# IDENTIFYING RISKY PLACES FOR CRIME:

# AN ANALYSIS OF THE CRIMINOGENIC SPATIOTEMPORAL INFLUENCES OF LANDSCAPE FEATURES ON STREET ROBBERIES

by

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## ABSTRACT

Identifying Risky Places for Crime: *An Analysis of the Criminogenic Spatiotemporal Influences of Landscape Features on Street Robberies*

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In environmental criminology, it is widely accepted that crime risk is affected by the legitimate and illegitimate activities hosted at places. Most studies exploring this influence use the concepts of environmental criminology to explain how landscape features (such as cash businesses, illegal markets) can promote criminal behavior. However, studies based on place-based indicators provide an incomplete picture of crime emergence. First, most studies assume a temporally uniform crime-generating influence of landscape features, ignoring the social relevancy of these features at different times. Second, in most crime and place studies, the spatial influence—the ways in which features of a landscape affect places throughout the landscape (Caplan, 2011, p. 57)— is operationalized arbitrarily (Ratcliffe, 2012). Moreover, few studies examine the interactivity of the criminogenic spatial influences of different landscape features on crime risk (Caplan et al., 2011). To address these limitations, this dissertation examined the individual and combined criminogenic spatiotemporal influences of landscape features on 2010 street robbery risk in the City of Newark, NJ, using the principles of Risk Terrain Modeling.

Street robberies were classified into six daily and hourly temporal groups. According to the results of this dissertation, criminogenic features are different for different time models, and the extent and weight of their criminogenic influences vary between and within time nested models. At-risk housing, schools, churches, grocery stores, hair and nail salons, pawn shops, sit-down restaurants, and take-out restaurants are the only features that have round-the clock criminogenic influences on street robberies in all time models. Drug charges, pawn shops, grocery stores, take-out restaurants, and hair and nail salons exert the strongest criminogenic spatial influences in different time models. At-risk housing's, schools', and churches' criminogenic influences are statistically significant, albeit weak. High-risk micro places identified by the combined criminogenic spatiotemporal influences of landscape features are high likely places for street robberies in Newark, NJ.

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# TABLE OF CONTENTS

## LIST OF TABLES

## LIST OF FIGURES

# INTRODUCTION

Scholars have recently started analyzing the complex and non-linear interactions between multiple precursors of crime (Sullivan et al., 2012). This interest in the complex dynamics of crime rose due to the "perceived failure of the simple linear models" in explaining the variation in crime (Sawyer, 2012, p.23). As a recent example, after reviewing the statistical modeling work published in the journal *Criminology* between the years 1968 and 2005, Weisburd and Piquero (2008) concluded that the ability of researchers to explain crime patterns has not improved over time. Wikström (2007) further suggested that it would be more advantageous for scholars to understand the processes and interactions that produce the crime outcome. The explanation of the dynamics of crime is fundamental to crime science because crime prevention is not possible without identifying the correlates of crime events.

Given these considerations, criminologists have started using the emergence framework to further the understanding of crime. According to the emergence framework, new things arise or appear "based on the complex interaction of elements, forming a pattern where a certain degree of organizational cohesion can be clearly identified" (Sullivan et al., 2012, p.6). While embracing the role of emergence in crime occurrence, criminologists are advised to comprehend the effects of the interaction of the individual and the situation on future criminal behavior and incorporate this interactive nature into a "range of alternative methodologies necessary to gain perspectives on the complex dynamics involved in explaining crime" (Britt et al., 2012, p. xii).

Understanding crime patterns requires one to know the processes that result in a crime event and to simultaneously explore the elements that increase the probability of an event.

In criminology and crime prevention, in an effort to explain the mechanisms of crime, many risk factors have been identified to have a relationship with different crime outcomes. These risk factors generally include individual, event-based, or contextual characteristics that increase the odds of a criminal outcome. The extensiveness of the list of crime risk factors have led some criminologists to question which one of these many factors matter, if they matter at all (Wikström, 2007). In studies of environmental criminology, several features of an environmental setting have been identified to increase crime risk. In this dissertation, following the definition of Caplan and Kennedy (2010, p.7), the term risk and risk values are used to describe “a place’s potential for a crime event to occur.”

Environmental crime studies have been successful in introducing the importance of micro places in criminological research. However, studies based on place-based indicators provide an incomplete picture of crime emergence. In context-based analysis of crime risk, studies of the relationship between environmental risk features and crime assume a temporally uniform criminogenic influence of a risk feature. Following the literature on criminogenic needs in criminology, this dissertation defines criminogenity as the crime promoting environmental settings at micro places that are strongly correlated with robbery risk.   Despite the stationary nature of landscape features, even when thought in the crudest temporal divisions—such as months, weeks, days, holidays, or hours—it is intuitive that the criminogenic influence of environmental risk features will not be uniform across time. Human activities occur at specific locations for a limited duration (Miller, 2004). Past research has addressed the spatial and temporal aspects of crime risk separately, “ignoring the necessary interaction of space and time to produce criminal opportunities” (Grubesic and Mack, 2008, p. 285). According to Grubesic and Mack (2008), in most studies either the space-time interaction is neglected, or space and time are treated as independent entities rather than interdependent ones. Situations are deeply dynamic in the sense that “no space retains its social relevancy permanently” (Kinney, 2010, p. 485).

At different times of the day, week, month, and year, places assume different functions for human activity. Therefore, a criminogenic land feature can lose this characteristic (or vice versa) depending on the social relevancy of the place at different times. Furthermore, in most crime and place studies, what counts as within the spatial influence of a landscape feature is justified arbitrarily (Ratcliffe, 2012). In this dissertation adapting Caplan’s definition (Caplan, 2011, p. 57), spatial influence is defined as “the way in which features of a landscape affect places throughout the landscape”. According to McCord and Ratcliffe (2007), Ratcliffe (2012), and Rengert et al. (2005), the extent of the criminogenic spatial influence of landscape features may differ across cities, locales, or times. Moreover, the extent of spatial criminogenic influence of one feature might be different from another feature. Last but not least as suggested by Kennedy and Caplan (2012, p. 1), defining vulnerable places to crime risk “is a function of the combined spatial influence of criminogenic features throughout a landscape.” Despite the large number of potential risk factors for a crime outcome, emergence of crime might be the result of processes that involve the simultaneous existence of a smaller number of most necessary factors (Wikström, 2007). In the analysis of vulnerability to crime, risk can be used as “a metric to tie different parts of the crime problem together as it offers a probabilistic interpretation to crime analysis that allows us to suggest that certain things are likely to happen” (Kennedy and Gibbs Van Brunschot, 2009, p. 11).

This dissertation does not aim to provide a mechanistic explanation for the robbery emergence at places. Rather, it aims to augment the literature on crime emergence by representing environmental features’ temporal criminogenic effects on the environments in which street robberies occur. Previous research has found various variables to be associated with street robbery outcome. However, little is known as to the spatiotemporal influence of these factors. As mentioned earlier, one of the key tasks in emergence framework is to identify the conditions under which a crime will occur. With a Geographical Information System (GIS) based analysis of the time-geographical vulnerability to street robbery emergence, this dissertation aims to identify the characteristics of places at different times that gave rise to the street robbery outcomes in 2010 via a thorough examination of environmental features in the study extent.

Street robbery was an ideal crime type to be examined in this dissertation. According to the 2010 Uniform Crime Reports (UCR), robberies are the second most frequently reported violent crime—following aggravated assault—occurring once every 1.4 minutes in 2010 (Federal Bureau of Investigation, 2011d), with almost 367,000 incidents throughout the United States (Federal Bureau of Investigation, 2011c).

According to the 2010 UCR, robberies in metropolitan statistical areas (MSAs)[1] account for 95% of all incidents (Federal Bureau of Investigation, 2011a) and streets are the main locale of robberies (43%; Federal Bureau of Investigation, 2011f). Place characteristics play an important role in the offender's decision to engage in robberies. Robbers rob for thrill and revenge at times, but most robberies are financially oriented (Miller, 1998). Therefore, places offering less risk of detection, more accessible targets, and greater rewards are more attractive to offenders (Braga et al., 2011; Conklin, 1972; Feeney, 1986; Felson, 2006; Jacobs, 2000; Wright and Decker, 1997). Robbery is also an ideal crime type to predict with place-based indicators because it is a volume crime that can be analyzed using statistical and spatial tools (Sherman, 1992; Van Patten et al., 2009). Finally, with the fear it induces, robbery has an ineluctable effect on the quality of life (Braga et al., 2011).

[1] MSAs include the metropolitan city; the county in which the city is located; and other adjacent counties that have a high degree of integration with the metropolitan city.
[2] RTM toolbox is publically available at http://www.rutgerscps.org/rtm/
[3] hot spot cells in pink
[4] The minimum difference for drug charges and takeout restaurants between Model 0 and Model 2

# CHAPTER 1: CONCEPTUAL FRAMEWORK

## 1.1. Why Location Matters

Police officers know the most problematic places in their beats such as: certain blocks or the surroundings of specific shops, restaurants, hotels, schools, and more. Citizens avoid some places and seek out others in their daily routines; in some places they do not pay attention to strangers whereas in others they perceive strangers with suspicion and secure their belongings (Eck et al., 2005). Law enforcement's and citizens' shared sentiment of increased risk of crime and victimization at certain geographies is well supported in criminology with the studies of areas that have "a greater than average number of criminal or disorder events"—namely, *hot spots* (Eck et al., 2005, pp. 1-2).

In their famous study of calls for service in Minneapolis, Sherman et al. (1989), found hot spots of crime "in which the occurrence of crime is so frequent that it is highly predictable, at least over a 1-year period" (Sherman, 1995, p. 36). The hot spots research following Sherman et al. (1989), has been successful in informing the researchers on where different crimes cluster such as: specific block groups (e.g., Van Patten et al., 2009), census tracts (e.g., Bernasco and Block, 2009; Sorg and Taylor, 2011), street segments, face blocks and street intersections (e.g., Braga et al., 2011; Groff et al., 2010; McCord and Ratcliffe, 2007; Smith et al., 2000; Taniguchi et al., 2011; Taylor, 1997), grid cells (e.g., Cohen et al., 2007; Van Patten et al., 2009), and residential units (e.g., Bernasco, 2010).

Near-repeats analysis of crime events—which is "an extension of, or companion to hot spot analysis" (Kennedy and Caplan, 2012, p. 1)—on the other hand, has proven in different studies (Block and Fujita, 2013; Bowers and Johnson, 2004; Bowers et al., 2004; Johnson and Bowers, 2004a; Johnson and Bowes 2004b, Johnson et al., 2007; Lockwood, 2012; Ratcliffe and Rengert, 2008; Townsley et al., 2003; Townsley et al., 2003; Wells et al., 2012; Youstin et al., 2011) that, "not only are locations at risk of repeat victimization, but nearby locations are also at increased risk of crime up to a certain distance and for a certain time" (Haberman and Ratcliffe, 2012, p. 2). Different studies also compared the concentration of crimes among places to the concentration of crimes among offenders. For instance, Spelman and Eck (1989) concluded that crime concentration among repeat places is greater than among repeat offenders. After analyzing the crime incidents between 1989 and 2002 in Seattle, Weisburd et al. (2004) also concluded that crime was more concentrated at places than it was among offenders. According to the results of this study, Weisburd et al. (2004) found that police can approach four times fewer targets to identify the level of overall crime when they focus on places instead of people.

As supported by the aforementioned research, crimes cluster at micro places, and furthermore, focusing policing efforts on places rather than persons is a more cost and time effective strategy as it provides a fewer number of targets for police operations. The directing of the police interventions to crime hot spots has been successful in reducing the crime and disorder at particular geographies. However, these interventions have been more successful for certain crimes than others, and overall provided a greater benefit for reducing disorder than crime (Taylor, 1997).

According to a recent evaluation of the effect sizes of five randomized hot spot experiments on calls for service, only two out of five hot spot interventions had significant effect sizes. Among all five experiments, only two had a large and significant effect size, whereas one had a medium but non-significant effect size, and the remaining two had small and non-significant effect sizes (Braga, 2007). Furthermore, according to the same study, none of the aforementioned five experiments exhibited a significant effect size for the relationship between hot spot policing and violent disorder calls with or without hard crimes, including robberies (Braga, 2007). According to Taylor (1997, p. 1), some benefits of hot spot interventions were "more modest and short lived than expected." In their study of the near repeat patterns of armed robbery in Philadelphia, Haberman and Ratcliffe (2012, p. 1) concluded that despite the presence of armed robbery hot spots primarily derived of near repeat robberies, the relatively short span of the near repeat armed robbery chains—where the number of days between the initiation and the termination is rarely more than seven days—the temporal stability of hot spots were also found to be not associated with the "proportion of near repeat events within the hot spots." Hot spots and near repeats research has successfully proved the merit of shifting crime prevention efforts from offenders to places, however the study of the crime at places require the consideration of the environmental context at micro places.

According to Kelling and Coles (1996), channeling patrol deployments to hot spots of crime without knowing the spatiotemporal details has only a modest effect in crime prevention. A hot spot or a near-repeat, when analyzed solely based on the physical place (i.e., a specific street block), alienates the emergence of a crime incident from the environmental context that nourishes the conditions for that particular crime incident. For instance, street robbery incidents that happened in the early morning on a street block might be related to the early operating hour of a light rail station nearby. As Taylor (1997, p. 10) suggested, “features of the site itself and the surrounding area jointly contribute to the high crime rate.” Now, realizing the importance of the criminogenic influence of environmental context, researchers and crime analysts should focus on the analysis of spatiotemporal setting that promote the conditions for crime concentration at micro places.

### 1.2. Predecessors of Contextual Crime Analysis

The relationship between situational context and crime was incorporated into traditional criminology through the socioecological explanation of criminality. The forerunner of this approach was Robert E. Park and Ernest W. Burgess’s examination of how urban environments affect human criminal behavior. The authors referred to the conflict found in the urban city as a consequence of the heterogeneous contact of different racial and ethnic groups (Park et al., 2005). According to the authors, this heterogeneous interaction resulted in the emergence of natural areas that serve specific functions.

