support for community organizations from government and other external actors. Second is a more specific application of the first: the ability of the smaller area to achieve and maintain a successful relationship with local law enforcement agencies.

4. Reciprocal effects

Most social disorganization models including Bursik and Grasmick's (1993) fail to consider reciprocal effects between crime and neighborhood structure. Rose and Clear (1998) posit that social organization is affected by crime just as crime is affected by organization. They argue for a reciprocal or non-recursive model, accommodating the effects of crime on social organization. Neighborhood structure influences crime and crime and violence shape neighborhood conditions. Rose and Clear also argue that the controls exercised by a community through private and parochial channels and those exercised by extra-community forces through the public channel are not independent of one another. The implicit relationship between these levels is additive – public controls are applied in addition to those applied at the private and parochial level. Rose and Clear argue that controls at one level may supplant those at another. An over-reliance on public controls may diminish the capacity of private and parochial controls as communities learn to rely on outsiders (Rose and Clear 1998).

5. Collective Efficacy

In between the undesirable structural conditions and crime, certain variables mediate the relationship and make people break the law at a high rate. These variables have been identified by Sampson, Raudenbush, and Earls (1997). They argued that there are two separate contextual factors that would explain what went on between the structural conditions (concentrated disadvantage) and crime rates. One factor was "informal social control" or the willingness of neighbors to intervene if they saw wrongdoing going on. The second factor was "social cohesion and trust" or how closely people in an area were tied to and supported each other. Neighborhoods vary in their ability to activate informal social control. Informal social control involves residents behaving proactively when they see wayward behavior such as by calling the police, rescuing someone in trouble, and telling unruly teenagers to quiet down and behave. The likelihood that residents will take such steps is contingent on whether there is mutual trust and solidarity among neighbors. As a result, in neighborhoods where the social cohesion and trust prevails, residents can depend on one another to enforce rules of civility and good behavior. Such places have collective efficacy. Collective efficacy is social cohesion among neighbors combined with their willingness to intervene on behalf of the common good.

When neighborhoods are racked by concentrated disadvantage (e.g. poverty, disrupted families), residential instability, and large populations of immigrants, the residents are less able to forge close ties, to trust one another, and to exercise informal social control. In short, lacking collective efficacy causes disorder and crime to emerge and to spiral out of control.

Sampson et.al (1997) also argued that collective efficacy is not evenly distributed across neighborhoods. Rather, in communities marked by a concentration of immigrants, residential instability, and concentrated disadvantage, collective efficacy is weak and the communities will not have the social capital to assert informal social controls and to keep the streets safe.

6. Dynamic Models

The changing spatial distribution of crime in a city is the product of larger economic and social processes characterizing the history and growth of the city and of the local communities which comprise it (Shaw and McKay 1969, Kubrin 2003). But social disorganization researchers have not adequately examined change and long-term processes of urban development (Bursik 1988). As Kubrin (2003) pointed out, the full set of dynamics that may lead to disorganization can only be discerned when long-term processes of urban development are considered, yet the majority of studies that test social disorganization theory are cross-sectional.

The methods used to model change have hampered research on neighborhood change (Kubrin 2003). Most studies employ residual change scores or the cross-lagged correlation approach. The most notable limitation of these approaches is that the information provided in these models centers on the between-variable relations rather than changes in the neighborhood over time (Bursik and Grasmick 1992, Kubrin 2003). An attractive method for modeling change is the hierarchical growth-curve model (Kubrin 2003). This model offers a number of advantages. First, a major strength of growth-curve model is the ability to model first level regression coefficients as random variables at the second level. Second, this method is able to examine the effects of nonlinear trends (Kubrin 2003).

7. Modeling Spatial Dynamics

Spatial interdependence is important as geographic units are seldom spatially independent and levels of crime in one neighborhood likely influence levels of crime in adjacent neighborhoods. A related issue is the potential clustering of neighborhood characteristics linked to crime, such as poverty or residential mobility, that crosscut geographic areas (Baller et al. 2001, Kubrin 2003). These patterns are formally indicated by the concept of spatial autocorrelation, or the coincidence of similarity in value with similarity in location (Anselin et al. 2000). As Messner et al (1999) suggested, in analyses using spatial data, estimates and inferences from regression analyses must include an adjustment for spatial autocorrelation; ignoring spatial dependence in the model may lead to false indications of significance, biased parameter estimates, and misleading suggestions of fit.

The reasons that spatial interdependence is important are summarized in Kubrin's article (2003). First, spatial dependence is expected as a result of the inexact correspondence between census tract boundaries and the ecological factors that shape social interaction. Residents who live across the street from one another are likely to identify themselves as living in the same neighborhood, yet if they reside in different census tracts, they are not counted as neighbors. Spatial models address this problem by recognizing the possible interdependence of neighborhoods. Second, spatial dependence is implicated by the fact that many interpersonal crimes such as assault and homicide are based on social interactions that may cross neighborhood boundaries. Acts of violence can generate a sequence of events that lead to further violence in a spatially diffused way. Interpersonal crimes that are subject to diffusion processes are likely to exhibit spatial dependence (Kubrin 2003).

Spatial dependence can be controlled for using either a spatial lag or spatial error model (Baller et al. 2001, Kubrin 2003). The spatial error model evaluates the extent to which the clustering of crime rates not explained by independent variables can be accounted for with reference to the clustering of error terms. In this sense, it captures the spatial influence of unmeasured independent variables. In contrast, the spatial lag model incorporates the spatial influence of unmeasured independent variables but also stipulates an additional effect of neighbors' crime rates, i.e. the lagged dependent variable. This is the model most compatible with notions of diffusion processes because it implies an influence of neighbors' crime rates that is not simply an artifact of measured or unmeasured independent variables. Rather, crime in one place may increase the likelihood of crime in nearby locales (Kubrin 2003).

For both models, the first step in the process involves determining whether spatial autocorrelation exists. A number of tests have been developed, the most common of which is Moran's I – a cross-product coefficient similar to a Pearson correlation coefficient and scaled to be less than 1 in absolute value. Significant positive values for Moran's I indicate positive spatial autocorrelation or clustering. Assuming that spatial dependence is observed, researchers then include spatial lag or error variables in the regression analyses. These variables capture the spatial dependence of crime in a given area on crime in surrounding areas, and the significance of their coefficients in the regressions provides a test for spatial autocorrelation (Baller et al 2001, Kubrin 2003).

8. Measuring Disorganization, Instability, and Racial Heterogeneity

1) Selecting appropriate level of aggregation

Most previous research on the structural correlates of crime has been conducted at the macro level, typically states or cities. Bailey (1984) advocated the need to shift to city-level analyses for three reasons. First, cities are more homogeneous than larger levels. Secondly, cities have long been the center of the country's homicide problem. Finally, cities may be more enlightening because of the greater degree of heterogeneity between cities than larger levels. Messner and Tardiff (1986) argue for even small levels of the unit of analysis such as neighborhoods. "Neighborhoods are more appropriate units of analysis for studying inequality and homicide than are larger political and statistical units because neighborhoods are more likely to constitute meaningful frames of reference for social comparison". Bursik and Grasmick (1993) defined a neighborhood as: a small physical area embedded within a larger area inhabited by people who perceive that they have a common interest in the area, with some tradition of identity and continuity over time.

Much of previous research on social disorganization has used the census tract as a proxy for neighborhood. The census is the most widely used source of demographic data in social disorganization analyses and its units of geographic aggregation tend to be used often as proxies for communities and neighborhoods.

The basic unit of aggregation for the census is the census block. The blocks are then aggregated to block groups, the lowest level of aggregation generally available without restriction to researchers. These block groups are then aggregated into census tracts that are wholly contained within counties and do not cross county boundaries (Bureau of the Census).

The establishment of census tracts and smaller units is guided by a local census tract committee, comprised of five or more local community members (Bureau of the Census). The boundary requirements for census tracts would match those commonly used when residents perceive boundaries. The directions passed on to the local committee when establishing a census tract should generally follow permanent, visible features, such as streets, roads, highways, rivers, canals, railroads, and high-tension power lines. The most important attribute of census tract/BNA boundaries is that they be visible, that is, readily identifiable in the field (Bureau of the Census).

The committee is obliged to follow similar requirements for socioeconomic characteristics. It is requested that when first delineated, the census tract contain a population whose housing and socioeconomic characteristics are similar (Bureau of the Census).

2) Measuring disadvantage and instability

The most prevalent indicator of socioeconomic disadvantage for a given spatial aggregation (tract, city, county, state) used to date has been poverty (Blau and Blau 1982; Elliott et al 1996; Krivo and Peterson 1996; Messner and Tardiff 1986; Shihadeh and Maume 1997; Warner and Pierce 1993). Although the definition of poverty is often varied, it is generally some measure involving earned income. The application of income poverty as a measurement of disadvantage varies in its operationalization. Krivo and Peterson (1996) and Elliott et al (1996) employed an absolute measure of poverty: the percent of unit population receiving income below the census-established poverty level. Blau and Blau (1982) and Messner and Tardiff (1986) employed both the absolute measure and a relative measure of income inequality known as Gini coefficient. It is not only absolute income deprivation but also income disparity within or across communities that drives disorganization (Rosenfeld 1989).

Sampson (1995) reports that in general previous research at the community level has observed a relationship between poverty and crime. However, Blau and Blau (1982) found that the relationship between absolute poverty and crime is not significant when controlling for income inequality. Messner and Tardiff (1986) found that when looking at Manhattan neighborhoods, a significant effect for absolute poverty with a negligible effect for relative poverty. Sampson et al (1997) found that high socioeconomic status contribute to high levels of collective efficacy. Under Bursik and Grasmick's (1993) systemic model, stronger private and parochial controls, which strengthen the community's ability to regulate the behavior of its residents, will result in lower crime.

Another widely used indicator of socioeconomic disadvantage is employment (Heitgerd and Bursik 1987; Krivo and Peterson 1996; Sampson et al 1997; Shihadeh and Maume 1997). As with poverty, the use of employment measures generally follows one of two tracks. The first is the traditional construct of unemployment: the percent of persons age 16 and over in the labor force and unemployed. In the study of predictors of collective efficacy, Sampson et al (1997) found a negative relationship between their measure of disadvantage, based in part on unemployment and their measure of collective efficacy. Krivo and Peterson (1996) and Shihadeh and Maume (1997) employed a different concept of employment information responding to a common criticism of unemployment measures: the traditional unemployment measure is limited to those who are unemployed but seeking work, discounting those who are not seeking work. They did not restrict only to those in the labor force because that can underestimate the extent of black joblessness due to the significant numbers of blacks who exit the labor force as discouraged workers. They employed the percent jobless; the percent jobless corrects for the underestimation of the truly unemployed by adding the percentage of adult population unemployed to the percentage not in the labor force.

Residential instability is the second major predictor. Instability has been operationalized through a concentrated set of variables. The most widely used are measures of housing tenure (Sampson and Groves 1989; Sampson et al 1997; Elliott 1996) and home ownership and occupancy patterns (Krivo and Peterson 1996). Housing tenure refers to the percent of the population ages five and over residing in the same house five years ago. Elliott et al (1996) found that disadvantage was negatively associated with informal social controls. Sampson et al (1997) found that residential stability was positively associated with collective efficacy.

Sampson and Groves (1989) employed a more direct application of housing tenure with survey data from British Crime Survey. They found that residential stability (measured as percent of people brought up within a 15 minute walk of their current residence) had a positive effect on local friendship networks. This increase in friendship networks, in turn, let to a decrease in crime. Morenoff and Sampson (1997) reminded researchers of the totality of this system. They found a relationship between a neighborhood's spatial proximity to homicide events and subsequent population loss. They pointed out that proximity to homicide was associated with black population gain, while similar proximity was associated with white population loss.

The second alternative in assessing residential instability involves patterns of home ownership and occupancy. Heitgerd and Bursik (1987) included a measure of owner occupancy among their neighborhood characteristics for the Chicago neighborhoods they analyzed. They found that a given neighborhood's residential stability mitigated the effect of changes in racial composition on changes in delinquency, concluding that these changes in racial composition were only significant to the extent that they disrupted existing networks of relationships. Krivo and Peterson (1996) adopted a slightly different measure for instability: housing vacancy. Their results indicate that after controlling for the effects of residential stability, disadvantage remains significantly related to crime.

Based on previous research, this dissertation takes advantage of several measures of disadvantage and instability and employs a data reduction method to provide insight regarding the core variation in disadvantage and instability across multiple indicators.

3) Including racial components

Ethnic heterogeneity was considered as a key ingredient for social disorganization. Heterogeneity was understood to undermine community cohesiveness, value consensus, and communication. Recent research on the demography of urban America has implications for some of the most common indicators of heterogeneity, especially racial composition indicators such as percent black (Massey, Condran and Denton 1987, Massey and Denton 1988, Massey, Gross and Shibuya 1994, Peterson and Krivo 1993, Shihadeh and Maume 1997, Wilson 1987). Massey (1998) argued that race and disadvantage are not conceptually identical and should not be considered as proxies.

4) Linking context to control

Attachment and community organization and cohesion connect community contextual factors and levels of crime. Attachment, the community attribute that is affected by disadvantage, instability, and heterogeneity, is often treated as a latent construct and not directly measured as a contributor to rates of crime.

8. Summary

Communities and crime have been an important perspective studying crime and place. The theoretical rationale stems from Shaw and McKay's work in the 1940s. Shaw and McKay noted that delinquency has its roots in the dynamic life of the community. Structural conditions lead to higher levels of social disorganization, especially of weak social controls, in inner-city neighborhoods, which in turn results in high rates of crime. The structural conditions include concentrated disadvantage, ethnic heterogeneity, and residential mobility. These social conditions promote crime and violence. Social disorganization theory suggests the importance of macro level area effects on crime.

In the 1980s, interests in social disorganization theory reemerged. Robert Sampson et al. (1997) argue that social cohesion within communities and shared expectations of community members combine to affect both crime and social disorder. Bursik and Grasmick (1993) built the systemic model of social disorganization. In this hierarchical conception of networks, Bursik and Grasmick (1993) envision three levels of social control: private control from families and intimates, parochial controls by the institutions and organizations, and the public controls. Rose and Clear (1998) looked at the reciprocal effects between crime and neighborhood structure. They posits that neighborhood structure influences crime and crime and violence shape neighborhood conditions.

Chapter 4. Proactive Policing

Policing is facing increasing obstacles. Unstoppable economic, social and political forces are having a profound effect, not only upon the world in which we function but also upon the manner in which each and every one of us does his or her job. And while we may be able to take some comfort from the fact that criminals do not change appreciably over time, the resources and opportunities available to them have increased exponentially along with the magnitude of their potential profits. Police forces are now dealing with crime that would be unrecognizable to the police officers of a generation ago and must do so with a rapidly shrinking resource base. The old models of policing no longer apply. We can no longer afford simply to react to each new situation, nor can we rely upon our traditional notions of crime and criminal behavior. Proactive policing may hold the key to our survival.

Intelligence led policing is a collaborative law enforcement approach combining problem-solving policing, information sharing and police accountability, with enhanced intelligence operations. The collection and analysis of information related to crime and conditions that contribute to crime, resulting in an actionable intelligence product intended to aid law enforcement in developing tactical responses to threats and/or strategic planning related to emerging or changing threats.

An essential part of the intelligence process is collecting raw information that may be used in the analysis. Collection should be focused to identify and understand threats that emerge within a jurisdiction. This focus is often determined by an analyst, who will define intelligence requirements, and it is based on information received from both officers and citizens in the form of suspicious activity reports. The key point to note is that collection seeks raw information within defined threat parameters that is essential for effective analysis.

Intelligence led policing can be conceptually defined as a proactive, future-oriented management philosophy and business model for collection and enforcement activities. As such, the integration of an intelligence function should assist police administrators in determining how to strategically prioritize and manage competing demands facing the organization and how to allocate resources to best achieve their goals of crime prevention, disruption and reduction.

As Ratcliffe explains, "the application of criminal intelligence analysis as an objective decision-making tool in order to facilitate crime reduction and prevention through effective policing strategies and external partnership projects drawn from an evidential base" (2003). Ratcliffe emphasizes that three components to this form of policing – the interpretation of intelligence, the influence that this has on decision-makers, and the ultimate impact that this has on the criminal environment – all contribute to crime prevention. Intelligence is a constant process of data collection, analysis, distribution, and assessment and. It can be done by specialized groups, crime analysts or the police members themselves. It is proactive rather than reactive and continuously changes as each of three elements (intelligence, decision makers and criminal environment) change.

While traditional, reactive policing will not be wholly replaced, nor should it, intelligence led policing advocates a proactive orientation to crime control. Rather than policing activities be largely ad hoc and post-incident interventions, the police should investigate and intervene potential problems before they occur. Moreover, they should try to understand who the major criminal players are, how said actors are connected to one another, how series of criminal activities are linked, and how to strategically implement enforcement strategies based on the combination and understanding of these factors.

Risk-based policing has grown from a larger movement of the conceptual risk-based society (Ericson and Haggerty, 1997; Beck, 1992). The rise of the risk society refers to a movement towards increasing institutional social control via regulation and rules where various social institutions collect and broker information via various technological channels to provide society-wide governance and security. Crime control strategies have traditionally focused on deviance, control and order; however, discourse on crime control is becoming couched in concepts of defining deviance in terms of risk (rather than morality), arguing that security professionals can collect information on risk from a number of sources, process it and further communicate the information between various social institutions to produce knowledge. Security professionals then use this knowledge to make strategic decisions about how to distribute limited resources most efficiently and effectively.

Public security was once perceived to primarily be the responsibility of public law enforcement. However, security demands increased as cities became larger, technology developed, globalization flourished, and society became progressively more complex. Out of this complexity, a number of social institutions, both public and private, provide risk assessment, mitigation and governance, and thus various forms of security.

Policing by risks is a probability-based approach that seeks to balance the possibility of an event occurring to the costs of the actions taken to managing that risk (Van Brunschot and Kennedy, 2007). It is a strategic, future-oriented and targeted approach that relies on the identification, analysis and management of problems, which may be people, places, or activities, to cost effectively reduce and prevent crime (Maguire, 2000). Since all things cannot be protected at all times, a systematic approach should be utilized to spatially and temporally determine priorities (Van Brunscot and Kennedy, 2007; Leson, 2005). Problem identification and response plans are not random; rather, these perspectives are theoretical approaches that purposefully employ targeted strategies to achieve a desired outcome. In essence, security professionals attempt to predict future threats, vulnerabilities and consequences in order to make strategic decisions about how to allocate limited resources so they may have the greatest impact.

Summary

An important task facing police executives in today's demanding environment is determining where and how best to deploy limited resources. With increased demands for effective policing and resource allocation, coupled with increased volumes of data, improved technology to process and manage such data, and an evolving criminal environment, the police are expected and pressed to use improved decision-making strategies.

As proactive policing focuses on threats, it becomes essential to identify variables that support the generation and maturation of crime. Opportunities theories and social ecology theories provide theoretical framework for analysis. As crime patterns and the effects of social disorganization are predictable, the police can use the knowledge to forecast crime distributions and make strategic decisions about how to distribute limited resources most efficiently and effectively. Policing by risks is a proactive, rather than reactive, approach that seeks to balance the possibility of a criminal event and the costs of actions taken to manage the risk.

Chapter 5 The Spatial Nature of Shootings

1. Social and Economic Structure

According to Moore and Tonry (1998), social and economic structure, drugs, gangs, and guns are the main risk factors for the epidemic of violent crimes. Why did violent crimes become epidemic in the last two decades? Moore and Tonry (1998) provided their reasoning as follows: In the late seventies and early eighties, changes in structural factors produced conditions in inner-city minority communities that were ripe for an epidemic. The social and economic structure of many urban neighborhoods collapsed under a variety of social and economic pressures. Employment opportunities disappeared and small businesses moved away from the inner city. Under these economic pressures, families broke apart and children grew up under increasingly adverse conditions. In response to these conditions, some youth joined gangs in search of affiliation and security. Gangs produced fear and rivalries and caused other gangs to form and more youth to join gangs. An epidemic of crack cocaine hit these troubled communities during the mid to late eighties. Some existing youth gangs and other youth not involved in gangs participated in street-level drug markets and armed themselves with guns to protect themselves and resolve business disputes. The arming of youth participating in street drug sales produced both dangerous conditions on the street and a cultural style that encouraged other youth to acquire guns in response. A large supply of available guns made it possible for other youth to acquire guns out of self-protection, style, and status concerns. The widespread arming of youth in these disadvantaged neighborhoods made conflicts much more lethal (Moore and Tonry 1998; Braga 2003).

2. Drugs

Back to the 1980s, the most popular explanation for the explosion of violence is drug problem, especially crack. Crack was so propitious an issue in the prevailing conservative political climate so that politicians and the media chose to proffer drug war. Reinarman and Levine (1989) argue that all of the hype surrounding "crack scare" essentially served a scapegoating function, as crack came to dominate discourse relating to almost all social ills. Typical of drug scares, response policies were driven not by empirical research, but by media portrayals, political considerations, and public pressure (Fagan 1990).

The usual set of issues with regard to drugs and crime has to do with whether drug use causes violent and other criminal behavior. Generally speaking, there are three types of explanations. First, reflecting the long held supposition that doing drugs makes people excitable, irrational, and more violent, pharmacological effects are those associated with drug use. Second, economic compulsive violence refers to the crimes that users engage in to sustain their expensive addictions. Third, systemic violence is that attributable to the drug distribution system. As Jacobs (1999) argued, "there is constant exposure to violence in drug distribution system. Transactions are highly vulnerable to exploitation.

Duplicity on the part of customers and sellers is so common as to be institutionalized. Overall, instability reigns, and predatory arrangements thrive between actors at all levels".

Empirical support for pharmacological violence is sparse. No research has concluded that drugs account for a substantial proportion of drug-related violence. In a study of adolescent drug users in Miami, Inciardi (1990) reported that only 5.4% had participated in pharmacological violence. Some studies have affirmed drug-induced violence, but they have been marred by methodological weaknesses ranging from small, specialized samples to a lack of relevant control variables. When adequate controls are introduced, direct relationships between drug use and violence are attenuated or eliminated completely (Collins 1990).

Explanations based on economic compulsive violence has tended to gain more support. Individuals addicted to costly drugs such as cocaine and heroin occasionally resort to violent crime, typically robbery, to generate money (Ball et al 1981; Chaiken and Chaiken 1982; Johnson et al 1985). Inciardi (1990) found that 59.1% of the adolescent drug users had engaged in robberies, and that the majority did so for the purpose of purchasing more drugs. However, Inciardi also revealed that in the overall venue of financing drug activities, robbery paled in comparison to shoplifting, stolen goods offenses, and burglary. Drug users do commit violent crime to feed their habit, but they are significantly more likely to resort to nonviolent property crime.

Systemic violence has gained much more genuine concern. Although available evidence asserts that the natural history of crack use differed little from that of previous drug epidemics, selling patterns for crack were distinct (Fagan and Chin 1989). Prior to crack, organized crime groups and networks controlled the drug trade. This domination in turn produced a reasonably stable marketplace. Violence existed, but as an instrument of internal control. The crack manufacturing process, cheaper and more efficient than that of freebase cocaine, helped loose the reigns of this sovereignty. Fagan and Chin (1990) argued that “crack was marketed at a low unit cost in a rock or pebble form that was concealed and ingested. Its crystalline appearance conveyed an image of purity. The ingenious production and marketing strategy for crack gave it the appearance of a cheaper ‘high’ from a purer form of cocaine”.

The introduction of this new highly popular product created unprecedented levels of demand. The expansion of the drug economy eventually outstripped the capacity of established distribution networks and engendered new opportunities for street-level drug-selling for new groups and individuals. Start-up costs were removed as an impediment, as entry-levels roles now required only modest capital investment (Fagan 1992). But all of this entrepreneurial spirit was purchased at the cost of stability. With the decentralization of drug markets, peaceful enterprise quickly devolved into normative violence (Hamid 1990; Goldstein et al 1989). Competition between rival drug sellers led to defensive clashes over territory. Transactions became more tense and unpredictable: by carrying both drugs and cash, sellers were also prime robbery targets. Deregulation similarly served to embolden employees, thereby escalating violence as a means of disciplining the rank and file. Given the dangers of the crack trade, it was more appealing to those individuals willing to be exposed to risk and use violence. This self-selection process more or less ensured the perpetuation of violence.

Kennedy et al (1996) argued that although crack markets may have sparked the youth violence, crack was no longer the main driver of youth violence. Rather, the youth violence has became more importantly tied to a complex mix of fear, gangs, guns, and subcultural norms guiding appropriate responses to resolving interpersonal disputes.

3. Gangs

Conflicts between street gangs have long been noted to fuel much of the youth violence in major cities. City-level studies in Pittsburgh (Cohen and Tita, 1999) and St. Louis (Rosenfeld et al., 1999), using micro-level data on the circumstances of youth homicides, suggest that youth gangs were the dominant factor in the growth of youth homicides. These studies found that crack markets did precede the epidemic of youth homicide and gang members were involved in the street-level drug trade. However, the increase in youth homicide in both Pittsburgh and St. Louis was linked to the emergence of intergang conflicts that spread from gang youth to nongang youth.

No empirical support exists tying street gangs to systematic drug trafficking. Gangs, with their low levels of cohesiveness, were far from tailor-made for crack distribution; they were poorly suited to control street level distribution. Gangs are undeniably aggressive, but their violence has always been mostly expressive, as opposed to the instrumental violence of drug trade. The two are not readily or easily interchangeable.

Gangs did not exported their crack structures across the country, and even law enforcement has come to question the existence of drug gangs. Some research demonstrated that crack thrived without gangs in New York (Fagan and Chin 1989), Miami (Inciardi 1990), and Detroit (Mieczkowski 1990).

4. Guns

While studies may not agree on the specifics of the trajectory of gangs, crack markets, and increases in violence, there seems to be a general consensus that guns are the explanation for escalating drug and gang violence. Evidence indicates that the primary factor in the increase in youth homicides in the mid- to late-80s was greater access to handguns by youth. The juvenile age bracket is significant because the dramatic rise in overall homicide rates is wholly attributable to this group. During the period in question, the number of homicides committed by older offenders actually declined. Thus, discussions of gun violence invariably turn on younger offenders, as they were disproportionately affected by increases in homicide. Blumstein and Cork (1996) identified the drug market recruitment of juveniles as the probable cause of emergent homicide trends. The dangerous nature of drug enterprise makes weapons, specifically guns, a prerequisite for doing business. The drug trade precipitated neighborhood arms races, as other youth in connected networks felt compelled to follow suit. Whether the guns were acquired for protection or as a status symbol, their presence elevated the games, as confrontational situations escalated into homicide. Lethal violence was facilitated by the seeming recklessness with which male teenagers appeared ready to use guns (Blumstein and Cork 1996).

The convergence of gangs and guns further compounded the spiral of violence. Ultimately, the escalation in violence could not be reduced to the effects of drugs, or gangs, or even to guns. Rather, it was the symbiosis of guns with both gangs and drug trade that drove up violent rates. Drug market and gangs contributed both directly, through the behavior of their participants, and indirectly, by serving as key conduits for the diffusion of guns (Cohen and Tita 1999). The guns diffused to gangs, which dispersed guns further.

The gun violence problem was a gang problem, at least insofar as the worst offenders driving a large cycle of fear, gun acquisition, and gun use were gang members; most victims and offenders were gang members, known to authorities, and had been formally court-involved.

Kennedy et al (1996) discussed the structure of the illicit gun market. This market appeared to be primarily composed of many small, multi-faceted operations rather than large, dedicated ones. The large dedicated gun market did exist and seemed most often organized to move large quantities of weapons from states with few restrictions on gun purchases to states with strict ones. However, for the most part, both the multiplicity of sources for illegal weapons – thefts from homes, thefts from gun dealers, improper sales from licensed dealers, private dealers, and diversion of guns obtained through legal purchase – and the ease and convenience of dealing them alongside other contraband eliminated the need for powerful organizations to acquire and distribute black-market guns. Sources for illegal weapons are multiple: thefts from homes, thefts from gun dealers, improper sales from licensed dealers, private dealers, and diversions of guns obtained through legal purchases. Since many stolen firearms are taken from private residences, and since there are estimated to be some 200 million guns in private hands, the pool of available weapons, even if other supplies could be interrupted, is enormous (Kennedy et al 1996).

5. Public Housing

Public housing is perceived a breeding ground for crime especially violence. Rates of violent crimes are generally higher at public housing sites than other areas. Public housing is consistently evoked as a metaphor for dangers of urban living. Roncek et al. (1981) studied the relationship of public housing and crime in Cleveland's 4000 residential city blocks and found that proximity to public housing projects has a small, but statistically significant, effect on the incidence of violent crime, even controlling for the size of the population of all the blocks in the city. Concentrating public housing results in more crime on the blocks where the projects are located. Also, distance has moderate negative correlations with crime. This suggests that public housing projects affect crime in their surroundings.

For violent crimes, when rates of violence in public housing differ from rates of violence elsewhere, the rates of violence are higher and sometimes dramatically higher (Fagan and Davies 2000). Studies by Poplin et al (2000) and Sullivan (1989) show the most troubled public housing projects house at least some gang-involved residents who are involved in violent and aggressive behavior, drug use and sales, and other criminal activities. It indicates that violent offenders may be particularly likely to reside in public housing.

Studies on victimization experiences of public housing residents illustrate that they experience greater vulnerability than do their non-public housing counterparts (DeKeseredy et al 2003). Also, a much larger proportion of public housing residents indicate that crime is a problem in their neighborhood and they are markedly more likely to report that it is so objectionable that they wish to move.

The presence of public housing in a neighborhood has a strong effect in concentrating poverty within that community (Massey and Kanaiaupuni 1993). Public housing may contribute to social disorganization and in turn violence. By design, public housing is inhabited by persons in poverty, especially the poorest segments of the impoverished, thereby necessarily increasing the poverty rate within neighborhoods where such housing is located. In addition, public housing commonly was built in already poor neighborhoods because of substantial mobilization against locating the poor in middle-class areas (Bickford and Massey 1991). As such, communities in which there are public housing projects frequently have high poverty rates. Residential turnover also tends to be high in neighborhoods where housing projects are located (Bursik 1988;

Sampson 1989). Under conditions of high poverty and population turnover, residents of communities with housing projects are less able to form networks of formal and informal social control, and hence have more difficulty controlling crime. Thus, public housing policies that have led to the development of projects that concentrate deprivation may have inadvertently contributed to the crime problem of neighborhoods.

6. Bus Stops

Bus stops are common settings for transit crime. Bus stops provide a cover for criminals who can hang out waiting for potential victims without arousing suspicion. Bus stops are populated by anonymous riders who represent easy targets under specific circumstances.

Scholars found that the environmental factors play a key role in crime rates around bus stops. Levine et al. (1986) found that nine percent of the respondents had experienced a serious (Part I) crime in Los Angeles sometime in their lives, and 19 percent had witnessed a bus-related crime; 43 percent had some contact with bus crime in Los Angeles. Fifty-four percent of the crimes reported occurred at or on the way to and from bus stops. Other research has shown that most bus crimes in Los Angeles occur in the late afternoon and early evening. At one of the high-crime bus stops, the probable existence of a drug trade fosters crime, and at a second corner, sidewalk crowding encourages pick-pocketing and purse snatching. At a third corner, crime is influenced by the presence of a high school in the midst of a sizeable elderly residential population.

Loukaitou-Sideris (1999) looked at the connection between criminal activity at bus stops and environmental factors based on empirical observations, mapping and survey research. Ten high crime bus stops were analysed along with four low crime ‘control’ stops in Los Angeles. Across the whole system incidents were rare (there were fewer than 5 crimes per 100,000 passengers). Ten high crime bus stops accounted for 18 percent of the total crimes reported out of 19,650 stops. Although passenger levels at these stops were high, other nearby high patronage stops exhibited little or no crime. By examining the physical and social context of the surveyed bus stops, there appeared an abundance of “negative” environmental factors and a general lack of defensible space at the high crime stops, whereas the four comparative low crime rate stops lacked negative environmental factors and offered better surveillance opportunities. These negative factors (within 300 feet of a stop) included “liquor stores, bars, check cashing establishments, seedy motels, pawn shops, vacant lots/buildings and adult book stores and movie theatres” (Loukaitou-Sideris 1999). This empirical research indicates that environmental attributes and site conditions at bus stops do have an impact on crime levels. This finding is supported by Newton (2004) who examined criminal damage to bus shelters in Merseyside (UK), and found damage was related in a systematic and predictable way to known attributes of a shelter’s location.

7. Liquor Stores and Bars

The alcohol establishments such as liquor stores and bars are notorious for their roles in producing crimes. Interpersonal violence appears to occur in and around these alcohol establishments more often than others. Alcohol outlets are places that attract clientele more likely to be involved in violent acts (e.g. young males). Bars and liquor stores are often located in community areas with less guardianship (e.g. retail areas), offer opportunities for social interactions that may lead to violence (Haines & Graham 2005), and provide an intoxicating substance that appears to disinhibit aggression among males (Pihl, Lau & Assaad 1997; Giancola, Saucier & Gussler-Burkhardt 2003). Indeed, across repeated empirical studies over the past 14 years the locations of bars and taverns (Roncek & Maier 1991; Scribner, MacKinnon & Dwyer 1995; Gorman et al. 2001; Lipton & Gruenewald 2002) and sales through alcohol outlets (Stevenson, Lind & Weatherburn 1999) have been correlated with higher rates of violence. These studies suggest consistently that violence among at-risk populations may be greater in areas in which alcohol is more available. Alcohol outlets may be selected by social groups at risk for violence. Notably, similar arguments have been put forward to support empirically observed cross-sectional relationships between rates of violence and locations of off-premise establishments (e.g. liquor or grocery stores, Scribner et al. 1995). These effects, however, may be related to other problems associated with these environments (e.g. illegal drug activity and prostitution: Alaniz et al. 1998).

Although evidence exists connecting alcohol consumption to levels of violence, a limited number of studies have been conducted examining the specific relationship between alcohol availability, as defined by alcohol establishment density, and violence. Scribner (1995) conducted the first of these recent studies, examining the risk of assaultive violence and alcohol availability in cities within Los Angeles County (Scribner et al., 1995). He discovered that after adjusting for socio-demographic factors, higher levels of alcohol outlet density were significantly associated with higher rates of assaultive violence (i.e., criminal homicide, forcible rape, robbery, aggravated assault and domestic violence) within a geographic unit. A subsequent replication study, examining the same relationship in New Jersey municipalities, however, did not find that higher alcohol outlet density was associated with elevated rates of violence (Gorman et al., 1998), nor did a follow-up study focusing only on domestic violence (Gorman et al., 1998).