Based on the notion of natural areas, Burgess (1925) developed a theory in which urban cities take the form of concentric zones. Burgess (1925) argued that Chicago had five concentric zones surrounding the central business district, “The Loop” (Zone I). Of these five zones, the zone immediately surrounding the loop, Zone II, was the city’s least desirable area to live in, as a result of the zone’s high population turnover and community heterogeneity. Zone II became less attractive as a residential area because of industrialization and the inhabitation of the zone by poor residents. Criminal enterprises were also attracted to Zone II because the noncriminal immigrant residents in this zone were less effective in complaining to the authorities. Furthermore, in this zone the rents were low, and customer access was easier. As people became wealthier they moved to Zones III, IV, and V surrounding Zone II. However, since the criminogenic features of Zone II remained the same, the crime level in this zone did not decline.

Park and Burgess's notions of natural areas and concentric zones inspired the members of the Chicago School to perform field research on the effects of urban environments on crime and disorder. In his analysis of the career of gangs, Thrasher (1927) considered the physical structures such as businesses, brothels, and hotels as factors that can shape the development of gangs in addition to broader contextual factors such as the availability of resources and the level of competition among gangs. Shaw and McKay (1942) pointed to the pathological criminality of certain neighborhoods and attributed this criminality to the endemic social disorganization rather than the criminal tendency of residents in these neighborhoods. According to the Chicago School, "one cannot understand social life without understanding the arrangements of particular social actors in particular social times and places" (Abbott, 1997, p. 1152). Environmental studies following the Chicago School emphasized that criminal behavior can be understood by understanding how people react to their physical environments (Savage and Vila, 2003).

**1.3. Determinants of Vulnerability to Crime Risk at Micro Places**

*Crime Opportunities and Risky Places*

According to the micro assumptions of the Routine Activities Theory (RAT), the occurrence of a crime requires the spatiotemporal convergence of a likely offender, a suitable target, and the absence of a capable guardian (Cohen and Felson, 1979). Absence of any of these elements is sufficient to prevent the successful completion of a direct contact predatory crime (Cohen and Felson, 1979). Cohen et al. (1980), adding to the fundamental assumptions of RAT, suggested that increased number of situational opportunities at places will provide likely offenders more favorable conditions to offend. Caplan (2011), revisiting the explanation of opportunity in RAT, suggested that despite RAT's well known statement of "crime is more likely to occur when motivated offenders converge, suitable targets exist, and capable guardians are lacking":

> What is more likely to occur is that motivated offenders will commit crime against suitable targets at certain places according to the environmental characteristics of those places that make it easier to complete the crime successfully and reap the rewards without punishment (p. 60).

Caplan (2011, p. 61) further noted that, despite the popularity of RAT, the research adapting this theory "has been constrained in its ability to operationalize opportunity and to develop a metric for assessing it." Groff (2007, p. 76), elaborating more on the history of the adaptation of RAT to research, also concluded that the attempts to empirically validate this approach have produced inconsistent support due to "the lack of individual-level data and the inability to adequately model the complex and dynamic interactions of individuals that produce observed crime patterns." Caplan (2011), emphasizing the event focused nature of RAT, noted that the application of RAT to policing will be challenging as it requires the police to focus on future events by controlling for the behaviors of individuals. According to the Caplan (2011):

> what is more manageable for police agencies is to allocate resources to places that are most attractive to motivated offenders and to places where crime is most likely to occur given certain environmental characteristics. (p. 11)

Kennedy and Caplan (2012) further argued that the concentration of crimes at places is not necessarily about the number of opportunities at places (such as a higher number of offenders/targets) but rather a function of the conditions that make it more or less likely for the offender to complete the crime event (such as mechanical or tactical protection of targets). This spatial approach to crime incidents stems from Brantingham and Brantingham's well-known notion of *environmental backcloth*. Environmental backcloth refers to the elements of an environment (such as land uses, design features, physical infrastructure of buildings, transportation systems) that can influence individuals' criminal behavior (Brantingham and Brantingham, 1981). Brantingham and Brantingham (1995) differentiated between *crime generators* and *crime attractors* in an environmental backcloth. Crime generators are activity nodes that provide greater opportunities for crimes because of the high number of people that use these nodes, whereas crime attractors are activity nodes that attract offenders because of their well-known criminal opportunities (Brantingham and Brantingham, 1995).

Through the use of the concepts of crime generators and crime attractors as the features of a landscape that aggravates vulnerability to crime outcomes, the environmental backcloth notion provides the basis for a context dependent analysis of street robbery outcomes. As such, this dissertation explores what nourishes spatiotemporal vulnerability to robbery following Caplan's (2011, p. 61) suggestion that "opportunity for crime is an attribute of all places."

In the analysis of vulnerability to crime, risk is suggested to be used as "a metric to tie different parts of the crime problem together as it offers a probabilistic interpretation to crime analysis that allows us to suggest that certain things are likely to happen" (Kennedy and Gibbs Van Brunschot, 2009, p. 11). Following the notion of "risk metric," Caplan and Kennedy (2010, p. 7) conceptualized risk as a "continuous dynamic value that increases or decreases intensity and clusters or dissipates in different places over time." According to the Caplan and Kennedy (2010) crime risk is first and foremost tied to geography. Kennedy and Caplan (2012) suggested a theory of risky places which considers the effect of "threats, vulnerabilities, and consequences" on creating distinct, identifiable areas that are conducive to crime.

According to Kennedy and Caplan (2012), the vulnerability of places to crime risk comes from a very important attribute of places: their spatial influence. The idea of spatial influence of features helps the researcher to define vulnerable places via observations of the attributes of a landscape. Kennedy and Caplan (2012) further suggested that places within the simultaneous spatial influence of different criminogenic features should be more vulnerable to crime than places that are not influenced by one or more criminogenic features.

The concept of spatial influence is another key component for the conceptual framework for testing the vulnerability to street robbery emergence at micro places. First, it allows testing and quantifying the criminogenity of each individual robbery risk factor at micro places. Second, by using risk as a metric tied to micro geographies, the calculation of the combined criminogenic spatial influence of landscape features on street robberies offers a way to test the vulnerability to robberies at micro places with multiple criminogenic elements of a landscape.

*Risky Places and Risky Times*

As suggested by Kennedy and Caplan (2012), spatial influence, in addition to changing over geographies, can also change over time. The testing of the dynamic criminogenic influence of landscape features on street robbery outcomes is the most important contribution of this dissertation to the most current literature on crime and place. As Cohen and Felson (1979) argued, patterns of crime are affected by the temporal and spatial organization of the society. According to Cohen and Felson (1979):

> Strong variations in specific predatory crime rates from hour to hour, day to day, and month to month are reported often ... and these variations appear to correspond to the various tempos of the related legitimate activities upon which they feed. (p. 592)

According to Lersch (2007, p. 6), “just as there are dangerous high risk places and spaces, there are also blocks of time in which victimization for certain types of crime is more likely than others.” For instance, as suggested by Miethe et al. (2006), a person has a higher risk of becoming a homicide or aggravated assault victim at night, on the weekend, and especially on Saturday night. According to Lersch (2007) weekends turn into dangerous times as people tend to spend more time in public space, and consume more drugs and alcohol. As argued by the author, hourly and daily trends should be taken into consideration in crime research in addition to the current scholarship that considers the monthly, seasonal, and yearly trends.

As Groff (2007, p. 77) cautioned “although the importance of spatiotemporal elements in routine activities is often acknowledged, the spatial structure and timing of these activities has been widely overlooked.” Space and time are fundamental and co-existing entities of human life, and only when considered together, it helps us to understand how people use places over time (Abler et al., 1971). As such, “investigating both spatial and temporal aspects of crimes is crucial in understanding spatial crime patterns” (Kim, 2008, p. 141). Ratcliffe (2006) attributed the under-emphasis on the temporal differences to the increased popularity of spatial analysis after the introduction of Geographical Information Systems (GIS). Ratcliffe (2006) further argued that the patterns of opportunity-based crime are dependent on the temporal constraints placed on offenders and targets, such as work or school.

The exploration of how the daily and hourly relevance of features of a landscape control the rhythms of individuals can close the gap in crime and place research in understanding the settings that give rise to crime incidents. For instance, in their studies of hot spot formation, Tompson and Townsley (2010) explored if hot spot forecasting can be improved when the data is divided into time-of the-day cycles. According to the results of this study, Tompson and Townsley (2010) concluded that predictive accuracy of hot spots can be improved when temporal cycles are incorporated into analysis.

According to the time geography framework (Hägerstrand, 1970), rather than explaining an individual's allocation of time among activities in space, researchers should try to understand how spatial factors restrict an individual's choices. The time geography framework acknowledges both spatial and temporal dimensions of human activity (Miller, 2004; Miller, 2005). All human activities are interconnected on temporal and spatial dimensions (Pred, 1977). Time geography mainly focuses on the interrelationships between activities in time and space, and how these interrelationships impose constraints on human behavior (Miller, 2004; Miller, 2005). One of the constraints that places can exert on human activities is *coupling constraints* which dictate "where, when, and for how long, an individual has to join with others to produce, transact or consume" (Miller, 2005, p. 221). Activities at home and work, shopping, recreation, socializing, etc., occur only at specific locations for a limited duration (Kwan, 2000; Miller 2004; 2005; Yule and Griffiths, 2009).

The need for the spatiotemporal coordination and sequencing of human activity results in the formation of spatiotemporal bundling at locations that provide the means for different activities (Miller, 2004). Miller (2004; 2005) further commented on the pliability of human activities. According to Miller (2004), people engage in fixed activities that are difficult to reschedule or relocate such as: working or going to school, familial obligations, and biological needs that require regular intervals and fixed places (at least over the short run). However, there are also flexible activities such as shopping, recreation, and socializing that are relatively easy to reschedule and relocate compared to fixed activities.

Although individuals can plan where and when flexible activities occur, dependent on the locations and operating hours of the venues offering these activities, even flexible activities might be restricted in time and space (Miller, 2004). Based on the restrictions that settings put on the movement patterns of offenders and targets, different places can become risky places for crimes at different times.

The notions of the time geography framework are used to augment the contextual analysis of robberies. Focusing on what a person can do, bundling the basic human activities such as work, leisure and rest in time and space justifies the analysis of the criminogenic spatial influence of landscape features at different times of the day and different days of the week. This temporal dimension of this dissertation is believed to be of particular importance for police enforcement as the data on the extent and strength of the persistent criminogenic influence of different landscape features at different times can be used in planning the type, time and length of the interventions to control or reduce crime at particular geographies.

The study and detection of expected and unexpected criminogenic influences is of particular importance for crime analysis. As Taylor suggests (1997, p. 12), "an understanding of setting dynamics would provide guidance on" the most effective and minimally intrusive interventions at problem places. These interventions can include a mixture of interventions from law enforcement, place managers, business owners, citizens, and public and private organizations.

In light of the aforementioned time geography argument on the constraints imposed on human activities by the changing social relevancy of places at different times, and building on the notions of environmental backcloth and risky places, this dissertation tests the dynamic criminogenic spatial influence of landscape features on street robberies at different times of the day and different days of the week following the principles of Risk Terrain Modeling.

*Risk Terrain Modeling*

Risk Terrain Modeling (RTM) was developed by Caplan and Kennedy (2010) to assess risk for crime events based on the spatiotemporal interaction effects of risk correlates identified by research and practice. In many ways, the methodological approach to RTM resembles the assessment of risky behavior in offender risk management studies.

In the studies focusing on the psychology of criminal conduct, several risk factors have been examined such as: history of anti-social behavior, anti-social behavior patterns, anti-social cognition, anti-social associates, low nurturance and supervision in the family, low level of performance and satisfaction at school or work, heightened level of involvement and satisfaction in anti-criminal leisure pursuits, and abuse of alcohol and drugs (Andrews et al., 2006).

Studies of criminal risk assessment discovered different predictive powers for different risk factors. The current actuarial criminal risk assessment tools have been built upon a statistical background of risk appraisal through use of an instrument that statistically identifies, weighs, and combines several risk factors to reach a composite numerical risk score for the relevant outcome behavior.

Similarly, the research assessing childhood problems have considered risk factors such as: ineffectiveness of social policies; low quality of schooling; low quality of parenting; low level of personal skills, social skills, and self-efficacy; and lack of social support, simultaneously (Sreenivasan et al., 2000). These studies argued that rather than considering one explanation for a negative outcome, identifying multiple risk factors and understanding how these factors add up is more crucial because multiple risk factors have multiplicative effects on undesirable outcomes.

RTM, also recognizing the simultaneous influence of multiple risk factors on undesired outcomes, assesses the risk of a crime event at geographies based on the spatiotemporal factors “that precede, interact with, and follow” an incident’s occurrence (Caplan and Kennedy, 2010, p. 8). RTM, driven by producing intelligence that is meaningful and actionable, provides a methodological framework for law enforcement, crime analysts and researchers to assess risk through the completion of a series of analytical steps using statistical software and GIS.

In RTM, “Risk” refers to the probability of an occurrence of an undesired outcome (e.g., crime, disorder) determined by the increased contextual vulnerability and past incident exposure at places. “Terrain” refers to a study extent of equally sized grid cells that contain the contextual and event-based risk values. And “Modeling” refers to “attributing the presence, absence, or intensity of qualities of the real world to places within a terrain”, to study their simultaneous effect on the risk for undesired outcomes (Caplan and Kennedy, 2010, pp. 22-23).

In RTM, the ways in which micro geographical level effects combine “is an important aspect for setting up the ‘meaning’ that a risk terrain model will carry” (Caplan and Kennedy, 2010, p.24). Despite the relatively static characteristic of features at places, RTM considers the interactive effect of the influences of these static features as dynamic over space and time. With the ability to compute the criminogenic patterns at micro places based on the changing weights of the criminogenic influences of landscape features and their interaction effects, RTM offers the conceptual and methodological framework to operationalize and test the dynamic criminogenic influences of landscape features on robbery outcomes at different times of the day and different days of the week.

In RTM, a risk terrain model is produced in ten steps that are explained in detail by Caplan and Kennedy (2010). The first three steps of RTM follows the first steps of any scientific inquiry: identification and clarification of a broad area of interest.

In the first step, the researcher identifies a problem of interest and chooses an outcome event that matches the problem of interest. Since the risk factors that give rise to undesired outcomes might be different from one another, it is very important in crime analysis to subcategorize crimes into different categories with different criminogenic signatures (Clarke, 1995; Yu and Maxfield, 2014). As such, in this dissertation, with the interest in the emergence of robberies in open space, outcome events were limited to street robberies.

In the second and third steps of RTM, the researcher chooses a study extent and a time-period for creating the risk terrains. These steps are of particular importance in RTM since the meaningfulness and actionability of the produced risk terrain maps depends on the spatiotemporal boundaries created by the researcher in exploring the relationship between outcome events and risk correlates. In this dissertation the City of Newark, NJ and the calendar year 2010 have been chosen as the spatiotemporal extent of this study. The fourth, fifth and sixth steps of RTM follows the literature review and data collection steps in the scientific inquiry process.

In the fourth step, the researcher obtains the geographical base maps of the study extent. In the fifth step, the researcher compiles an exhaustive list of related correlates to include in the analysis through means such as “meta-analysis, or other empirical methods, literature review, professional experience, and practitioner knowledge” (Caplan and Kennedy, 2010, p. 79). In the sixth step of RTM, the researcher chooses which correlates among the ones identified in step five, to include in the risk terrain models. Caplan and Kennedy (2010) devise two ways to decide on these correlates: the ad-hoc method of including all the variables pertaining to risk of the particular outcome of interest or the empirical method of factor selection following a series of statistical tests.

In this dissertation the exhaustive list of risk correlates for street robberies were compiled with a thorough review of street robbery literature and the observation of the 2009-2010 landscape features at the 2010 street robbery hot spots using Google Earth. The risk factors to be included in the analysis were chosen following a series of Negative Binomial Regression analyses of the criminogenic influence of features identified through literature review and Google Earth observations of 2010 street robbery hot spots.

The seventh, eighth, and ninth steps of RTM follow the analysis steps of a scientific inquiry process. In the seventh step, the researcher creates risk map layers for each risk correlate selected in step six to represent the criminogenic spatial influence of each risk correlate. While operationalizing the spatial influence of a risk factor, one can represent the absence, presence or intensity of each risk factor (Caplan and Kennedy, 2010; Caplan, 2011). In the eighth step, the researcher weighs the risk factors in relation to one another using a statistical method.

In this dissertation the weights of risk factors were calculated using the Relative Spatial Influence (RSI) tool in RTM Toolbox[2] developed by Rutgers Center on Public Security. In the ninth step, the produced and weighted risk map layers are combined in a GIS. In RTM, the equal size of the cells of raster risk layers makes it possible to combine multiple risk map layers within the same geography to produce a composite risk terrain map that represents the overall criminogenic influence of multiple features at a particular place. In the tenth step, the composite risk terrain map produced in the previous step is finalized in a GIS. In the optional eleventh step, the predictive ability of the risk terrain model can be tested with statistical testing using outcome events.

The value and suitability of RTM for spatial crime risk assessment and police resource allocation has been tested and proved in various studies. For instance, in their study of shootings in Irvington, NJ, Caplan et al. (2011) used risk terrain maps that were produced following the steps of RTM, using risk correlates of  gang member dwellings, locations of retail businesses (bars, strip clubs, bus stops, check cashing outlets, pawn shops, fast food restaurants, and liquor stores), and locations of drug arrests. In this study

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[2] RTM toolbox is publically available at http://www.rutgerscps.org/rtm/

of Irvington, for each of these three risk factors, the density of the features was calculated in a GIS with a raster cell size of 100 ft. x 100 ft. and a search distance of 1,000 feet. After calculating the densities of these three feature groups, the resulting density values in each of the three map layers were reclassified into four groups according to standard deviational breaks from the mean density values. For testing the predictive ability of the risk terrain, the shooting data between January 2007 and June 2008 were classified into three consecutive six-month periods (January-June 2007, July- December 2007, January-June 2008). After creating two separate risk terrain maps for January-June 2007 and July-December 2007, the predictive validity of the January-June 2007 risk terrain map was tested with the shooting data from July-December 2007, and the predictive validity of the July-December 2007 risk terrain map was tested using shooting data from January-June 2008. The results of a logistic regression analysis of the odds of shootings at high-risk cells revealed that for every increased unit of risk at a study extent cell, the odds of a shooting at the same cell increased by 56% for the risk terrain map of January-June 2007, and 69% for the risk terrain map of July-December 2007 (Caplan et al., 2011, p. 372). Caplan et al. (2011) further compared the predictive power of the risk terrain maps to the predictive power of shooting hot spot maps produced with only past shooting events. To do that, Caplan et al. (2011) used the density maps of the January-June 2007 and July-December 2007 shooting incidents—which were produced the same way as the density risk maps of features in risk terrain modeling—to forecast the locations of shootings between July and December 2007, and January and June 2008, respectively. This additional step was done to show the improvement of a contextual analysis with RTM over hot spot mapping with only prior outcome events. Following a comparison of the

RTM maps and hot spot maps pertaining to the same time periods, Caplan et al. (2011, p. 374) proved that risk terrains are “substantially more accurate than retrospective hot spot mapping.” Based on the aforementioned results Caplan et al. (2011, p. 378) concluded that RTM as a contextual analysis framework can augment “tactical operations, case management, and resource allocation,” and it might be specifically valuable to police agencies with fiscal constraints. In this paper of proof of concept for RTM, Caplan et al. (2011) suggested extending the use of RTM to different types of crimes and settings, and also considering different ways to operationalize and test variables other than the ones used in this first paper. Caplan et al. (2011) further suggested the development of strategies to integrate RTM to policing and testing the influence of the effectiveness of such strategies.

Following Caplan et al.’s (2011) suggestion, Kennedy et al. (2011) tested the utility of RTM for a police resource allocation strategy. In their study of the shootings in Newark, Kennedy et al. (2011) further elaborated on the selection criteria for risk factors in RTM, the comparison of the best risk terrain models with contextual data to hot spot mapping with past crime events, and the exploration of the use of risk clusters in risk terrain maps as an alternative to hot spot maps for police resource allocation. In this study, Kennedy et al. (2011) suggested an empirical selection method for the risk factors to be included in the RTM analysis. From a pool of  seven risk factors identified for shootings—namely drug arrests, gang territory, at-risk housing, risky facilities, shootings, gun robberies, and parolees— Kennedy et al. (2011) selected only the risk factors that were the most significant and influential for the shootings in Newark through a set of Chi-squared tests. The authors first classified the shootings in Newark into five consecutive time periods: July-September 2008 (Period 1), October-December 2008 (Period 2), January-March 2009 (Period 3), March-June 2009 (Period 4), and July-September 2009 (Period 5). Then they tested the significance of the seven risk factors that existed during Period 1 with the shooting incidents from Period 2. The results of the Chi-squared tests indicated that among the initial seven risk factors, six risk factors were significant predictors of shootings in Period 2 at a 0.05 significance level, four factors were significant predictors of shootings at a 0.01 significance level, and three risk factors were significant predictors of shootings at a 0.01 significance level "whose proportions of cells experienced 20% or more shootings at places with each risk factor" (Kennedy et al., 2011, p.349). Following the Chi-squared tests, Kennedy et al. (2011) created four composite risk terrain maps for: 1) all seven risk factors, 2) risk factors significant at 0.05 significance level, 3) risk factors significant at 0.01 significance level, and 4) risk factors significant at 0.01 significance level and whose proportions experience 20% or more shootings. The researchers then tested the statistical significance of these risk terrain maps for Periods 1-4. In all periods, the risk terrain maps produced with significant risk factors at 0.01 significance level and 20% or more shootings had the highest predictive ability (Kennedy et al., 2011, p.350). Kennedy et al. (2011) further compared the predictive ability of risk terrain maps of shootings with hot spots of shootings and found that risk terrain maps had a better predictive ability than the hot spot maps in all time periods. Lastly, Kennedy et al. (2011) suggested the identification of risk clusters for resource allocation as identification of high-risk of crimes based on place based characteristics can help the police to decide on where additional resources should be allocated, whereas areas of lower risk can be exposed to routine police activities.

Caplan (2011), furthering the discussion of spatial influence in RTM, tested the effects of different spatial influence operationalization schemes for crime analysis and criminal justice practice. With an example of a risk terrain model for the shootings in Irvington, Caplan (2011) exemplified three ways for operationalizing the spatial influence of risk factors: noting their presence or absence, calculating the density of features, and calculating the distance from features. Caplan (2011) further illustrated the individual contribution of each statistically significant risk map layer to the predictive ability of a risk terrain and, more importantly, the added value of these risk map layers to the predictive ability, when their combined effect is taken into consideration. Caplan (2011), further suggested that the key to producing reliable and valid forecasting models using place-based indicators require, empirically and theoretically grounded variables with spatial influences that are operationalized thoughtfully.

In their study of the joint utility of RTM, hot spots, and near-repeats, Caplan et al. (2013) concluded that the inclusion of an environmental risk value to hot spot and near-repeat analyses produced better violent crime prediction models than those produced solely with hot spots or near repeats of violent crimes. Similarly, in their study of the joint utility of RTM and near-repeat analysis Moreto et al. (2013) found that residential burglaries are more likely to occur at places that are under the spatial influence of criminogenic landscape features (i.e., residential land use, at-risk housing, pawn shops, burglar residences, and drug markets), and furthermore, residential burglaries that were identified to be instigators for near repeats and near repeats are more likely to occur at places that are under the spatial influence of criminogenic features. The study of the effects of Kansas City's Violence Crime Initiative (VCI) on micro level crime frequency and patterns with RTM also revealed that in both pre-VCI and post-VCI periods, the locations of the aggravated assaults were affected by both past incidents and the criminogenic spatial influence of environmental factors, and pre-VCI and post-VCI aggravated assaults happened at geographies that were contextually similar (Caplan et al., 2012). In his analysis of robberies in Milan, Italy using RTM, Dugato (2013) concluded that RTM was as effective as Kernel Density Estimation (KDE) in identification of crime hot spots. In her study of burglaries in a mid-sized city, Yerxa (2013) used day cycles with different lengths (14-days, 28-days, 84-days, and 168- days) to test the predictive validity of RTM and discovered that in shortened time-cycles a smaller number of predictor variables were found to be significant enough to be included in the RTM analysis. Yerxa (2013) compared the effectiveness of RTM with KDE and concluded that RTM was an improvement over KDE and, regardless of the time cycles used to test the significance of RTM models, a risk terrain model was effective for residential burglary prediction.

Following the suggestions by Caplan et al. (2011) on extending RTM to different crime types and settings with different ways to operationalize and test variables, this dissertation extends the use of RTM to street robberies and tests the extent and weight of the criminogenic spatial influence of different risk factors for street robberies at different times of the day and different days of the week. Furthermore, based on the identified criminogenic influence of individual risk factors at different time periods, this dissertation produces combined risk terrain maps to test the predictive validity of risk terrain maps for robberies in each time period.

## 1.4. Determinants of Street Robbery Risk at Micro Places

*Street Robberies and Cash Economies*

Cash economies, which are also known as cash businesses, are defined as "micro places with specific functions, such as bars, fast-food restaurants, check-cashing centers, and pawn shops, that is, places that bring together, often in large numbers, people who carry cash, some of whom are distracted and vulnerable" (Bernasco and Block, 2011, p. 34). In this section several studies on street robberies are overviewed to explore the relationship between cash economies and street robberies.

In his ethnographic study of the crime on Chicago streets, St. Jean (2007) used the concept of *ecological advantage* to explore the mechanisms that make certain blocks in a high-crime neighborhood more crime-prone than the others. Based on the testimonies from robbers, police officers, and residents in high-crime neighborhoods, St. Jean (2007, p. 165) concluded that "ecological advantages a place offers to robbers" was the missing ingredient that makes certain places more attractive to robbers than others in a neighborhood with the same levels of physical disorder and/or low collective efficacy. *Collective efficacy*, or the "social cohesion among neighbors combined with their willingness to intervene on behalf of common good," is suggested as a mechanism to control deviancy in neighborhoods (Sampson et al., 1997, p. 918).

The level of collective efficacy indicates the degree to which individuals and objects in a bounded locale possess an "aggregated capable guardianship" over the crime enabling nature of geographies (Wilcox et al., 2003, p. 61). St. Jean's study (2007, p. 162) of the hot spots of robberies in high-crime and low-collective efficacy neighborhoods revealed that robbers do not select locations to rob based on the signs of physical and social disorder in a neighborhood, rather they frequent the surroundings of cash businesses where they "anticipate several people to be walking around in a state of distraction with money or other valuable items in their possession".

St. Jean (2007, p. 163) suggested that low-collective efficacy by itself is "insufficient to produce high-robbery rates if the block in question does not additionally offer robbers the ecological advantages." His interviews with the robbers also revealed that robbers are most attracted to street blocks in the vicinity of businesses where people are likely to have cash in possession such as: check-cashing establishments, banks, grocery stores, hair salons, sit-down and take-out restaurants, retail stores, gas stations and liquor stores. Interviews with the robbers also revealed also some temporal patterns in the robberies, such as robbers frequenting business locations when they know that there are people, but not too many people. Furthermore, some robbers which are referred to as "night peoples" do "robberies very often, but only or mostly in the nighttime" (St. Jean, 2007, p. 158).

Several other studies also emphasized the criminogenic spatial influence of cash businesses on street robberies. For instance, in another study of the street robberies in Chicago, Bernasco and Block (2011) found that businesses such as, bars and clubs, fast food restaurants, barbers and beauty salons, liquor stores, grocery stores, general merchandise stores, gas stations, laundromats, and pawn shops have a criminogenic spatial influence on street robberies.

According to Wright and Decker (1997) and Tilley et al. (2004), proximity to pubs, bars, and exotic dance clubs present a high risk for robbery, as offenders prefer to target their victims when they are drunk and less attentive to their personal safety. Tilley et al. (2004) also suggested that the proximity to leisure and food outlets increase the victimization chance as these venues attract a great number of young school age people and young adults.