In an attempt to clarify the inconsistency regarding the relationship of density to violence, researchers in New Jersey decided to focus on one city, Newark, and to geographically link violence rates to outlet density in census tracts and census block groups, rather than using larger city or municipality definitions of geographic areas. In doing so, the regression models revealed that alcohol outlet densities were significant predictors of rates of violent crime at both the census tract level and the census block group level (Speer et al., 1998). Similar analyses conducted on census tracts in New

Orleans, block groups in California and Camden, New Jersey, and census tracts in Kansas City, Missouri, revealed that outlet density (whether defined as outlets per square mile or outlets per person) was strongly associated with rates of various types of assaultive violence (Alaniz et al., 1998; Scribner et al., 1999; Gorman et al., 2001; Reid et al., 2003).

8. Schools

Research has linked large and impersonal school settings with violence (Alexander and Curtis 1995; Olweus 1993; Newmann 1981). Roncek et al. (1983, 1985) found that residential areas in San Diego that were adjacent to public high schools had more crime than areas that were more than one city block away from these schools. This effect was both statistically significant and substantively meaningful even after controlling for demographic, social, and housing characteristics of residential areas. Astor's study examining violence in high schools found that all of the 166 reported violent events occurred in locations where there were students but few or no adults (Astor, Meyer, and Behre 1999). Other school violence studies examining school structural characteristics found large school size and high student-teacher ratios to be predictive of crime and disorder in schools (Duke 1989; Gottfredson and Gottfredson 1985).

Social disorganization theory makes provision for the location and nature of schools. Powerful communities can influence the location and nature of schools. Schools with ample resources are less likely to be overcrowded and will have adequate supervision provided by ample staff (Gottfredson and Gottfredson 1985; Felson 1994). Thus, schools that are organized will be less likely to promote contexts conducive to victimization in neighborhoods around or nearby organized schools. In other words, schools constitute a layer of influence regarding crime on blocks. Schools may be risky places because they bring large numbers of youth into contact with each other. Furthermore, violent crimes can increase if the same number of offenders can find more targets for crime in the absence of a guardian or guardians. In Crime and Everyday Life (1994), Felson discusses dangerous places, risky routes and unassigned space as having the chemistry for crime to occur. Although each crime has its particular chemistry, crimes also have a common chemistry, such as the situation in which clusters of young males with no adults present implies a risk of higher crime of all types (Felson 1994). A key argument that Felson makes is that opportunity for crime will arise not only in and on school grounds, but nearby and over a larger area.

9. Concentration and Stability of Shooting

Braga et al (2010) uses 29-year shooting data in Boston to uncover distinctive developmental trends at street segments and intersections. They find that Boston gun violence is intensely concentrated at a small number of street segments and intersections rather than spread evenly across the urban landscape between 1980 and 2008. Gun violence trends at these high-activity micro places follow two general trajectories: stable concentrations of gun assaults incidents over time and volatile concentrations of gun assault incidents over time. Micro places with volatile trajectories represent less than 3%

of street segments and intersections, generate more than half of all gun violence incidents, and seem to be the primary drivers of overall gun violence trends in Boston.

10. Near Repeat Patterns of Shooting

The near repeat pattern states that if a location is the target of a crime, the homes within a relatively short distance have an increased chance of being victimized for a limited number of weeks. This communicability of risk to nearby locations for a short amount of time raises the possibility that other crime types may also suffer from a near-repeat spatio-temporal pattern of behavior (Ratcliffe and Rengert 2008). In the study of shooting in Philadelphia, Ratcliffe and Rengert (2008) found that there are elevated patterns of near-repeat shootings within 2 weeks and one city block of previous incidents. The elevated risk of a shooting during this period is found to be 33% greater than expected.

11. Summary

Gun shootings are highly clustered. A small number of street segments and intersections account for the majority of gun shootings (Braga et al. 2010). Also, there are near-repeat patterns in shooting. Locations within one city block of previous shooting incidents have an increased chance to have shootings again within two weeks.

The social and economic structures of urban settings account for violence epidemic. The economic and social turmoil in neighborhoods with the highest concentration of urban underclass population make the environmental conditions ripe for violence. The mechanisms of gangs, drugs, and guns escalate the violence. The adverse conditions turned some youths into gangs. Drugs attract gangs and other youths participating in drug market. A large supply of guns made it possible for youths to acquire guns for self-protection, style, and status concerns.

There are other land uses that have been found to be at the center of clusters of violence. For example, public housing, alcohol establishments, bus stops, and schools, are found to be the main risk factors for some crimes. Public housing affects crime in the surroundings. Perhaps it is because public housing has a strong effect in concentrating poverty within the community and in turn violence. Bus stops are found to influence crimes in their surroundings. Loukaitou-Sideris found that the environmental factors around bus stops play a key role in crime rates.

Empirical research shows that locations of bars and liquor stores are correlated with higher rates of violence. At-risk populations may be greater in the areas of bars and liquor stores and thus promote the crime rates. Also, these effects may be related to other problems such as drugs and prostitution. In terms of schools, research shows that areas adjacent to high schools have more crime than areas farther away from high schools. Schools are risky places which may be because schools bring at-risk population together and thus create opportunities for crime.

Chapter 6 Research Design and Methodology

Based on the theoretical framework on crime and place, this study is designed in three parts: the first part will focus on crime generator analysis to identify crime generators of shootings; the second part will examine the influences of neighborhood characteristics on shootings; and the last part will build a forecasting model using place-based risk assessment approaches. Also, in order to test the predictability of this model, a logistic regression will be conducted to test how well this model can predict subsequent time period shooting locations.

1. Study Areas

The study areas are Newark and Irvington, New Jersey. Newark is the largest city in New Jersey, United States, and the county seat of Essex County. Newark has a population of 278,154, making it the largest municipality in New Jersey and the 68th largest city in the U.S.

Newark is located in the heart of New Jersey's Gateway Region. It is approximately 8 miles (13 km) west of Manhattan (New York City). Its location near the Atlantic Ocean on Newark Bay has helped make its port facility, Port Newark, the major container shipping facility for the New York metropolitan area (Port of New York and New Jersey), and the largest on the East Coast. It is the home of Newark Liberty International Airport, one of the first major, and now one of the busiest, airports in the United States. This ethnically diverse city is divided into five wards, and contains a variety of neighborhoods ranging in character from bustling urban districts to quiet suburban enclaves.

Newark is surrounded by residential suburbs to the west (on the slope of the Watchung Mountains), the Passaic River and Newark Bay to the east, dense urban areas to the south and southwest, and middle-class residential suburbs and industrial areas to the north. The city is the center of New Jersey's Gateway Region.

Newark has over 300 types of business. These include 1,800 retail, 540 wholesale establishments, eight major bank headquarters (including those of New Jersey's three largest banks), and twelve savings and loan association headquarters. Deposits in Newark-based banks are over $20 billion.

Newark is the third-largest insurance center in United States, after New York City and Hartford. The Prudential Financial and Mutual Benefit Life companies originated in Newark. The former, one of the largest insurance companies in the world, is still headquartered in Newark. Many other companies are headquartered in the city, including International Discount Telecommunications, New Jersey Transit, Public Service Enterprise Group (PSEG), and Horizon Blue Cross and Blue Shield of New Jersey.

Though Newark is not the industrial colossus of the past, the city does have a considerable amount of industry. The southern portion of the Ironbound, also known as the Industrial Meadowlands, has seen many factories built since World War II, including a large Anheuser-Busch brewery. The service industry is also growing rapidly, replacing those in the manufacturing industry, which was once Newark's primary economy. In addition, transportation has become a growing business in Newark, accounting for 24,000 jobs in 1996.

In the 2006 Morgan Quitno survey, Newark was ranked as the 22nd most dangerous city in the United States out of 371 municipalities. In the 2007 rankings, now performed by CQ Press, Newark was the 20th most dangerous city in America of 378 cities surveyed. In 2008, Newark was ranked as the 24th most dangerous city, and as of 2010, stands at 23rd. In March, 2010, Newark enjoyed its first month without a homicide since 1966. In 1996, TIME Magazine ranked Newark "The Most Dangerous City in the Nation." By 2007, however, the city recorded a total of 99 homicides for the year, representing a significant drop from the record of 161 murders set in 1981.The number of murders in 2008 dropped to 65, a decline of 30% from the previous year and the lowest in the city since 2002 when there were also 65 murders.

Irvington, a small yet populous town bordering Newark, had gained a reputation as New Jersey's crime capital. Irvington experienced the crack epidemic of the 1980s and the city still struggles with the aftermath today. The city still has a violent crime rate six times higher than New Jersey overall and a murder rate eight times higher than statewide statistics. In 2007, Irvington’s violent crime rate was 4.6 times of violent crime rate in the nation. The community has drawn great attention of local and state law enforcement as it has become extremely violent community with a large number of gun shootings and other crimes. Recent improvements in policing have reduced the crime incidents in Irvington but problems remain.

The nature of the southeast land in Newark makes this heavy industrial area dramatically different from other areas in Newark. The southeast area contains Newark Liberty International Airport and Port Newark neighborhoods. There is no residential area here and the road network is very poor. Our data show that few crimes occur in this area. Thus, this heavy industrial area is masked out from our study area. Land use data and census data were included to develop a study area.

Because this is a study in locating interdependency, we need to take account of facilities that fall outside of the study area of Newark and Irvington, as they produce an edge effects that may corrupt this study. The Passaic River and the Newark Bay bound Newark on the east, for this reason cities that border Newark on the north, west and south were selected. These additional cities are Belleville, Bloomfield, East Orange, Maplewood, Hillside, and Elizabeth.

If a calculated interpoint distance is greater than the distance between the point and its nearest plot boundary, part of the spatial neighborhood of this point lies outside the plot and cannot be evaluated without a certain bias. Hence, edge effects are usually considered in spatial pattern analysis. The first part of this study is about spatial pattern analysis which may be affected by edge effects. In order to solve this edge effects issue, a 1500 feet buffer zone is created along the study area. The relevant points in the buffer zone are included in the analysis.

Figure 1 shows the two cities, Newark and Irvington. Figure 2 displays shooting locations from Jan. 2007 till Aug 2010 in these two cities. Figure 3 shows the study area. Figure 4 displays buffer zone along the study area.

Figure 1. Newark and Irvington, NJ

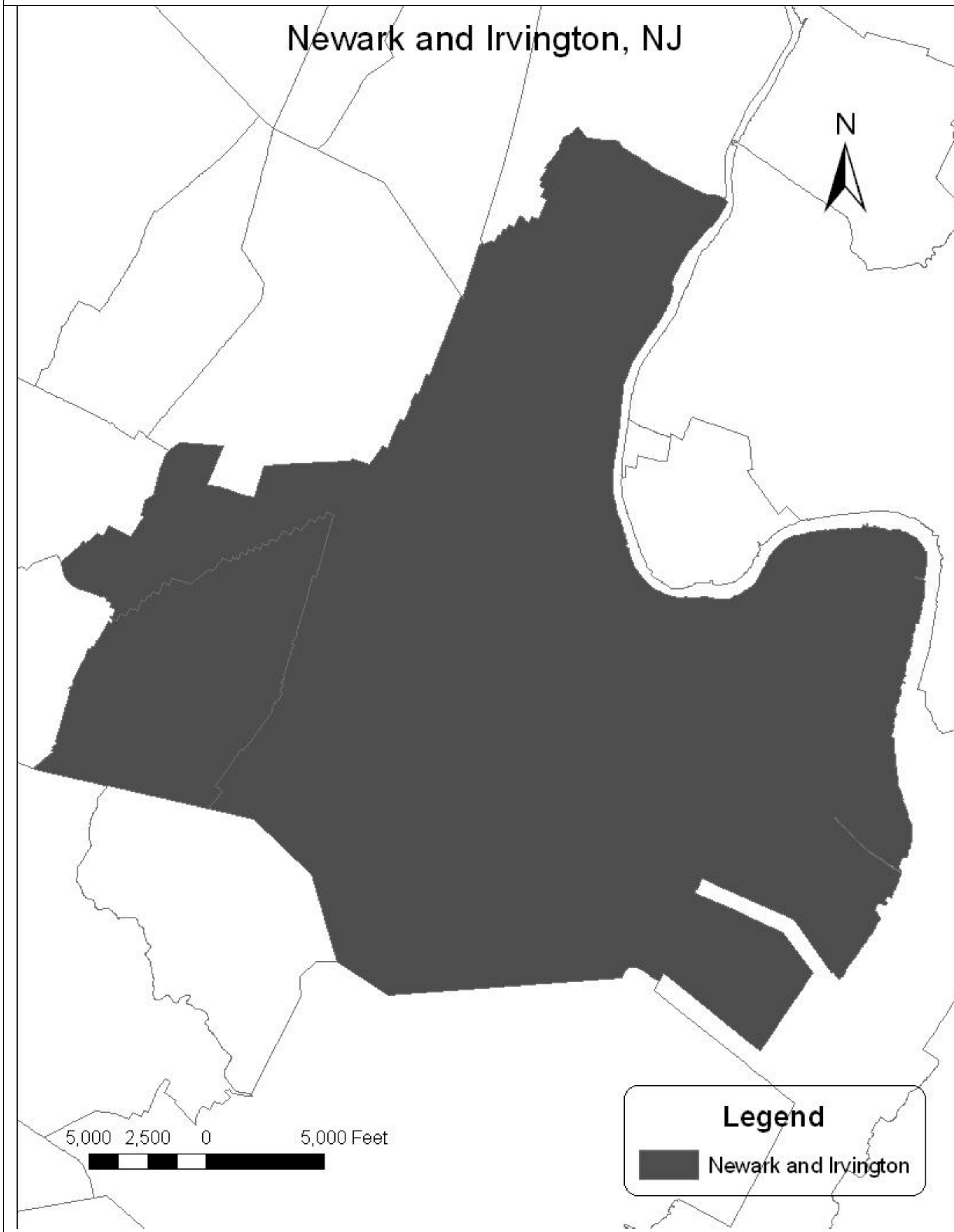


Figure 2. Shooting Distributions, 2007-2010

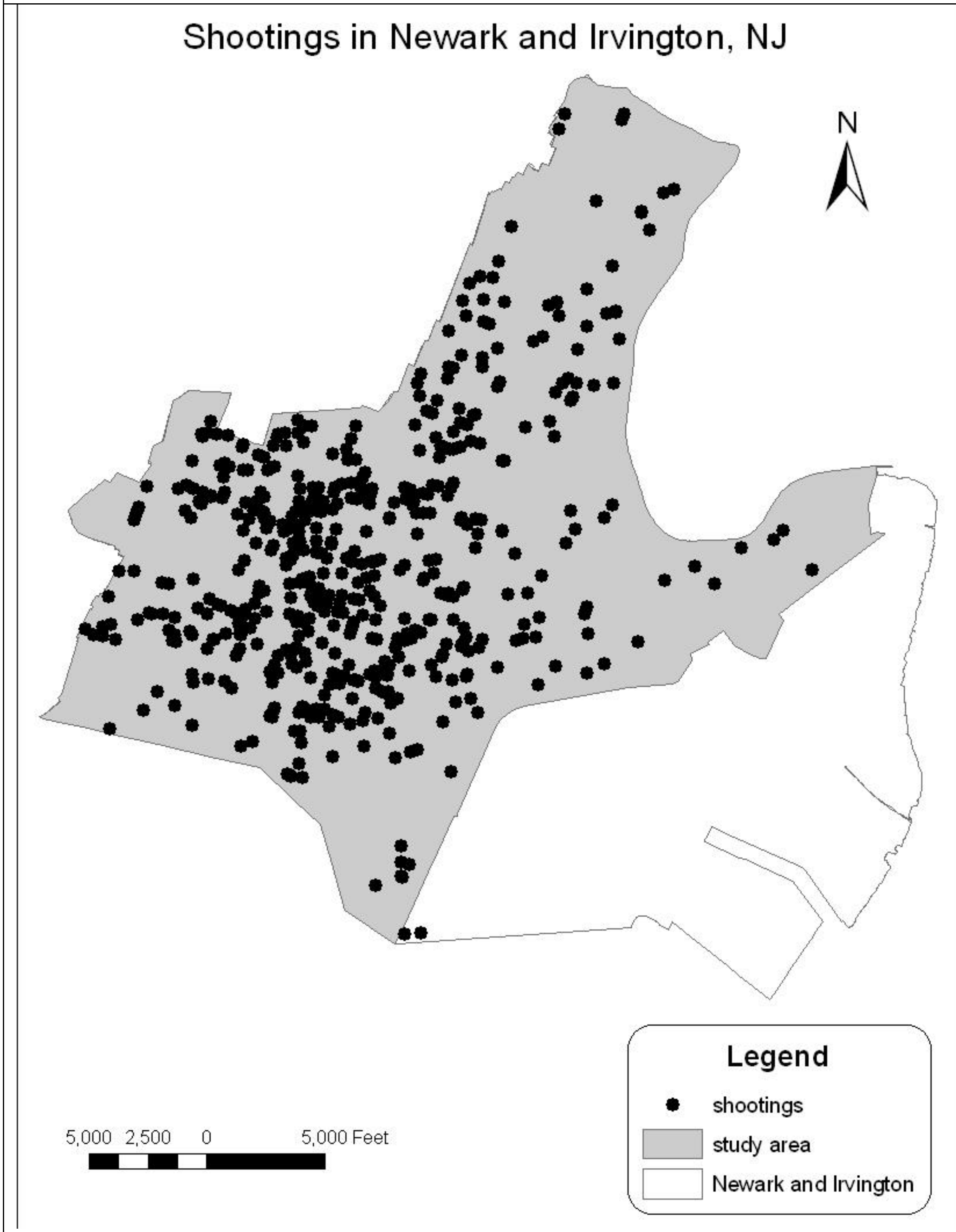
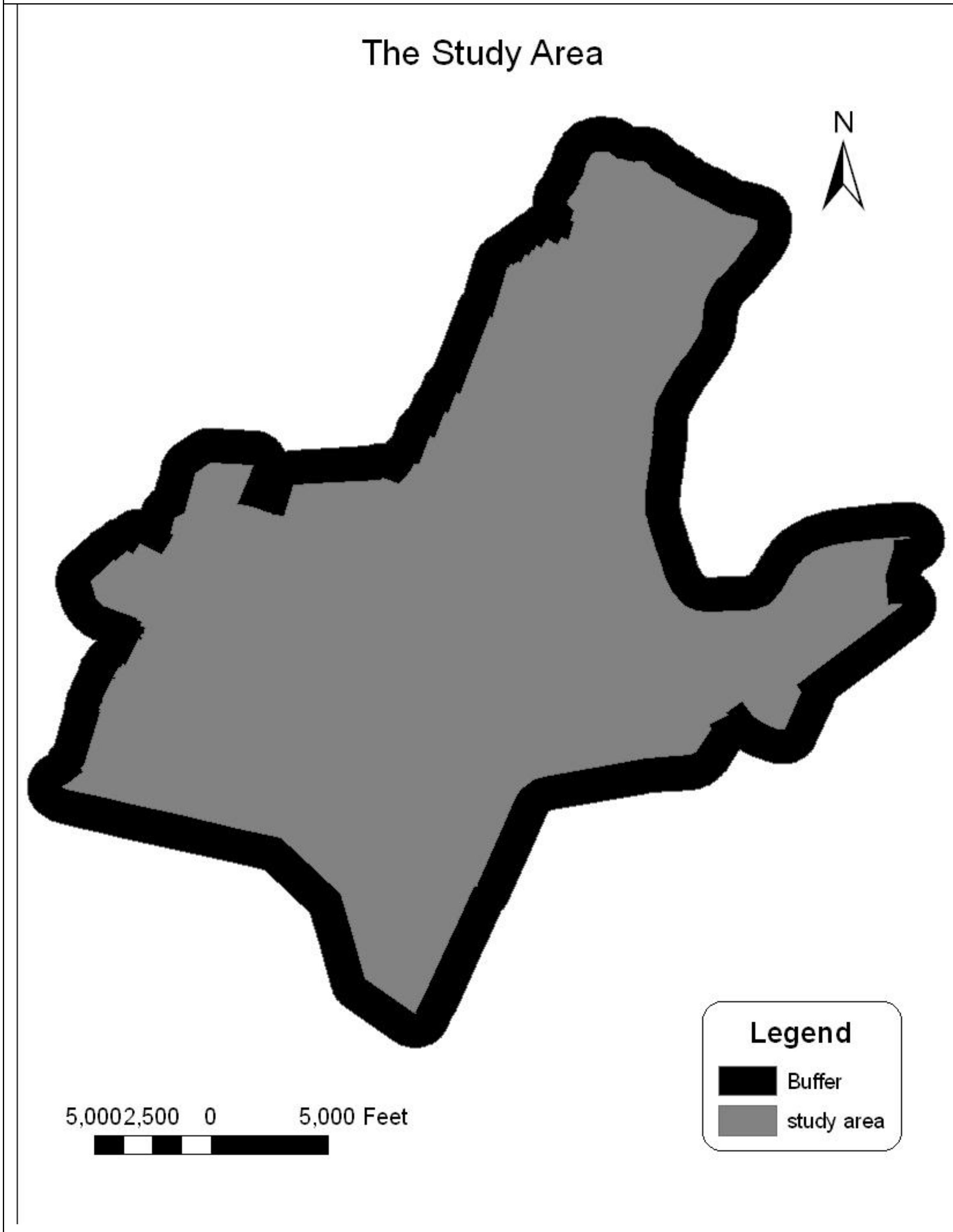


Figure 3. Study Area

Figure 4. Buffer



2. Data

The data used for this study come from different sources. Several agency data were used for the addresses of bus stops, liquor stores, bars, middle and high schools, and public housing. As the edge effects were considered, the data include not only Newark and Irvington, but also their surrounding cities. The New Jersey Transit provided the addresses of bus stops in NJ. In order to do RTM, 2008 bus stops data were used in this paper. The operational definition of bus stops in this study is the geographical locations of bus stops, excluding train stations, light rail stations, and subway stations, operated by NJ Transit in the study area and the buffer area in 2008.

Newark Police Department provided the addresses of liquor stores and bars in Newark in 2008. The Irvington data of liquor stores and bars in 2008 were from the State Police database. The operational definition of liquor stores and bars in this study is the geographical locations of liquor stores and bars known to the police in the study area and the buffer area in 2008.

The middle and high schools were downloaded from New Jersey Geographic Information Network. The data were originally derived from the public school, non-public school, and district tables published by the New Jersey Department of Education; the records were address-matched and cases were checked against orthophotography. This data cover the period from 2008 till 2009. The addresses of schools teaching grades

5 and higher were used for this study. The operational definition of middle and high schools is the geographical locations of public schools and non-public schools teaching grades 5 and higher in the study area and the buffer area in 2008.

The public housing data were drawn from several different local agencies. The Newark Police Department provided the Newark public housing data. Public housing data from 2008 were used in this paper. Irvington public housing addresses were obtained from Irvington Housing Authority. All other public housing addresses in the surrounding areas were obtained from local Housing Authority. The operational definition of public housing is the geographical area locations of public housing in the study area and the buffer area in 2008.

The gun shooting data in Newark and Irvington are from the New Jersey State Police. The shooting data include nonfatal shooting cases, including aggravated assault and armed robbery; the data do not include shooting-related homicide. The data range from Jan. 2008 until Aug.2010. The operational definition of gun shootings is the geographical locations of nonfatal shooting incidents including aggravated assault and armed robbery, but not including shooting-related homicide, that are known to the police in the study area from January 2008 to August 2010.

For the CLI analyses, shooting data from Jan.2008 till Aug. 2010 were used. But, in testing predictability of RTM modeling, only 2009 shooting data were used, because the RTM models are built on 2008 risk factors data. Street addresses with zipcodes are recorded in the data. These incidents are geocoded to a local street file, a procedure whereby the locations of these crimes are derived from street addresses.

"Known to the police" is a significant measure issue. The shooting addresses reported to the police may be not accurate. For example, the real shooting locations may be different from witnesses' statements based on their memories. Also, sometimes several shootings may be only reported as one incident.

3. Analyses Plans

Part I: Crime Generator Analysis

The purpose of the first part, crime generators analysis, is to identify crime generators of gun shootings. The method used is Conditional Locational Interdependence (CLI). The detailed explanations of CLI are introduced in chapter 7. Based on the literature review, five types of facilities were considered to be risky: public housing, schools, bus stops, liquor stores and bars, and hospitals. This study will test whether these facilities are crime generators for shootings.

The results of crime generator analysis are used to build crime forecasting models. The crime forecasting models in this study are Risk Terrain Modeling (RTM). The description of RTM is introduced in chapter 8.

In order to test whether crime generator analysis can improve the predictability of crime forecasting, three experiments are conducted. The first model is a base forecasting model incorporating three crime generators with middle-level crime generating strength. The second model is an improved forecasting model that adds a stronger risk factor into the base model. If the validity of the second model is increased, we can conclude that the predictability of crime forecasting can be improved by using stronger risk factors identified by crime generator analysis.

The third model is a forecasting model that adds a weak or no effect risk factor into the base model. If the validity of crime forecasting is reduced, we can conclude that crime generator analysis can improve forecasting models; if the validity of the forecasting is not reduced, we cannot get the conclusion. The validity test of the crime forecasting is logistic regression.

Part II: Neighborhood Analysis

Facilities do not stand alone; rather, they are nested within the broader demographic fabric of surrounding community. It is also important to take community demographic factors into account. Actually, in the meta-analysis study by Pratt and Cullen (Pratt and Cullen 2005), they found that across all studies, social disorganization theory receives strongest empirical support, and indicators of concentrated disadvantage are among the strongest and most stable predictors. This part is based on social disorganization theory and its related studies. Social disorganization theory suggests three structural factors account for the variations of crime rates: low economic status, ethnic heterogeneity, and residential instability. This study examines the influences of neighborhood characteristics on shootings in Newark and Irvington, NJ, taking spatial interdependence into account.

The unit of analysis is census block group. There are three different units in census data: census tract, block group, and block. There are two reasons to use block group as the unit: first, smaller unit allows more homogeneity than larger unit. Second, there is no demographic data at block level; the smallest unit that contains demographic data is block group.

The study area is the same as the area in Part I. Before doing the analysis, first join the census demographic data onto the census block group shapefile in ArcMap. Then spatial join the census block group shapefile and the shapefile of the study area. In this way, we can get demographic data in each block group within the study area.

Measures

Dependent Variable

The dependent variable is the number of shootings in each census block group within the study area from Jan.2007 till Aug.2010. The shooting data in Newark and Irvington is from NJ state police. The data are the locations of shooting incidents. After geocoding the addresses of shooting locations, the distribution of shootings is shown on the map of Newark and Irvington. Then use clip function under the Analysis Tools in the ArcToolBox to get the distribution of shootings within the study area. Finally, spatial join the clipped shooting shapefile with spatial joined block group shapefile. In this way, we get a shapefile in the study area with both shooting locations and demographic information in each block group.

Explanatory Variables

According to social disorganization theory and previous research, three structural latent factors are needed to measure: disadvantage, heterogeneity, and instability. Five explanatory variables in census data are used to measure disadvantage: the first variable is the percent of family households with children under age 18 who have a female householder and no male present. This is a measure of female-headed households, indexing family disruption. The second variable is the percent of families with 1999 income below the poverty level. This variable is a measure of family poverty. The third variable is the percent of households receiving public assistance income (public assistance). The fourth variable is the percent of males age 16 and over in the labor force who are unemployed (male unemployment). The fifth variable is the percent of all males age 16 and over who are either unemployed or not in the labor force (male joblessness). To measure ethnic heterogeneity, we use the percent of African American.

To measure instability, three variables are used: the percent of housing units that are vacant (Housing vacancy), the percent of occupied housing units that are renter occupied

(Renter occupancy), and the percent of persons age 5 and older who did not reside in the same house (Population turnover).

Control Variables

Besides the dependent variable and explanatory variables, we have two control variables: population and spatial lag. The reason to add spatial lag is that we need to take spatial pattern into account.

Modeling spatial nature of the data is important for a couple of reasons: first, most statistics are based on the assumption that the values of observations in each sample are independent of one another. Positive spatial autocorrelation violates this assumption. Ignoring spatial dependence in the model may lead to false indications of significance, biased parameter estimates, and misleading suggestions of fit. Second, spatial data contain information on locations, but traditional statistics do not use spatial information for analysis.

The modeling of spatial processes will begin with a visual inspection of the data, followed by diagnostics designed to determine the nature of the spatial processes operating. Some types of observed spatial autocorrelation suggest a “spatial error” process, in which the geographic patterning in the data is concentrated in the error terms, and is attributed to geographic patterning in unmeasured predictor variables. Others suggest a “spatial lag” process, which may indicate diffusion or displacement processes in that the observed spatial patterning is attributed to more than the patterning of the predictor variables, and is assumed to be in part due to some substantive contribution of the phenomenon of interest in one location to the occurrence at another (Baller et al 2001).

Spatial lag model is used when there is spatial autocorrelation in dependent variable. Spatial error model is used when there is spatial autocorrelation in error term. In spatial lag model, the spatial dependence is added as an additional variable. In spatial error model, the ordinary least squares is considered to be inefficient in its estimation but unbiased. For this study, spatial lag model will be used.

The first step is to determine whether spatial autocorrelation exists. The most common approaches are spatial autocorrelation test and calculating Moran's I (Baller et al 2000). Moran's I is a cross-product coefficient. When the Moran's I is significantly positive, it indicates clustering or positive spatial autocorrelation; when the Moran's I is negative, it indicates dispersion or negative spatial autocorrelation. The spatial autocorrelation test, Moran's I calculation, and spatial lag calculation will all be conducted in GeoDa.

Data for independent variables are drawn from census 2000 data. It is the most recent census data that are available. Census 2000 presents counts and information on basic demographic and socioeconomic data, for example, age, sex, race, housing, social, and economic characteristics of the household.

Analytic Strategies

The analysis starts from spatial autocorrelation test. Spatial autocorrelation is essentially the nature of geography and consequently is always present in spatial data. Events or phenomena affect each other more when they are closer together than when they are farther apart. Griffith (1987) explained the impacts of spatial autocorrelation. Analyses without considering spatial autocorrelation may cause incorrect conclusions regarding whether the relationships between variables are true or not. This is because if observations are dependent on each other, that is essentially the same as having duplicate observations. However, most statistics are based on the assumption that the values of observations in each sample are independent of one another. If a large number of observations indicate the relationship, that will lead us to believe that there is a strong relationship between the variables. However, if we have duplicate or autocorrelated observations, the actual relationship should be weaker. Therefore it is important to examine spatial autocorrelation first.

Spatial autocorrelation refers to the degree of similarity between points or events occurring at these points and points or events in nearby locations. If significant positive spatial autocorrelation exists, points with similar characteristics tend to be near each other. If spatial autocorrelation is weak or nonexistent, nearby points do not exhibit nay similar or dissimilar pattern or a random pattern exists.

A good measure for spatial autocorrelation is Moran’s I. Moran’s I uses the mean of the attribute’s data values as the benchmark for comparison when neighboring values are evaluated. The value of Moran's I ranges from -1 for an extremely negative spatial autocorrelation to 1 for an extremely positive spatial autocorrelation. Positive spatial autocorrelation means that nearby areas have similar rates, indicating global spatial clustering. Nearby areas have similar rates when their populations and exposures are alike. When rates in nearby areas are similar, Moran's I will be large and positive. When rates are dissimilar, Moran's I will be negative. When the Moran's I is significantly positive, it indicates clustering or positive spatial autocorrelation; when the Moran's I is negative, it indicates dispersion or negative spatial autocorrelation.

The modeling of spatial processes will begin with a visual inspection of the data, followed by diagnostics designed to determine the nature of the spatial processes operating. Some types of observed spatial autocorrelation suggest a "spatial error" process, in which the geographic patterning in the data is concentrated in the error terms, and is attributed to geographic patterning in unmeasured predictor variables. Others suggest a "spatial lag" process, which may indicate diffusion or displacement processes in that the observed spatial patterning is attributed to more than the patterning of the predictor variables, and is assumed to be in part due to some substantive contribution of the phenomenon of interest in one location to the occurrence at another (Baller et al 2001).

Spatial lag model is used when there is spatial autocorrelation in dependent variable. Spatial error model is used when there is spatial autocorrelation in error term. In spatial lag model, the spatial dependence is added as an additional variable. In spatial error model, the ordinary least squares is considered to be inefficient in its estimation but unbiased. For this study, spatial lag values will be calculated in GeoDa and then be added into our model as a control variable if spatial autocorrelation exists in this study.

To select a regression method for the neighborhood analysis, we need to examine the distribution of this dependent variable first. If it follows normal distribution, we can use the common regression method, Ordinary Least Squares, to do the analysis. If it is highly skewed, we may have to use poisson-based regression, eg. poisson regression or negative binomial regression.

To analyze aggregate crime rates that solves problems arising from small populations and low base-rates, poisson-based regression is a better method to use than OLS. Crime rates based on small counts of crimes present two serious problems for least squares analysis. First, because the precision of the estimated crime rate depends on population size, variation in population sizes across the aggregate units will lead to violating the assumption of homogeneity of error variance. We must expect larger errors of prediction for per capita crime rates based on small populations than for rates based on large populations. Second, normal or even symmetrical error distributions of crime rates cannot be assumed when crime counts are small. The lowest possible crime count is zero, so the error distribution must become increasingly skewed (as well as more decidedly discrete) as crime rates approach this lower bound. As populations decrease, an offense rate of zero will be observed for a larger and larger proportion of cases. Thus, there is an effective censoring at zero that is dependent on sample size, which has considerable potential for biasing the resulting regression coefficients (Osgood 2000).

Poisson-based regression analysis explicitly addresses the heterogeneous residual variance that presented a problem for OLS regression analysis of crime rates. The standard form for a poisson-based regression model is that the outcome measure is a count of events, and its mean is expected to be the natural logarithm of a linear model, eg, the sum of a set of explanatory variables each multiplied by a regression coefficient. In this study, both poisson regression and negative binomial regression will be conducted. Then a comparison test will be used to test which model is better, poisson regression or negative binomial regression.

Part III: Forecasting Future Shooting Areas

The first two parts provide the basis for building a forecasting model to predict future shooting risk areas. From the analyses in the first two parts, we will find risk factors that increase shooting opportunities. These risk factors will be used to build our forecasting model. The forecasting method that will be used is Risk Terrain Modeling (RTM) (Caplan, Kennedy and Miller 2010). RTM is an approach to spatial risk assessment to aid in event forecasting by incorporating underlying causes of crimes and standardizing all of those factors to common geographic units over a continuous surface. A final composite risk map is produced by combining all risk map layers that represent the presence, absence, or intensity of each risk factor at every place. This composite map accounts for all risk factors at every location throughout the geography and shows the level of future crime risk for each place.

To standardize all factors to common geographic unit, we need to first set a unit for all the risk maps. The unit used in this study is 140 feet grid size. The reason to use 140 feet is because this is half of the average block length in the city. It is believed that half block is a reasonable area within which crime events can happen and is small enough for targeted interventions should risk in these areas be found to be high.

One problem that needs to be dealt with before building the forecasting model is how to disaggregate census data to our unit. As we know, there are only two units in census data that contain demographic information: census tract and block group. But both units are larger than our unit 140 feet. So we have to first disaggregate census data into our unit and the disaggregated data still contain the demographic information. The method of disaggregating census data is smoothing. Smoothing is a process by which data points are averaged with their neighbors in a series. The results of smoothing in this study should give us risk layers of neighborhood risk factors that have the same unit 140 feet as other risk layers.

After doing smoothing to census data, the units of all the risk layers have been standardized to 140 feet grid size. Now these risk layers are ready for RTM processes. We can create distance map or density map based on the calculations in CLI part. Then reclassify the values of the grids in the raster maps. Finally we can combine all the risk layers to create a composite map. This composite map shows us places with different risk values.

Finally, the predictability of this model will be tested using statistics methods. I will first test whether spatial autocorrelation exists. If there is spatial autocorrelation, spatial lag values need to be calculated and included into the model. Then conduct a logistic regression with “presence or absence of shooting, yes/no” as the dependent variable, and risk value and spatial lag as the covariates.

4. Summary

Based on opportunities theories and social disorganization theories, this study examines the determinants of gun shootings from two perspectives: crime generators analysis and neighborhood analysis. Crime generators analysis focuses on the influences of urban features on gun shootings. According the literature review, four urban features are selected for testing: public housing, bars and liquor stores, bus stops, and schools. Another feature, hospital, is also included for testing in order to evaluate the function of crime generator analysis in forecasting. Three experiments are designed in order to test whether crime generator analysis can improve the predictability of forecasting models.

Neighborhood analysis focuses on the effects of neighborhood conditions on gun shootings. According to social disorganization theory, three structural factors are measured using 2000 census data: concentrated disadvantage, ethnic heterogeneity, and residential mobility. The analysis starts from spatial autocorrelation test and Moran's I calculation. If spatial autocorrelation exists in this study, spatial lag will be computed and included in regression analysis. Due to the count nature of the dependent variable, two poisson-based regression analyses will be conducted: poisson regression and negative binomial regression. A comparison test will be used to find a better method.

The results of crime generator analysis and neighborhood analysis are used to build a forecasting model to predict shooting distributions. Smoothing method will be used to disaggregate census data. Straight line distance maps will be built for each risk factors identified in crime generator analysis and neighborhood analysis. The values of grids in raster maps will be reclassified to binary values. A final composite risk map will be built combining all the risk layers. In order to test the validity of this forecasting map, spatial autocorrelation tests and a logistic regression will be used.

Chapter 7. Crime Generator Analysis

This chapter looks at identifying crime generators of shootings. The last chapter concluded that the demographic characteristics of neighborhoods create broader fabrics for crimes to occur. However, certain types of facilities also generate crime concentration. Eck, Clarke and Guerette (2007) name these facilities as risky facilities. A small proportion of the risky facility group accounts for the majority of crime experienced by the entire group.

The analytic method to identify crime generators is Conditional Locational Interdependence (CLI). CLI is a better method to identify crime generators than current common method such as thiessen polygon method. The reason to use this new method is because there are limitations in the current common method – quadrat method. This method requires creating polygons, such as thiessen polygons, and then doing regression analysis to examine correlations between factors. This quadrat method suffers from two biggest problems.

First, the polygon size is arbitrarily determined by researcher. The researcher can set the polygon size as 50 feet, or 5000 feet. However, results will change dramatically if we use different polygon sizes. Second, the quadrat method requires data aggregation. However, data aggregation masks important variations in smaller ecological areas. Also, this polygon method suffers from modifiable areal unit problem (MAUP). The modifiable areal unit problem is a source of statistical bias from data aggregation that can radically affect the results of statistical hypothesis tests. MAUP can cause the correlation, or association, between two variables to range from -0.99 to +0.99. Even if X is generated as a function of Y (where we would expect cor(X,Y) = 1.000) alternate aggregations of the same two variables can lead to wide variance of the re-aggregated association (cor(X,Y) = 0 +/- 0.99). However, to create thiessen polygons, we have to aggregate data, and hence, we always have MAUP problem.

However, CLI does not have these limitations. The computation of CLI is straightforward. The calculations are based on calculating minimum distances.

Conditional Locational Interdependence

The crime analyst may be able to address the temporal problem by selecting out crime events according to time of day or day of week of a particular incident (e.g. burglary in residential neighborhoods occurring during the daytime or assaults occurring in bars in the evening). The crime generator problem is much more difficult to solve because it requires a complicated set of analytical assumptions about the spatial relationship between crime generators and crime events. This concept was introduced in geographical literature as conditional locational interdependence (CLI) by Okabe and Miki (1984). The underlying concept is simple. Locational interdependence occurs where the locational patterns of two types of entity depend on each other – the locations of each entity are neither random nor independent of each other. The co-location of auto body and auto parts shops is an example of locational interdependence. In this case, a symbiotic relationship is recognized through which the location of each type of entity is influenced by the other. Conditional locational interdependence occurs where the locational patterns of one type of entity are dependent on the other and in which the dependence does not extend in the other direction. The co-location of crimes and bars is an example of CLI. It is recognized that the locations of crimes would be dependent on the locations of bars, whereas locations of bars are not affected by the location of crimes. So, if we are to consider certain facilities as crime generators, we need to establish the locational interdependence of these to the distribution of crime incidents.

Visual inspection cannot accurately identify CLI: an objective procedure is required to assess the degree and statistical significance of the conditionally interdependent relationship. The theoretical underpinnings of such procedures are also quite simple. If the mean distance from the hypothetically dependent distribution (crimes) to the independent distribution (e.g. bus stops) is significantly less than that from a spatially random pattern of crime, then CLI is established. This statement is predicated on the knowledge that independent distribution is truly uninfluenced by the dependent (the locations of bus stops are not influenced by the locations of crimes).

The distribution of two types of points, called A-points and B-points, on a plane are considered. The locations of the A-points are fixed and known. The null hypothesis is that B-points are distributed randomly in relation to A-points. Distances from B-points to the nearest A-points define the distributional state of B-points in relation to A-points. If B-points are distributed randomly over the plane, then their distribution is independent of the distribution of A-points. If B-points are significantly closer than random to A-points, they are implied to be dependent on the A-point locations – conditional interdependence exists. Okabe and Miki define a conditional nearest-neighbor spatial-association statistic:

$$\bar{R}_C = \frac{\bar{r}}{\mu}$$

where:

$\bar{r}$ = observed mean distance from the actual B-points to their nearest A-points.

μ = expected mean distance from randomly distributed B-points to their nearest A-points.

The CLI statistic, $\bar{R}_C$, compares the mean value of r in an empirical distribution to its expected value in a random, independent, distribution. Okabe and Miki deemed the task of deriving the frequency distribution of r to be "hopeless," but invoked the Central Limit Theorem to assess the statistical significance of the comparison of the actual and theoretical mean distances with the Z statistic:

$$Z = \frac{\bar{r} - \mu}{\sigma(\mu)}$$

where:

$$\sigma(\mu) = \sqrt{\frac{Var(\mu)}{n}}$$

$Var(\mu)$ = the variance of μ

n = the number of randomly distributed B-points

The aim of CLI analysis is to determine if an empirical distribution of B-points is closer than random to the nearest set of facilities or A-points. The null hypothesis is that the empirical distribution is random, that the empirical is not significantly smaller than μ; the research hypothesis is that it is smaller. Calculating the statistic and assessing its statistical significance requires the empirical mean distance from actual B-points to their nearest A-points, , the expected mean distance from randomly distributed B-points to their nearest A-points, μ, the variance of μ, and the number of randomly distributed B-points. Okabe and Miki's (1984) computational procedure is complex; all the calculations are based on computational geometry. Its practical achievement is, like many of the tools of spatial analysis, beyond the reach of most applications researchers. Here we use different computational methods - Nearest Neighbor Analysis and Monte Carlo Simulation - to generate randomly distributed B-points and to obtain the expected mean distance from randomly distributed B-points to their nearest A-points. Such randomness implies that every location has an equal probability of containing a given B-point. The computational methods will be discussed below.

Spatial Analysis

The objective determination of spatial distributions is a problem that has surfaced in many fields, such as physical cosmology (Peebles 1980), archaeology (Donnelly 1978), and ecology (Clark and Evans 1954). Several methods have been used to analyze spatial patterns. Perhaps the best known is that of quadrat analysis (Whittaker 1975). By this approach, the space is divided into quadrats of equal area, and the number of points falling within each quadrat is determined. The distribution of points per quadrat is compared to the distribution that would be expected for a random array of points. This approach is limited because it is scale-dependent: changing the size of the quadrat changes the apparent degree of clustering of points (Davis 1986).

Several approaches are based on the distances among points. For example, the autocorrelation function of physical cosmology (Peebles 1980) compares the number of points within a certain distance of a given point to that which would be expected for a random distribution of points. The autocorrelation function is continuous and varies with distance from the point. Therefore, it is possible to determine the different scales at which there is clustering.

The method of tessellation, used in mineralogy to determine the coordination number of solids (David and David 1982), has been applied in several ecological studies. An "area polygon" (in two dimensions) is constructed around each point, reflecting the proximity of each of its neighbors. Smaller polygons reflect relatively close neighbors, i.e., relative clustering of points (e.g. Vincent et al. 1976).

Nearest-neighbor analysis compares the distance of each point to its closest neighbor to the distance that would be expected for a random distribution of points (Clark and Evans 1954). If the average observed nearest-neighbor distance is less than expected, there is clustering among the points. This approach is attractive in that it is conceptually straightforward and computationally simple. It is therefore the method adopted here. No claim is made that this represents a generally superior approach.

Conventional nearest-neighbor analysis involves the determination of the point density, which requires that the bounds of the space be known. Even if there are known bounds, the problem of edge effects does not vanish. It is well known that the expected nearest-neighbor distance is greater near the periphery of a space than in the interior (Clark and Evans 1954). Several approaches have been used to circumvent edge effects. One approach involves discarding points near the periphery of the space, creating a so-called guard region (Kenkel et.al. 1989). This solution is undesirable because it may cause a large proportion of the data to be discarded. Furthermore, there may be something special about the points near the edge so that we would especially not want to discard them. (for example, if trees near the periphery of a forest receive more sunlight they may be able to utilize more energy and encroach upon their neighbors.) Another solution is to make the space toroidal (Ripley 1988: p 24). By this approach, the right edge of a two-dimensional map, for example, would be made to abut the left edge of that map. While this may work technically, it is questionable whether points that are in reality quite distant from each other should be brought into close proximity for the sake of analysis. Furthermore, Ripley (1988:p.24) points out that this method eliminates edges, but not edge effects. Many sophisticated mathematical corrections have also been discussed (Ripley 1988).

Donnelly (1978) applied computer simulation to investigate edge effects on nearest-neighbor analysis. The simulation procedure has the advantages that it is straightforward, determines directly the expected nearest-neighbor distance, and does not entail discarding data. Donnelly's approach was to generate a family of solutions so that the simulation procedure would not be needed for every analysis. However, the intensity of edge effects can in general be expected to vary with the details of the point distribution. Therefore, this study adopts Donnelly's approach of simulation but determines the expected nearest-neighbor distances separately for each case, rather than assuming that a single solution will apply universally.

Monte Carlo Simulation

Monte Carlo Simulation is one of the largest and most important classes of numerical method for computer simulations or computer experiments. Monte Carlo simulation can be defined as a method to generate random sample data based on some known distribution for numerical experiments. In shortsighted view, Monte Carlo Simulation always involves random number (though actually not all methods that involve random number can be categorized as Monte Carlo Simulation, they may be better described as part of Monte Carlo Method). Generation of pseudo random number R that distributed uniformly over interval $0<R<1$ is the heart of any Monte Carlo simulation. The random number generated must be independent (no correlation to other random number)

A simulation model allows us to examine system behavior under different scenarios in virtual computational world. It can be used to identify bottlenecks in a process, provide a safe, and relatively very cheap (in term of both cost and time) testbed to evaluate the side effects and to optimize the performance of the system before transferring them to real world.

Monte Carlo Simulation has three characteristics: random sample generation, known input distribution, and numerical Experiments. Numerical experiments characteristic of Monte Carlo simulation lead us to run many samples before we can get the result. Monte Carlo Algorithm works based on the Law of Large Numbers. It says that if you generate large number of samples, eventually you will get the approximate desire distribution.

Applying CLI to Crime Generators

The purpose of this chapter is to identify crime generators of shootings using conditional locational interdependence method. Also, in order to do risk terrain modeling in the next chapter, the cut-off values of maximum distances are calculated in this chapter based on CLI calculations.

Five variables are selected to test whether they are crime generators of shootings: liquor stores and bars, bus stops, middle and high schools, public housing, and hospitals. The first four variables are selected based on literature reviews. The last variable hospital is included in the analysis for two reasons: first, to test whether hospitals are crime generators of shootings. No study has ever examined this variable as crime generators. Second, to test the predictability of RTM by using CLI. If hospitals don't have CLI effects, the RTM model that includes hospital as one of the risk factors is predicted to decrease its predictability.

For each of the five variables, the following computational procedures are conducted to analyze their CLI effects:

Boundary and Edge Effects

Nearest-neighbor procedure requires that the boundary be known. Actually, for simulating spatially random points, the boundary is a required parameter.

If a calculated interpoint distance is greater than the distance between the point and its nearest plot boundary, part of the spatial neighborhood of this point lies outside the plot and cannot be evaluated without a certain bias. Hence, edge effects are usually considered in spatial pattern analysis. CLI analysis may also be affected by edge effects. The most common method to account for edge effects is the addition of a buffer zone around the ecumene. The relevant points in the buffer zone are included in the analysis.

Observed mean distances from actual B-points to their nearest A-points

If a projected coordinate system is used for map projections, Euclidean distance is the method to measure the observed distances. If a geographic coordinate system is used for map projections, the following formula should be used to calculate the distance between points. As the earth is a sphere, not a plane, the following cosine formula is proposed to calculate the distance between two points P1(long1,lat1) and P2(long2,lat2) on earth which is a sphere:

$$D(P1,P2) = r \times a\cos(\sin(lat1) \times \sin(lat2) + \cos(lat1) \times \cos(lat2) \times \cos(long1 - long2))$$

…….. (Formula (1))

where r is 6371km, the radius of the earth. That is, we obtain the distance between two points on earth by assuming that the earth is a perfect sphere and calculating the shortest distance between two points on a sphere.

For each B-point, use formula (1) to get the distances from all the A-points. We compared all the distances to each B-point and determine the minimum distance to each B-point. The average of all the minimum distances is the observed mean distance from actual B-points to their nearest A-points.

Monte Carlo Simulation of Nearest-Neighbor Distance

Monte Carlo simulation is used to generate random sample data based on some known distribution of the population to resemble the real world problem. In our study, Monte Carlo Simulation randomly generates B-points that are uniformly distributed within the ecumene boundary. For each randomly generated B-point, calculate the distances from each observed A-point to this random point. The minimum of these distances is the nearest-neighbor distance. The minimum distance varies from one run of the computer simulation to the next. Thus, the procedures of randomly generating B-points and determining the minimum distance from the observed A-points to the random points are repeated many times. The average of the minimum distance over all the runs is the minimum expected mean distance from simulated B-points to their nearest A-points.

Statistical significance

To test statistical significance, we need to get four statistics beforehand: the observed mean distance from actual B-points to their nearest A-points; $\bar{r}$, the expected mean distance from randomly distributed B-points to their nearest A-points; μ, the variance of μ, Var(μ); and the number of randomly distributed B-points. Now we can assume that B-points are randomly distributed in the bounded area and have no correlation with the locations of A-points. This is our null hypothesis. Based on this null hypothesis and Central Limit Theorem, we know that $\bar{r}$ would satisfy the normal distribution with mean equal to μ and standard deviation equal to σ(μ), since the sample size is large.

We can test the above null hypothesis by computing the following equations:

$$Z = \frac{\bar{r} - \mu}{\sigma(\mu)}$$

where, $\sigma(\mu) = \sqrt{\frac{Var(\mu)}{n}}$

We can then compute the p-value of Z and see whether the null hypothesis can be rejected or not. The following are the detailed computation steps to test CLI.

ANALYSIS AND RESULTS

Edge Effects

As stated, the results of CLI analysis may be affected by edge effects. These occur when data in a bounded area may be affected by phenomena outside of this area. In order to solve for this, the independent variables of bus stops, schools, and public housing were selected for both the study area, and in the regions outside the study area. A buffer of 1,500 feet was created outside of the study area and all facilities from the surrounding communities that fell within that buffer were included in the analysis. This buffer is displayed in Figure 4 in the last chapter. Figure 5-9 display the distributions of public housing, bus stops, liquor stores and bars, middle and high schools, and hospitals.

Figure 5. The Distribution of Public Houses

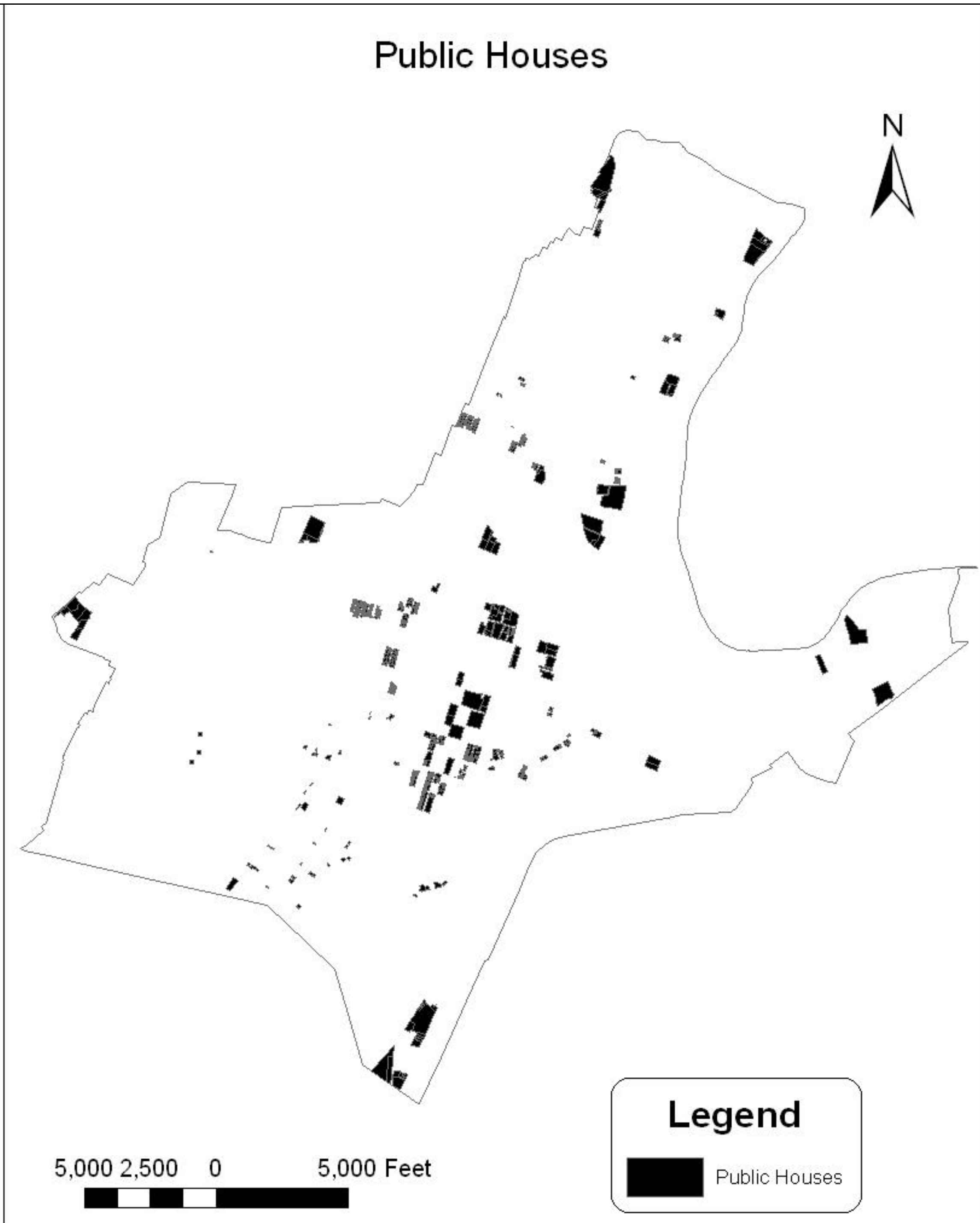


Figure 6. The Distribution of Bus Stops

Figure 7. The Distribution of Liquor Stores and Bars

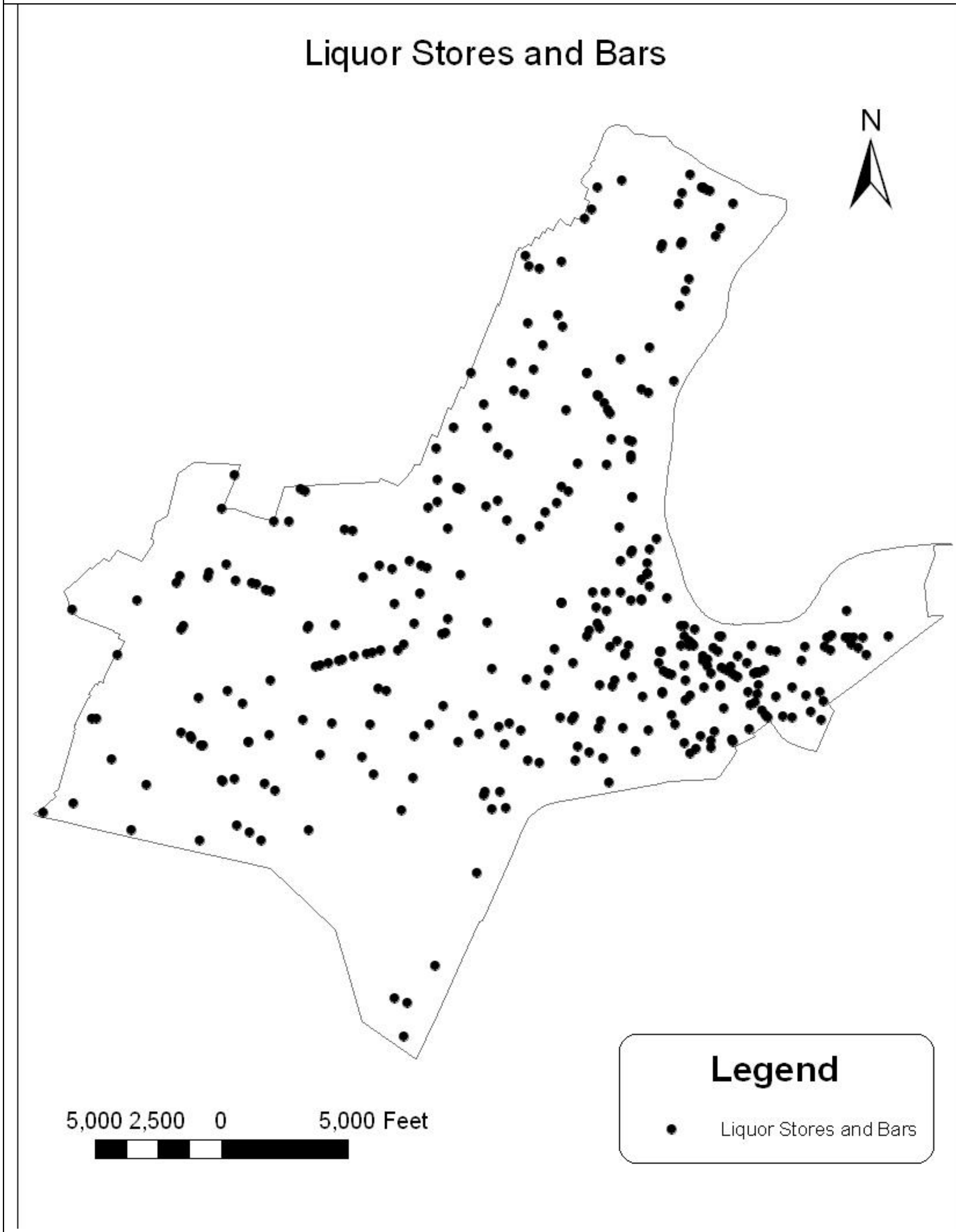


Figure 8. The Distribution of Middle and High Schools

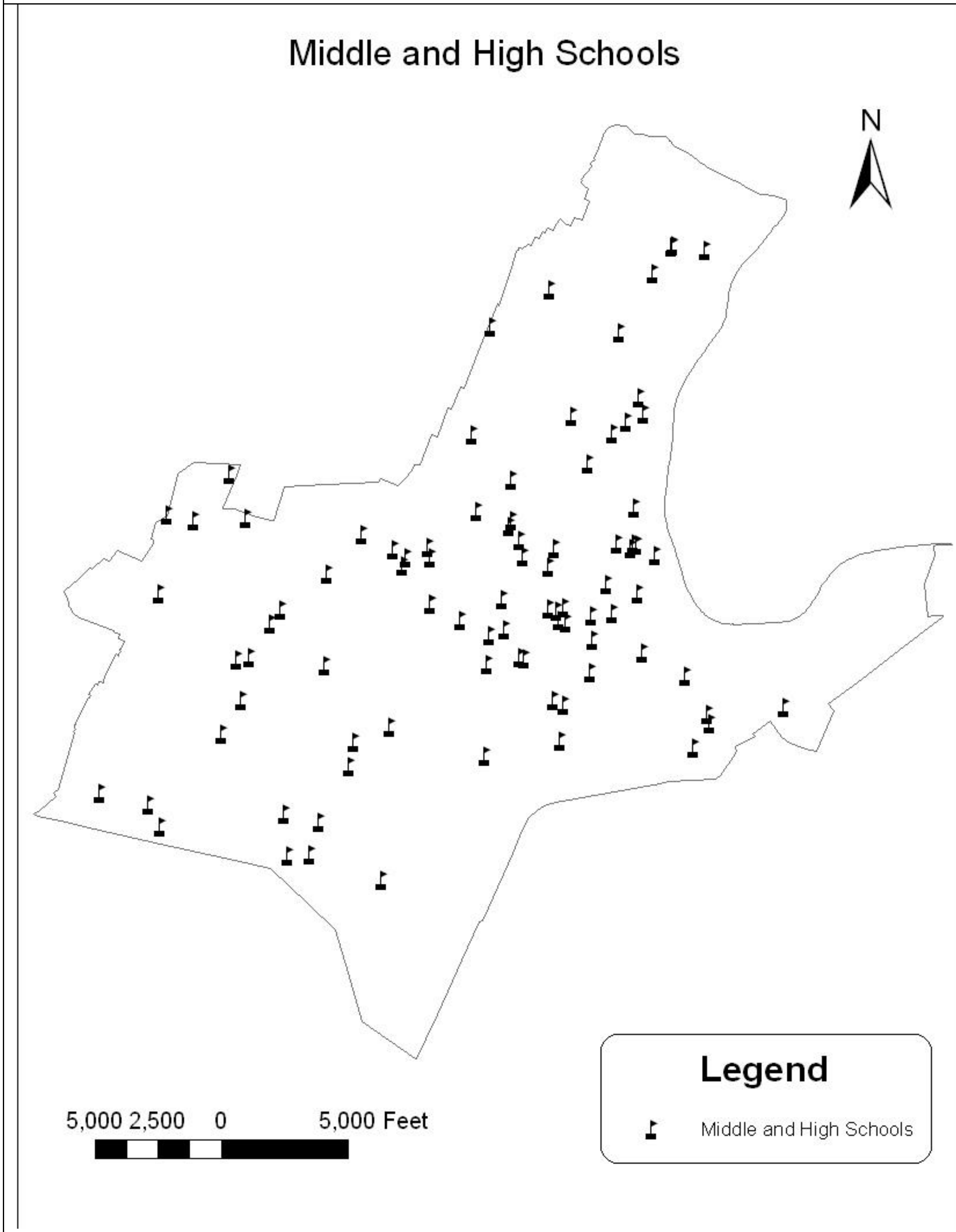
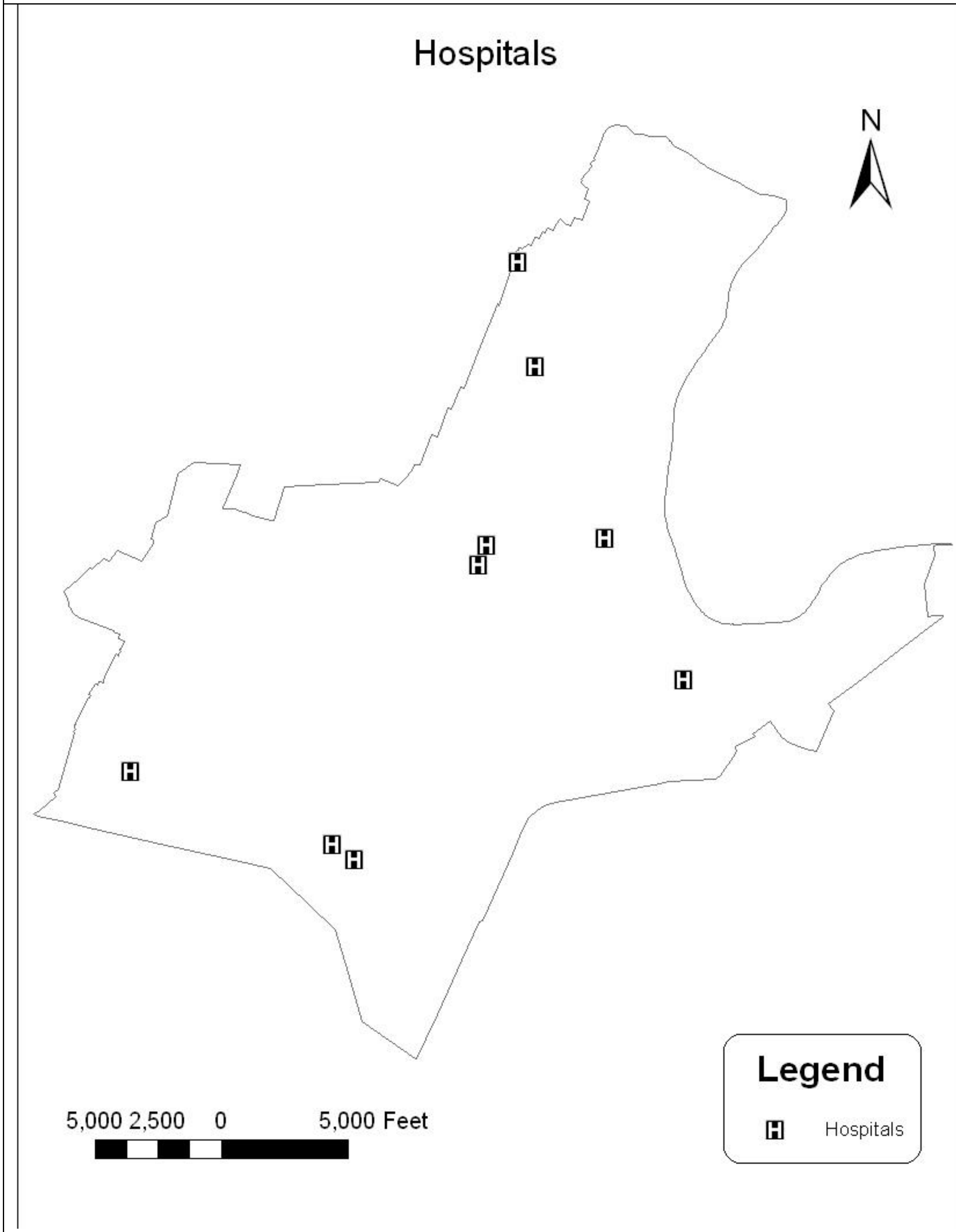


Figure 9. The Distribution of Hospitals



Observed mean distances from actual shooting points to their nearest risk factors points

A projected coordinate system is used for map projections in this paper. Euclidean distance is a good method to measure the observed distances between two points. Calculate the observed mean distance from the actual shooting locations to their nearest bus stop locations**.** Then export all the gun shooting points into R by using ArcGIS to get the coordinates of all the shooting points. Similarly, export all the bus stops points both in the ecumene and buffer areas into R. Then, calculate the distances between each bus stop and each shooting point based on Euclidean distance. For each shooting s(i), compare all the distances d(s(i), b(j)) for all j (bus stop) and find the smallest one. This was denoted by dsb(i), the shortest distance from the shooting s(i) to all bus stops. This process was repeated to get all the shortest distances between shootings and bus stops. Finally, compute the observed mean distance from the actual bus stops to their nearest shooting locations. To get the observed mean distance, take the average of dsb(i), i.e., $\bar{r}$ = sum dsb(i)/Ns, where Ns is the total number of shootings. The observed mean minimal distance to bus stops $\bar{r}$ =482.65 feet.

Similarly, compute the observed mean of minimal distance to liquor stores and bars (663.80), public housing (997.12), schools (1322.02), and hospitals (4485.65).

Monte Carlo Simulation of Nearest-Neighbor Distance

The Monte Carlo Simulation method was employed to generate randomly uniformly distributed points in the ecumene. In this study, the programming engine to generate the Monte Carlo process was Spatstat. Spatstat uses a rejection method to generate uniformly randomly distributed points in a polygon. Before doing Monte Carlo Simulation, use ArcGIS to get the coordinates of the ecumene boundary points and then export the boundary coordinates into R. Then, generate random, uniformly distributed shooting points in the boundary using Spatstat in R. Thirdly, use the Euclidean distance method to calculate the distance between each simulated shooting points and each bus stop. Fourthly, determine the minimum distances from simulated shootings to their nearest bus stops.

The minimum distance varies from one run of the Monte Carlo Simulation to the next. Monte Carlo Simulation relies on repeated trials to produce sufficient output for generalization. Although a large number of trials is recommended, earlier research found that averages taken over 20 repetitions vary very little (Foote 1989). Therefore, the procedure of generating simulated shooting points and determining the minimum distance from simulated shooting points to their nearest bus stops was repeated 20 times.

Finally, calculate the expected mean distance from simulated shootings to the nearest bus stops μ, and the standard deviation of μ, $\sigma(\mu) = \sqrt{\frac{Var(\mu)}{n}}$. The expected mean minimal distance μ = 606.97 feet. The standard deviation of μ is 20.33.

In sum, we calculated the following statistics for bus stops:

The observed mean distance to the nearest bus stops, $\bar{r}$ =482.65

The expected mean distance to the nearest bus stops, μ = 606.97

The standard deviation of μ, σ(μ) = 20.33

The conditional nearest-neighbor spatial-association statistic

$$\bar{R}_C = \frac{\bar{r}}{\mu} = \frac{482.65}{606.97} = 0.80$$

This value indicates that there is some concentration of gun shootings around bus stops. If the number had been 1, then there would have been complete randomness with regard to the location of the gun shootings to the bus stops.