Tilley et al. (2004) further suggested that offenders prey on students along the routes and shortcuts between main university teaching sites and residence halls. Furthermore, proximity to cash points and cash economies (such as banks, gas stations, hair salons, laundromats, pawn shops, post offices) also increases the likelihood of street robberies as the suitable targets will be cash rich when entering or leaving these sites (Bernasco and Block, 2011; Tilley et al., 2004; Wright and Decker, 1997). The majority of the offenders are mostly interested in locating targets carrying a substantial amount of money to acquire the dollar sum they need in just one offense (Wright and Decker, 1997). The presence and proximity to leisure and food outlets are also believed to increase the victimization chance as these venues attract a great number of young school age people and young adults (Tilley et al., 2004).

In their study of street robberies on face blocks in a medium size southeastern U.S. city, Smith et al. (2000) also concluded that cash businesses such as bars, restaurants, and gas stations have a criminogenic spatial influence on street robberies on the blocks they are located on. Similar to Smith et al. (2000), in their study of the criminogenic influences of bars and taverns in Cleveland, Roncek and Meier (1991) found that bars have a criminogenic influence on robberies on the blocks they are located. In his study of robberies in Milan, Italy, Dugato (2013) also found that one-block vicinity of alcohol-licensed premises, banks, and post offices had a criminogenic influence on robberies.

*Street Robberies and Public Transit Stations*

Criminals specifically travel to public transport stations to commit crime and they target victims waiting around isolated bus stops and train stations (Tilley et al., 2004). Rail transit stations attract offenders as they provide anonymity and easy entry and exit for potential offenders (Suttles, 1972). Suttles (1972) argued that riders become potential targets for the offenders because most of the time targets live away from the transit station, thus, they are not familiar with the surrounds of stations. It has been also noted that public transit stations increase the risk for crime victimization as they provide more targets for likely offenders by transporting large number of high-risk targets along the stations (Brantingham and Brantingham, 1995). Ihlanfeldt (2003) on the other hand argued that the opening of rail stations in a neighborhood can decrease the crime rate with the movement of potential offenders from their residences to other areas to commit their crimes anonymously.

In their study of the surrounds of rapid transit stations in four police districts in Chicago, Block and Davis (1996) found that in northeast districts with low robbery rates, street robberies were concentrated around near rapid transit stations whereas in west districts with high robbery rates, street robberies were more dispersed. In the northeast districts, where the vicinity of the rapid transit stops are poorer and more transient than the rest of community, the stops were primarily used for commuting to work and for recreational purposes, and the transit stations were working on a 24-hour schedule. In the west districts, where the population is quite homogeneous, with the increased level of gang activity and lack of businesses and recreational facilities, the stations were mainly used to go to work or shopping in downtown Chicago.

According to the results of this study by Block and Davis (1996), in northeast districts, 36% of the robberies were observed to occur within two blocks (1,300 feet) of a transit station, and 56% of the robberies were observed to occur within four blocks (around 2,500 feet) of transit stations. From all the robberies that occurred within two blocks of the stations in the northeast, 20-25% of robberies occurred between 12 a.m. and 4 a.m. Block and Davis (1996) attributed the concentration of robberies in late night-early morning hours in the northeast to the closing time of bars and taverns, the scarce transport opportunities for the patrons of bars and taverns, and reduced community policing and resident patrols in late hours.

In the west districts of this study, although the surrounds of transit stations were dangerous for robberies, the robbery incidents were more homogenously distributed compared to the northeast districts. Compared to the 39% of robberies in the northeast districts which occurred within two blocks of the rapid transit stations, only 17% of the robberies in the west districts occurred within two blocks of rapid transit stations. Similar to the spatial distribution of the robbery incidents, robberies were temporally more homogenously distributed in the west districts compared to the northeast districts. The number of robberies in the west districts peaked between 3 p.m. and 11 p.m., declining significantly into the late night and early morning hours. Block and Davis (1996) attributed this trend to the lack of bars and taverns in the west districts. Furthermore, the authors noted that in the west district, with the exception of the lack of robberies around industrial areas and railway yards, robberies were homogenously distributed around residential or commercial blocks. In their study of rapid transit stations in New York City and Chicago Block and Block (1999) also found that street robberies were mostly in one to one and a half block radius from the transit stations.

In their analysis of a newly opened Green Line in Los Angeles, Liggett et al. (2003) concluded that the introduction of the new light rail line did not increase the Part I crimes in the neighborhoods around the light rail stations, especially for the affluent suburban neighborhoods, and caused a small increase for the neighborhoods around the stations in the inner city. The authors further attributed the formation of Part I crime hot spots to the proximity to other features such as retail stores, high schools and public housing.

Similar to Liggett et al. (2003), in his study of the MARTA line in Atlanta, Ihlanfeldt (2003) also found that after the opening of the stations, there were slightly more robberies around the stations in the inner city, whereas there were either less or the same amount of robberies around the stations in the suburbs.

In another earlier study of MARTA line in Atlanta, Poister (1996) found that when the stations were opened, there was an increase in the number of reported crimes, including robberies, in a one to one and a half mile distance to the stations; however crimes stayed at the same level following the launch of the stations.

Plano's (1993) analysis of the Part I crimes around three Baltimore Metro stations concluded that the rise in crime rate could not be attributed to the rail stations. In their study of the crimes around Charlotte light rail line, Billings et al. (2011) found that robberies decreased within half a mile of the light rail stations after the announcement of the new light rail line. Following the opening of the rail line, there was not an increase in the number of reported robberies.

In her analysis of crimes around bus stops, Yu (2009) found that the number of bus stops was statistically significant to increased robbery in Newark, NJ. In his study of robberies, Dugato (2013) also found that proximity to stations increased robberies in Milan. In their intensity value analysis of the robberies around the subway stations in Philadelphia, McCord and Ratcliffe (2009) also found a concentration of street robberies around subway stations.

*Street Robberies and Illegal Markets*

Proximity to drug dealing areas is a strong correlate of street robberies when the motive of robbery is to acquire cash in exchange for drugs, especially when small-scale drug dealers and customers are targeted as victims (Wright and Decker, 1997). In some occasions, drug dealers rob customers when they have a payment due from the customer and the customer does not pay the dealer or, in other cases, dealers might rob other dealers that make more money than them (St. Jean, 2007).

People seeking illegal sexual activities also become ideal robbery targets because they carry cash for the transactions and they are more reluctant to report the crime incident (Tilley et al., 2004). Furthermore as suggested by Scott and Dedel (2006) and Tilley et al. (2004), since many prostitutes are addicted to drugs, proximity to prostitution areas might increase robbery victimization risk with the interacting criminogenic influence of drug markets and prostitution areas on places. In their study of street robberies in Chicago, Bernasco and Block (2011) discovered that not only the blocks that hold illegal markets but also their adjacent blocks have a heightened robbery risk. In his study of robberies in Milan between 2007 and 2010 Dugato (2013) also found that locations in high-density prostitution activities are risky places for street robberies.

*Street Robberies, Public Housing, and Schools*

Tilley et al. (2004) suggested that robbers prey on students around schools and along the routes and short-cuts between teaching sites and residence halls. In different studies proximity to public housing was also found to have a criminogenic spatial influence on robberies or violent crimes including robberies (Dugato, 2013; Fagan and Davies, 2000; Haberman et al., 2013, Holzman et al., 2005, Roncek et al., 1981).

In his study of robberies in Milan, Dugato (2013) found that robberies were more likely within one block distance to public housing. In their study of public housing in Bronx, NY, Fagan and Davies (2000) found that violent crimes were the highest within 0-100 yards to the public housing. In their study of the robberies within the immediate vicinity (50 feet), one block, and two blocks of public housing, Haberman et al. (2013) found that not all public housing had increased robberies around them, but public housing located in close proximity to other non-residential facilities had an increased robbery risk. In their study of the effect of different types of public housing designs on violent crime, Holloway and McNulty (2003) concluded that not all public housing has the same criminogenic influence.

Focusing on the public housing in large cities, Holzman et al. (2005) found that robberies were more within 1,000 feet of public housing. However the authors suggested that public housing had a smaller criminogenic influence on crimes compared to cash economies. In their study of the public housing in Cleveland, Roncek et al. (1981) found that proximity to public housing had a small, but nonetheless significant, criminogenic influence on violent crime. However, Roncek et al. (1981) also suggested that, when the socio-demographic characteristics of the households in the adjacent blocks of public housing were taken into consideration, the proximity to public housing is one of the least important predictors of violent crime.

As aforementioned, many landscape features at some point or another were identified to have a criminogenic spatial influence on street robberies. As suggested by Wilcox and Eck (2011), the emergence of crimes at places is more of a function of the human interaction at places rather than the presence of particular features. This suggestion is further supported by Eck et al.'s (2007) finding that not all facilities are equally criminogenic. This dissertation, considering the literature on the place-based determinants of crime in general, and robberies in particular, explores the dynamic criminogenic influence of robbery risk correlates at different times of the day and different days of the week. The following section provides the research questions and hypotheses for this dissertation.

### 1.5. Research Questions and Hypotheses

The review of the literature on the determinants of crime at risky places and risky times, and particularly the determinants of robberies at micro places raises two research questions about the spatiotemporal emergence of street robberies. The first question is: "To what extent do the spatial influences of criminogenic features of the landscape effect the occurrence of street robbery incidents at micro places at different times of the day (i.e. day, night) and week (i.e. weekday, weekend)"? Based on this question, it is assumed that:

- *Hypothesis #1 (H1): The spatial extents of the criminogenic influence of landscape features on street robberies are different from one another at different times of the day and different days of the week.*
- *Hypothesis #2 (H2): The criminogenic landscape features for street robberies are different at different times of the day and different days of the week.*

Several studies identified that cash economies have a criminogenic spatial influence on street robberies (Bernasco and Block, 2011; Dugato, 2013; Roncek and Meier, 1991; Smith et al., 2000; St. Jean, 2007; Tilley et al., 2004; Wright and Decker, 1997). Assuming cash economies primarily attract offenders during operating hours three sub-hypotheses are formulated from H2:

  - *H.2.1. Cash economies that have regular business hours exert a significant criminogenic spatial influence on street robberies during business hours on the weekdays and the weekend.*
  - *H.2.2. Cash economies with late business hours exert a significant criminogenic spatial influence on street robberies during late hours on the weekdays and the weekend.*
  - *H.2.3. Cash economies with regular and late business hours exert a significant criminogenic influence on street robberies during business hours and late hours on the weekdays and the weekend.*

Regarding rail stations, based on the extensive literature on the non-criminogenic effect of rail stations on street robbery outcomes in the long-term (Billings et al., 2011, Ihlanfeldt, 2003; Ligett et al., 2003; Plano, 1993), it is hypothesized that:

- *H.2.4. Light rail stations do not have a significant criminogenic influence on street robberies.*

Any non-commercial features of the landscape are assumed to have an overall criminogenic influence on street robberies at different times of the days and different days of the week. Non-commercial features are used to represent any feature that is not zoned to particular geographies like cash economies. Despite the fact that certain non-commercial features, such as schools and churches, have particular times and days of operation, non-commercial features are assumed to have a round-the clock criminogenic influence on street robberies with their homogeneous geographical presence in municipal zones. Based on this assumption the following sub-hypothesis is formulated:

- *H.2.5. Non-commercial features of the landscape have a significant criminogenic influence on robberies during all times of the day and the week.*

With that being said, such features are expected to exert their strongest criminogenic influence during operation hours and days.

Illegal markets are also assumed to have an overall criminogenic influence on street robberies at all times of the day and different days of the week. Based on this assumption it is hypothesized that:

- *H.2.6. Illegal markets have a significant criminogenic influence on robberies during all times of the day and the week.*

In her study of the effectiveness of RTM on predicting residential burglaries Yerxa (2013) found that in shortened time-cycles a smaller number of predictor variables were significant in the RTM models. Following the result of this study it is hypothesized that:

- *H.2.7. Robbery forecasting model with no time-of-the-day and day-of-the-week cycles has more criminogenic features than time-nested forecasting models.*

In recent literature it was also suggested that the weight of the criminogenic spatial influence of landscape features might be different for different types of crimes and different study extents (Caplan et al., 2011, Caplan, 2011; Ratcliffe, 2012). To augment the discussion on the extent and weight of the criminogenic spatial influences of landscape features, the following hypothesis is formulated:

- *Hypothesis #3: The weights of the criminogenic spatial influences of landscape features on street robberies are different from one another at different times of the day and different days of the week.*

In Hypotheses 1, 2, and 3, the overall argument that different features will have different effects on street robberies might be argued to be a result of statistical challenges such as the infrequency of crime, the unexplained variation in the sample. This difference might also be argued to be true by definition. This dissertation aims to overcome these challenges by an in-depth discussion of the criminogenic effects of each feature within and between time models and identifying certain features that exert a similar trend in comparison to the rest of the features.

The second research question of this dissertation is “Are places under the combined criminogenic spatial influence of landscape features more vulnerable to street robberies”? The literature on RTM has already proved that different crimes emerge at risky places based on the combined criminogenic spatial influence of different landscape features (Caplan, 2011; Caplan et al., 2011, Caplan et al., 2012; Dugato, 2013; Kennedy et al., 2011; Moreto et al., 2013, Yerxa, 2013). Based on the results in the RTM literature, the following two hypotheses are formulated:

- *Hypothesis #4: Street robberies emerge at places when there is high risk based on the combined spatial influence of criminogenic features of landscape at different times of the day and at different days of the week.*
- *Hypothesis #5: A robbery forecasting model with no time-of-the-day and day-of-the-week cycles has a weaker prediction power than forecasting models with time cycles.*

# CHAPTER 2: STUDY SETTING AND DATA SOURCES

## 2.1. Study Setting

The study setting is the City of Newark, the largest city in the State of New Jersey. New Jersey has the ninth greatest number of robberies in the United States, with a rate of 134 per 100,000 population (Federal Bureau of Investigation, 2011b). Newark has a long-standing reputation as a tumultuous urban environment. In 2010, the rate of robbery in Newark (572 per 100,000 population) was more than four times the state's overall rate (Federal Bureau of Investigation, 2011e). Given the current figures of crime in Newark, and the metropolitan characteristic of robberies, Newark was chosen as the study extent. In this study, the industrial areas including Newark Liberty International Airport and Port Authority were excluded from the study extent because these areas prohibit residency and they do not fall within the Newark Police Department (Newark PD) jurisdiction (see Fig. 1). The unit of analysis of this research is defined as 145 ft. x145 ft. cells (N=21,931) within the Newark study extent. This cell size was chosen as it represents half the approximate median length of a Newark city block (290 ft.) and this length is believed to be small enough to capture micro-level detail yet large enough so that policing efforts can be directed efficiently. This length is also believed to provide a better estimate than average street length as highway street segments skew the average length of Newark streets. As can be seen in Figure 2, in Newark, street robberies are evenly distributed throughout the landscape. In this particular regard, the Newark study extent can be argued to be different from a majority of study extents with a more heterogeneous robbery distribution. Therefore, the study of the distribution of street robberies at different times, considering the changing environmental setting at different times, is of particular research value.