Similarly, we can obtain the following statistics for liquor stores and bars:

The observed mean distance to the nearest liquor stores and bars, $\bar{r}$ =663.80

The expected mean distance to the nearest liquor stores and bars, μ = 822.87

The standard deviation of μ, σ(μ) = 23.67

The conditional nearest-neighbor spatial-association statistic

$$\bar{R}_C = \frac{\bar{r}}{\mu} = 0.81$$

This value indicates that there is some concentration of gun shootings around liquor stores and bars.

The statistics for public housing:

The observed mean distance to the nearest public housing, $\bar{r}$ =997.12

The expected mean distance to the nearest public housing, μ = 1520.9

The standard deviation of μ, $\sigma(\mu)$ = 44.78

The conditional nearest-neighbor spatial-association statistic

$$\bar{R}_C = \frac{\bar{r}}{\mu} = 0.66$$

This value indicates that there is concentration of gun shootings around public housing.

The statistics for middle and high schools:

The observed mean distance to the nearest schools, $\bar{r}$ =1322.02

The expected mean distance to the nearest schools, μ = 1608.03

The standard deviation of μ, $\sigma(\mu)$ = 50.45

The conditional nearest-neighbor spatial-association statistic

$$\bar{R}_C = \frac{\bar{r}}{\mu} = 0.82$$

This value indicates that there is some concentration of gun shootings around schools.

The statistics for hospitals:

The observed mean distance to the nearest hospitals, $\bar{r}$ =4485.65

The expected mean distance to the nearest hospitals, μ = 4290.67

The standard deviation of μ, $\sigma(\mu)$ = 96.38

The conditional nearest-neighbor spatial-association statistic

$$\overline{R}_C = \frac{\bar{r}}{\mu} = 1.04$$

This value of 1.04 indicates that there is randomness with regard to the location of shootings to the hospitals. There is no CLI effect.

Test for statistical significance

Now if we assume that the shootings are randomly distributed in the boundary and have no correlation with the locations of bus stops, then $\bar{r}$ would satisfy the normal distribution with mean equal to μ and standard deviation equal to σ (μ). This is true according to the well-known central limit theorem in statistics since the sample size Ns (total number of actual shootings) is large.

We test the above null hypothesis by computing the following statistic:

$$Z = \frac{\bar{r} - \mu}{\sigma(\mu)}$$

Z satisfies the standard normal distribution N(0,1).

The observed mean distance to the nearest bus stops, $\bar{r}$ =482.65

The expected mean distance to the nearest bus stops, μ = 606.97

The standard deviation of μ, σ(μ) = 20.33

So, Z = -6.11

We can then compute the p-values of Z and see whether the null hypothesis can be rejected or not. The p-value is smaller than 0.001, indicating that the null hypothesis, that the shootings are uniformly randomly distributed in the whole region and have no relation with the locations of bus stops, is rejected. Therefore, we can conclude that there is conditional locational interdependence of gun shootings around bus stops.

Repeat all the above steps, testing CLI for liquor stores and bars, public housing, middle and high schools, and hospitals. The results are as follows:

For liquor stores and bars:

The observed mean distance to the nearest liquor stores and bars, $\bar{r}$ =663.80

The expected mean distance to the nearest bus stops, $\mu = 822.87$

The standard deviation of μ, $\sigma(\mu) = 23.67$

$Z = \frac{\bar{r} - \mu}{\sigma(\mu)}$ =-6.72 with $p<0.001$

These results indicate that the null hypothesis, that the shootings are uniformly randomly distributed in the whole region and have no relation with the locations of liquor stores and bars, is rejected. Therefore, we can conclude that there is conditional locational interdependence of gun shootings around liquor stores and bars.

For public housing:

The observed mean distance to the nearest public housing, $\bar{r}$ =997.12

The expected mean distance to the nearest public housing, $\mu = 1520.90$

The standard deviation of μ, $\sigma(\mu) = 44.78$

$Z = \frac{\bar{r} - \mu}{\sigma(\mu)}$ =-11.70 with $p<0.001$

These results indicate that the null hypothesis, that the shootings are uniformly randomly distributed in the whole region and have no relation with the locations of public housing, is rejected. Therefore, we can conclude that there is conditional locational interdependence of gun shootings around public housing.

For middle and high schools:

The observed mean distance to the nearest schools, $\bar{r}$ =1322.02

The expected mean distance to the nearest schools, $\mu = 1608.03$

The standard deviation of μ, σ(μ) = 50.45

These results indicate that the null hypothesis, that the shootings are uniformly randomly distributed in the whole region and have no relation with the locations of middle and high schools, is rejected. Therefore, we can conclude that there is conditional locational interdependence of gun shootings around middle and high schools.

$Z = \frac{\bar{r} - \mu}{\sigma(\mu)}$=-5.67 with p<0.001

For hospitals:

The observed mean distance to the nearest liquor stores and bars, $\bar{r}$ =4485.65

The expected mean distance to the nearest bus stops, μ = 4290.67

The standard deviation of μ, σ(μ) = 96.38

$Z = \frac{\bar{r} - \mu}{\sigma(\mu)}$=2.02 with p=0.99

These results indicate that the null hypothesis, that the shootings are uniformly randomly distributed in the whole region and have no relation with the locations of hospitals, cannot be rejected. Therefore, we can conclude that there is no conditional locational interdependence of gun shootings around hospitals. Table 1 displays all the CLI analyses results.

Table 1. CLI Results

Statistic	**Public Housing**	**Bus Stops**	**Liquor Stores and Bars**	**Middle and High Schools**	**Hospitals**
μ	1520.90	606.97	822.87	1608.03	4290.67
$\bar{r}$	997.12	482.65	663.80	1322.02	4485.65
$\sigma(\mu)$	44.78	20.33	23.67	50.45	96.38
$\bar{R}c$	0.66	0.80	0.81	0.82	1.05
Z	-11.70	-6.11	-6.71	-5.67	2.02
p	<.001	<.001	<.001	<.001	0.98

Therefore, we can conclude that there are conditional locational interdependence for gun shootings around bus stops, liquor stores and bars, public housing, and middle and high schools. But there is no conditional locational interdependence for gun shootings around hospitals. With regard to gun shootings, public housing has the higher degree of CLI, then liquor stores and bars, bus stops, and finally middle and high schools.

In order to create the RTM model, the cutoff values of maximum distance for distance maps are calculated. The cutoff values are chosen empirically from the real data. Specifically, we compute the distance of each shooting to the nearest bus stop. We then obtain an empirical distribution of distances of all collected shootings to the nearest bus stops. We set the cutoff value to be within which 80% of real shootings occurred inside the disk of radius bounded by the cutoff value centered around a bus stop (i.e., the nearest bus stop to that shooting). In other words, the buffer bounded by the cutoff value covers 80% of real shootings. In this study, the cutoff value for bus stops distance map is 652 feet. Similarly, we calculated the cutoff values for schools (1769.73 feet) and the cutoff value for public housing (1647.84 feet).

Summary and Conclusions

This chapter uses CLI to do crime generator analyses for shooting. Five urban features are tested for crime generators of shooting: public housing, bus stops, liquor stores and bars, middle and high schools, and hospitals. The results show that only four of them are crime generators for shooting: public housing, bus stops, liquor stores and bars, and middle and high schools. But hospital is not a crime generator for shooting. Among the four crime generators, public housing has the highest risk in attracting shootings, followed by bus stops, then liquor stores and bars, and finally middle and high schools.

Chapter 8 Improving Predictive Efficacy of Risk Terrain Modeling

The last chapter identifies four risk facilities as crime generators of shootings: public housing, liquor stores and bars, bus stops, and middle and high schools. Based on these results, this chapter looks to the forecasting of future shootings locations by combining all the map layers of crime generators. The method used here is called Risk Terrain Modeling (RTM), originally proposed by Caplan, Kennedy and Miller (2010).

Risk Terrain Modeling

Risk Terrain Modeling (RTM) is an approach to risk assessment that standardizes risk factors to common geographic units over a continuous surface. Separate map layers representing the presence, absence, or intensity of each risk factor at every place is created in a Geographic Information System (GIS), and then all risk map layers are combined to produce a composite risk terrain map that accounts for all risk factors at every location throughout the geography. Risk terrain maps aid in strategic decision-making and tactical action by showing where conditions are ripe for events to occur in the future (Caplan and Kennedy 2010).

Risk Terrain Modeling was originally proposed by Caplan, Kennedy and Miller (2010). This is a way of looking at the coincidence of socio-physical factors that enhance risk of crime. RTM offers a way of looking at criminality as less determined by previous events and more a function of a dynamic interaction between characteristics of places. The ways in which these variables combine can be studied to reveal consistent patterns of interaction that can facilitate and enhance the risk of crime. The computation of the conditions that underlie these patterns is a key component of RTM, with the ability to weigh the importance of different factors at different geographic points in enabling crime events to occur. These attributes themselves do not create the crime. They simply point to locations where, if the conditions are right, the probability of crime or victimization will go up. This offers an approach that provides a means of testing for the most appropriate qualities of space (i.e. risk factors) that contribute to these outcomes through a statistically valid selection process. It also promotes the idea of the concentration of risk leading to these problems, in a way that these "risk clusters" can be used to help forecast future crime and direct interventions, such as police patrols, to these locations. This strategy can also be used to support the resiliency and expansion of the mitigating attributes that are in the low risk areas (Kennedy, Caplan and Piza 2011).

The technical approach to risk terrain modeling is straightforward (Caplan et al., 2010): identify, through meta-analysis or other empirical methods, literature review, professional experience, and practitioner knowledge (Ratcliffe & McCullagh, 2001), all factors that are related to a particular outcome for which risk is being assessed then operationalize each risk factor to a common geography. Essentially, RTM assigns a value signifying the presence, absence or intensity of each risk factor at every place throughout a given geography. Each factor is represented by a separate terrain (risk map layer) of the same geography. When all map layers are combined in a GIS, they produce a composite map—a risk terrain map—where every place throughout the geography is assigned a composite risk value that accounts for all factors associated with the particular crime outcome. The higher the risk value the greater the likelihood of a crime event occurring at that location. Risk terrain modeling of crimes produces maps that show places with the greatest risk or likelihood of becoming spots for crime to occur in the future. This occurs not just because police statistics showed that reported crimes occurred there yesterday, but because the environmental conditions are ripe for crime to occur there tomorrow (Kennedy, Caplan and Piza 2011).

Risk terrain modeling uses a grid of cells to represent a continuous surface, so aggregations to "arbitrary" geopolitical boundaries, police sectors, ZIP codes, census tracts, etc., are not necessary and the modifiable aerial unit problem (MAUP) is less of an issue (Harries, 1999). RTM will only be of value, however, if it can be shown to be more accurate, complete, and flexible in its application than current analytical strategies adopted in policing. Risk is defined as the likelihood of an event occurring given what is known about the correlates of that event, and it can be quantified with positive, negative, low or high ordinal values. A terrain is a grid of the study area made up of equally sized cells that represent a continuous surface of places where values of risk exist. Raster data is used to represent terrains in RTM. Places are defined by cells of size x2 (e.g. 100ftx100ft). Modeling broadly refers to the abstraction of the real world at certain places. Specifically within the context of RTM, modeling refers to the acts of attributing the presence, absence, or intensity of qualities of the real world to places within a terrain, and combining multiple terrains together using map algebra (Tomlin, 1994) to produce a single composite map where the new derived value of each place represents the aggregated—synthesized or collinear—qualities of those places irrespective of all other places within the terrain (Kennedy, Caplan and Piza 2011).

Risk terrain modeling (RTM) is an approach to spatial risk assessment to aid in event forecasting by incorporating underlying causes of events, such as crimes, and standardizing all of those factors to common geographic units over a continuous surface (Caplan et al., in press). It can be seen as a variation of conventional offender-based risk assessment whose principles were established many decades ago as research began to demonstrate that the characteristics of offenders were correlated with their subsequent behavior (Burgess, 1928; Glueck & Glueck, 1950). Except, RTM is place-based and combines actuarial risk prediction with environmental criminology to assign risk values to places according to their particular attributes (Kennedy, Caplan and Piza 2011).

In developing risk layers, Caplan et al have suggested using different components of the environmental backcloth as a series of screens that would identify risks at specific locations. In combining these layers, Kennedy, Caplan, and Piza (in press) have shown that the risk clusters created by this approach improve on the predictive capacity of hot spot analysis in crime analysis. To date, however, RTM has relied on averaging the effects of risk layers and could be enhanced using an approach that incorporates the assessment of the influence of certain features in the environment in “generating” crime, extending the analysis beyond correlation to causation.

Methodology

To do RTM, the very first step is to select risk factors. This step can be completed by CLI analysis introduced in the last chapter. By using CLI, we understand which variables have high degrees of CLI effects and should be selected into RTM model and which variables don't have CLI effect and should not be included in RTM model. In the last chapter, we have proved that there are CLI effects for shootings around public housing, liquor stores and bars, bus stops, and middle and high schools. But there is no CLI effect for shootings around hospitals.

In this chapter, we will build three RTM models. The first RTM model will include three risk factors: liquor stores and bars, bus stops, and middle and high schools. All these three factors are proved to have statistically significant effects of CLI. This first RTM model is the base model for the latter two RTM models.

The second RTM model will include four risk factors. Besides the three risk factors in the first model or the base model, a fourth risk factor – public housing- will be added. The CLI results show that public housing has the highest degree of CLI. The purpose to add this factor into the model is to test whether the predictability of RTM model can be improved by adding risk factors that have stronger CLI effect.

The third RTM model will add the variable hospital into the base model. So in this model, four variables are included: liquor stores and bars, bus stops, middle and high schools, and hospitals. The purpose to build this RTM model is to test whether the validity of RTM will be reduced by including variables that have no CLI effect.

Besides risk factor selection, we need to decide on a study area and a time period. The study area is the same as in the last chapter. The time period for the RTM models covers the entire year 2008, from January 1, 2008 till December 31, 2008. Thus, the shooting data cover the entire year 2009. In this way, we can use 2008 RTM model to predict 2009 shooting risks and then compare the predicted risk areas and the real 2009 shooting areas.

To operationalize risk factors to risk map layers, we need to create separate raster map for each risk factors. Each raster map represents the influence of each risk factor. Each of the vector shapefiles was converted into a raster layer by using ArcView's Spatial Analyst Extension. Each raster map contains equally sized 140x140 cells to reflect the average street length in Newark and Irvington. A cell size of 140 feet was used on all the three distance maps. The reason to use 140 feet is because this is the half median block length in the city. It was believed that about half block was a reasonable area within which crime events can happen and was small enough for targeted interventions should risk in these areas be found to be high.

The spatial influence of liquor stores and bars is operationalized as: The distance of 929 feet from a liquor store or bar poses the greatest risk of shootings because victims are often targeted when arriving at or leaving the facility. 929 feet is the result we compute from CLI analysis. This is the maximum distance cutoff value. A straight line distance map up to 929 feet from the points of liquor stores or bars is created. Similarly, the spatial influence of bus stops is operationalized as: The distance of 652 feet from a bus stop poses the greatest risk of shootings. A straight line distance map up to 652 feet from the points of bus stops is created. The spatial influence of schools is operationalized as: the distance of 1770 feet from a middle or high school poses the greatest risk of shootings. A straight line distance map up to 1770 feet from the points of schools is created.

In model II, a fourth variable-public housing is added into the model. The spatial influence of public housing is operationalized as: The distance of 1648 feet from a public housing poses the greatest risk of shootings. A straight line distance map up to 1648 feet from the points of public housing is created.

In model III, hospital is added as the fourth variable. The spatial influence of hospitals is operationalized as: areas with greater concentrations of hospitals will increase the risk of those places having shootings. A density map is created from the points of hospitals. Each cell receives a count of points falling within its boundaries, with those falling near the center of the cell being weighted more heavily than those near the edges. The final density values represents the total concentration of points.

We use a simple binary system for the risk values of each terrain. Cells are then reclassified into two groups. We assign risk value 1 for the interior of the buffer bounded by the maximum distance cutoff value 929 feet centered at a liquor store, and 0 for its exterior domain. We treat the bus stops, schools and public housing similarly, but with different cutoff values: for bus stops 652, schools 1770, and for public housing 1648.

For the density map layer of hospitals, cells are classified into two groups according to standard deviational breaks. The reason standard deviation is used as a classification scheme is because it is not affected by positively skewed distributions or outliers and it is statistically meaningful. Places with density values greater than 1 standard deviation are assigned values of 1, and all other places are assigned 0.

For Model I, we now have three risk map layers, operationalized from three risk factors: liquor store and bars, bus stops, and middle and high schools. Each cell within each risk map layer is designated with a value of 1 or 0 according to whether the influence of the risk factor on that place makes it high risk or not high risk. Since the cells of different map layers are the same size and were classified in a consistent way, the risk map layers can be summed together to form a composite risk terrain map.

The three risk map layers are combined using “raster calculator” in Spatial Analyst extension. The end result is a composite risk terrain map with each cell exhibiting the summed risk value of all risk map layers. Risk values for cells range from 0 to 3 with value of 3 the highest risk. Figure 10 displays the result. Figure11 overlaps the RTM result layer and 2009 real shootings layer.

Figure 10. RTM Map of Model 1

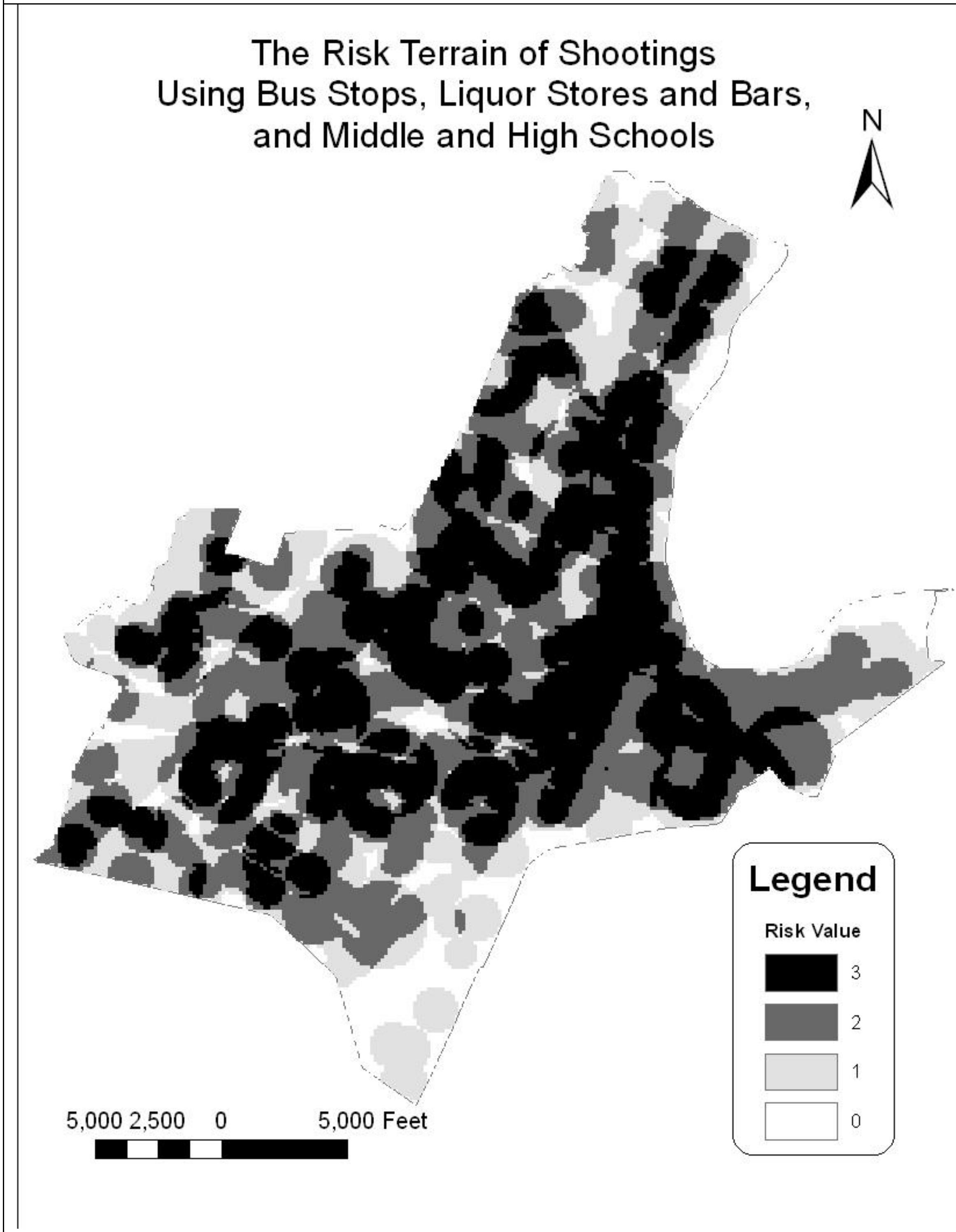
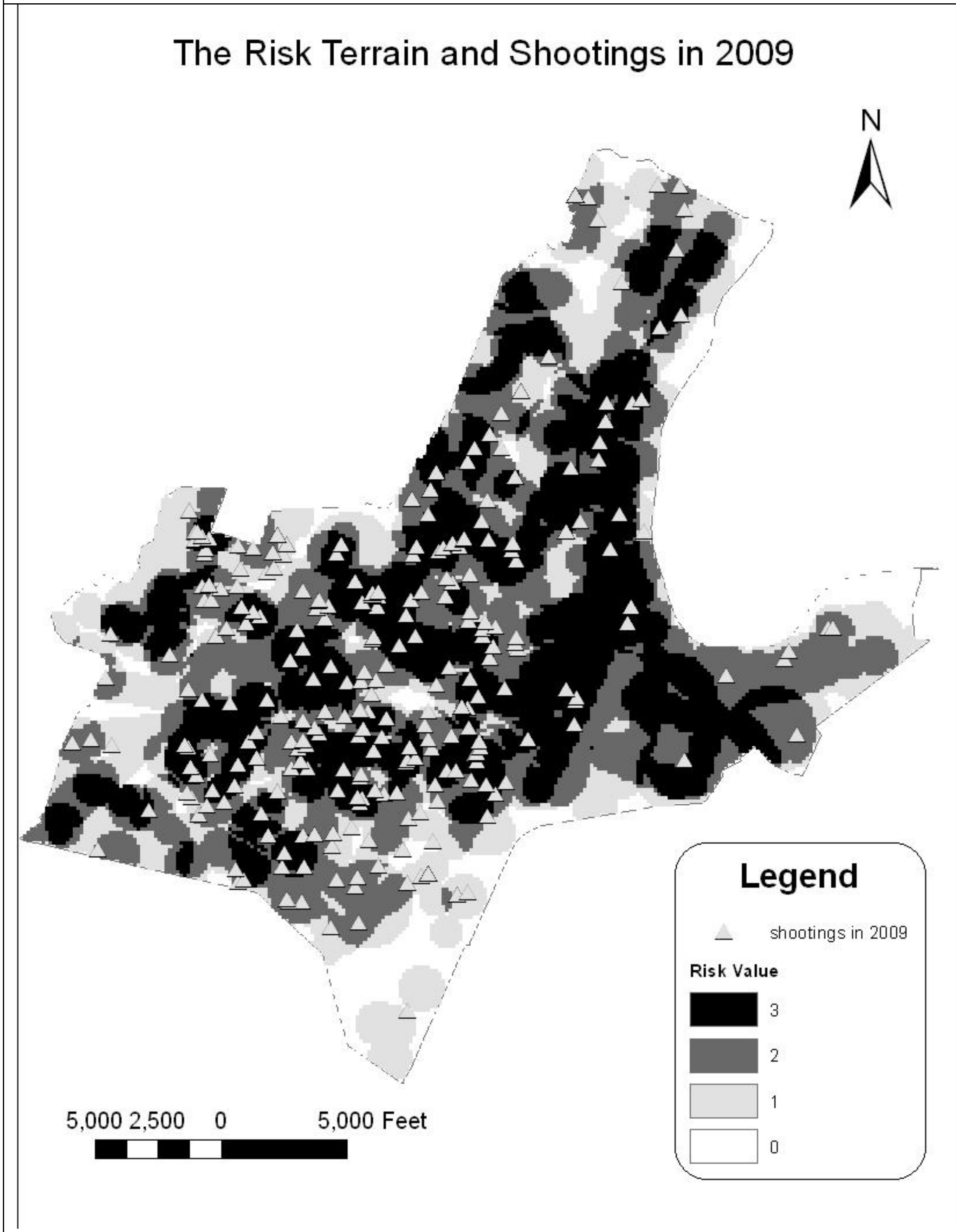


Figure 11. RTM (2008) and Shootings (2009), Model 1



For Model II, four risk map layers are created for four risk factors: liquor stores and bars, bus stops, middle and high schools, and public housing. Each cell within each risk map layer is designated with a value of 1 or 0 according to whether the influence of the risk factor on that place makes it high risk or not high risk. Since the cells of different map layers are the same size and were classified in a consistent way, the risk map layers can be summed together to form a composite risk terrain map.

The four risk map layers are combined using “raster calculator” in Spatial Analyst extension. The end result is a composite risk terrain map with each cell exhibiting the summed risk value of all risk map layers. Risk values for cells range from 0 to 4 with value of 4 the highest risk. Figure 12 displays the result. Figure 13 overlaps the RTM result layer and 2009 real shootings layer.

Figure 12. RTM of Model II

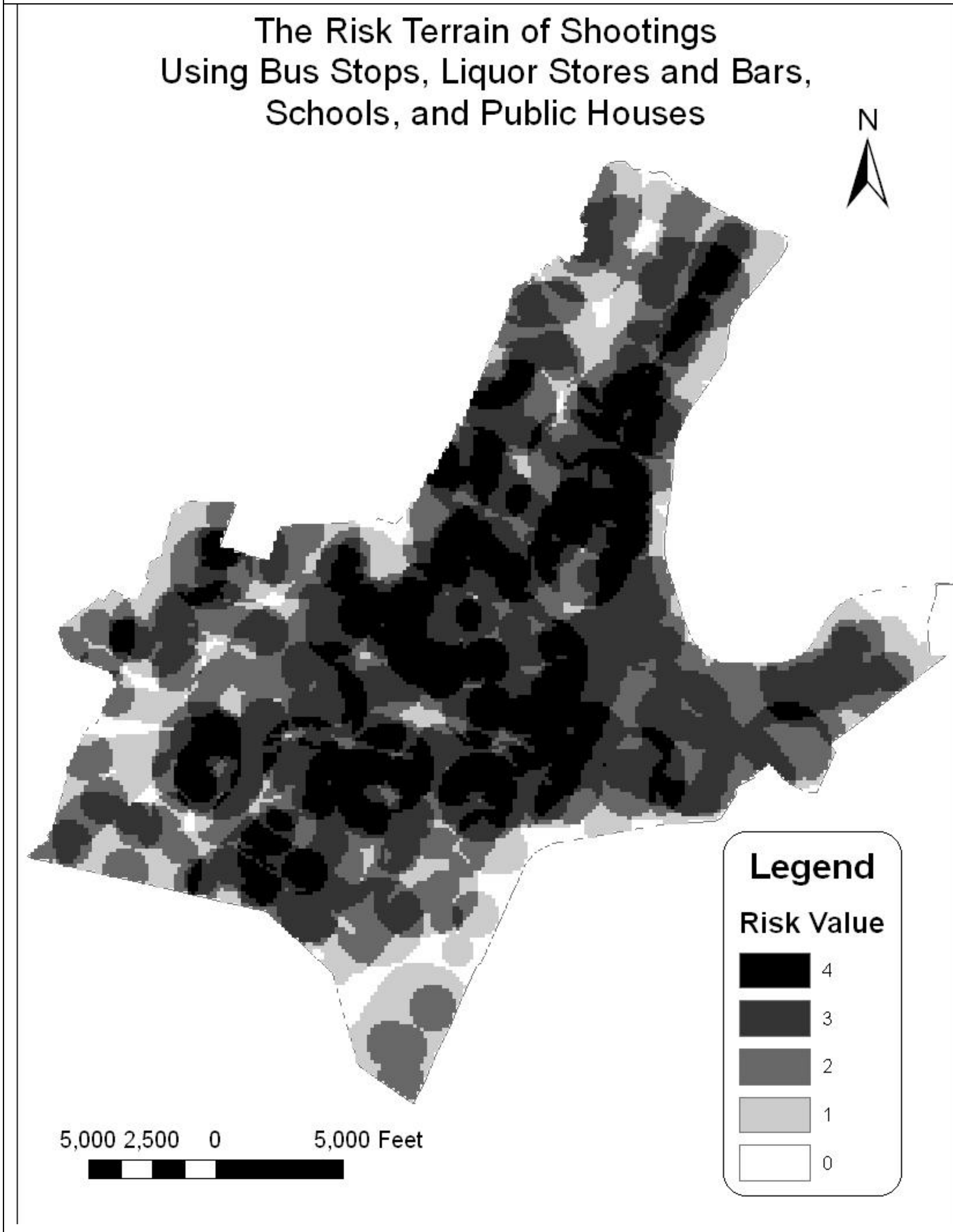
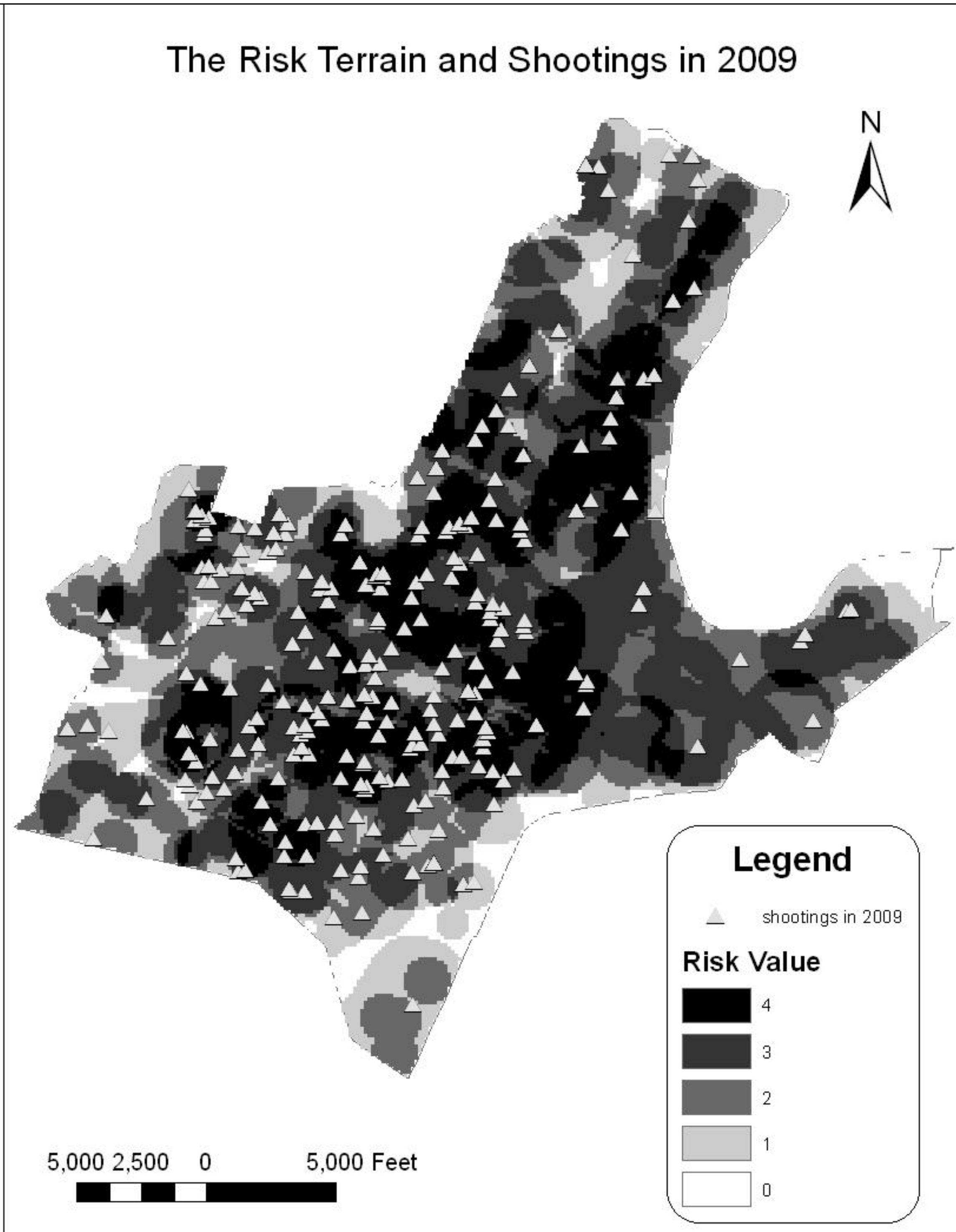


Figure 13. RTM (2008) and Shootings (2009), Model II



For Model III, four risk map layers are created for four risk factors: liquor stores and bars, bus stops, middle and high schools, and hospitals. Each cell within each risk map layer is designated with a value of 1 or 0 according to whether the influence of the risk factor on that place makes it high risk or not high risk.

The four risk map layers are combined using “raster calculator” in Spatial Analyst extension. The end result is a composite risk terrain map with each cell exhibiting the summed risk value of all risk map layers. Risk values for cells range from 0 to 4 with value of 4 the highest risk. Figure 14 displays the result. Figure 15 overlaps the RTM result layer and 2009 real shootings layer.