**Figure 1. Newark Study Extent**

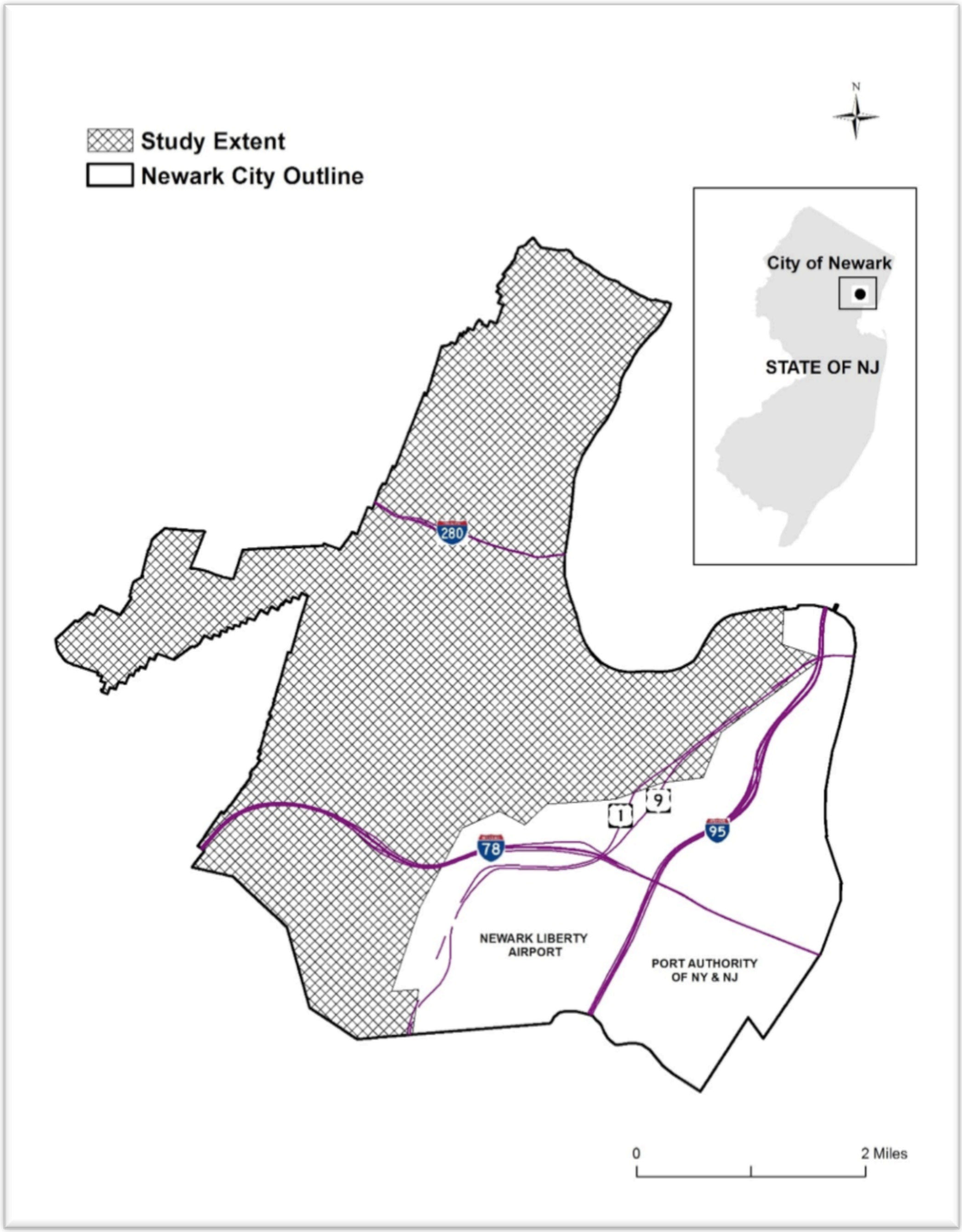
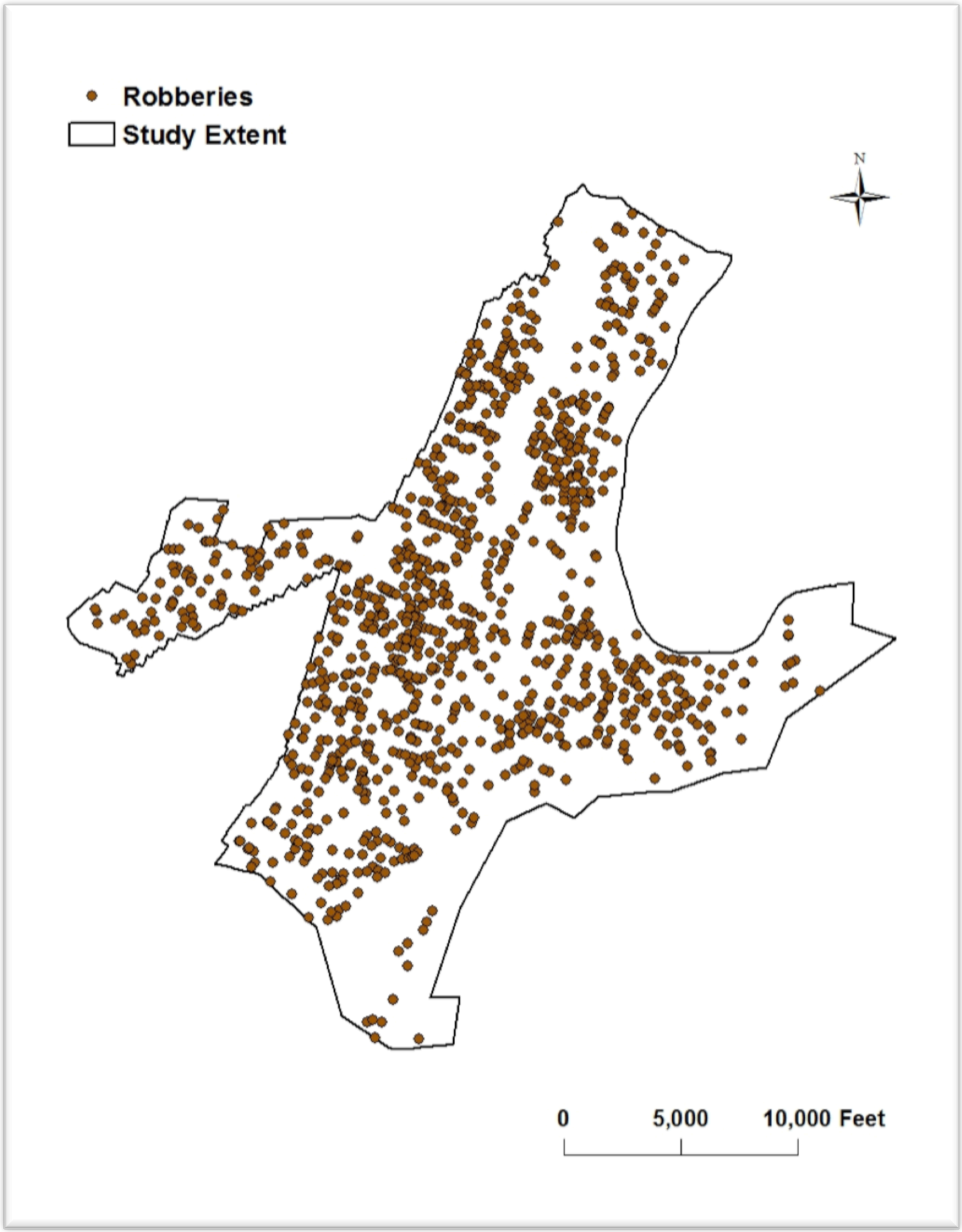


**Figure 2. Calendar Year 2010 Street Robberies in Newark, NJ**



## 2.2. Data Sources

*Dependent Variable*

The dependent variable of this dissertation is the count of street robbery incidents at micro places in Newark, NJ, in calendar year (CY) 2010 (N=1228). The robbery data were acquired from the Newark PD. CY 2010 was chosen as the study time period as this is the most recent calendar year preceding the Newark PD's leadership change from Garry McCarthy to Samuel DeMaio in mid-2011. As backed by the management literature, leadership change can be a challenge to an organization's stable, predictable environment (Weinstein et al., 2009). Police department directors hold a unique position of power and influence by virtue of coordinating functions such as patrols, investigations, and tactical operations. Considering the unintended disruptive consequences of leadership change on the police organization, policing effectiveness, and community life, CY 2010 constitutes the most recent stable year under the four-year leadership of Gary McCarthy.

Adapting UCR Part I crime definitions (Federal Bureau of Investigation, 2010), Newark PD defines robbery as "the taking or attempting to take anything from the care, custody, or control of a person or persons by force or threat of force or violence and/or by putting the victim in fear." Newark PD geocodes all crime incidents daily, groups them according to their type, and merges these with "year-to-date" incident layers that contain other incidents occurring during the same calendar year. To account for reclassifications of crimes based on additional intelligence about crime incidents, crime incidents for the previous month in the year-to-date layers are updated each week with current data for the corresponding time periods. This additional step increases the content validity of the crime data, including robbery data, by ensuring that each incident is placed in the appropriate crime-type layer.

Given that a clear distinction between offense subtypes is imperative since every crime is built on different situational factors, this dissertation selectively analyzed street robberies, which took place in public space (e.g., streets, sidewalks, parking lots, lots/yards, in front of commercial dwellings). The robbery dataset acquired from Newark PD codes robberies as committed inside (e.g., in a residence, in a facility etc.) or outside (e.g., on the street). The dataset further classifies the incidents according to their date (e.g., 07.28.2010), day (e.g., Monday or Saturday), and hour (0 to 23; where 0 denotes 12 a.m.) of occurrence. To evaluate the temporality of the criminogenic influence of landscape features, the dependent variable was classified into six groups according to time of occurrence. The temporal groups were formed to reflect the most general temporal constraints that the landscape features exert on human activities through labor, commute, leisure, and rest. As explained earlier, the routine activities people engage in on a daily basis require regular intervals and fixed places and most activities are dependent on the location and operation hours of venues offering these activities.

In this dissertation, robberies were assigned to three different time intervals to reflect these temporal constraints: 6 a.m. to 6 p.m., 6 p.m. to 2 a.m., and 2 a.m. to 6 a.m. The first time interval, between 6 a.m. and 6 p.m., represents working hours and is called "Business Hours." The second time interval between 6 p.m. and 2 a.m., represents leisure hours and is called "Happy Hours." The third time interval, between 2 a.m. and 6 a.m., represents rest hours and is called "Bedtime Hours." These temporal groups made intuitive sense for the Newark study extent and were also backed up with the time use data. According to the 2011 Bureau of Labor Statistics (United States Department of Labor, 2013), on any day of the week, on average, a full time worker works 8.10 hours, and a civilian spends 5.21 hours for leisure activities. During weekdays and on the weekend, the majority of the train service inbound to and outbound from Newark begins between 5:30 a.m. and 6 a.m. and extends through 2 a.m. A majority of the entertainment venues in Newark (such as restaurants and bars etc.) are open until 1 a.m. or 2 a.m. Considering the general time use trends and the temporal restrictions placed on citizen behavior by leisure and transportation outlets in Newark, the 6 a.m., 6 p.m. and 2 a.m. thresholds for the time intervals were meaningful for the study setting of Newark. For the day-of-the-week grouping, the robberies in the three time slots were further classified into weekday and weekend robbery groups. Monday, Tuesday, Wednesday, Thursday, and Friday signify the weekdays, while Saturday and Sunday signify the weekends, with the exceptions of the time intervals between 6 p.m. and 12 a.m. on Fridays and between 12 a.m. and 6 a.m. on Mondays. These two time intervals were included in the weekend models to reflect the end and beginning of weekly business hours (see Table 1).

As illustrated in Table 1, the temporal groupings described above resulted in six time models. Model 1, “Weekday Business Hours,” included all 2010 robberies that occurred between 6 a.m. and 6 p.m. on a weekday (N=363). Model 2, “Weekday Happy Hours,” included all 2010 robberies that occurred between 6 p.m. and 2 a.m. on a weekday (N=343). Model 3, “Weekday Bedtime Hours”, included all 2010 robberies that occurred between 2 a.m. and 6 a.m. on a weekday (N=92).