Figure 14. RTM, Model III

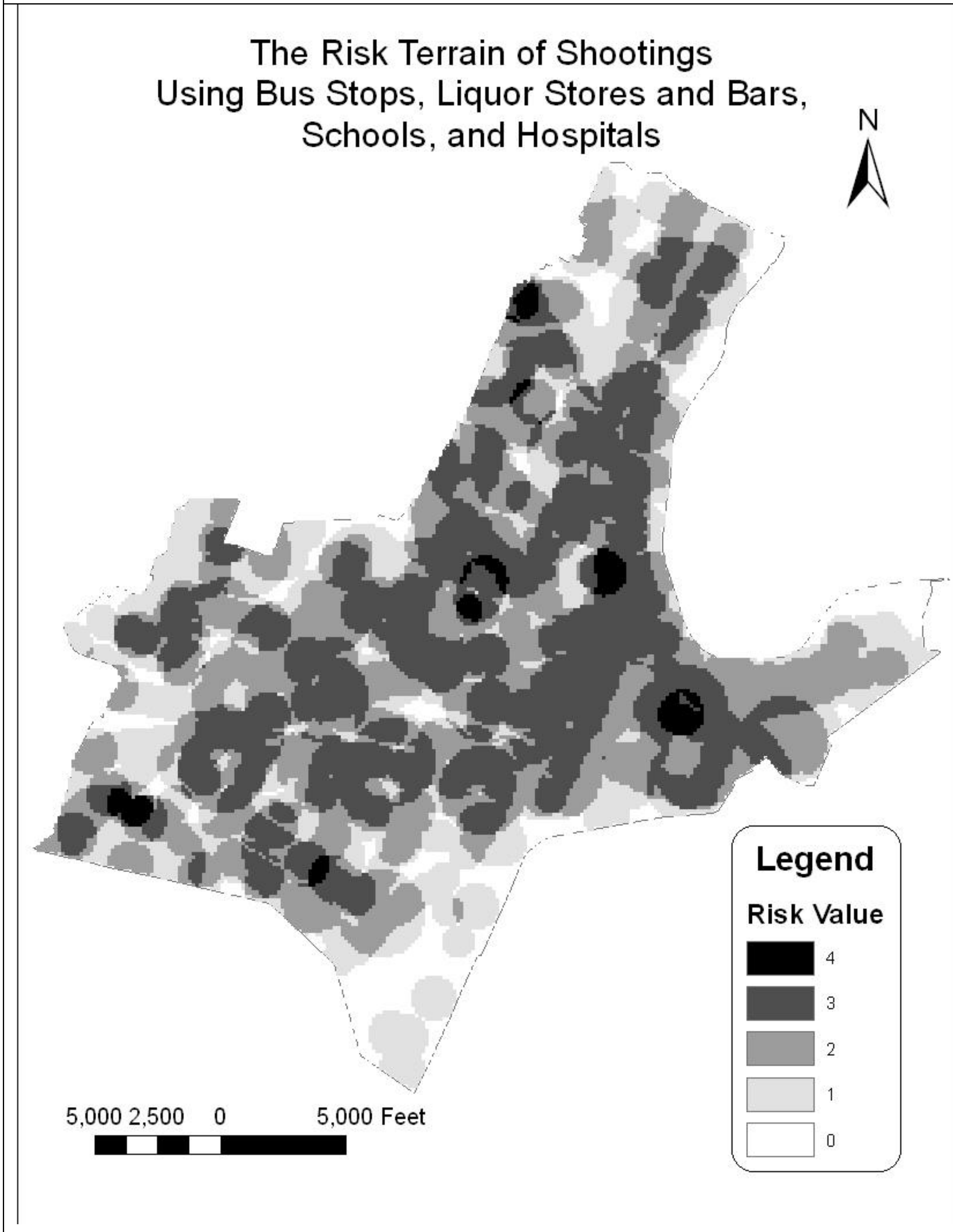
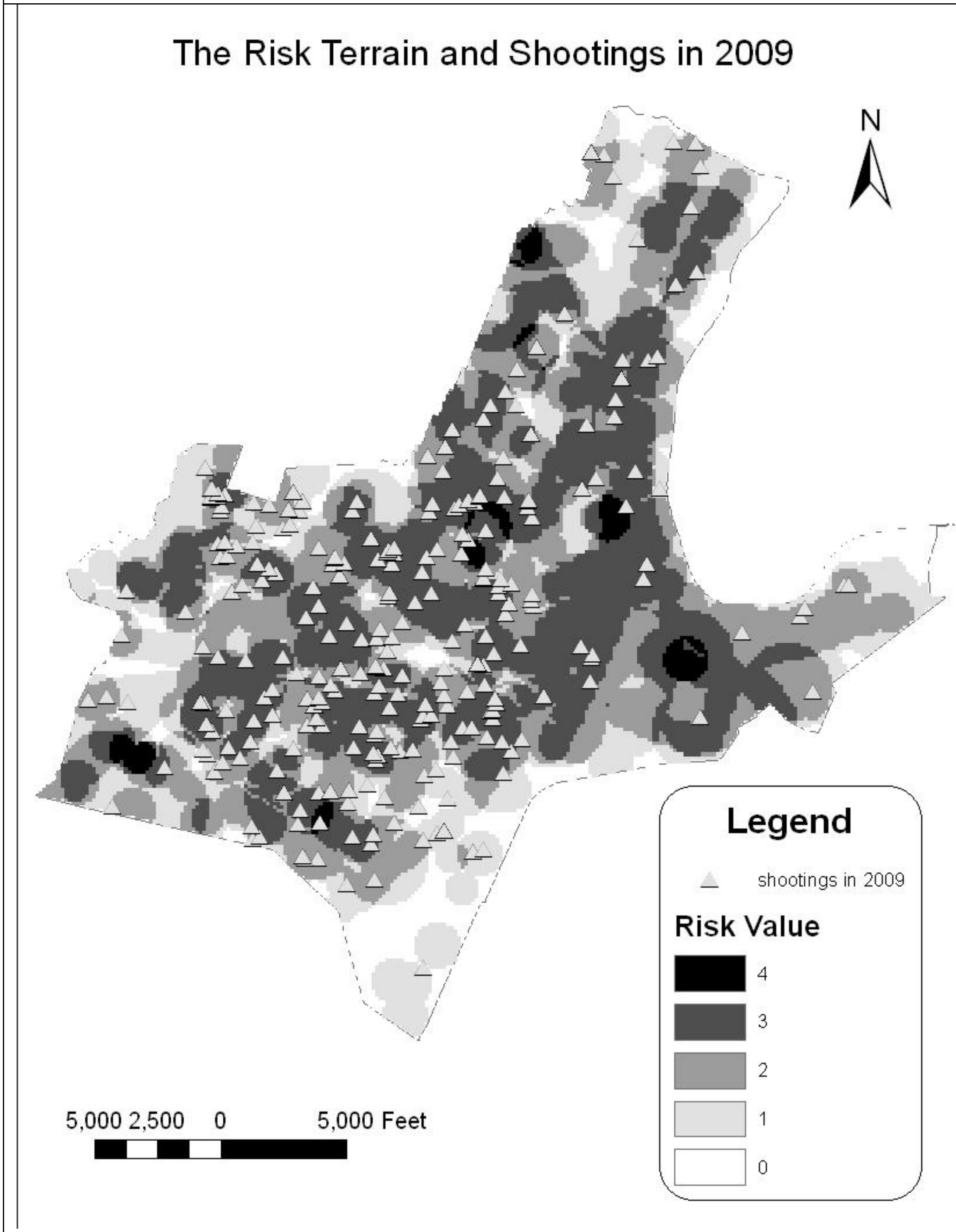


Figure 15. RTM (2008) and Shootings (2009), Model III



Test the Statistical Validity of the RTM Models

In order to test the statistical validity of the RTM models, first the raster maps were converted into vector maps by using RTM Toolbox. Then spatial join the 2009 shooting shapefile to the vector risk terrain map. Thus we get an attribute table with two variables: count of shooting incidents for each cell and the composite risk value for each cell.

To test whether spatial autocorrelation exists, a spatial autocorrelation test and a calculation of Moran's I were conducted. Spatial autocorrelation analysis tests whether the observed value of a variable at one locality is independent of the values of the variable at neighbouring localities. If a dependence exists, the variable is said to exhibit spatial autocorrelation. Spatial autocorrelation measures the level of interdependence between the variables, and the nature and strength of that interdependence. It may be classified as either positive or negative. In a positive case all similar values appear together, while a negative spatial autocorrelation has dissimilar values appearing in close association.

Moran's I measures spatial autocorrelation with values approaching 1 when geographical units are situated near other similar geographical units, and approaching –1 when geographical units are situated near dissimilar geographical units. A Moran's I value of 0 indicates the absence of autocorrelation, or independence, among geographical units.

The spatial autocorrelation test gave a significant result ($p<0.01$), indicating that the null hypothesis that there is no spatial clustering should be rejected. We used Geoda to compute the spatial lag values and included these spatial lag values as a control variable in the logistic regression analysis.

A logistic regression analysis, with "Risk Value" and "Spatial lag" as the independent variables and "Presence of shooting (Yes or No)" as the dependent variable, was used to determine the extent to which shootings occurred in higher risk cells.

In the base model Model I, the logistic regression analysis results show that the model is statistically significant with a Chi-square value of 57 ($p<.001$). The risk value is statistically significantly related to the occurrence of shooting with a Wald value of 48 ($p<.001$). The odds ratio is 1.73, indicating for every one unit increase in risk, the odds of occurrence of gun shooting happening in a 140x140ft area during the subsequent time period increase by 73%.

Adding a variable with strong CLI effect can increase forecasting power. In the model II with public houses as the fourth variable added to the base model, the logistic regression results show the model is statistically significant with a Chi-square value of 87 ($p<.001$). The risk value is statistically significantly related to shooting with a Wald of 73 ($p<.001$). The odds ratio is 1.80, indicating for every one unit increase in risk, the odds of occurrence of gun shooting happening in a 140x140ft area during the subsequent time period increase by 80%.

However, using a variable without CLI effect can reduce the forecasting power significantly. In Model III with hospitals as the fourth variable added to the base model, the odds ratio of the risk value is 1.50, much lower the odds ratio of 1.73 in the base model. It shows the predict efficacy is reduced.

Therefore, CLI is critical in improving the predicting accuracy of crime forecasting methods such as RTM. By using CLI method, including only those risk factors that have been proved to be crime generators can produce the best place-based risk assessment of future events.

Summary

This chapter looks at whether crime generator analysis can improve the predictive efficacy of crime forecasting method Risk Terrain Modeling. Three experiments are conducted to test this question. The first model is a base model creating RTM with three factors: bus stops, liquor stores and bars, and middle and high schools. The second model is an add-on model creating RTM with four factors: the three factors in the base model plus the factor with strongest CLI effect: public housing. The third model is an add-on model creating RTM with four factors: the three factors in the base model plus the factor without CLI effect: hospital. The results show that by adding public housing that has the strongest CLI effect, the predictability of RTM improves significantly; while, by adding hospitals that have no CLI effect, the predictability of RTM decreases. Therefore, using crime generators with strong CLI effect to create RTM can improve forecasting capability.

Chapter 9. Neighborhood Analysis

This chapter looks to the study area's 302 census-defined block groups to explore the relationship between shooting and the indicators of neighborhood characteristics. In this chapter, three regression models are employed and the results are compared. The three models are OLS, Poisson Regression, and Negative Binomial Regression. The findings in this chapter establish general support for social disorganization theory at the block group level in Newark and Irvington.

Statistical Preliminary

Count data are usually defined as the number of occurrences of an event recorded in a fixed period of time or region of space. Number of shootings, number of crimes known to the police, number of successes on parole… are all examples of count data. Osgood (2000) explained that because arrests are discrete events, the possible crime rates for any given population size are those corresponding to integer counts of crimes. If the population sizes of the aggregate units are large relative to the average arrest rate, then the calculated rates will be sufficiently fine-grained that there is no harm in treating them as though they were continuous and applying least squares statistics. For almost any measure of offending, populations of several hundred thousand should prove adequate in this regard. When populations are small relative to offense rates, however, the discrete nature of the crime counts cannot be ignored. Indeed, for a population of a few thousand, even a single arrest for homicide might correspond to a high crime rate.

Crime rates based on small counts of crimes present two serious problems for least squares analysis. First, because the precision of the estimated crime rate depends on population size, variation in population sizes across the aggregate units will lead to violating the assumption of homogeneity of error variance. We must expect larger errors of prediction for per capita crime rates based on small populations than for rates based on large populations. Second, normal or even symmetrical error distributions of crime rates cannot be assumed when crime counts are small. The lowest possible crime count is zero, so the error distribution must become increasingly skewed (as well as more decidedly discrete) as crime rates approach this lower bound. As populations decrease, an offense rate of zero will be observed for a larger and larger proportion of cases. Thus, there is an effective censoring at zero that is dependent on sample size, which has considerable potential for biasing the resulting regression coefficients (Osgood 2000).

Poisson Regression

Poisson regression is designed to explain variation in a count-level-dependent measure by regressing one or more independent variables onto the dependent variable. Unlike linear regression, which is normally estimated by OLS, Poisson regression is estimated with maximum likelihood. OLS estimation seeks to minimize the sum of squared deviations between the predicted values (ypred) and the observed values (yobs) of the dependent variable.

Maximum likelihood estimation (MLE) attempts to identify the population parameters that maximize the probability of finding the best overall fit for the data. Arbitrary values of the population parameters are iteratively generated to determine the likelihood that they fit the sample data, with the best fit eventually being selected.

Linear and nonlinear regression can be estimated using either OLS or MLE, although linear models are normally estimated with OLS, whereas nonlinear models are more often estimated with MLE. Even when linear regression is estimated with MLE, it is inappropriate for analyzing count data because count data violate the homogeneity assumption on which linear models are based (Long, 1997). Poisson regression is not constrained by the homogeneity assumption, but it does have its own set of restrictions. First, it assumes that all variation in the dependent variable can be accounted for by the regression model. Thus, although Poisson regression measures observed heterogeneity, it makes no provisions for unobserved heterogeneity (Winkelmann, 2003). Statistically, the Poisson regression model can be written as $\mu = \exp(XB)$, where X stands for the independent variables in one's regression and B stands for the weighted coefficient. Negative binomial regression, on the other hand, makes allowances for unobserved heterogeneity as represented by εi in the negative binomial equation, $\mu = \exp(XiB + \varepsilon i)$. As was previously stated, Poisson regression is rarely found in social science research. This is partly a consequence of general inattention to the special status of count data in many areas of social science (Osgood, 2000) and partly a consequence of the difficulties that researchers face when trying to analyze social science data with Poisson regression.

Poisson regression assumes that the conditional mean and the conditional variance are roughly equivalent, a condition known as equidispersion. Violations of the independence and population homogeneity assumptions, however, result in the conditional mean either exceeding the conditional variance (underdispersion) or the conditional variance exceeding the conditional mean (overdispersion). It has been noted that in an overdispersed distribution, the Poisson regression model underestimates the standard errors of the independent variable coefficients, thereby inflating the significance test results (Greene, 2003). Overdispersion is a far more common problem in social science research than underdispersion is and can be managed by recalculating the standard error with quasi-likelihood techniques (Gardner et al., 1995) or computing a negative binomial regression. Alternately, the number of zero counts may exceed what the Poisson or negative binomial can comfortably handle, and so special zero modified models have been developed. Finally, the sample may be truncated (values like 0 are missing) or the data censored (grouped responses: 5 or more, 2 or less). Under such circumstances, a special truncated or censored model is required (Walters 2007).

Negative Binomial Regression

If the equidispersion assumption made by the Poisson model (conditional variance = conditional mean) is violated, then Poisson regression is clearly inappropriate.

Considering the fact that negative binomial regression makes allowances for unobserved heterogeneity, it is often the model of choice for count data that are overdispersed (conditional variance > conditional mean). The Lagrange multiplier test (Cameron & Trivedi, 1986), the conditional-moment-based specification test (Greene, 2003), and an OLS regression–based test (Cameron & Trivedi, 1990) can all be used to evaluate for overdispersion. The Lagrange multiplier test is distributed as a chi-square statistic with one degree of freedom, the conditional-moment-based specification test is a chi-square statistic with k (number of independent variables) degrees of freedom, and the OLS–regression–based test is distributed as a t test that is evaluated asymptotically. Monte Carlo investigations have shown that the third option, the simple OLS regression test, produces optimal results as a measure of overdispersion in count-level dependent variables (Cameron & Trivedi, 1990).

The negative binomial model assumes that one's data have been generated by the Poisson process but that unexplained intercase differences or unobserved heterogeneity exist. To account for unobserved heterogeneity, the negative binomial model calculates a dispersion parameter (α) that acts to increase the conditional variance of y (Long, 1997). When α equals zero, the negative binomial model reduces to the Poisson model, but when α is statistically significant, the results of the negative binomial model are more conservative than the results of the Poisson model (Cameron & Trivedi, 1998). In an analysis of eight different models for count data (OLS regression, OLS with a transformed dependent variable, Tobit, ordinal logistic regression, ordinal probit regression, Poisson, overdispersed Poisson, and negative binomial regression), Sturman

(1999) determined that the Poisson model displayed a high rate of false positive designations, whereas the negative binomial model generated fewer false positives than any other model.

ANALYSES AND RESULTS

Descriptions of the Phenomena

The analysis starts with a detailed examination of the distribution of shooting. This is followed by analysis of indicators for neighborhood characteristics.

Shooting

Table 2 displays basic descriptive information on the number of shootings in Newark and Irvington's block groups from Jan. 2007 through Aug. 2010. The 302 block groups exhibited an average four-year shooting frequency of 5.30, with a standard deviation of 7.62. 27.81% of the block groups experienced no shooting during the four-year period. The mode of the frequency is 0. Figure 12 illustrates the shooting count in the block groups of the study areas is non-normally distributed.

Table 2. Descriptive Information of Shootings

Mean	5.3
Variance	57.8
Minimum	0
Maximum	56

Figure 16. 2007-2010 Shooting Count

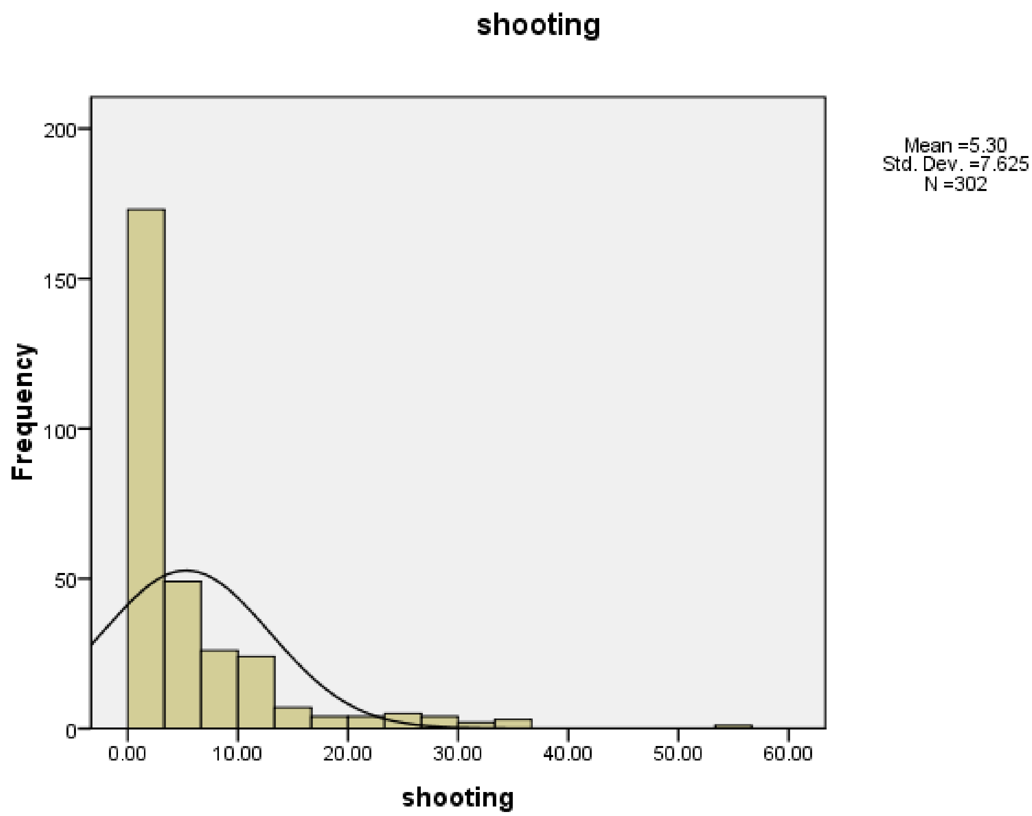
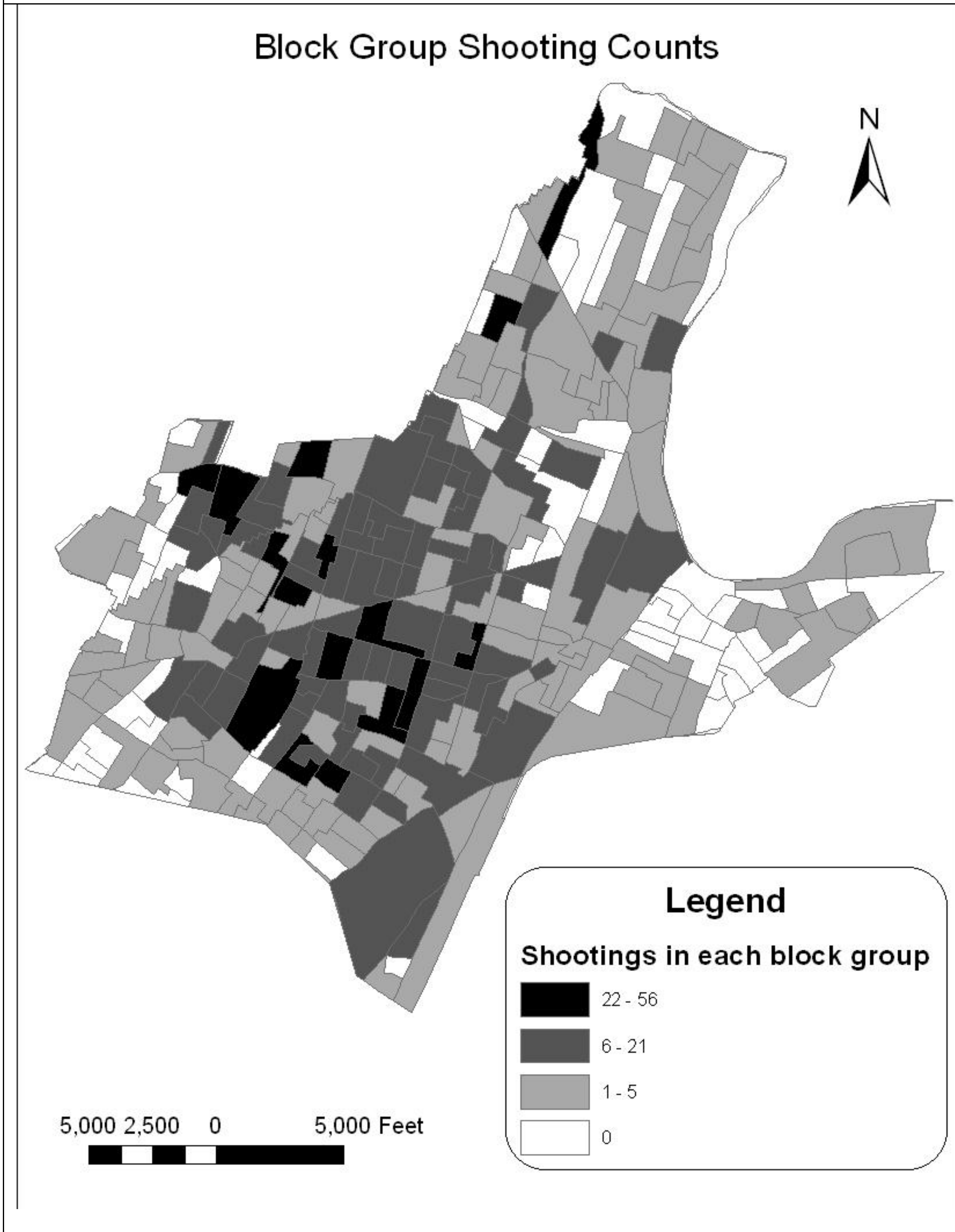


Figure 17 maps the distribution of block group shooting counts, and confirms the skewness of the homicide distribution. The yellow points are shooting locations from Jan. 2007 till Aug. 2010. The white areas represent those block groups without shooting. The light pink areas represent the block groups with 1-5 shootings. 5 is the mean of the shooting counts. The light red areas represent the block groups with 6-13 shootings. 13 is the sum of mean and one standard deviation. The dark red areas are the block groups with the highest shooting count. A few of block groups have 14 or more shootings, whereas the majority has fewer than 5.

Figure 17. Block Group Shooting Counts, Newark and Irvington, NJ 2007-2010



Neighborhood Characteristics Indicators

Social disorganization theory states that communities with higher levels of poverty, mobility, and heterogeneity are less able to organize to control the behavior of residents and visitors, and therefore experience higher levels of crime. In line with this theory, the dissertation begins with multiple indicators of socioeconomic disadvantage, heterogeneity, and residential mobility commonly used in previous tests of the theory.

Table 3 displays the means and standard deviations of the indicators of disadvantage, heterogeneity, and instability selected from the literature: percent of female headed households, male unemployment, male jobless, family poverty, public assistance income, housing vacancy, renter occupancy, African-American, and residential mobility. These means and standard deviations give one with the impression that the study area is ripe with disorganization. In the average block group, 22% of households with children are headed by females with no male present; 44% of males age 16 and over are either unemployed or not in the labor force. These two indicators help understand how the average block group has 21% of families reporting their income below the poverty level. Regarding heterogeneity. 56% are African-American. As for residential mobility, 61% of households are renter occupied and 42% of residents did not reside in the same house five years ago.

Table 3 Descriptive Statistics on Indicators of Disadvantage, Heterogeneity, and Instability, Newark and Irvington Block Groups, 2000 (N=302)

	Mean/Percentage	S.D.
Total Population	1199.84	783
Black	.63	.35
Female-headed Households	.24	.15
Unemployment	.17	.15
Joblessness	.49	.17
Public Assistance	.12	.10
Family Poverty	.23	.15
Housing Vacancy	.09	.10
Renter Occupancy	.69	.21
Residential Mobility	.48	.15

Spatial Interdependence

Baller et al. (2001) and Anselin (1995) argue that models that do not account for the spatial patterning through either spatial effect or spatial disturbance controls may suffer the effects of under-specification. Following the analytical framework established by Baller et al (2001), an exploratory analysis of the global and local patterns of spatial autocorrelation is the starting point in exploring spatial structure.

A spatial autocorrelation test and calculation of Moran's I are conducted in GeoDa to test whether spatial autocorrelation exists in this study. The results of the spatial autocorrelation test indicate that spatial autocorrelation exists in this study (p<.01).

Moran's I is one of the most commonly used method to assess spatial clustering in data assigned to geographic points. For the purpose of this analysis, Moran's I was calculated by assigning each block group centroid the value of the variable for that block group. An inverse distance matrix was then computed for the centroids, and the matrix was row standardized. The result of Moran's I is 0.25, indicating clustering or positive spatial autocorrelation. Therefore, a new variable spatial lag is created for spatial dependence. The values are calculated in GeoDa.

Multivariate Estimation

Figure 12 shows that counts of shooting are not normally distributed, but highly skewed, which violates the assumption of Ordinary Least Squares. Therefore, we cannot use OLS for this study.

By comparing the mean and variance of the dependent variable, we found that the variance of dependent variable is more than 10 times of the mean, indicating that an over-dispersion sign of the distribution of dependent variable. Both poisson regression and negative binomial regression are conducted and then a comparison test is used to compared their fits to the distribution of dependent variable.

Table 4 displays the results of poisson regression and negative binomial regression. Overall, both models are statistically significant (p<.001). But the findings of the two models are quite different. In poisson regression model, 7 out of 11 covariates are found to be statistically significantly related to count of shootings. These covariates include female-headed households rate, black rate, jobless rate, public assistance rate, housing vacancy rate, renter occupancy rate, and residential mobility rate. But in negative binomial regression, only 3 covariates are found to be statistically significantly related to count of shootings: female-headed household rate, black rate, and jobless rate.

Table 4. Poisson Regression and Negative Binomial Regression Results for Neighborhood Factors on Shootings, 2007-2010

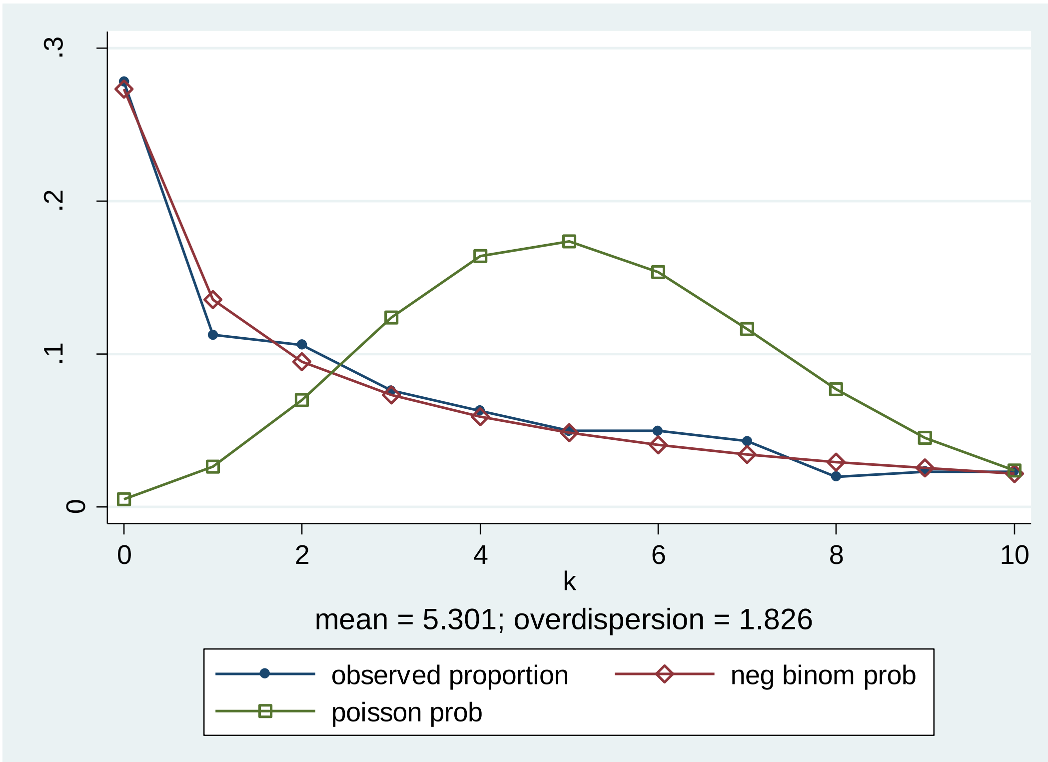
Variables	**Poisson Regression**	**Negative Binomial Regression**
Female-headed Households	1.96(.25) ***	1.79(.64) **
African American	1.16(.12) ***	.79(.27) **
Male Unemployment	.46(.24)	1.08(.62)
Male Joblessness	-1.34(.27) ***	-1.81(.66) **
Public Assistance	.87(.36) *	1.47(.99)
Poverty Rate	-.01(.29)	.47(.77)
Housing Vacancy	.78(.29) *	.89(.89)
Renter Occupancy	.73(.22) ***	.66(.54)
Residential Mobility	-.81(.23) ***	-.53(.59)
Population	.00(.00) ***	.00 (.00) ***
Spatial Lag	.42(.04) ***	.64(.14) ***
Constant	.03(.18)	.09(.33)
	Log Likelihood = -1169.1183 χ^2_{11df} = 894.09***	Log likelihood = -751.19584 χ^2_{11df} = 123.04*** Likelihood-ratio test of alpha=0: χ^2 = 835.84 ***

Notes: 1) Standard errors in parentheses.
2) * Significant at 5 percent.
3) ** Significant at 1 percent
4) *** Significant at .1 percent

Actually, there are several signs that indicate that poisson regression is not a good model for this study. Firstly, the large value for chi-square is an indicator that the poisson regression is not a good choice. Secondly, the likelihood ratio test at the bottom of the analysis is a test of the over-dispersion parameter alpha. When the over-dispersion parameter is zero, the negative binomial distribution is equivalent to a Poisson distribution. In this case, alpha is significantly different from zero and thus reinforces that the Poisson distribution is not appropriate.

A comparison analysis is then conducted to test how well the dependent variable fits both the Poisson and negative binomial distributions. The results are displayed in Figure 18. The red line is negative binomial line, the green line is poisson regression line, and the blue line is the distribution of dependent variable proportion. Clearly, the red line (negative binomial) fits the blue line (dependent variable) very well; but the green line (poission regression) does not fit the blue line. Therefore, we can conclude that negative binomial regression is the best method for this study. The results from negative binomial regression show that the model is statistically significantly related to count of shootings. Particularly, three neighborhood characteristics are very important risk factors that are related to shootings: female-headed household rate, black rate, and jobless rate.

Figure 18. Comparison Test Result



Summary

The purpose of this chapter is to find the neighborhood determinants for shooting. The spatial nature of the data is analyzed first to test whether spatial autocorrelation exists. The results show that spatial autocorrelation exists in this study. So spatial lag values are calculated and are included in all statistical tests. Due to the count nature of the dependent variable number of shootings in each block group, OLS is not appropriate for this study. Both poisson regression and negative binomial regression are employed in analyzing neighborhood influence on shooting. Then a comparison test is used to test how well the distribution of the dependent variable fits both poission regression and negative binomial regression, and which model is better. The results show that negative binomial regression is the best method for this study. Three neighborhood characteristics factors are found to be statistically related to count of shooting: female-headed household rate, African-American rate, and jobless rate.

Chapter 10. Place-based Crime Forecasting for Shooting

Chapter 7 identified crime generators of shootings by using CLI methods. Chapter 9 examined the influences of disorganizing factors such as neighborhood disadvantage, population heterogeneity, and residential mobility on shooting. The results of negative binomial regression of shooting counts on socioeconomic disadvantage, residential instability, and population heterogeneity revealed significant coefficients for all three.

This chapter builds a forecasting model to predict future shooting places using the results from crime generator analysis and neighborhood analysis. Crimes are not only a product of crime generators, but also a product of the conditions of the larger community in which it sits. In Chapter 7 I have proved that certain urban facilities generate crime. Risky facilities, however, do not stand alone, but rather are nested within the broader demographic fabric of the surrounding community. Neighborhood ecological conditions shape crime rates. According to Sampson and Groves, neighborhood structural factors decrease a neighborhood’s capacity to control the behavior of people in public and hence increase the likelihood of crime. Therefore, it is important to consider both risky facilities and communities. This chapter will disaggregate census data by using smoothing method and build a composite risk map that locates the highest risk areas for shootings, combining all the neighborhood risk factors and all the risky facility factors.

From a methodological position, RTM is the technique to build the composite risk map. The unit of analysis is 140 feet cell size, the same as the unit in last chapter. But, to build map layers for census data, we need to convert the unit of block group to the unit of 140 feet cell size. The detailed methods are discussed below.

Methodology

To incorporate census data into RTM models, we need to convert census data to our unit of analysis. As we know, the units for census data are census tract, block groups and blocks. However, the unit of analysis in our RTM models is 140 feet raster cell size. How to convert census data to our unit of analysis? The answer is disaggregating census data.

The reason to use disaggregating rather than aggregating method is to avoid masking out important variations in small ecological areas and to avoid the problem of the Modifiable Areal Unit Problem (MAUP) (Openshaw and Taylor 1979). The modifiable areal unit problem arises from the fact that areal units are usually arbitrarily determined and “modifiable”, in the sense that they can be aggregated to form units of different sizes or spatial arrangements. Thus the MAUP has two related but distinctive components: the scale problem and the zoning (or aggregation) problem (Openshaw and Taylor 1979, Openshaw 1984). The scale problem is “the variation in results that may be obtained when the same areal data are combined into sets of increasingly larger areal units of analysis”. The zoning problem, in contrast, is “any variations in results due to alternative units of analysis where n, the number of units, is constant” (Openshaw and Taylor 1979).

Openshaw and Taylor (1977) studied the effects of the MAUP through three related experiments under different spatial and statistical conditions. The basic areal units in the data set were the 99 counties in the state of Iowa. By correlating the percentage of elderly voters with Republican voters in Iowa, they showed that if the 99 counties making up the state were grouped together into fewer larger districts, and all possible combinations of the larger-scale districts were considered, correlations ranging from + 0.979 to - 0.811 could be produced by varying the scale and zoning strategies. Similar results were found in several earlier studies of aggregation effects. The MAUP also carries implications for multivariate statistical analyses and spatial interaction models. Fotheringham and Wong (1991) showed that model calibration was sensitive to variations in scale and zoning systems, leading to highly unreliable results in multivariate analyses.

The technique to disaggregate census data is smoothing. Smoothing is a process by which data points are averaged with their neighbors in a series. The procedures of smoothing are conducted in ArcGIS (Caplan 2010). In ArcGIS, we first create centroid points for block groups. Figure 19 is the centroid map. Then use Average Nearest Neighbor tool in ArcToolBox to calculate the average distance between the block centroids. Convert the vector map to raster map using Spatial Analyst extension. Set the census variable as the reference value and the cell size as 140 feet. Figure 20-22 are the resulting raster maps of African-American Rate, Female-Headed Households Rate, and Jobless Rate. The darker areas represent higher rates of female-headed households, African American rates, or jobless rate; the brighter areas have lower rates.

Figure 19. Centroids of Block Groups

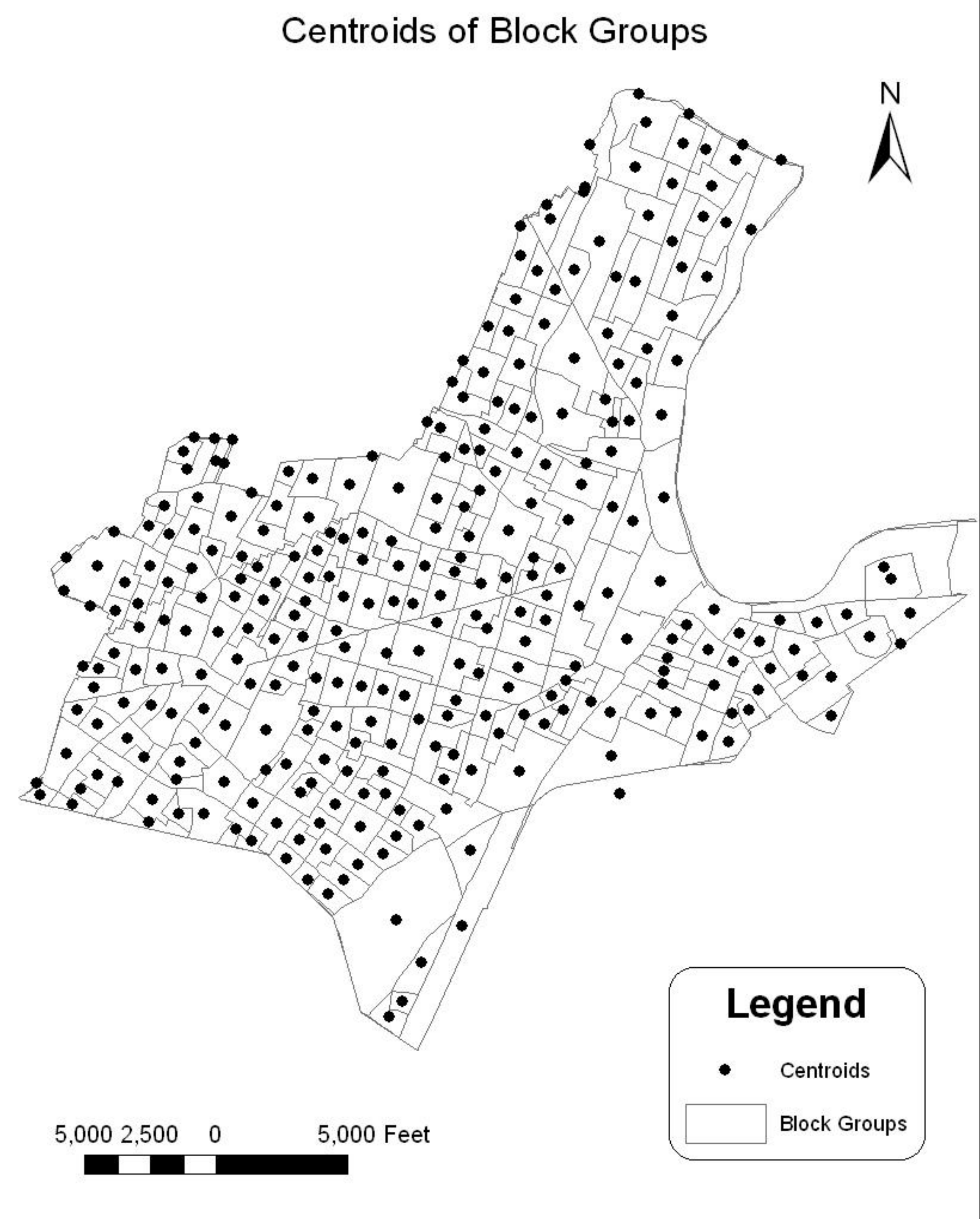


Figure 20. African-American Rate Raster Map

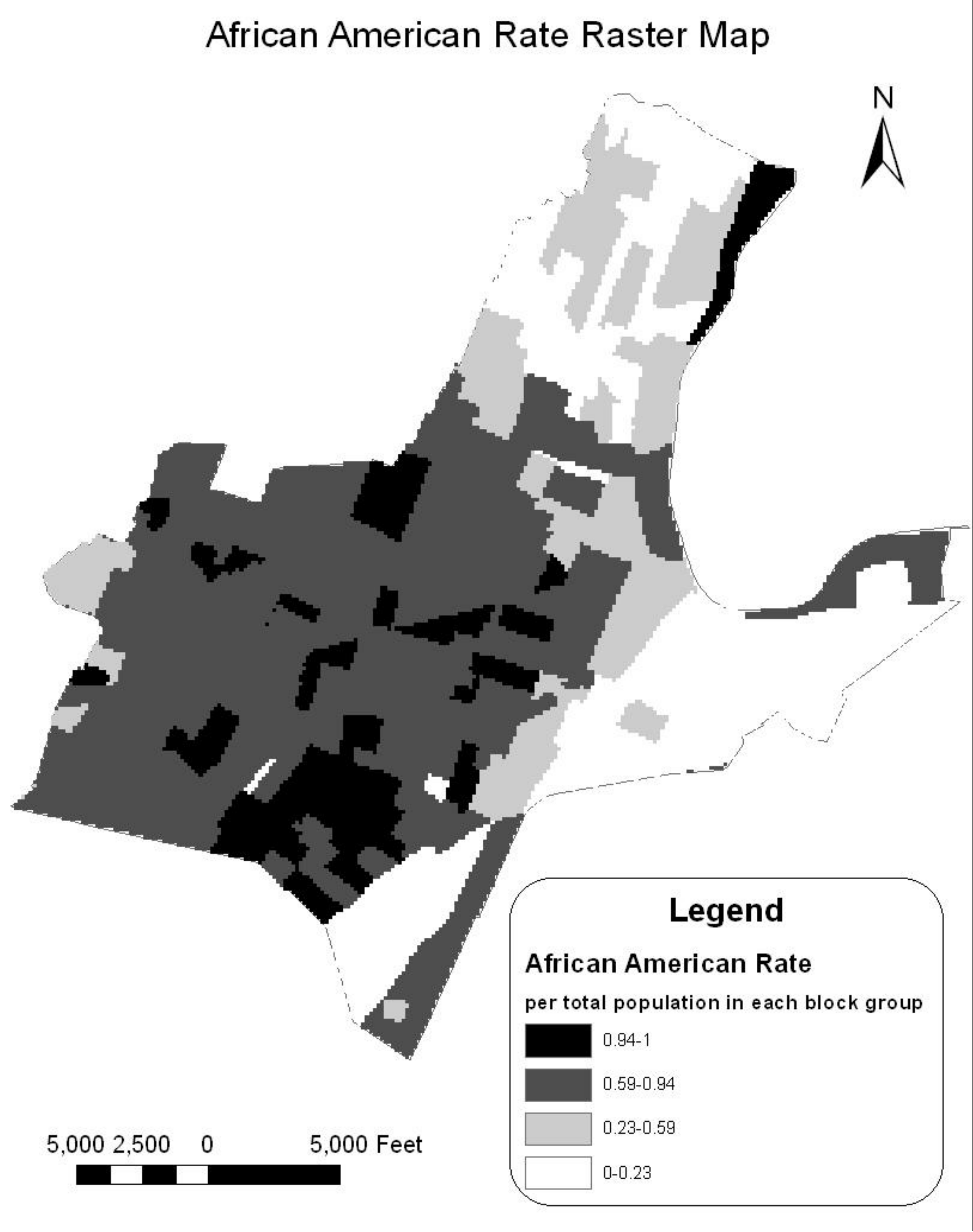


Figure 21. Female-Headed Households Rate Raster Map

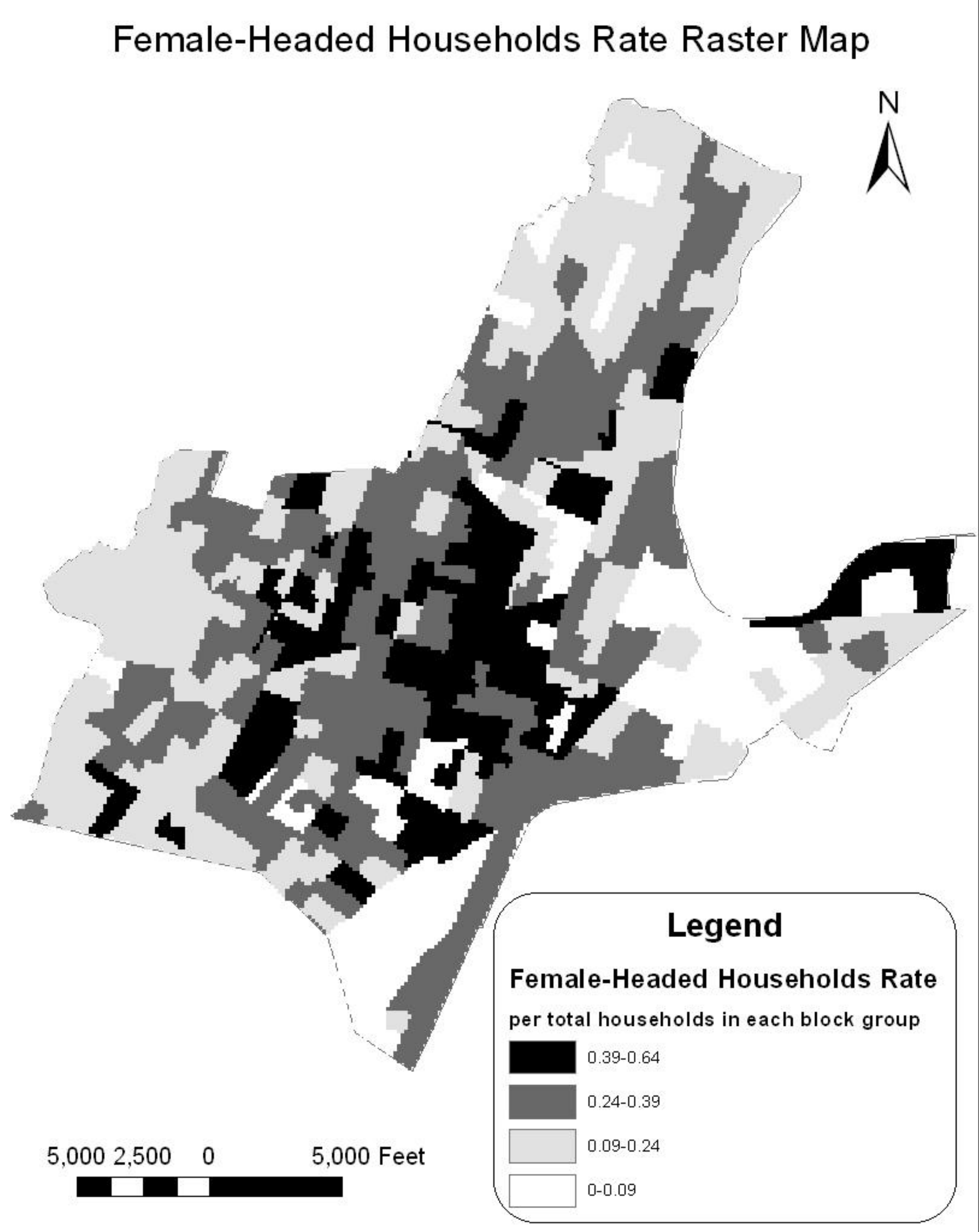
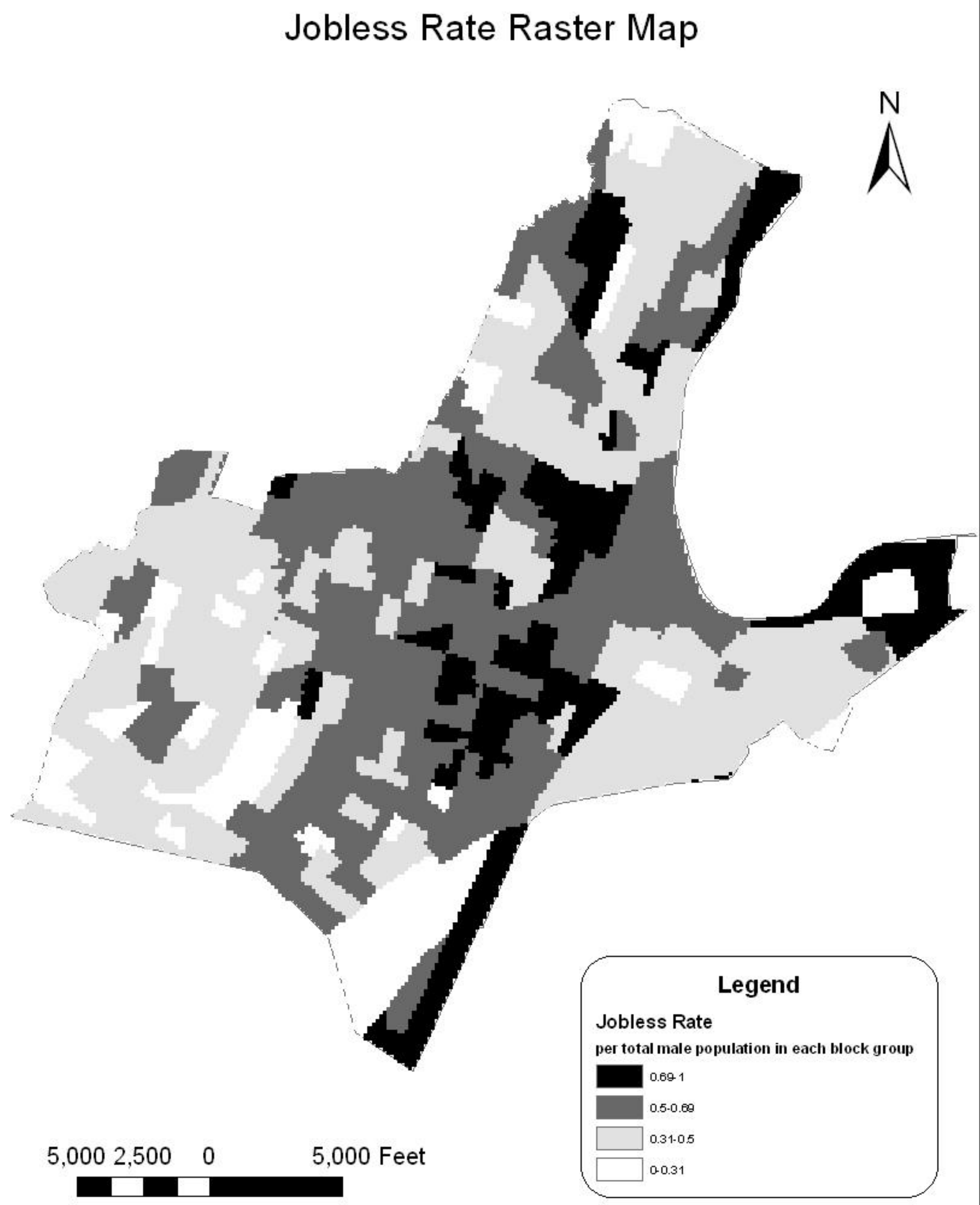


Figure 22. Jobless Rate Raster Map



The smoothing tool is the Neighborhood Statistics in the Spatial Analyst. Under this function, the radium is set as 950 feet as it is the average nearest neighbor distance between the centroid points. Repeat on the resulting layer for three times. Figure 23-25 are the smoothing results of African-American Rate, Female-Headed Households Rate, and Jobless Rate. In this way, the unit has been changed from block groups to 140 feet unit. Though we can continue to smooth the map layers many many times, three iterations are enough, as there is not much changes on the map after the third iteration.

Figure 23. Smoothed African-American Rate

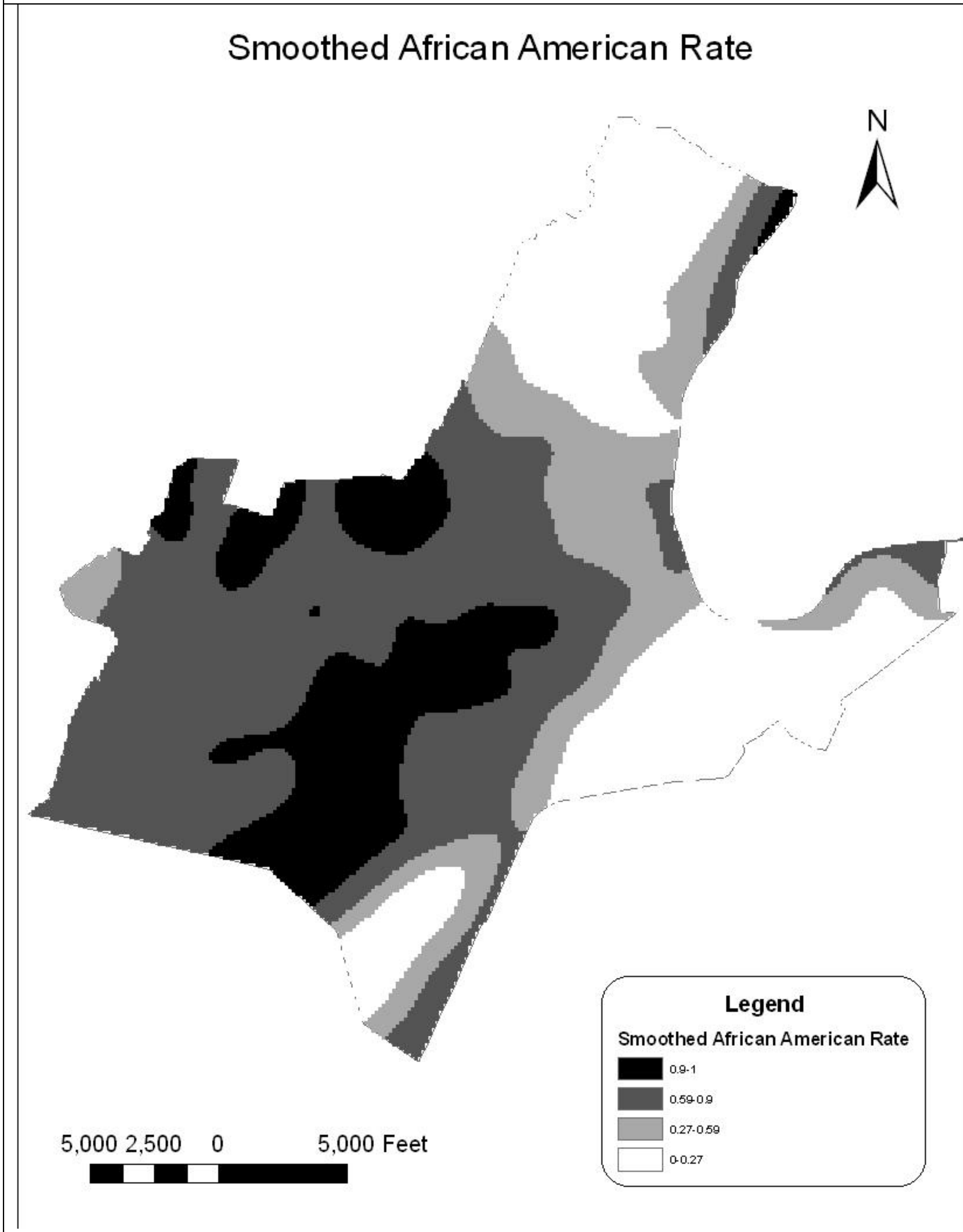


Figure 24. Smoothed Female-Headed Households Rate

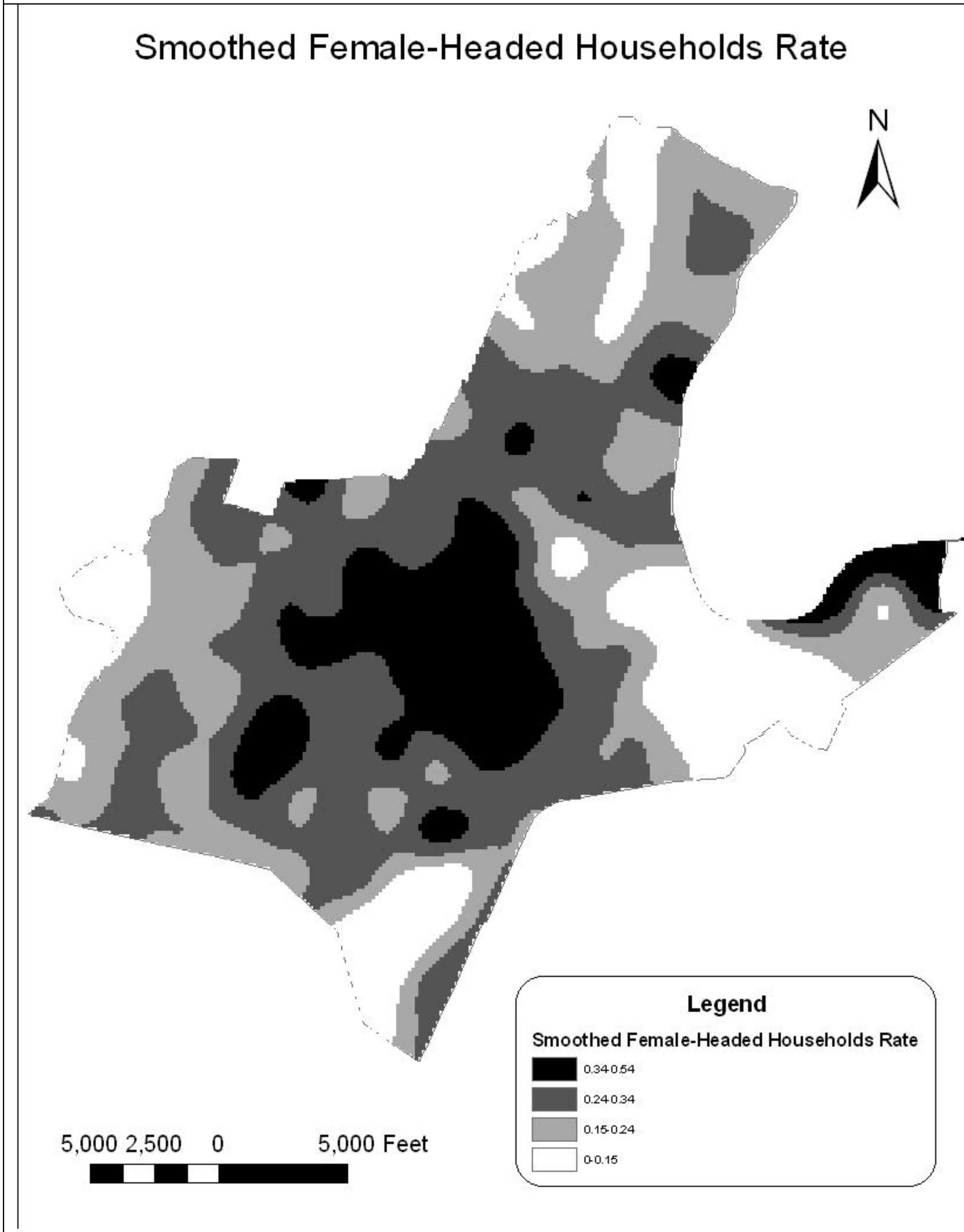
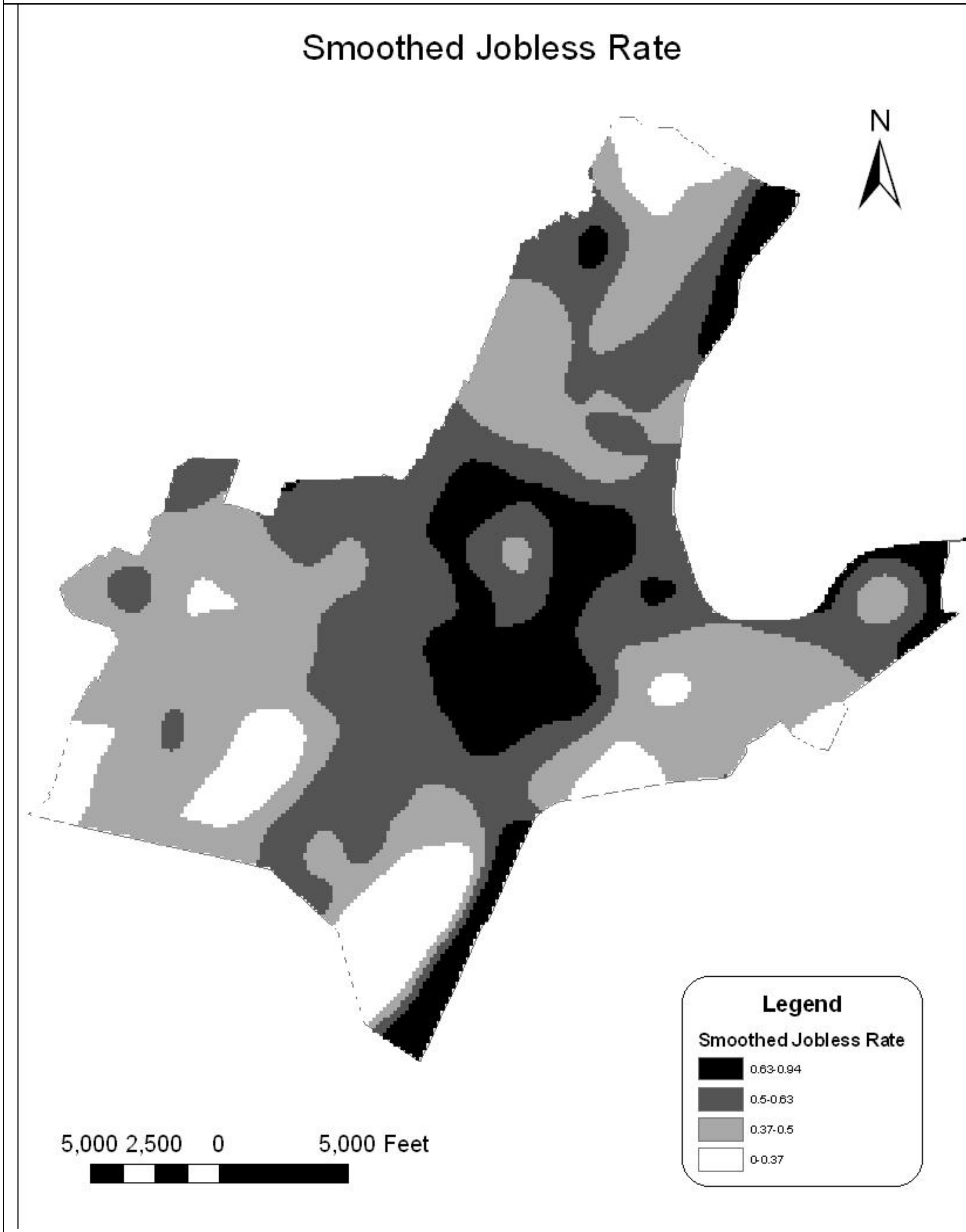


Figure 25. Smoothed Jobless Rate



The next step is to create RTM composite risk map combining all the crime generators and all the census risky factors. Now we have four crime generators raster maps and four census variable raster maps. All of them have the same unit of analysis - 140 feet cell size. Using a simple binary system for the risk values of each terrain, cells are reclassified into two groups. For crime generators, assign risk value 1 for the interior of the buffer bounded by the maximum distance cutoff value and 0 for exterior domain. We assign value 1 for interior buffer area bounded by 929 feet centered at a liquor store, and 0 for its exterior domain. We treat the bus stops, schools and public housing similarly, but with different cutoff values: for bus stops 652, schools 1770, and for public housing 1648. Figure 26-29 show the distance maps with reclassified values for these four risk factors. For census variables, assign risk value 1 for the interior of the buffer bounded by the mean and 0 for exterior domain. Use "Raster Calculator" in Spatial Analyst to create the composite risk map. The final result is displayed in Figure 30. Figure 31 overlaps 2009 shooting locations and this RTM built with 2008 risk factors data. It shows that the higher risk areas in the RTM and the 2009 shooting locations overlap very well.