**Table 1. Temporal Groupings for 2010 Street Robberies (N=1228)**

| Model # | Model Name | Day of the Week & Time of the Day | # of 2010 Robberies |
|---|---|---|---|
| 0 | Model 0 | All days and all times | 1228 |
| 1 | Weekday Business Hours | Monday 6 a.m. - 5.59 p.m.<br>Tuesday 6 a.m. - 5.59 p.m.<br>Wednesday 6 a.m. - 5.59 p.m.<br>Thursday 6 a.m. - 5.59 p.m.<br>Friday 6 a.m. - 5.59 p.m. | 363 |
| 2 | Weekday Happy Hours | Monday 6 p.m. - 11.59 p.m.<br>Tuesday 12 a.m. - 1.59 a.m. & Tuesday 6 p.m. - 11.59 p.m.<br>Wednesday 12 a.m. - 1.59 a.m. & Wednesday 6 p.m. - 11.59 p.m.<br>Thursday 12 a.m. - 1.59 a.m. & Thursday 6 p.m. - 11.59 p.m.<br>Friday 12 a.m. - 1.59 a.m. | 343 |
| 3 | Weekday Bedtime Hours | Tuesday 2 a.m. - 5.59 a.m.<br>Wednesday 2 a.m. - 5.59 a.m.<br>Thursday 2 a.m. - 5.59 a.m.<br>Friday 2 a.m. - 5.59 a.m. | 92 |
| 4 | Weekend Business Hours | Saturday 6 a.m. - 5.59 p.m.<br>Sunday Monday 6 a.m. - 5.59 p.m. | 121 |
| 5 | Weekend Happy Hours | Friday 6 p.m. - 11.59 p.m.<br>Saturday 12 a.m. - 1.59 a.m. & Saturday 6 p.m. - 11.59 p.m.<br>Sunday 12 a.m. - 1.59 a.m. & Sunday 6 p.m. - 11.59 p.m.<br>Monday 12 a.m. - 1.59 a.m. | 235 |
| 6 | Weekend Bedtime Hours | Saturday 2 a.m. - 5.59 a.m.<br>Sunday 2 a.m. - 5.59 a.m.<br>Monday 2 a.m. - 5.59 a.m. | 74 |

Model 4, “Weekend Business Hours”, included all 2010 robberies that occurred between 6 a.m. and 6 p.m. on a weekend (N=121). Model 5, “Weekend Happy Hours”, included all 2010 robberies that occurred between 6 p.m. and 2 a.m. on a weekend (N=235). Model 6, “Weekend Bedtime Hours”, included all 2010 robberies that occurred between 2 a.m. and 6 a.m. on a weekend (N=74). A temporally nonnested model of all street robberies in CY 2010 (N=1228) was also included to serve as a comparison group in the analysis. This null model was called Model 0 “All Time” robberies.

*Independent Variables*

The independent variables (risk factors) of this dissertation were the operationalized spatial influences of the criminogenic features of the landscape at micro places in Newark, NJ. The criminogenic features were identified by a careful review of previous research on street robberies and by observation of landscape features at sample hot spots for 2010 street robberies in Newark, NJ with Google Earth. As discussed earlier, previous research has identified environments of cash economies (i.e., bars, banks, post offices, laundromats, pawn shops, gas stations, retail stores, hair salons, grocery stores, and fast-food stores), illegal markets (i.e., prostitution areas and drug markets), places where youth congregate (i.e., schools and libraries), and public housing as high-risk places for street robberies. To observe the presence of these known risk factors and to identify any other features pertaining to street robbery locations in Newark, a series of hot spot analyses were conducted and the sample of hot spots of street robberies were examined with Google Earth. The following section explains how sample hot spots were selected.

**Identification of 2010 Street Robbery Hot Spots with Getis-ord Gi* Statistic**

The hot spots of street robberies in Newark, NJ were identified using the Getis-Ord Gi* statistical tool in ArcMap. The Getis-Ord Gi* statistic is a Z-statistic which shows "whether features with high values or features with low values tend to cluster in a study area" (ArcGIS Resource Center, n.d.). In the analysis of hot spots, the Getis-Ord Gi* tool identifies the hot spots of a feature by looking at each feature's value in connection to its neighboring features' values. Depending on the distance threshold set to search for neighboring values, a small or a large number of neighboring values might be included in the hot spot analysis. The hypothetical red, blue, and gray distance thresholds in Figure 2 exemplify how different search thresholds around a feature value (grid value with the red background) can affect the number of neighboring values included in the hot spot analysis. A feature becomes a part of a hot spot only if the feature's and its neighboring features' values are both high. Getis Ord-Gi* z-statistic becomes significant only when “the local sum for a feature and its neighbors is very different from the expected local sum, and that difference is too large to be the result of random chance” (ArcGIS Resource Center, n.d.). The Getis-ord Gi* tool in ArcMap, with a set of weighted features, helped to identify the hot spots of 2010 street robberies in Newark with  the z-statistic.

**Figure 3. Hypothetical Search Thresholds for Hot Spot Analysis**

| | | | | | | |
|---|---|---|---|---|---|---|
| 1 | 0 | 2 | 3 | 0 | 0 | 1 |
| 5 | 4 | 3 | 2 | 7 | 4 | 0 |
| 6 | 0 | 6 | 5 | 6 | 3 | 0 |
| 0 | 0 | 10 | 7 | 6 | 2 | 0 |
| 0 | 0 | 4 | 4 | 1 | 1 | 0 |
| 2 | 0 | 0 | 5 | 1 | 1 | 0 |
| 0 | 0 | 2 | 3 | 6 | 0 | 0 |
| 0 | 1 | 1 | 4 | 2 | 0 | 0 |
| 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 2 | 0 | 0 | 2 | 0 | 3 | 2 |
| 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 2 | 0 | 4 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 4 | 6 |
| 0 | 5 | 2 | 1 | 3 | 0 | 1 |

To conduct the hot spot analysis with the Getis-Ord Gi* tool, first the count of street robberies was aggregated to the units of analysis using the RTM toolbox. This toolbox calculated the number of street robbery incidents that intersected with each of the 145 ft. by 145 ft. grid cells in the Newark study extent. The aggregated street robbery incidents were input into the Getis Ord Gi* tool as the input. The spatial relationship between aggregated street robberies was conceptualized with a fixed Euclidean distance. The fixed distance for identifying the statistically significant spatial clusters of street robberies were set to 205 feet. While identifying the hot spot of street robberies for each robbery feature, the street robberies that are beyond the 205 feet straight line distance from that feature were ignored in the hot spot analyses for that feature. The 205 feet cutoff distance was chosen according to Chainey's (2010) suggestion that only immediate neighbors of a cell should be included in hot spot analysis. In hot spot analysis, the selection of a proper distance for hot spot calculations is crucial because choosing a too small or a too large distance can reduce the reliability of the z-scores to test significance as these distances as shown in Figure 3 dictate how many neighboring values will be added to the hot spot analysis along with a feature's value in calculating the local sum of values. According to Chainey (2010), for the reliability of the z-scores, the distance threshold—also known as lag distance— in hot spot analysis should be only big enough to include only the immediate neighbors of a feature. According to Chainey's formula (2010, p.35) the Getis-ord Gi* distance threshold is calculated in relation to the cell size as below:

$$\sqrt{((X*X) + (X*X))}$$

In this formula, "X" refers to the size of the equally-sized grid-cell. Following this formula, with the 145 ft. by 145 ft. grid cell size of this dissertation, the distance threshold for the hot spot analysis was set to 205 feet:

$$\sqrt{((145*145) + (145*145))} = 205$$

Getis-ord Gi* statistic as indicated earlier is a Z statistic. For a 99.9% confidence interval the critical Z-score is 3.291 and a Z-score that is ≥ 3.291 in hot spot analysis indicates an exceptionally unusual spatial clustering of crime (Chainey, 2010). As can be seen in Table 2, according to the results of the hot spot analysis, approximately 3,400 cells in the time-nested models 1-6 were identified to be extremely hot cells of CY 2010 street robberies, with a Z-score ≥3.291 ($p<0.001$).

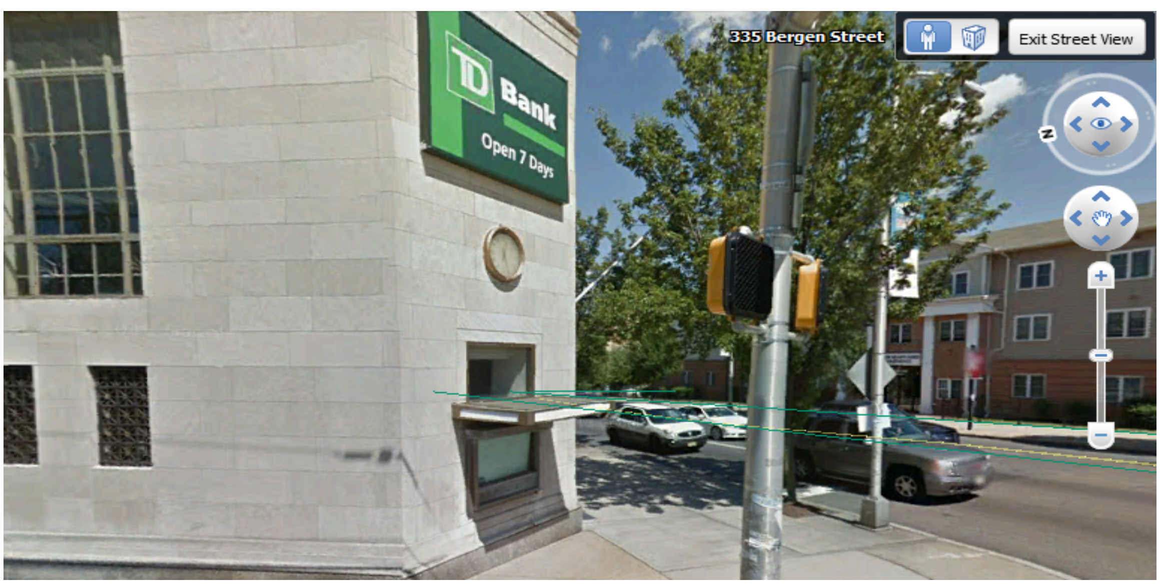
**Table 2. Number of Hot Cells of 2010 Street Robberies**

| | Number of Hot Cells (z≥3.291) | Number of Sample Hot Cells |
|---|---|---|
| Model 1 "Weekday Business Hours" | 243 | 150 |
| Model 2 "Weekday Happy Hours" | 203 | 135 |
| Model 3 "Weekday Bedtime Hours" | 465 | 210 |
| Model 4 "Weekend Business Hours" | 602 | 235 |
| Model 5 "Weekend Happy Hours" | 1283 | 300 |
| Model 6 "Weekend Bedtime Hours" | 632 | 240 |
| **Total** | **3428** | **1270** |

From these 3,400 cells, a random sample of 1270 cells (approximately 36% of all hot spots) was selected using STATA (see Table 2). These street robbery hot cells were exported to Google Earth as a KML file and the landscape features that fell into these hot cells were observed using Google Earth Images (see Fig. 4 and Fig. 5). All images were observed in Google Earth in 2012. However, Google Earth acquires data over time with a 1-3 years lag (Google Earth, n.d.), and at the time of the observation of hot spots of robberies in Newark, NJ, the Google Earth images were from either 2009 or 2010. The observation of hot cells in Google Earth showed that all of the criminogenic landscape features identified by the literature were present in hot spots for 2010 robberies. As expected, in addition to these known features, other landscape features were also observed to be located in the robbery hot spots of the time-nested models: auto repair shops, car dealerships, car wash shops, cemeteries, and churches.

**Figure 4. Google Earth Screenshot of 2010 Street Robbery Hot Spots in Newark, NJ, 2010 (zoomed out)** [3]

**Figure 5. Google Earth Screenshot of a 2010 Street Robbery Hot Spot in Newark, NJ, 2010 (zoomed in)**




[3] hot spot cells in pink

Based on these known and observed risk factors, the following criminogenic features were included in the analysis to represent the spatial influences of criminogenic features of the landscape in Newark (see Table 3 for the rationale for including each risk factor): public housing, auto repair shops, banks, bars and social clubs, car dealers, car wash shops, cemeteries and crematories, churches, gas stations, grocery stores, hair and nail salons, laundries and drycleaners, libraries, light rail stops, liquor stores, pawn shops, post offices, retail stores, schools, sit-down restaurants, and take-out restaurants. To represent the spatial influence of locations of other crimes that attract robberies to the same geography, the locations of the CY 2010 drug charges and prostitution charges were also included in the analysis.

Public housing features included public housing complexes under the direct control of the Newark Housing Authority, and private residential buildings in the city with ten or more units that resemble public housing structurally. The data for these features are compiled by the Newark PD Compstat unit, with the cooperation of the Newark Housing Authority and other City of Newark departments. These two features are coded under the heading of "at-risk housing" data by Newark PD and will be referred to as at-risk housing from here and on. The shapefiles for bars, liquor stores, schools, and light rail stops were also acquired from Newark PD in a shapefile format. The bars shapefile contained the addresses of bars and social clubs, whereas the liquor store shapefile included liquor stores. The schools shapefile included the addresses of elementary schools, high schools, vocational training schools, and daycare centers. The X and Y coordinates of the CY 2010 drug and prostitution charges were also acquired from the Newark PD CompStat unit in a shapefile format. In each case with the same case number, if the individual was charged with more than one drug offense, only one charge was included in this study's drug charge dataset.