Figure 26. Public Houses Distance Map

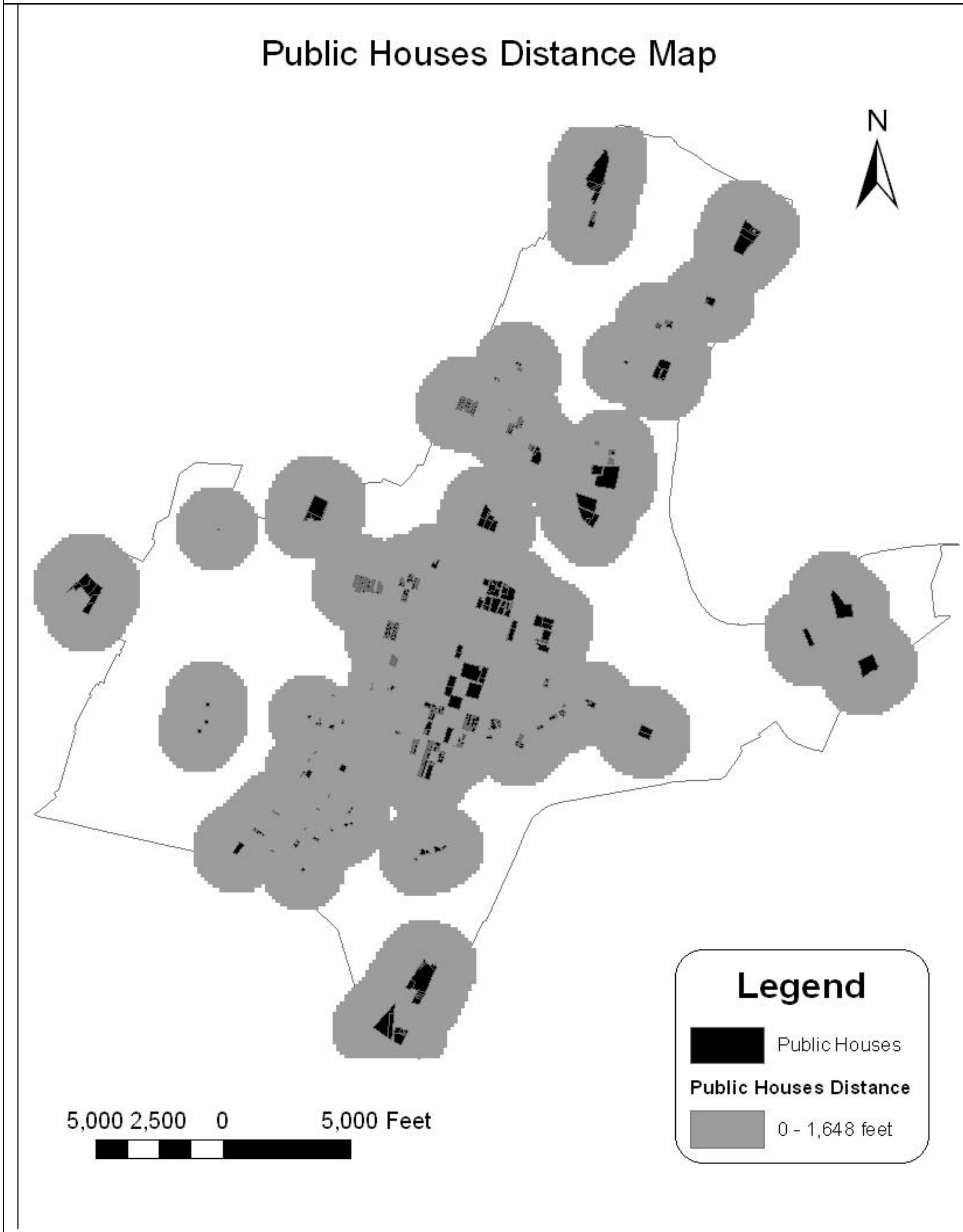


Figure 27. Bus Stops Distance Map

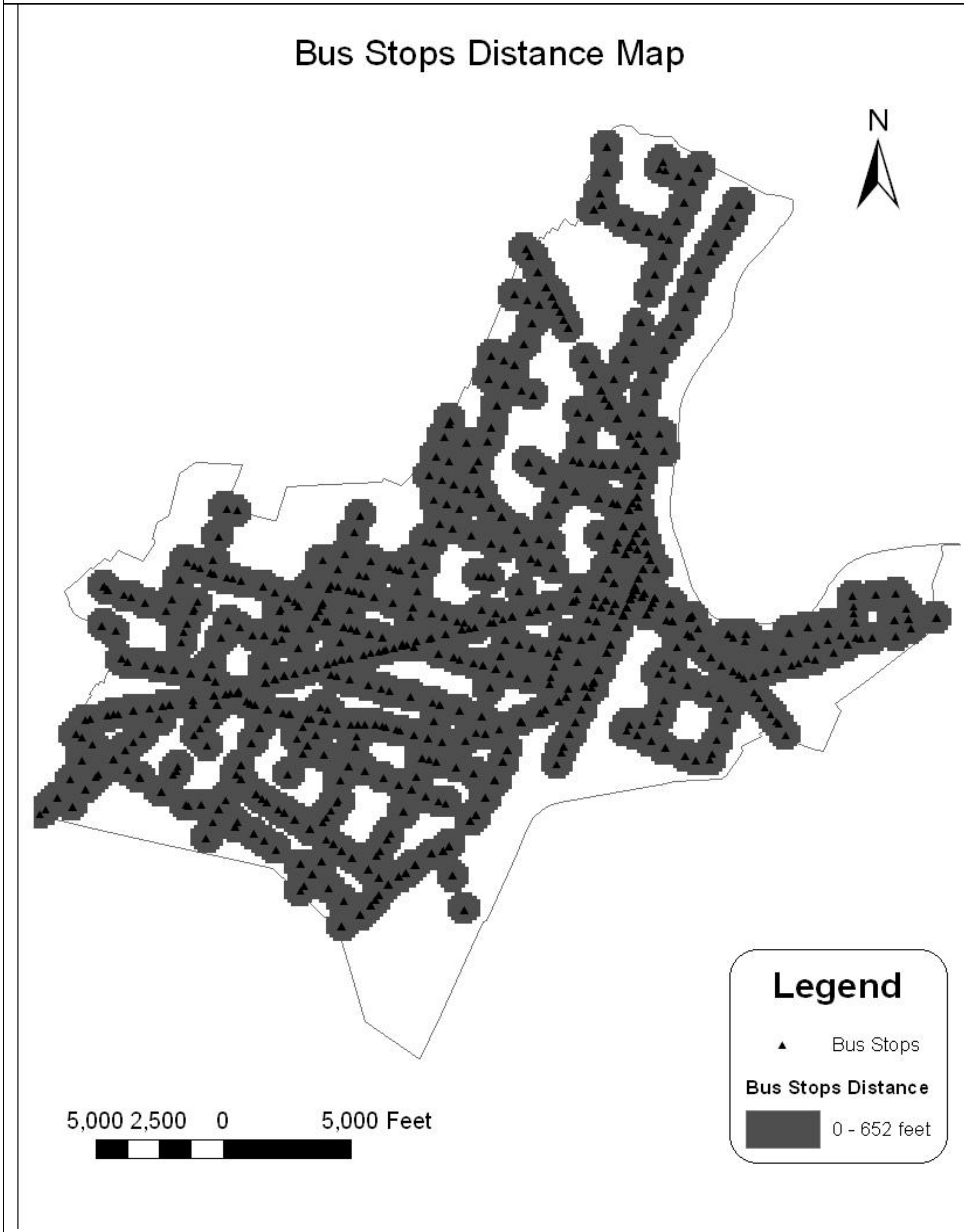


Figure 28. Liquor Stores and Bars Distance Map

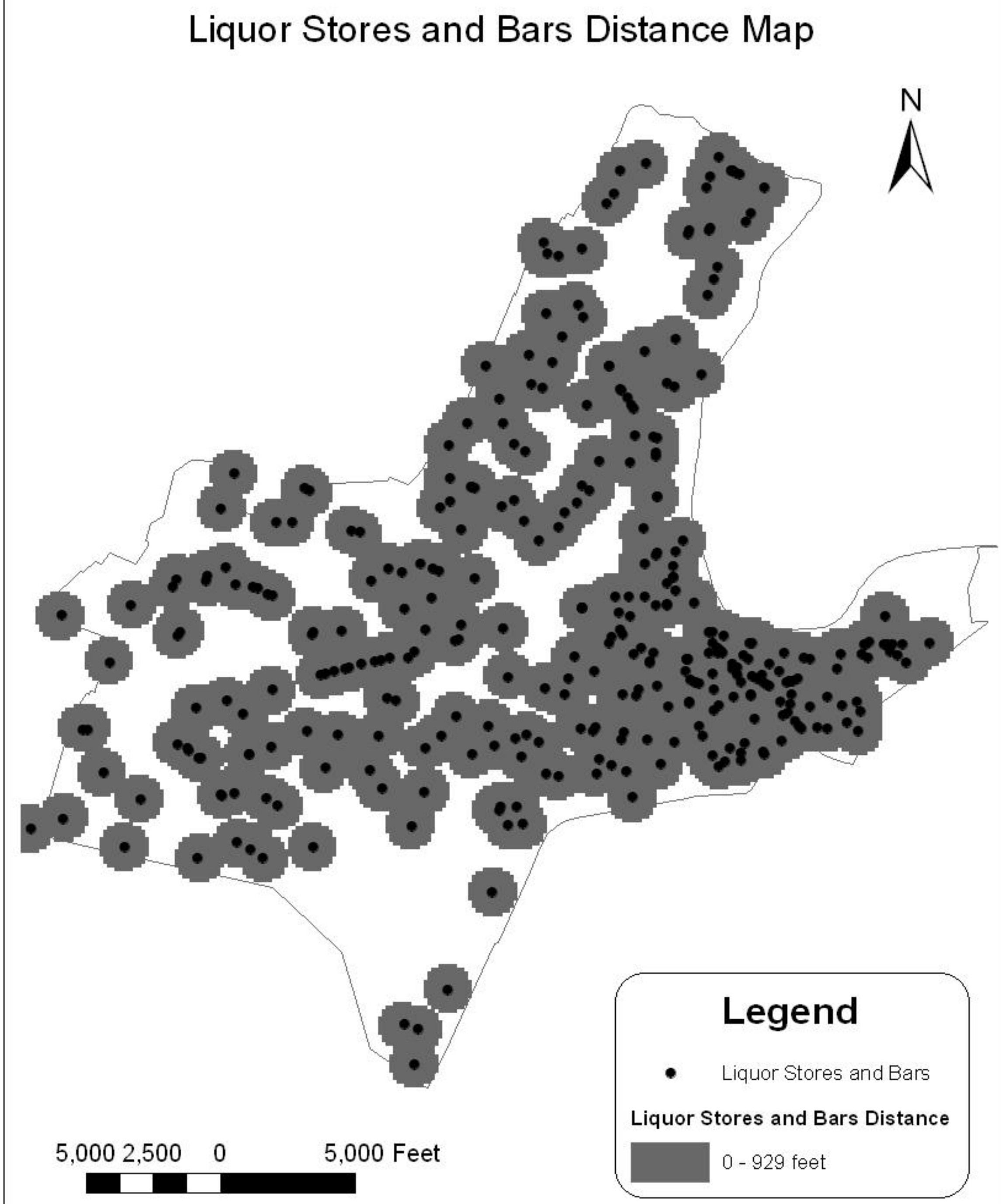


Figure 29. Middle and High Schools Distance Map

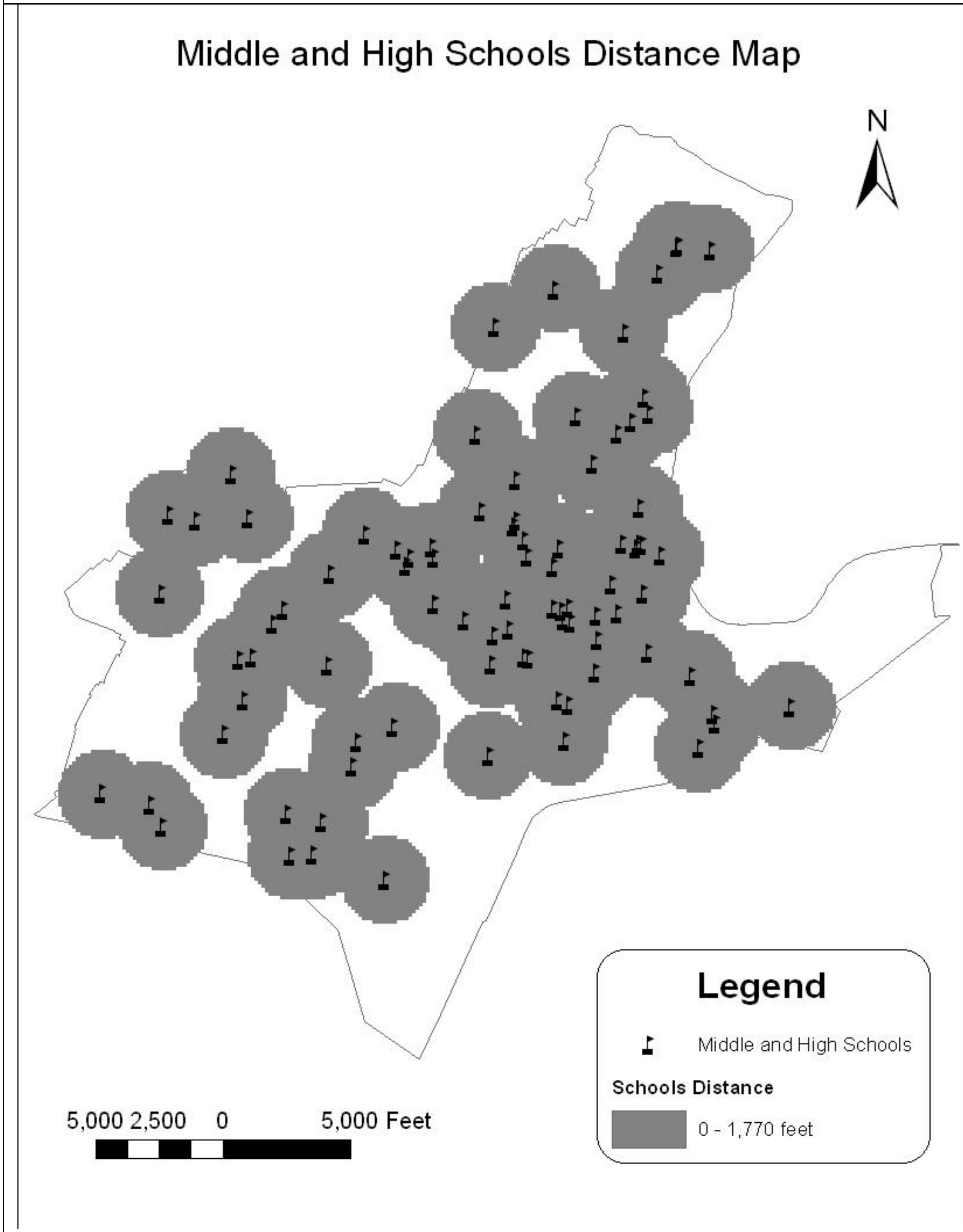


Figure 30. The final risk terrains of shootings

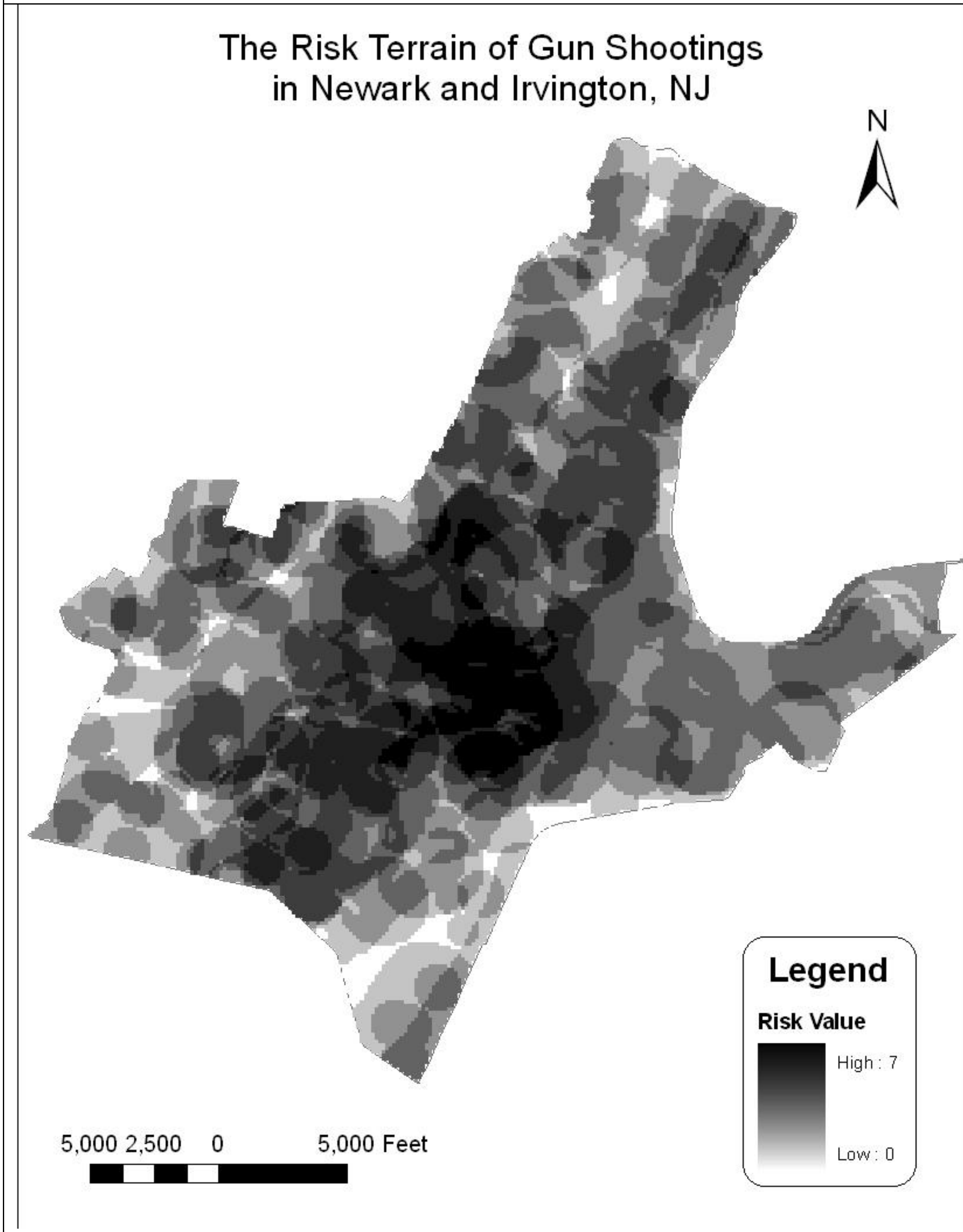
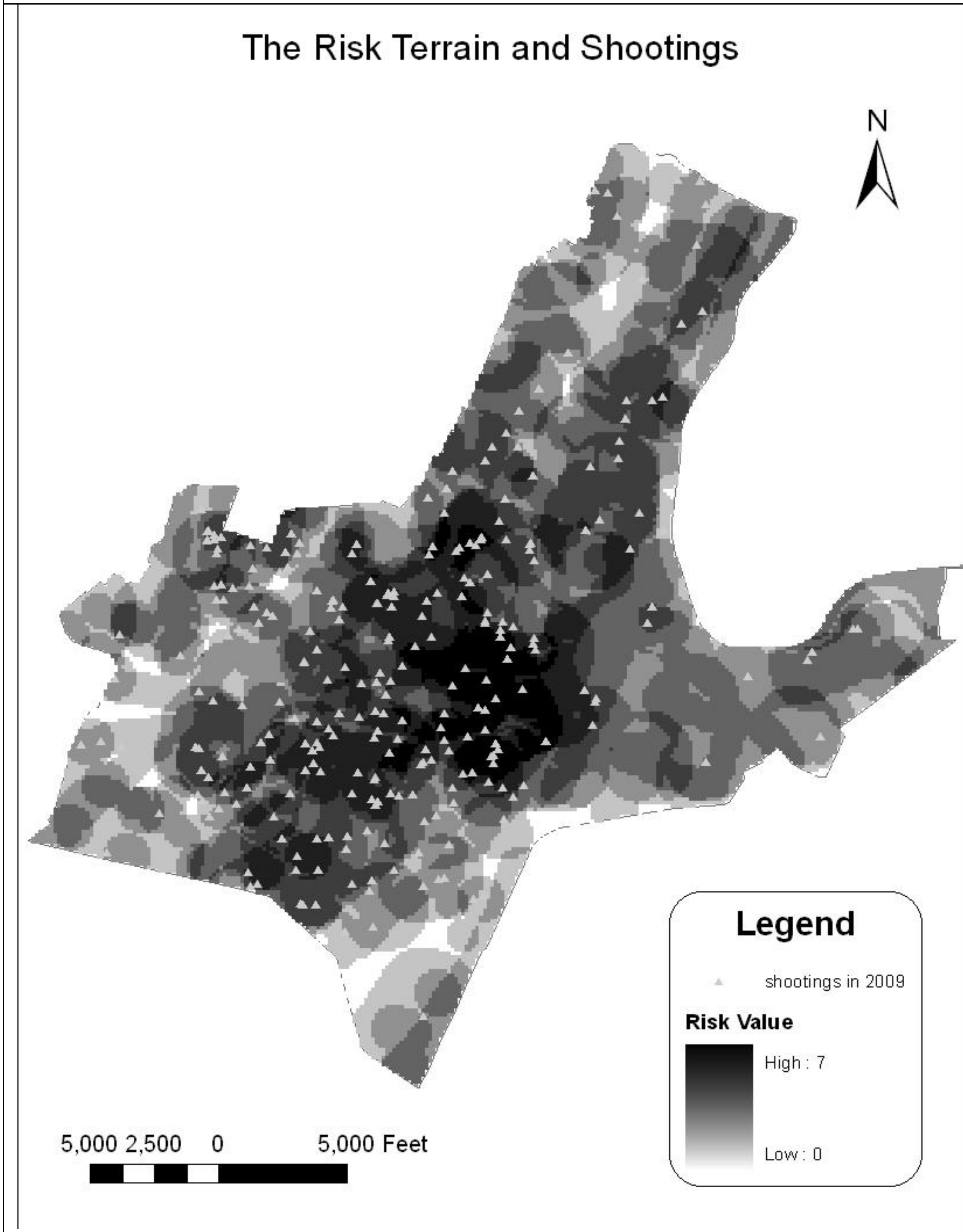


Figure 31. Risk Terrain Modeling (2008) and Shootings (2009)



Assess Predictive Efficacy of the RTM

A spatial autocorrelation test shows that spatial autocorrelation exists ($p<.01$). Also, Moran's I is .025, indicating positive spatial autocorrelation. So spatial lag values are calculated and are included as a new variable.

A logistic regression, with risk value and spatial lag as two independent variables and presence of shooting (yes/no) as the dependent variable, was used to determine the extent to which shootings occurred in higher risk cells. As the RTM is created on 2008 risk factors data, 2009 shooting locations data is used in this regression to test how well the RTM predict shooting locations in the subsequent time period. The results show that the model significantly predicted ($p<.001$) locations of future shootings. The odds ratio for risk value is 1.56, which means for every one unit increase in risk, the odds of shooting happening in a 140x140ft area during the subsequent time period increase by at least 56%.

Summary and Conclusions

This chapter intends to build a RTM forecasting model to predict shooting distributions by using the results from crime generator analyses and neighborhood analysis. To build RTM, we need to standardize the units of all the risk factors' layers. To disaggregate census data, smoothing method in GIS is used. By smoothing, the units of all the census risk factors' layers are reduced from block group to the unit we use in this study 140 feet. Each layer (total seven layers) is converted into a distance raster layer. The cutoff values of maximum distances for the distance maps are calculated based on CLI analyses. Cells are then classified into two groups based on the cutoff values. Then risk map layers are combined to a final composite risk terrain map with each cell exhibiting the summed risk value of all risk map layers. The risk values range from 0 to 7 with 7 as the highest risk cells.

A logistic regression, with risk value and spatial lag as two independent variables and presence of shooting (yes/no) as the dependent variable, was used to determine the extent to which shootings occurred in higher risk cells. As the RTM is created on 2008 risk factors data, 2009 shooting locations data is used in this regression to test how well the RTM predict shooting locations in the subsequent time period. The results show that the model significantly predicted ($p<.001$) locations of future shootings. The odds ratio for risk value is 1.56, which means for every one unit increase in risk, the odds of shooting happening in a 140x140ft area during the subsequent time period increase by at least 56%.

Chapter 11. Conclusions, Discussions, and Implications

This study presents a systematic approach to identify the determinants of gun shooting and forecast the distribution of gun shooting. The study applies opportunities theory and social disorganization theory to examine the micro-level crime generators of gun shooting and the macro-level neighborhood attributes that increase crime opportunities. The results show that gun shooting is not randomly distributed throughout the study area but rather is concentrated in a statistically significant way around major facilities: public housing, bus stops, liquor stores and bars, and middle and high schools. Also, shooting is clustered in poor neighborhoods with high single parents rate, low ethnic heterogeneity, and high jobless rate. This research provides another tool in establishing how risk clusters emerge and influence the distribution of crime. The clustering that takes place relates not only to the interrelationship between crime incidents but also to interdependence established between crime behavior, facilities, and neighborhoods.

The hot spots theory demonstrates that a small percent of places account for majority of crimes. However, it does not clarify what kinds of places are more likely to become these dangerous places. Besides, it is solely based on previous crime locations. This study changes the perspective to the environment and claims that certain environmental conditions promote crime. Why is crime not randomly distributed?

Because negative land use, such as public housing, liquor stores, bars, bus stops, and middle and high schools, and certain neighborhood characteristics, concentrate crime and encourage anti-social behavior.

Crime forecasting is still in its early stage. The most common method in police deparment is simply to assume that the hot spots of yesterday are the hot spots of tomorrow. Different from hot spots analysis, Risk Terrain Modeling offers a new way of looking at criminality as less determined by previous events and more a function of a dynamic interaction between characteristics of places. The ways in which these variables combine can be studied to reveal consistent patterns of interaction that can facilitate and enhance the risk of crime. However, what has been missing in RTM are what risk factors should be included in the model and how to find the risk factors. This study has answered these questions. This study introduces CLI method to find risky facilities and uses social disorganization theory to examine neighborhood risk factors.

In fact, identifying crime determinants is critical to crime forecasting. Forecast accuracy is the criteria in evaluating the value of a crime forecasting method. In a crime forecasting method that needs to use risk factors, such as RTM, the risk factors incorporated in the method determine the accuracy of this forecast method. The study has proved that using strong crime determinants, identified by CLI, can improve the predictability of RTM; while, using weak risk factors can reduce the predictability of RTM. The three experiments in chapter six are designed to test the forecast accuracy of RTM: the first model is a base model; the second experiment adds in a stronger crime generator into RTM and the result shows that it improves the predictability of RTM; the third experiment adds in a weak factor that does not have CLI effect and the result shows that it decreases the validity of RTM. Therefore, we can conclude that the risk factors selection determines the accuracy of this forecast method.

Additionally, this study fills another gap in RTM that is how to find the cutoff values of maximum distances in straight line distance map. When we create straight line distance maps that convert vector risk layers to raster risk layers, we always have the question that what the maximum distance cutoff values should be used to create the buffer areas. We can compute how long the distances are that can cover 80% or 90% crime incidents. This distance value can be used as the cutoff values of maximum distance for distance map.

The study introduces a spatial statistics method, CLI, to identify crime generators. CLI overcomes the limitations in traditional common method quadrat method to locate crime generators. CLI does not require arbitrarily determining any quadrat size such as thiessen polygon size. CLI does not aggregate data. Data aggregation may mask important variations in smaller ecological areas. CLI tests crime generators based on nearest neighbor analysis and simulation. If the mean distance from the hypothetically dependent distribution (crimes) to the independent distribution (e.g. bus stops) is significantly less than that from a spatially random pattern of crime, then CLI is established. Not only CLI can find crime generators, but also CLI can give the rank of risk levels of the generators.

Different types of crime occur under different environmental conditions. This study focuses on gun shooting. For gun shooting, this study reveals that public housing is the most dangerous crime generators for gun shooting, followed by bus stops, liquor stores and bars, and finally middle and high schools.

Public housing has the highest CLI value among all the facilities. This finding echoes other research on public housing and crime. Public housing facilitates crime by focusing human activities in and around its place where social control is weaker and social interactions that lead to crime are more likely. Public housing concentrates poverty and contributes to social disorganization. There are more drugs problems and other crime problems in and around public housing. Public housing attracts both potential offenders and victims, and thus creates many opportunities for crime and violence to occur. One of the potential approaches to reduce violence in and around public housing may be building new public housing projects in less disorganized neighborhood and with less negative land use around.

Bus stops are important settings for many people. They are places that bus riders have to spend time waiting for their buses. Bus stops attract a large number of people to come and thus create a lot of crime opportunities. The approaches to decrease violence in and around bus stops may include intensive policing, increasing surveillance such as CCTV, better lighting, and better visibility.

Alcohol establishments are considered a breeding ground for crime. Alcohol establishments such as bars are places where idle individuals may spend significant amounts of time and where nonconventional role modeling and defensive posturing may become prevalent. In alcohol establishments, individuals are not only involved in a situation of company that may be conductive to criminal activity but they also may be intoxicated and as such exhibit impaired judgement and weaken internal social control (Roncek and Maier 1991). Parker and Rebhun (1995) have elaborated a selective disinhibition perspective on alcohol consumption and homicide. They note that the disinhibiting effect of alcohol is to undermine the operation of active constraint in situations where there is potential violence. The presence of alcohol establishments may be an indirect indicator of social disorganization. The approaches to curb its effects on crime may be stricter license policies, limiting the store hours in disadvantaged neighborhood, and sitting alcohol establishments in less disorganized neighborhood and less negative land use.

Middle and high schools concentrate youths. The ebb and flow of youth going about their daily routines coincides with levels of violence (Roman 2003). Areas where large numbers of youth come together are particularly vulnerable and these areas' violence rates are much higher than others. Greatest concentration of youth results in highest rates of violence. Rates of violence are highest in the after-school period in places that have youth hangouts. As the afternoon passes into the evening and late night, rates of violence decrease in blocks that have youth hangouts. Therefore, police surveillance and parental oversight may be important in limiting opportunities for violence.

Neighborhood conditions provide fabrics for violence to occur. Just like other disorganized cities, in Newark and Irvington single-parent households, ethnicity, and job factors are important neighborhood factors that result in high violent crime. High rates of concentrated disadvantage and deprivation reduce informal and formal social control mechanisms, which, in turn, lead to increased crime including violence. Also, disadvantaged neighborhoods have difficulty attracting and maintaining the types of local institutions that impede violent behavior by providing community stability, social control, and alternative activities to occupy the time of residents. Employers that provide jobs and retail services are unlikely to find it profitable to locate in poorer neighborhoods. Indeed, many inner city areas have been devastated by economic disinvestment of a range of businesses (Wilson 1996). Residents of disadvantaged areas also lack the power to demand that local government and private agencies develop institutions to meet community needs and to fight the development of establishments, such as public housing, bars, that foster deviant behavior.

The policy implication of this neighborhood analysis results is that dealing with violent crime in cities like Newark and Irvingotn requires decisive intervention on such issues as economic opportunities, especially in poor neighborhoods where single parents and African American are prevalent. Take the reentry program for example that is related to youth offending. The New York Times once reported that New Jersey had the most crowded prison system in the country, according to the Justice Department, operating at 143 percent of capacity. Data from the New Jersey DOC reveals that 20 to 25 percent of all state prison inmates come from Essex County, mainly from Newark and Irvington. Most released prisoners returned to those neighborhoods (Newark and Irvington). These ex-offenders face significant barriers to obtaining employment, housing, medical care and other basic necessities, and recidivism rates are alarmingly high.

Perhaps a more important implication of this study lies in police practice. The identification of risky areas permits public safety practitioners to intervene and allocate limited resources more effectively and efficiently. They can reduce risk at the unit of analysis that they are operationally conditioned for—the geography. The current most method in police department is hot spots analysis. However, this method relies on yesterday's crime location to predict tomorrow's crime. This study changes the perspective to environment. The environmental conditions facilitate crime to occur. The method presented here may be more stable for forecasting. If the law enforcement resources are allocated more in high risk value areas, shootings are expected to be reduced more efficiently.

Limitations and Discussions

Interestingly, this study found that adding more variables into RTM can reduce the forecasting power. However, there is only one exception: adding variables with strong CLI effects can increase the forecasting power. In chapter 8, three RTM models are compared: a base model with three variables with moderate CLI effects, an enhanced model adding a variable with stronger CLI effects onto the base model, and a reduced model adding a variable without CLI effect onto the base model. The results show the enhanced RTM model has the strongest forecasting power; while, the reduced model decreases the forecasting power. It indicates that using variables with strong CLI effects can improve the forecasting power of the forecasting methods such as RTM. However, in Chapter 10, three neighborhood factors are added into the enhanced model. The forecasting power of this RTM with both facility variables and neighborhood variables is reduced compared to the three models in chapter 8.

This reducing forecasting power effect might be explained by the homogeneous nature of the characteristics of the neighborhood. There is high ethnic homogeneity in the study area. Majority of the study area are ethnic homogeneous. These areas have high percentages of African-Americans. Only a small percent of places have low percentage of African-American and these places are industrial areas and business districts. Using such a variable with homogeneous effects may not help to improve predictability.

Another concern about using census data in RTM forecasting is that census data are collected in every decade. It assumes that there is no change within the ten years. Thus it is impossible to get yearly or monthly census data. However, crime forecasting works well in shorter term forecasting. Therefore, we have to be cautious in using census data to predict short term crime.

There are several limitations in this study. First of all, the census data used in this study do not match other facilities data and shooting data well. All the facilities data are in 2008. The shooting data are from 2007 till 2010. But the census data are still in 2000. Neighborhood demographics may change a lot during the past ten years and the 2000 census data may not describe the communities in the late 2000s very well. However, the 2000 census data are the most recent available census data. The 2010 census data are still not available at the time of completion of this study.

Secondly, this study does not include known risk factors of shooting, such as gang residence dwellings and drug arrests locations, due to inaccessibility of these data from police records. Fortunately, former studies show that dwellings of known gang members (Brantingham and Brantingham 1981; Fagan and Wilkinson 1998; Klein 1995) and locations of drug arrests (Blumstein 1995; Lum 2008) increase risks of shooting incidents. RTM models built with these variables can predict future shooting locations very well (Caplan, Kennedy and Miller 2010).

Thirdly, this study does not examine the interactions of these risk facilities. Future work can take the interactions of facilities into account. Though the CLI analyses indicate that adding variables with stronger CLI effects can improve predict efficacy of forecasting model, this study does not examine the interactions effects between facilities, that is, whether the interactions between facilities can enhance or reduce the power of crime forecasting. For example, are there interaction effects between public houses and alcohol establishments? If there are interaction effects between them, how does the interaction affect crime? Future research should study the compound effects of facilities on shooting.

Fourthly, this study does not consider spurious correlation. This study has proved that certain facilities can attract violence and certain neighborhood characteristics influence violence. However, this study does not assess nested effects of risk facilities within neighborhood conditions on violent crime, and does not examine whether risk facilities mediates between social conditions and violent crime. For example, Eck, Clark and Guerette (2007) argued that a few of the facilities account for most of crime in these facilities. They created the term “risky facility” to represent the dangerous facilities. This 20-80 phenomena might be due to neighborhood conditions. If the facility is located in bad neighborhood, more crime occurs around this facility; if the facility is located in good neighborhood, less crime occurs. In addition, there are arguments about public housing and crime. Massey and Kanaiaupuni (1993) have demonstrated that traditional structural sources of social disorganization are present in public housing because low income is a requirement for residency, and the presence of public housing in a neighborhood has a strong effect in concentrating poverty within that community. Future work of this dissertation should examine the direct and indirect effects of facilities and neighborhood conditions.

Other future work on this topic should look at the ways in which different types of crime exhibit spatial interdependence and the importance of law enforcement and situational crime prevention strategies in ameliorating the crime problem. In addition, the ways in which these facilities intensify or reduce their attractiveness need to be more clearly understood. This analysis provides an initial step in this attempt to articulate the generator dynamics and document the role that opportunity structures actually play in creating crime concentration. A further puzzle in this research is the relative importance of each type of crime generator in influencing gun shooting. In addition, Does gun shooting interact with other forms of crime, for example, drug dealing which are, in turn, influenced by these crime generators. These types of innovative attempts at applying spatial analysis techniques to these types of problems will further the understanding of the relationship between the features of the urban landscape and crime that occurs there.

REFERENCES

Alaniz, M.L., Cartmill, R.S., and Parker, R.N. (1998) Immigrants and violence: The importance of neighborhood context. Hispanic Journal of Behavioral Sciences, 20(2), 155–74

Alexander, Rand Curtis, C.M. (1995). A critical review of strategies to reduce school violence. Social Work in Education 17 (2): 73-82.

Anselin, Luc, Jacqueline Cohen, David Cook, Wilpen Gorr, and George Tita. (2000). “Spatial Analyses of Crime.” Pp. 213-62 in Criminal Justice Vol. 4. Measurement and Analysis of Crime and Justice, edited by David Duffee. Washington, D.C. National Institute of Justice.

Astor, R.A., H.A. Meyer, and W.J. Behre. (1999). Unowned places and times: Maps and interviews about violence in high schools. American Educational Research Journal 36(1): 3-42

Ball, John, Lawrence Rosen, John Flueck, and David Nurco (1981) “The criminality of heroin addicts: when addicted and when off opiates”. In James Inciardi, The drug-crime connection. Thousand Oaks, CA: Sage Publications, Inc.

Baller, Robert, Luc Anselin, Steven Messner, Glenn Deane, and Darnell Hawkins (2001) Structural covariates of U.S. county homicide rates: incorporating spatial effects. Criminology 39:561

Barr, Robert and Kenneth Pease (1990) Crime placement, displacement, and deflection. In Michael Tonry and Norval Morris, Crime and Justice: A Review of Research. Vol 12. Chicago: University of Chicago Press.

Beck, U. (1992). Risk society: Towards a new modernity. London: Sage Publications.

Blau, Judith R. and Peter M. Blau (1982) The cost of inequality: metropolitan structure and violent crime. American Sociological Review 47:114

Blau, Peter M. (1977) Inequality and heterogeneity: a primitive theory of social structure. New York: Free Press

Block, Richard and Carolyn R. Block (1995) Space, place, and crime: hot spots areas and hot places of liquor-related crime. In John E. Eck and David Weisburd, Crime and Place. Monsey, NY: Criminal Justice Press.

Blumstein, Alfred and Jacqueline Cohen (1979) Estimation of individual crime rates from arrest records. Journal of Criminal Law and Criminology 70:561.

Blumstein, Alfred and Daniel Cork (1996) “Linking gun availability to youth gang violence”. Law and Contemporary Problems 59(1)

Brantingham, Paul J. and Patricia L. Brantingham (1991) Environmental Criminology. 2nd ed. Prospect Heights: Waveland Press.

Brantingham, Paul J. and Patricia L. Brantingham (1993) Paths, nodes, and edges: considerations on the complexity and crime and the physical environment. Journal of environmental psychology 13:3

Brantingham, Paul J. and Patricia L. Brantingham (1978). A Theoretical Model of Crime Site Selection. In: M.D. Krohn and RX. Akers, Crime, Law and Sanctions, pp.105-118. Beverly Hills, CA: Sage Publications.

Brantingham, Paul J. and Patricia L. Brantingham (1995). Criminality of place: crime generators and crime attractors. European Journal on Criminal Policy and Research 3(3)

Braga, Anthony A. (2002) Problem-Oriented Policing and Crime Prevention. Monsey, NY: Criminal Justice Press.