**Table 3. Street Robbery Risk Factors Included in the Analysis**

| Risk Factor | Reference Robbery Study |
|---|---|
| At-risk Housing (N=137) | Dugato, 2013; Fagan and Davies, 2000; Haberman et al., 2013; Holzman et al., 2005; Roncek et al., 1981 |
| Auto Repair Shops (N=162) | Not applicable. Factor included based on Google Earth observation |
| Banks (N=52) | Dugato, 2013; St. Jean, 2007; Tilley et al., 2004 |
| Bars (N=288) | Bernasco and Block, 2011; Dugato, 2013; Roncek and Meier, 1991; Smith et al., 2000; Tilley et al., 2004; Wright and Decker, 1997 |
| Car Dealers (N=83) | Not applicable. Factor included based on Google Earth observation |
| Car Wash Shops (N=22) | Not applicable. Factor included based on Google Earth observation |
| Cemeteries and Crematories (N=7) | Not applicable. Factor included based on Google Earth observation |
| Churches (N=421) | Not applicable. Factor included based on Google Earth observation |
| Drug Charges (N=5325) | Bernasco and Block, 2011; St. Jean, 2007; Wright and Decker, 1997 |
| Gas Stations (N=37) | Bernasco and Blocks, 2011; Smith et al., 2000; St. Jean, 2007 |
| Grocery Stores (246) | Bernasco and Block; 2011; St. Jean, 2007 |
| Hair & Nail Salons (N=282) | Bernasco and Block, 2011; St. Jean, 2007 |
| Laundries & Drycleaners (N=38) | Bernasco and Block, 2011 |
| Libraries (N=9) | Tilley et al., 2004 |
| Light Rail Stops (N=19) | Billings et al., 2011; Block and Block, 1999; Block and Davis, 1996; Brantingham and Brantingham, 1995; Dugato, 2013; Ihlanfeldt, 2003; Ligett et al., 2003; Plano, 1993; Poister, 1996; Suttles, 1972; Tilley et al., 2004 |
| Liquor Stores (N=84) | Bernasco and Block, 2011; Dugato, 2013; St. Jean. 2007 |
| Pawn Shops (N=36) | Bernasco and Block, 2011; St. Jean, 2007 |
| Post Offices (N=10) | Dugato, 2013 |
| Prostitution Charges (N=230) | Bernasco and Block, 2011; Scott and Dedel, 2006; Tilley et al., 2004 |
| Retail Stores (N=49) | Bernasco and Block, 2011 |
| Schools (N=142) | Tilley et al., 2004 |
| Sit-down Restaurants (N=365) | Smith et al., 2000; St. Jean, 2007; Tilley et al., 2004 |
| Take-out Restaurants (N=201) | Bernasco and Block, 2011; St. Jean, 2007 |

This procedure was also followed for prostitution cases. The drug charges included charges of wandering for drugs, possession of drugs and drug paraphernalia, and possession with intent to sell. The prostitution charges included charges of prostitution and wandering for prostitution. If, in a single case, an individual/individuals was/were charged with both a drug offense and a prostitution offense, this case was merged to both the prostitution and the drug charge datasets. The addresses of auto repair shops, banks, car dealers, car wash shops, cemeteries and crematories, churches, gas stations, grocery stores, hair and nail salons, laundromats and drycleaners, libraries, pawn shops, post offices, sit-down restaurants, take-out restaurants, and retail stores were acquired from InfoGroup, a lead provider of business data which contacts over 100,000 businesses every day to verify and extend its dataset. The bank dataset included the addresses of all the branches of Wachovia (now Wells Fargo), Bank of America, NY Community Bank, PNC Bank, JPMorgan Chase Bank, Valley National Bank, City National Bank of NJ, Millennium BCP Bank, Banco Popular North America, Crown Bank, HSBC, Atlantic Center Bankers, Lusitania Savings Bank, and Citibank in Newark. The retail stores included apparel and garments retailers, department stores, dressmakers, fashion designers, hats retailers, custom shirt stores, sportswear retailers, and variety stores. The pawnshops included facilities that provide a monetary loan to customers for their personal property, and a number of businesses that purchase used property (e.g., jewelry and electronics) from customers. Take-out restaurants were businesses where food is intended to be eaten off the premises whereas sit-down restaurants were businesses where food is intended to be consumed on the premises.

# CHAPTER 3: THE INDIVIDUAL TEMPORAL CRIMINOGENIC INFLUENCES OF LANDSCAPE FEATURES ON STREET ROBBERIES

A critical overview of the crime analysis research and practice raised questions about the temporality, extent, and weight of different criminogenic influences of landscape features on crime outcomes. In this chapter, the individual criminogenic influences of different landscape features on street robberies are tested by exploring which landscape features had a criminogenic spatial influence on 2010 street robberies at different times of the day and different days of the week. While doing that, the spatial extent and weights of criminogenic influences are also computed to further showcase the dynamic criminogenic influences of landscape features. The discussion of the findings from this chapter is provided in Chapter 5.

## 3.1. Testing Hypothesis #1: Do spatial extents of criminogenic influences change temporally?

### *Choosing the Spatial Extents for Operationalizing the Spatial Influences of Landscape Features on Street Robberies*

In different studies, authors used different distance bandwidths around criminogenic landscape features to operationalize criminogenic spatial influence based on the densities of, or distance from, criminogenic features. For instance, Caplan et al. (2011) and Caplan (2011) used 3-4 block distance bandwidths for density calculations of drug arrests to test their spatial influence on shootings. Several researchers used spatial influence extents less than one city block or one to three city blocks around criminogenic landscape features to test the criminogenic spatial influence of these features (Caplan, 2011; Caplan et al., 2011; Caplan et al., 2012; Kennedy et al., 2011; Moreto et al., 2013; Ratcliffe and Taniguchi, 2008; Rengert et al., 2005; Rice and Smith, 2002; Yerxa, 2013).

Specifically in street robbery analysis, several authors tested or observed the criminogenic influence of different landscape features up to two blocks distance from these features (Bernasco and Block, 2011; Block and Block, 1999; Block and Davis, 1996; Dugato, 2013; Fagan and Davies, 2000; Haberman et al., 2013; Holzman et al., 2005; Ligett et al., 2003; Roncek et al., 1981; Roncek and Meier, 1991; Smith et al., 2000; Yu, 2009).

Furthermore, in their test of risk terrain modeling of shootings at micro places in Newark, as a part of their analysis, Kennedy et al. (2011, p. 349) developed RTM models with significant risk factors "whose proportions experienced 20% or more" outcome events at risky places defined by the spatial influence of landscape features. Based on the aforementioned research and a critical review of the studies on the spatial influence of landscape features, while choosing the spatial extent for operationalizing and testing the criminogenic influence of different landscape features, two things were taken into consideration.

First, the spatial extent of the criminogenic influence of landscape features can change from one feature to another or can be different for the same features at different time periods (Caplan 2011; Caplan et al., 2011, Caplan et al., 2012; Kennedy et al., 2011; Ratcliffe, 2012). Second, only the immediate or adjacent blocks of landscape features exert the maximum criminogenic spatial influence (Bernasco and Block, 2011; Block and Block, 1999; Block and Davis, 1996; Dugato, 2013; Fagan and Davies, 2000; Haberman et al., 2013; Holzman et al., 2005; Ligett et al., 2003; Roncek et al., 1981; Roncek and Meier, 1991; Smith et al., 2000; Yu, 2009). Following these ideas, the extent of the criminogenic influence of landscape features was identified separately for different landscape features for different time periods and the maximum criminogenic spatial influence extent of landscape features was set to 600 feet (around two median blocks distance) around features. The 600 feet maximum spatial extent distance is believed to be big enough to detect the differences between the criminogenic influences of features at different times, and small enough to translate into meaningful information to direct policing efforts to the most risky places. As suggested by Taylor (1996), understanding the effect of street block dynamics in crime emergence has important practical implications as these block cues can be used to increase the safety and order on the problem places.

The spatial extent for operationalizing and testing the criminogenic influence of different landscape features was calculated as follows. In the first step, adhering to the 20% rule of Kennedy et al. (2011), for each feature and for each time model, the exact distance where 20% of robberies fall around the feature was calculated using the "Choose by location" function in ArcMap. This exact distance was calculated to identify the minimum extent of the criminogenic reach of features where there were enough crime outcomes around a feature to conclude that the said feature has a criminogenic influence. In the second step, for each feature, the average minimum criminogenic influence distance for all time-nested models was identified by calculating the mean for exact distance for time-nested models 1-6. In the third step, for each feature, if the average exact distance identified was less than the maximum spatial extent of 600 feet, this distance was rounded up to the nearest block (either 300 feet— around 1 median block— or 600 feet—2 median blocks) to translate this information to a meaningful block distance for crime prevention efforts. For instance, if 20% of robberies were identified up to an average of 300 feet of feature "X", the operationalization distance was set to 300 feet, whereas if 20% of robberies were identified between an average 300-600 feet of feature "X", the operationalization distance was set to 600 feet. On the other hand, if the exact average distance identified was more than the maximum spatial extent of 600 feet, this average distance was rounded down to 600 feet as this distance was previously chosen as the most reasonable maximum spatial extent distance for crime prevention efforts around risky places (see Table 4).

### *Findings*

In time-nested models 1-6, eleven out of twenty-three landscape features (risk factors), namely auto repair shops, banks, car washes, cemeteries, gas stations, libraries, light rail stops, pawn shops, post offices, and prostitution charges did not include 20% of street robbery incidents within their 600 feet (about two median blocks) maximum spatial extent bandwidth (see Table 4).

**Table 4. The spatial extent (in feet) where exactly 20% of street robbery incidents are under the spatial influence of the landscape feature and final operationalization**

| # | Feature | Operationalization | Model 0 | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Average (excluding model 0) | Final Operationalization |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | At-risk Housing | Distance | 149 | 158 | 128 | 145 | 148 | 137 | 305 | 170 | 1 block |
| 2 | Auto Repair Shops | Distance | 1284 | 1193 | 1278 | 1400 | 1239 | 1335 | 1479 | 1320 | 2 blocks |
| 3 | Banks | Distance | 879 | 839 | 974 | 863 | 964 | 680 | 921 | 874 | 2 blocks |
| 4 | Bars | Distance | 288 | 274 | 305 | 290 | 291 | 262 | 281 | 283 | 1 block |
| 5 | Car Dealers | Distance | 600 | 520 | 657 | 534 | 648 | 668 | 510 | 589.5 | 2 blocks |
| 6 | Car Washes | Distance | 1358 | 1214 | 1316 | 1601 | 1334 | 1432 | 1345 | 1374 | 2 blocks |
| 7 | Cemeteries | Distance | 1583 | 1384 | 1650 | 1442 | 2132 | 1510 | 1869 | 1664.5 | 2 blocks |
| 8 | Churches | Distance | 266 | 242 | 298 | 265 | 289 | 259 | 268 | 270 | 1 block |
| 9 | Drug Charges | Density | 261 | 230 | 261 | 291 | 324 | 281 | 195 | 264 | 1 block |
| 10 | Gas Stations | Distance | 965 | 992 | 997 | 1006 | 911 | 933 | 801 | 940 | 2 blocks |
| 11 | Grocery Stores | Distance | 241 | 249 | 222 | 244 | 245 | 257 | 209 | 237 | 1 block |
| 12 | Hair & Nail Salons | Distance | 236 | 234 | 240 | 174 | 311 | 228 | 194 | 230 | 1 block |
| 13 | Laundries & Drycleaners | Distance | 591 | 621 | 569 | 574 | 586 | 625 | 459 | 572 | 2 blocks |
| 14 | Libraries | Distance | 1218 | 1250 | 1162 | 1049 | 1246 | 1282 | 1181 | 1195 | 2 blocks |
| 15 | Light Rail Stops | Distance | 1957 | 2058 | 1745 | 1999 | 1922 | 4688 | 2398 | 2468 | 2 blocks |
| 16 | Liquor Stores | Distance | 443 | 438 | 411 | 532 | 521 | 425 | 416 | 457 | 2 blocks |
| 17 | Pawn Shops | Distance | 1014 | 1064 | 1067 | 1014 | 1229 | 954 | 768 | 1016 | 2 blocks |
| 18 | Post Offices | Distance | 1817 | 1940 | 1882 | 1952 | 1802 | 1682 | 1661 | 1819 | 2 blocks |
| 19 | Prostitution Charges | Density | 732 | 687 | 836 | 658 | 762 | 703 | 518 | 694 | 2 blocks |
| 20 | Retail Stores | Distance | 791 | 817 | 849 | 698 | 846 | 769 | 599 | 663.1 | 2 blocks |
| 21 | Schools | Distance | 425 | 377 | 435 | 401 | 502 | 467 | 378 | 427 | 2 blocks |
| 22 | Sit-down Restaurants | Distance | 269 | 268 | 265 | 279 | 304 | 261 | 255 | 272 | 1 block |
| 23 | Take-out Restaurants | Distance | 299 | 294 | 299 | 320 | 299 | 287 | 262 | 294 | 1 Block |

For the eleven variables whose average minimum criminogenic spatial extent was identified above 600 feet, spatial influence operationalization distance was rounded down to 600 feet.

Among the remaining twelve risk factors, eight landscape features, namely at-risk housing, bars, churches, drug charges, grocery stores, hair and nail salons, sit-down restaurants, and take-out restaurants included 20% of the street robbery incidents at an average distance under 300 feet in time-nested models 1-6. For these variables whose average minimum criminogenic spatial extent was identified below 300 feet, spatial influence operationalization distance was rounded up to 300 feet.

The remaining four landscape features, namely car dealers, laundromats and drycleaners, liquor stores, and schools included 20% of the street robbery incidents at an average distance between 300 feet and 600 feet in time nested models 1-6. For these variables whose average minimum criminogenic spatial extent was identified between 300 feet and 600 feet, spatial influence operationalization distance was rounded up to 600 feet.

Table 5 shows the variability of the criminogenic spatial extents of landscape features within time-nested Models 1-6 in feet units. According to the standard deviation values and mean values provided in Table 5, in Models 1-6, on average, the spatial extent of the criminogenic influence of a landscape feature deviated two to three blocks from the mean spatial extent of landscape features.

**Table 5. Criminogenic Spatial Influence Extent Variability Between and Within Time-Nested Models**

| | Mean | Std. Deviation | Minimum | Maximum |
|---|---|---|---|---|
| Model1: Weekday Business Hours Criminogenic Spatial Influence Extent | 754.04 | 553.200 | 158 | 2058 |
| Model2: Weekday Happy Hours Criminogenic Spatial Influence Extent | 775.91 | 536.197 | 128 | 1882 |
| Model3: Weekday Bedtime Hours Criminogenic Spatial Influence Extent | 770.91 | 569.446 | 145 | 1999 |
| Model4: Weekend Business Hours Criminogenic Spatial Influence Extent | 819.78 | 579.314 | 148 | 2132 |
| Model5: Weekend Happy Hours Criminogenic Spatial Influence Extent | 875.00 | 953.932 | 137 | 4688 |
| Model6: Weekend Bedtime Hours Criminogenic Spatial Influence Extent | 750.96 | 618.412 | 194 | 2398 |

Furthermore, as illustrated by the minimum and maximum spatial extent values in Table 5, the spatial extent of the criminogenic spatial influences of different features varied around one-half block to seven blocks in Models 1, 3, and 4, one-half block to six and half blocks in Model 2, one-half block to sixteen blocks in Model 5, and one-half block to eight blocks in Model 6. For different landscape features included in the analysis, compared to the minimum criminogenic spatial influence extents in Model 0, the minimum criminogenic extents in the time-nested models varied between a minimum of 0 feet[4] to a maximum of 2731 feet[5] (see Table 4).