Braga, Anthony A. (2003) “Serious youth gun offenders and the epidemic of youth violence in Boston”. Journal of Quantitative Criminology Vol 19 NO 1

Braga, Anthony A. (2005). Hot spots policing and crime prevention: A systematic review of randomized controlled trials. Journal of Experimental Criminology 1:317–42.

Braga, Anthony A., David L. Weisburd, Elin J. Waring, Lorraine Green Mazerolle, William Spelman, and Francis Gajewski. (1999) Problem-oriented policing in violent crime places: A randomized controlled experiment. Criminology 37:541–80.

Braga, Anthony A., Andrew Papachristos, and David Hureau. (2010). The Concentration and Stability of Gun Violence at Micro Places in Boston, 1980-2008. Journal of Quantitative Criminology 26:33-53

Bickford, Adam and Douglas S. Massey. (1991). Segregation in the Second Ghetto: Racial and Ethnic Segregation in American Public Housing, 1977. Social Forces 69:1011–36

Burgess, E. W. (1928). Factors determining success or failure on parole. In A. A. Bruce, E. W. Burgess, & A. J. Harno (Eds.), The Workings of the Indeterminate Sentence Law and the Parole System in Illinois (pp. 221-234). Springfield: Illinois State Board of Parole.

Bursik, Robert (1988) Social disorganization and theories of crime and delinquency: problems and prospects. Criminology 26: 519

Bursik, Robert J. and Harold G. Grasmick. 1992. "Longitudinal Neighborhood Profiles of Delinquency: The Decomposition of Change." Journal of Quantitative Criminology 8:247-64.

Bursik, Robert and Harold Grasmick (1993) Neighborhoods and crime: the dimensions of effective community control. San Francisco: Jossey-Bass

Bursik, Robert and Harold Grasmick (1995) Neighborhood-based networks and the control of crime and delinquency. In Hugh Barlow, Crime and public policy: putting theory to work. Boulder, CO: Westview.

Burgess, Ernest (1925) The growth of the city. In Robert Park, Ernest Burgess, and Roderick McKenzie, The city. Chicago: University of Chicago Press.

Cameron, A. C., & Trivedi, P. K. (1986). Econometric models based on count data: Comparisons and applications of some estimators and tests. Journal of Applied Econometrics, 1, 29-53.

Cameron, A. C., & Trivedi, P. K. (1990). Regression-based tests for overdispersion in the Poisson model. Journal of Econometrics, 46, 347-364.

Cameron, A. C., & Trivedi, P. K. (1998). Regression analysis of count data. New York: Cambridge University Press.

Catalano, R. F., & Hawkins, J. D. (1996). The social development model: A theory of antisocial behavior. In J. D. Hawkins (Ed.), Delinquency and crime: Current theories. New York: Cambridge University Press.

Clark, P.J., and F.C. Evans. (1954). Distance to Nearest Neighbor as a Measure of Spatial Relationships in Populations. Ecology 35:445-453

Clarke, Ronald V. (1992) Situational crime prevention: successful case studies. Albany, NY: Harrow and Heston.

Clarke, Ronald V. and John Eck (2005) Crime Analysis for Problem Solvers in 60 Small Steps. Center for Problem Oriented Policing. Washington, DC.

Clarke, Ronald V. and Marcus Felson (1993) Routine activity and rational choice: advances in criminological theory. New Brunswick, NJ: Transaction Press.

Clarke, Ronald V., ed. (1997) Situational Crime Prevention: Successful Case Studies. 2nd ed. Albany, NY: Harrow and Heston.

Clarke, Ronald V., and David L. Weisburd. (1994) Diffusion of crime control benefits: Observations on the reverse of displacement. Crime Prevention Studies 2:165–84.

Cohen, Jacqueline and George Tita (1999) "Diffusion in homicide: exploring a general method for detecting spatial diffusion processes". Journal of Quantitative Criminology 15(4)

Cohen, L., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. American Sociological Review, 44, 588–608.

Collins, James (1990) "Summary thoughts about drugs and violence" In Mario De La Rosa, Elizabeth Lambert and Bernard Gropper, Drugs and Violence: Causes, Correlates, and Consequences. Rockville, MD: US National Institute on Drug Abuse.

Cornish, Derek and Ronald V. Clarke (1986) The reasoning criminal: rational choice perspectives on offending. New York: Springer-Verlag.

Cornish, Derek and Ronald, V. Clarke (1987) Understanding crime displacement: an application of rational choice theory. Criminology 25:933

Crow, W., & Bull, J. (1975). Robbery deterrence: An applied behavioral science demonstration—final report. La Jolla, CA: Western Behavioral Science Institute.

Davis, J.C. (1986). Statistics and Data Analysis in Geology. 2nd edition. John Wiley and Sons, NY.

DeKeseredy, Walter S., Martin D. Schwartz, Shahid Alvi, and Andreas Tomaszewski. (2003). Perceived Collective Efficacy and Women's Victimization in Public Housing. Criminal Justice 3:5–27

Donnelly, K.P. (1978). Simulations to Determine the Variance and Edge Effect of Total Nearest-Neighbor Distance. In Simulation Studies in Archaeology, I. Hodder, ed. Cambridge University Press, Cambridge, UK.

Duke, Daniel L. (1989). School organization, leadership, and student behavior. In Oliver C. Moles (ed.), Strategies to Reduce Student Misbehavior. Washington,D.C.: Office of Educational Research and Improvement

Eck, John E. (1994) Drug markets and drug places: a case-control study of the spatial structure of illicit dealing. University of Maryland, College Park

Eck, John E., Ronald V. Clarke, and Rob T. Guerette. (2007). Risky Facilities: Crime Concentration in Homogeneous Sets of Establishments and Facilities. Crime Prevention Studies, Vol 21:225-264

Eck, John E., and David L. Weisburd. (1995) Crime places in crime theory. In Crime and Place, eds. John E. Eck and David L. Weisburd. Monsey, NY: Criminal Justice Press.

Eck, John. E., & Weisburd, D. (1995). Crime and place: Crime prevention studies, volume 4. Monsey, NY: Criminal Justice Press.

Eck, John E. (2001) Policing and Crime Event Concentration. In Robert Meier, Leslie Kennedy, and Vincent Sacco, eds. The Process and Structure of Crime: Criminal Events and Crime Analysis. Theoretical Advances in Criminology. New Brunswick, NJ: Transactions.

Eck, John, Spencer Chainey, and John Cameron (2005) Mapping Crime: Understanding Hot Spots. Washington, DC: U.S. Department of Justice, National Institute of Justice.

Elliott, Delbert S. William J. Wilson, David Huizinga, Robert J. Sampson, Amanda Elliott, and Bruce Rankin (1996) The effects of neighborhood disadvantage on adolescent development. Journal of Research in Crime and Delinquency 33:389

Ericson, R. and Haggerty, K. (1997). Policing the Risk Society. Clarendon: Oxford.

Fagan, Jeffrey (1989) “Myths and realities about crack”. Contemporary Drug Problems 16(4)

Fagan, Jeffrey (1992) “ Drug selling and licit income in distressed neighborhoods: the economic lives of street-level drug users and dealers” In Adele Harrell and George Peterson, Drugs, Crime, and Social Isolation: Barriers to Urban Opportunity. Washington D.C.: Urban Institute Press

Fagan, Jeffrey and Ko-Lin Chin (1989) "Initiation into crack and cocaine: a tale of two epidemics" Contemporary Drug Problems 16(4)

Fagan, Jeffrey and Ko-Lin Chin (1990) "Violence as regulation and social control in the distribution of crack". In Mario De La Rosa, Elizabeth Lambert and Bernard Gropper, Drugs and Violence: Causes, Correlates, and Consequences. Rockville, MD: US National Institute on Drug Abuse

Fagan, Jeffrey and Garth Davies. (2000). "Crime in Public Housing: Two-Way Diffusion Effects in Surrounding Neighborhoods." Pp. 121–35 in Analyzing Crime Patterns: Frontiers of Practice, edited by Victor Goldsmith, Philip G. McGuire, John H.Mollenkopf, and Timothy A. Ross. Thousand Oaks, CA: Sage Publications

Farrington, D. P. (1983). Randomized experiments on crime and justice. In M. Tonry & N. Morris (Eds.), Crime and justice: A review of research, volume 4. Chicago:University of Chicago Press.

Farrington, D. P. (1991) Childhood aggression and adult violence: Early precursors and later life outcomes. In D. J. Pepler & K. H. Rubin (Eds.), The development and treatment of childhood aggression (pp. 5–29). Hillsdale, NJ: Erlbaum.

Farrington, D. P., Ohlin, L., & Wilson, J. Q. (1986). Understanding and controlling crime: Toward a new research strategy. New York: Springer.

Farrell, G and Pease K (1993) Once Bitten, Twice Bitten: Repeat Victimisation and its Implications for Crime Prevention. Crime Prevention Unit Paper 46. London: Home Office

Felson, M. (1994) Crime and everyday life: insight and implications for society. Thousand Oaks, CA: Pine Forge Press

Foote, Mike (1990) Nearest-Neighbor Analysis of Trilobite Morphospace. Systematic Zoology, 39: 371-382

Foote, Michael. (1989). Morphologic Evolution of Cambrian and Ordovician Trilobites. Chicago, Illinois: University of Chicago Press.

Fotheringham, AS. and Wong, D.W.S. (1991). The modifiable areal unit problem in statistical analysis. Environment and Planning A 23: 1025-1044.

Gabor, Thomas (1990) Crime displacement and situational prevention: toward the development of some principles. Canadian Journal of Criminology 32:41

Giancola, P. R., Saucier, D. A. & Gussler-Burkhardt, N. L. (2003) The effects of affective, behavioral, and cognitive components of trait anger on the alcohol–aggression relation. Alcoholism: Clinical and Experimental Research, 27, 1944–1954

Glueck, S. & Glueck, E. (1950). Unraveling Juvenile Delinquence. New York: Commonwealth.

Goldstein, P.J., H.H. Brownstein, P. Ryan, and P.A. Belluci (1989) "Crack and homicide in New York City 1988: a conceptually based event analysis". Contemporary Drug Problems 16(4)

Gorman, D.M., Labouvie, E.W., Speer, P.W., and Subaiya, A.P. (1998) Alcohol availability and domestic violence. American Journal of Drug Alcohol Abuse, 24(4), 661–73

Gorman, D., Speer, P. W., Gruenewald, P. J. & Labouvie, E. W. (2001) Spatial dynamics of alcohol availability, neighborhood structure and violent crime. Journal of Studies on Alcohol, 62, 628–636

Gottfredson, G.D. and D. Gottfredson. 1985. Victimization in Schools. New York:Plenum Press

Greene, Jack and Ralph Taylor (1988) Community-based policing and foot patrol: issues of theory and evaluation. In Jack Greene and Stephen Mastrofski, Community policing: rhetoric or reality? New York: Praeger

Greene, W. H. (2003). Econometric analysis (5th ed.). New York: Prentice Hall.

Griffith, Daniel (2003) Spatial Autocorrelation and Spatial Filtering. Springer.

Haines, B. & Graham, K. (2005) Violence prevention in licensed premises. In: Stockwell, T., Gruenewald, P. J., Toumbourou, J. & Loxley, W., eds. Preventing Harmful Substance Use: the Evidence Base for Policy and Practice, pp. 163–176. New York: John Wiley

Hamid, Ansley (1990) "the political economy of crack-related violence". Contemporary Drug Problems 17(1)

Hawkins, J. D., Arthur, M. W., & Catalano, R. F. (1995). Preventing substance abuse. In M. Tonry & D. P. Farrington (Eds.), Building a safer society: Strategic approaches to crime prevention, Crime and justice: A review of research, volume 19 (pp. 343–426). Chicago: University of Chicago Press.

Hawkins, J. D., Catalano, R. F., & Arthur, M. W. (2002). Promoting science-based prevention in communities. Addictive Behaviors, 27, 951–976.

Hawkins, J. D., Catalano, R. F., & Miller, J. Y. (1992). Risk and protective factors for alcohol and other drug problems in adolescence and early adulthood: Implications for substance abuse prevention. Psychological Bulletin, 112, 64–105.

Hunter, A. J., & Baumer, T. L. (1982). Street traffic, social integration, and fear of crime. Sociological Inquiry, 52, 122–131.

Heitgerd, Janet and Robert Bursik (1987) Extracommunity dynamics and the ecology of delinquency. American Journal of Sociology 92:775

Hessling, Rene (1994) Displacement: a review of the empirical literature. Crime Prevention Studies 3:197

Inciardi, James (1990) “The crack-violence connection within a population of hard-core adolescent offenders” In In Mario De La Rosa, Elizabeth Lambert and Bernard Gropper, Drugs and Violence: Causes, Correlates, and Consequences. Rockville, MD: US National Institute on Drug Abuse

Jacobs, Bruce (1999) Dealing crack: the social world of streetcorner selling. Boston: Northeastern University Press

John, T. and Maguire, M. (2004a). The National Intelligence Model: Early Implementation Experience in Three Police Force Areas. Working Paper Series, Paper 50.

John, T. and Maguire, M. (2004b). The National Intelligence Model: key lessons from early research. Home Office: London.

Johnson, B.D. P. J. Goldstein, E. Preble, J. Schmeidler, D. Lipton, B. Spunt, and T. Miller (1985) Taking care of business: the economics of crime by heroin abusers. Lexington, MA: Lexington Books.

Kenkel, N.C., J.A.Hoskins, and W.D.Hoskins. (1989) Edge Effects in the Use of Area Polygons to Study Competition. Ecology, 70: 272-274

Kennedy, D. M., Braga, A. A., and Piehl, A. M. (2001). Developing and implementing Operation Ceasefire. In Reducing Gun Violence: The Boston Gun Project’s Operation Ceasefire, National Institute of Justice, U.S. Department of Justice, Washington, DC.

Kennedy, D. M., Piehl, A. M., and Braga, A. A. (1996). Youth violence in Boston: Gun markets, serious youth offenders, and a use-reduction strategy. Law Contemp. Probl. 59: 147–196.

Kennedy, Leslie W. and E.G. Van Brunschot, (2008) The risk in crime.

Kleiman, Mark (1988) Crackdowns: the effects of intensive enforcement on retail heroin dealing. In Marcia Chaiken, Street-level drug enforcement: examining the issues. Washington D.C.: National Institute of Justice

Krivo, Lauren, and Ruth Peterson (1996) Extremely disadvantaged neighborhoods and urban crime. Social Forces 75:619

Kubrin, Charis E. and Ronald Weitzer (2003) New directions in social disorganization theory. Journal of Research in Crime and Delinquency. Vol 40, NO. 4

Land, Kenneth, Patricia McCall, and Lawrence Cohen (1990) Structural covariates of homicide rates: are there any invariance across time and social space? American Journal of Sociology 95:922

Laycock, Gloria and Charles Austin (1992) Crime prevention in parking facilities. Security Journal 3:154

Levine, N., M. Wachs, and E. Shirazi, (1986). Crime at Bus Stops. A Study of Environmental Factors. Journal of Architectural and Planning Research 3(4): 339-361

Leson, J. (2005). Assessing and Managing Terrorism Threats. U.S. Department of Justice, Office of Justice Programs, Bureau of Justice Assistance. NCJ 210680.

Lipton, R. & Gruenewald, P. J. (2002) The spatial dynamics of violence and alcohol outlets. Journal of Studies on Alcohol, 63, 187–195

Loeber, R. (1988). The natural histories of juvenile conduct problems, substance use, and delinquency: Evidence for developmental progressions. In B.B Lahey & A. E. Kazdin (Eds.), Advances in clinical child psychology, volume 11 (pp. 73–124). New York: Plenum Press.

Loeber, R., & Dishion, T. J. (1983). Early predictors of male delinquency: A review. Psychological Bulletin, 94, 64–99.

Loeber, R., & Farrington, D. P. (1998). Serious and violent juvenile offenders: Risk factors and successful interventions. Thousand Oaks, CA: Sage.

Loeber, R., & Farrington, D. P. (2001). Child delinquents: Development, intervention, and service needs. Thousand Oaks, CA: Sage.

Loeber, R., & Le Blanc, M. (1990). Toward a developmental criminology. In M. Tonry & N. Morris (Eds.), Crime and justice review: A review of research, volume 12(pp. 375–473). Chicago: University of Chicago Press.

Long, J. S. (1997). Regression models for categorical and limited dependent variables. Thousand Oaks, CA: Sage.

Loukaitou-Sideris, A. (1999). "Hot Spots of Bus Stop Crime: The Importance of Environmental Attributes." Journal of American Planning Association 65(4): pp.395 - 411.

Loukaitou-Sideris, A., R. Liggett and H. Iseki (2002). "The Geography of Transit Crime: Documentation and Evaluation of Crime Incidence on and Around the Green Line Stations in Los Angeles." Journal of Planning Education and Research 22: pp.131-151.

Loukaitou-Sideris, A., R. Liggett, H. Iseki and W. Thurlow (2001). "Measuring the effects of Built Environment on Bus Stop Crime." Environment and Planning B: Planning and Design 28(2): pp. 255-280.

Maguire, M. (2000). Policing By Risks and Targets: Some Dimensions and Implications of Intelligence-Led Crime Control. Policing and Society, 9, 315-336.

Maguire, M, and John, T. (2006). Intelligence-Led Policing, Managerialism, and Community Engagement: Competing Priorities and the Role of the Intelligence Model in the UK. Policing & Society, 16(1), 67-85

Massey, Douglas, Gretchen Condran, and Nancy Denton (1987) The effect of residential segregation on black social and economic wellbeing. Social Forces 66:29

Massey, Douglas and Nancy Denton (1988) The dimensions of residential segregation. Social Forces 67:281

Massey, Douglas, Andrew Gross, and Kumiko Shibuya (1994) Migration, segregation, and the geographic concentration of poverty. American Sociological Review 59:425

Massey, Douglas S. and Shawn M. Kanaiaupuni. (1993). Public Housing and the Concentration of Poverty. Social Science Quarterly 74:109–122

Mayer, Susan and Christopher Jencks (1989) Growing up in poor neighborhoods: how much does it matter? Science 243

McCord, J. (1991). Family relationships, juvenile delinquency, and adult criminality. Criminology, 29, 397–417.

Moffitt, T. (1993). Adolescence-limited and life-course-persistent antisocial behavior: A developmental taxonomy. Psychological Review, 100, 674–701

Messner, Steven, Luc Anselin, Robert D. Baller, Darnell F. Hawkins, Glenn Deane, and Stewart E. Tolnay. (1999). "The Spatial Patterning of County Homicide Rates: An Application of Exploratory Spatial Data Analysis." Journal of Quantitative Criminology 15:423-50.

Messner, Steven and Richard Rosenfeld (1994) Crime and the American Dream. Belmont, CA: Wadsworth

Messner, Steven and Kenneth Tardiff (1986) Economic inequality and levels of homicide: an analysis of urban neighborhoods. Criminology 24:297

Meier, Robert F., Leslie Kennedy, and Vincent Sacco (2001). The Process and Structure of Crime: Criminal Events and Crime Analysis. Theoretical Advances in Criminology. New Brunswick, NJ: Transactions.

Meier, Robert F. and Terence D. Miethe. (1993). "Understanding Theories of Criminal Victimization." Pp. 459-99 in Crime and Justice: A Review of Research, edited by M. Tonry and N. Morris. Chicago: University of Chicago Press.

Miethe, Terance D. and Robert F. Meier (1990) Crime and its social context: toward an integrated theory of offenders, victims, and situations. State University of New York Press. Albany: NY

Mieczkowski, Tom (1990) "Crack distribution in Detroit". Contemporary Drug Problems 17(1)

Moore, M., and Tonry, M. (1998). Youth violence in America. In Tonry, M., and Moore, M.(eds.), Youth Violence, Vol. 24. Crime and Justice: A Review of Research, University of Chicago Press, Chicago.

Moore, M. H. (1995). Public health and criminal justice approaches to prevention. In M. Tonry and D. P. Farrington (Eds.), Crime and justice: A review of research, volume 19 (pp. 237–262). Chicago: University of Chicago Press.

Morenoff, Jeffrey and Robert Sampson (1997) Violent crime and the spatial dynamics of neighborhood transition: Chicago 1970-1990. Social Forces 76:31

Newton, A. D. (2004). "Crime on Public Transport: 'Static' and 'Non-Static' (Moving) Crime Events." Western Criminology Review 5(3): pp. 25-42.

Newmann, F. W. (1981). Reducing student alienation in high schools: implications of theory. Harvard Educational Review 5 l(4): 203-220

Okabe, A. and Miki, F.,(1984) "A Conditional Nearest-Neighbor Spatial Association Measure for the Analysis of Conditional Locational Interdependence", Environment and Planning A, Vol.16, pp.163-171

Okabe, A. and Yoshikawa, T., (1989) "Multi Nearest Distance Method for Analyzing the Compound Effect of Infrastructural Elements on the Distribution of Activity Points", Geographical Analysis, Vol.21, No.3, pp.216-235

Olweus, D. (1993). Bullying at School. Oxford, England: B1ackwell

Openshaw, S. (1977). Optimal zoning systems for spatial interaction models. Environment and Planning A: 169-184.

Openshaw, S. (1984). The modifiable areal unit problem. CATMOG 38. GeoBooks, Norwich, England.

Openshaw, S. and Taylor, P. (1979). A million or so correlation coefficients: three experiments on the modifiable areal unit problem. In: Statistical Applications in the Spatial Sciences. pp. 127-144. Edited by N. Wrigley. Pion, London.

Openshaw, S. and Taylor, P.J. (1981). The modifiable areal unit problem. In: Quantitative Geography: A British View. pp.60-69. Edited by N. Wrigley and R. Bennett. Routledge and Kegan Paul, London.

Openshaw, S., Charlton, M., Wymer, C. and Craft, A. (1987). Mark I geographical analysis machine for the automated analysis of point data sets. International Journal of Geographic Information Systems 1: 35-5 1.

Osgood, D. Wayne (2000) Poisson-based regression analysis of aggregate crime rates. Journal of Quantitative Criminology 16:21

Osgood, D.Wayne and Jeff M. Chambers. (2000). “Social Disorganization Outside the Metropolis: An Analysis of Rural Youth Violence.” Criminology 38:81-115.

Pate, Anthony, Wesley Skogan, Mary Ann Wycoff, and Lawrence Sherman (1986) Reducing fear of crime in Houston and Newark: a summary report. Washington D.C.: Police Foundation.

Pease K and Laycock G (1996) Reducing the Heat on Hot Victims. Washington: Bureau of Justice Statistics

Peebles, P.J.E. (1980) The Large-Scale Structure of the Universe. Princeton University Press, Princeton, NJ.

Peterson, Ruth and Lauren Krivo (1993) Racial segregation and black urban homicide. Social Forces 71:1001

Pihl, R. O., Lau, M. L. & Assaad, J.-M. (1997) Aggressive disposition, alcohol, and aggression. Aggressive Behavior, 23, 11–18

Pierce, G. L., Spaar, S., & Briggs, L. R. (1986). The character of police work: Strategic and tactical implications. Boston: Center for Applied Social Research, Northeastern University.

Police Foundation (1981) The Newark foot patrol experiment. Washing D.C.: Police Foundation

Popkin, Susan J., Victoria E. Gwiasda, Lynn M. Olson, and Dennis P. Rosenbaum. (2000). The Hidden War: Crime and Tragedy of Public Housing in Chicago. New Brunswick, NJ: Rutgers University Press.

Poyner, Barry (1991) Situational prevention in two car parks. Security Journal 2:96

Pratt, Travis and Francis Cullen (2005). Assessing Macro-Level Predictors and Theories of Crime: A Meta-Analysis.

Ratcliffe, Jerry. (2003). "Intelligence Led Policing." Canberra: Australian Institute of Criminology.

Ratcliffe, J. H. & McCullagh, M. J. (2001). Chasing Ghosts? Police Perception of High Crime Areas. British Journal of Criminology, 41: 330-341.

Ratcliffe, Jerry and George Regert. (2008). Near-Repeat Patterns in Philadelphia Shootings. Security Journal 21:58-76

Rengert, G., Ratcliffe, J.H. and Chakravorty, S. (2005) Policing Illegal Drug Markets: Geographic Approaches to Crime Reduction. Monsey, NY: Criminal Justice Press

Reid, R.J., Hughey, J., and Peterson, N.A. (2003) Generalizing the alcohol outlet-assaultive violence link: evidence from a U.S. Midwestern city. Substance Use and Misuse, 38(14), 1971–82

Reiss, Albert J. (1985) Policing a city's central district: the Oakland story. Washington D.C.: National Institute of Justice.

Reinarman, Craig and Harry Levine (1989) "Crack in context: politics and media in the making of a drug scare". Contemporary Drug Problems 16(4)

Reppetto, Thomas (1976) Crime prevention and the displacement phenomenon. Crime and Delinquency 22:166

Ripley, B.D. (1988). Statistical Inference for Spatial Processes. Cambridge University Press, Cambridge, UK.

Roncek, Dennis and Pat Meier (1991) Bar blocks and crimes revisited: linking the theory of routine activities to the empiricism of hot spots. *Criminology* 29:725

Roncek, D. W. (2000). Schools and crime. In V. Goldsmith, P. G. McGuire, J. H. Mollenkopf, & T. A. Ross (Eds.), Analyzing crime patterns: Frontiers of practice (pp. 153–165). Thousand Oaks, CA: Sage.

Roncek, D.W. (1981). "Dangerous Places." Social Forces 60:74-96.

Roncek, D.W. and R. Bell (1981). "Bars, Blocks and Crimes." Journal of Environmental Systems 11:35-47.

Roncek, D.W. and J.M.A. Francik (1981). "Housing Projects and Crime." Social Problems 29:151 -166.

Roncek, D.W. and D. Faggiani (1985). "High Schools and Crime." Sociological Quarterly 26:491-505.

Roncek, D.W. and A. Lobosco (1983). 'The Effect of High Schools on Crime in their Neighborhoods." Social Science Quarterly 64:598-613.

Roncek, D.W. and P.A. Maier (1991). "Bars, Blocks, and Crimes Revisited: Linking the Theory of Routine Activities to the Empiricism of 'Hot Spots.'" Criminology 29:725-753.

Roncek, D.W. and M.A. Pravatiner (1989). "Additional Evidence that Taverns Enhance Nearby Crime." Sociology and Social Research 73:185-188.

Rose, Dina and Todd Clear. 1998. "Incarceration, Social Capital, and Crime: Implications for Social Disorganization Theory." Criminology 36:441-79.

Rosenfeld, Richard (1986) "Urban crime rates: effects of inequality, welfare dependency, region, and race" In James Byrne and Robert Sampson, The Social Ecology of Crime. New York:Springer-Verlag.

Rosenfeld, Richard and Timothy Bray (1997) The impact of neighborhood disadvantage and racial composition on youth homicide: race, place, and risk revisited.

Rosenfeld, Richard and Arlen Egley (1999) Facilitating violence: a comparison of gang-motivated, gang-affiliated, and non-gang youth homicides. Journal of Quantitative Criminology. 15:495

Rountree, Pamela Wilcox, Kenneth Land, and Terance Miethe (1994) Macro-micro integration in the study of victimization: a hierarchical logistic model analysis across Seattle neighborhoods. Criminology 32:387

Sacco, V and Leslie W. Kennedy. (2002). The Criminal Event: Explorations in Time and Space. CA: Wadsworth.

Sampson, Robert and Jacqueline Cohen (1988) Deterrent effects of the police on crime: a replication and theoretical extension. Law & Society Review 22:163

Sampson, Robert J. (1986). "Crime in Cities: The Effects of Formal and Informal Social Control." Pp. 271-311 in Crime and Justice, Vol. 8, edited by Albert Reiss and Michael Tonry. Chicago: University of Chicago Press.

Sampson, Robert J. (1995) The community. In James Q. Wilson and Joan Petersilia, Crime. San Francisco: ICS Press

Sampson, Robert J. and W. Byron Groves. (1989). "Community Structure and Crime: Testing Social-Disorganization Theory." American Journal of Sociology 94:774-802.

Sampson, Robert J. and StephenW. Raudenbush. (1999). "Systematic Social Observation of Public Spaces: A New Look at Disorder in Urban Neighborhoods." American Journal of Sociology 105:603-51.

Sampson, Robert J., StephenW. Raudenbush, and Felton Earls. (1997). "Neighborhoods andViolent Crime." Science 277:918-24.

Sampson, Robert J., Jeffrey D. Morenoff, and Felton Earls. (1999). "Spatial Dynamics of Collective Efficacy for Children." American Sociological Review 64:633-60.

Scribner, R. A., MacKinnon, D. P. & Dwyer, J. H. (1995) The risk of assaultive violence and alcohol availability in Los Angeles County. American Journal of Public Health, 85, 335–340

Scribner, R., Cohen, D., Kaplan, S., and Allen, S.H. (1999) Alcohol availability and homicide in New Orleans: conceptual considerations for small area analysis of the effect of alcohol outlet density. Journal of Studies on Alcohol, 60(3), 310–6

Shaw, Clifford and Henry McKay (1942) Juvenile delinquency and urban areas: a study of rates of delinquency in relation to differential characteristics of local communities in American cities. Chicago: University of Chicago Press

Shaw, C. R and H. D McKay. (1969). Juvenile Delinquency and Urban Areas. Chicago: The University of Chicago Press.

Shaw, C. R and H. D McKay. (1969). Juvenile Delinquency and Urban Areas. Chicago: The University of Chicago Press.

Sherman, Lawrence (1987) Repeat calls to police in Minneapolis. Crime control reports Number 4. Washington, D.C.: Crime control institute

Sherman, Lawrence (1991) Herman Goldstein: Problem-oriented policing. Journal of Criminal Law and Criminology 82: 693

Sherman, Lawrence W., Patrick R. Gartin, and Michael E. Buerger, (1989) Hot Spots of Predatory Crime: Routine Activities and the Criminology of Place. Criminology 27: 27-55.

Sherman, Lawrence W., Janell Schmidt, and Robert Velke (1992) High crime taverns: a RECAP project in problem-oriented policing. Final report to the National Institute of Justice. Washington, D.C.: Crime Control Institute.

Sherman, L. W., & Weisburd, D. (1995). General deterrent effect of police patrol in crime “hot spots”: A randomized, controlled, trial. Justice Quarterly, 12, 625–648.

Shihadeh, Edward and Michael Maume (1997) Segregation and crime. Homicide Studies 1:254

Skogan, Wesley G. (1990). Disorder and Decline: Crime and the Spiral of Decay in American Neighborhoods. New York: Free Press.

Speer, P.W., Gorman, D.M., Labouvie, E.W., and Ontkush, M.J. (1998) Violent crime and alcohol availability: relationships in an urban community. Journal of Public Health Policy, 19(3), 303–18.

Spelman, William (1993) Abandoned buildings: magnets for crime? Journal of Criminal Justice 21:481

Stevenson, R. J., Lind, B. & Weatherburn, D. (1999) The relationship between alcohol sales and assault in New South Wales, Australia. Addiction, 94, 397–410

Sturman, M. C. (1999). Multiple approaches to analyzing count data in studies of individual differences: The propensity for Type I errors, illustrated with the case of absenteeism prediction. Educational and Psychological Measurement, 59, 414-430.

Sullivan, Mercer. (1989). Getting Paid: Youth Crime and Unemployment in Three Urban Neighborhoods. Ithaca,NY: Cornell University Press.

Taylor, Ralph and Stephen Gottfredson (1986) Environment design, crime, and prevention: an examination of community dynamics. In Albert J. Reiss and Michael Tonry, Communities and Crime. Chicago: University of Chicago Press

Taylor, Ralph (1997) Crime, grime, and responses to crime: relative impacts of neighborhood structure, crime, and physical deterioration on residents and business personnel in the Twin Cities. In Steven P. Lab, Crime Prevention at a Crossroads. Cincinnati, Ohio: Anderson

Taylor, Ralph. (2000). Breaking Away from Broken Windows: Baltimore Neighborhoods and the Nationwide Fight against Crime, Grime, Fear, and Decline. NY: Perseus Publishing

Tita, G, J.K. Piley, and P Greenwood. (1994). Reducing Gun Violence: Operation Ceasefire in Los Angeles. Washington D.C.: National Institute of Justice

Tremblay, R., Masse, B., Perron, D., Le Blanc, M., Schwartzman, A. E., & Ledingham, J. E. (1992). Early disruptive behavior, poor school achievement, delinquent behavior, and delinquent personality: Longitudinal analyses. Journal of Consulting and Clinical Psychology, 60, 64–72.

Van Brunschot, E.G. and L.W.Kennedy. (2007). Risk Balance and Security. Los Angeles: Sage Publications, Inc.

Vessey, Bonita M. and Steven Messner (1999) Further testing of social disorganization theory: an elaboration of Sampson and Grove's "community structure and crime". Journal of Research in Crime and Delinquency 36:156

Vincent, P.J., J.M. Haworth, J.G. Griffiths, and R. Collins. (1976) The Detection of Randomness in Plant Patterns. J. Biogeogr. 3:373-380

Walters, Glenn. (2007) Using Poisson Class Regression to Analyze Count Data in Correctional and Forensic Psychology: A Relatively Old Solution to a Relatively New Problem. Criminal Justice and Behavior, 34: 1659

Warner, Barbara and Glenn Pierce (1993) Reexamining social disorganization theory using calls to the police as a measure of crime. Criminology 31:493

Weisburd, D., Maher, L., & Sherman, L. (1992). Contrasting crime general and crime specific theory: The case of hot spots of crime. In Advances in criminological theory, volume 4 (pp. 45-70). New Brunswick, NJ: Transaction.

Weisburd, D., & Green (Green-Mazerolle), L. (1994). Defining the drug market: The case of the Jersey City DMA system. In D. L. MacKenzie & C. D. Uchida (Eds.), Drugs and crime: Evaluating public policy initiatives (pp. 61–76). Newbury Park, CA: Sage.

Weisburd, D., & Green (Green-Mazerolle), L. (1995). Policing drug hot spots: The Jersey City DMA experiment. Justice Quarterly, 12, 711–735.

Whittaker, R. H. (1975). Communities and Ecosystems. 2nd Edition. Macmillan, NY.

Wikstrom, Per-Olof (1995) Preventing city-center street crimes. In Michael Tonry and David Farrington, Building a safer society: strategy approaches to crime prevention. Chicago: University of Chicago Press

Willis, H., Morrall, A., Kelly, T., Medby, A. (2005). Estimating Terrorism Risk. Santa Monica:RAND Corporation.

Wilson, James Q., and George Kelling. (1982). Broken windows: The police and neighborhood safety. Atlantic Monthly. March:29–38.

Wilson, William J. (1987) The truly disadvantaged: the inner city, the underclass, and public policy. Chicago: University of Chicago Press

Winkelmann, R. (2003). Econometric analysis of count data (4th ed.). New York: Springer

Wolfgang, M (1958). Patterns in criminal homicide. University of Pennsylvania Press, Philadelphia.

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