[4] The minimum difference for drug charges and takeout restaurants between Model 0 and Model 2
[5] The maximum difference for light rail stops between Model 0 and Model 5

**Table 6. Criminogenic Spatial Influence Extent Difference of Landscape Features Between Time-Nested Models 1-6**

| Cash Economies (Regular hours) | Mean | Std. Dev. | Minimum | Maximum |
|---|---|---|---|---|
| Auto-Repair Shops | 1320.67 | 106.167 | 1193 | 1479 |
| Car Dealers | 589.5 | 75.328 | 510 | 668 |
| Car Washes | 1373.67 | 131.375 | 1214 | 1601 |
| Hair & Nail Salons | 230.17 | 47.144 | 174 | 311 |
| Pawn Shops | 1016 | 152.07 | 768 | 1229 |
| Post Offices | 1819.83 | 126.741 | 1661 | 1952 |
| Retail Stores | 763 | 98.344 | 599 | 849 |
| **Cash Economies (Extended hours)** | **Mean** | **Std. Dev.** | **Minimum** | **Maximum** |
| Banks | 873.5 | 108.894 | 680 | 974 |
| Gas Stations | 940 | 78.128 | 801 | 1006 |
| Grocery Stores | 237.67 | 18.239 | 209 | 257 |
| Laundries & Drycleaners | 572.33 | 60.311 | 459 | 625 |
| Liquor Stores | 457.17 | 54.595 | 411 | 532 |
| Sit-down Restaurants | 272 | 17.595 | 255 | 304 |
| Take-out Restaurants | 293.5 | 18.96 | 262 | 320 |
| **Cash Economies (Late hours)** | **Mean** | **Std. Dev.** | **Minimum** | **Maximum** |
| Bars | 283.83 | 14.959 | 262 | 305 |
| **Transportation** | **Mean** | **Std. Dev.** | **Minimum** | **Maximum** |
| Light Rail Stops | 2468.33 | 1108.351 | 1745 | 4688 |
| **Non-commercial Features** | **Mean** | **Std. Dev.** | **Minimum** | **Maximum** |
| At-risk Housing | 170.17 | 66.829 | 128 | 305 |
| Cemeteries | 1664.5 | 287.278 | 1384 | 2132 |
| Churches | 270.17 | 20.39 | 242 | 298 |
| Libraries | 1195 | 84.612 | 1049 | 1282 |
| Schools | 426.67 | 50.725 | 377 | 502 |
| **Illegal Markets** | **Mean** | **Std. Dev.** | **Minimum** | **Maximum** |
| Drug Charges | 263.67 | 45.92 | 195 | 324 |
| Prostitution Charges | 694 | 106.949 | 518 | 836 |

As shown in Table 6 with the measures of variability and central tendency, the criminogenic spatial influence extent of each feature also showed difference for each landscape feature between time-nested Models 1-6. Among all features, light rail stops was the only feature with a criminogenic spatial extent difference close to four median blocks (s=1108, m=2468) between time nested Models 1-6. The rest of the landscape features included in the analysis deviated at a minimum of 15 feet up to 287 feet (about one median block) from their mean spatial extents (see Table 6).

As further illustrated in Table 6, according to the average criminogenic spatial extent values, at-risk housing was the only feature that included 20% of street robberies within almost half-a-median block (s=67, m=170) distance to the feature. According to the average criminogenic spatial extent values, in addition to at-risk housing, bars, churches, drug charges, grocery stores, hair and nail salons, sit-down restaurants, and take-out restaurants were the only features that included 20% of street robberies within almost one median block distance (see Table 6). As further shown with average criminogenic spatial extent values in Table 6, car dealers, laundries and drycleaners, liquor stores, and schools included 20% of street robberies within almost one to two median blocks; banks, gas stations, prostitution charges and retail stores included 20% of street robberies within two to three median blocks, and auto repair shops, car washes, cemeteries, libraries, light rail stops, pawn shops, and post offices included 20% of street robberies beyond three median blocks distance to these features.

*Summary*

The analysis conducted to test Hypothesis 1 supported the suggestion from recent studies that extent of the criminogenic spatial influence of landscape features vary (Caplan, 2011; Caplan and Kennedy, 2010; Caplan et al., 2011; Kennedy et al, 2011, Ratcliffe, 2012). The findings not only suggested that the spatial extent of criminogenic influences vary for different landscape features within each time model, the spatial extent of the criminogenic spatial influences of the same and different features varied between different time models. The groupings of CY 2010 all-time robberies to time-nested models revealed that when compared to landscape features whose minimum criminogenic influences were identified up to two-median blocks, landscape features whose minimum criminogenic influence extents were identified at two median blocks or more had more inflated spatial extent variance in time-nested models (see Table 6). Among all fifteen cash businesses included in the analysis, five particular businesses namely bars, grocery stores, hair and nail salons, sit-down restaurants, and take-out restaurants included 20% of the street robberies in the shortest distances. From the remaining eight landscape features including light rail stops, non-commercial features and illegal markets, only three features namely, at-risk housing, churches, and drug charges included 20% of street robberies in the shortest distances. When tested for the weight and significance of criminogenic spatial influence, these eight features that included the 20% of street robberies at the shortest distances, are expected to have a significant criminogenic spatial influence on street robberies in accordance with the social relevancy of these features in different time models. As indicated earlier in hypothesis 2.4, based on the literature, light rail stops were not expected to have a criminogenic influence on street robberies. The 2,468 feet mean spatial extent value where light rail stops included 20% of street robberies (see Table 6), flags light rail stops as a potentially non-criminogenic landscape feature. Solely based on the mean distances to features where 20% of the street robberies took place, on average, the overall criminological spatial extents of landscape features did not vary much between time-nested models 1-6. However, as indicated by the standard deviation values for each time model, the difference between the spatial extents of the criminogenic influences of features was higher for weekend time models compared to weekday models (see Table 5). Furthermore, for all landscape features included in the analysis, all are observed to include 20% of street robberies within longer distances in Models 2-6, especially in weekend models, when compared to their criminogenic spatial influence extents in Model 1 "Weekday Business Hours." All these findings, in parallel with the recent literature on the dynamic spatial influences of landscape features (Caplan et al., 2011, Caplan, 2011; Ratcliffe, 2012), support Hypothesis 1 that "the spatial extents of the criminogenic influence of landscape features on street robberies are different from one another at different times of the day and different days of the week."

### 3.2. Testing Hypothesis #2: Do criminogenic landscape features for street robberies vary temporally?

*Digitizing and Testing the Spatial Influence of Criminogenic Features of the Landscape with the Selected Spatial Extents*

As indicated earlier, there are different ways to analyze the spatial influence of features of landscape such as operationalizing the spatial influence in the form of presence of features, distance from features or the density of features. Once the researcher decides how to operationalize the spatial influence, the next step of exploring this influence requires mapping of this influence over space using a GIS. Looking at the use of spatial influence in context-based crime analysis, most recent studies have operationalized the spatial influence of criminogenic features of landscape as either distance to or density from features.

In this dissertation, based on the density operationalization of drug data to represent illegal markets in RTM (Kennedy et al., 2011), the spatial influences of drug and prostitution charges were operationalized as the density of these features whereas based on the common distance operationalization of the spatial influences of cash economies, train stations and non-commercial landscape features (Bernasco and Block, 2011; Billings et al., 2011; Block and Block, 1999; Block and Davis, 1996; Dugato, 2013; Fagan and Davies, 2000; Haberman et al., 2013; Holzman et al., 2005; Ihlanfeldt, 2003; Ligett et al., 2003; McCord and Ratcliffe, 2009; Plano, 1993; Poister, 1996; Roncek et al., 1981; Roncek and Meier, 1991; Smith et al., 2000), the spatial influence of the remaining landscape features were operationalized as places' distance from these features.

The spatial influences of drug and prostitution charges were digitized in two separate map layers using the "Kernel Density" function in ArcMap's "Spatial Analyst" tool. The density of the drug charges was calculated within a search radius of one block, and an output cell size of 145 feet x 145 feet within the study extent, which is the same cell size used in defining micro places as the unit of analysis. The density of the prostitution charges was calculated within a search radius of two blocks with the same output cell size. On the resulting raster density layers, cells within each layer were classified into two groups according to their standard deviational breaks. The cells with a density value more than two standard deviations of the mean density value of each feature were reclassified as “highest risk” and coded as “1” whereas the rest of the cells were classified as “not highest risk” and coded as “0” using the reclassify function in ArcMap’s Spatial Analyst tool.

The spatial influences of at-risk housing, bars, churches, grocery stores, hair and nail salons, sit-down restaurants, and take-out restaurants were digitized in seven separate map layers using the “Euclidean Distance” function in ArcMap's “Spatial Analyst” tool. After calculating distance of cells from each one of these features, in each one of the resulting four raster maps, the cells within a one block distance to the relevant feature were reclassified as “highest risk” and coded as “1” whereas the rest of the cells were classified as “not highest risk” and coded as “0” using the reclassify function in ArcMap’s Spatial Analyst tool.

The spatial influence of the remaining fourteen features, namely auto repair shops, banks, car dealers, car washes, cemeteries, gas stations, laundries and drycleaners, libraries, light rail stops, liquor stores, pawn shops, post offices, retail stores, and schools were digitized in fourteen separate map layers using the “Euclidean Distance” function in ArcMap’s "Spatial Analyst" tool. After calculation of the distance of cells from each one of these features, in each one of the resulting fourteen raster maps, the cells within a two block distance to the relevant feature will be reclassified as “highest risk” and coded as “1” whereas the rest of the cells were classified as “not highest risk” and coded as “0” using the reclassify function in ArcMap’s Spatial Analyst tool.

Following the digitizing of the risk map layers, a blank vector grid of the study extent was created with ArcMap using the “Create Blank Vector Grid of the Study Area” function in the RTM Toolbox. Then, the “Specify Risky Places” function in the RTM Toolbox was used to assign a new field to the vector grid. This new field showed if the grid cell is a “highest risk (1)” or a “not highest risk (0)” cell under the operationalized spatial influence of the tested feature. After that, the “Join Count of Outcome Events to Vector Grid” function in the RTM Toolbox was be used to assign a second new field to the vector grid. This new field showed the number of robbery features that intersect with each grid cell. The resulting map layer had two values attached to it: 1) A risk value of “1” or “0” in relation to the tested feature's spatial influence, and 2) a count of street robberies that occurred within the cell. The attribute table of the layer was exported to STATA, to run a negative binomial regression test for the test feature to validate the significance of its spatial influence on the counts of street robbery incidents. This process was repeated 161 times — 23 (for each feature) x 7 (for each time model) — as the RTM tool can assign only one risk value each time.

Negative binomial regression was chosen as the ideal test for testing the spatial influence of criminogenic features on the occurrence of robberies as the 2010 robberies do not exhibit a normal distribution in the Newark study extent. According to the results of the Kolmogorov-Smirnov test, the cumulative count of 2010 CY street robbery incidents at micro places in Newark and the assumed theoretical distribution is significantly different from each other ( $D(20633) = 0.532$, $p < 0.001$). Moreover, according to the results of the Global Moran's I test conducted in ArcMap to analyze the spatial correlation patterns in 2010 street robbery data: in Model 0 (Moran's I Index= 0.03

, z score= 4.84 , p< 0.001), Model 1 (Moran's I Index= 0.01, z score=2.21, p≤0.05), Model 2 (Moran's I Index= 0.02, z score= 2.61, p≤0.01), Model 5 (Moran's I Index= 0.01, z score=1.94, p=0.05), and Model 6 (Moran's I Index= 0.02, z score=2.51, p=0.01), robbery incidents were identified to be overly clustered; in Model 3 (Moran's I Index= -0.00, z score= -0.69, p=0.49) and Model 4 (Moran's I Index= 0.00, z score= 0.44, p=0.66), a random robbery distribution pattern was observed. According to Thomas (1977), in the geographical applications of quadrat analysis, negative binomial has had the greatest success in fitting observed clustered distributions. Piza (2012) further suggested the superiority of count regression models such as negative binomial regression in RTM to move beyond categorical dependent variable data in risk assessment. Given the aforementioned non-normal clustering of the robbery incidents for the majority of street robbery incidents over the study extent, negative binomial regression was chosen to test the criminogenic spatial influence landscape features on 2010 street robbery outcomes.

To test sub-hypotheses of Hypothesis 2, the landscape features were further classified into six groups (see Table 7). To test Hypothesis 2.1, auto-repair shops, car dealers, car washes, hair and nail salons, post offices, and retails stores were gathered under the category of cash businesses that dominantly operate during regular business hours. To test Hypothesis 2.2, bars were assigned to the groups of businesses that dominantly operate after business hours. To test Hypothesis 2.3, the remainder of the cash businesses, namely banks[6], gas stations, grocery stores, laundries and drycleaners,

[6] Banks were included in the category of cash businesses with long hours because they contain ATMs that can be accessed 24-hours.

liquor stores, sit-down restaurants, and take-out restaurants were included to the group of cash businesses that operate both during and after regular business hours.

**Table 7. Feature Classification for Testing Sub-hypotheses of Hypothesis 2**

| Hypothesis 2 | Sub-hypotheses | Landscape feature tested |
|---|---|---|
| The criminogenic landscape features for street robberies are different at different times of the day and different days of the week. | H.2.1. Cash economies that have regular business hours exert a criminogenic spatial influence on street robberies during business hours on the weekdays and the weekend. | * Auto Repair Shops<br>* Car Dealers<br>* Car Washes<br>* Hair & Nail Salons<br>* Pawn Shops<br>* Post Offices<br>* Retail Stores |
| | H 2.2. Cash economies with late business hours exert a criminogenic spatial influence on street robberies during late hours on the weekdays and the weekend. | *Bars |
| | H 2.3. Cash economies with regular and late business hours exert a criminogenic influence on street robberies during business hours and late hours on the weekdays and the weekend. | * Banks<br>* Gas Stations<br>* Grocery Stores<br>* Laundries & Drycleaners<br>* Liquor Stores<br>* Sit-down Restaurants<br>* Take-out Restaurants |
| | H 2.4. Light rail stations do not have a criminogenic influence on street robberies. | * Light Rail Stops |
| | H 2.5. Non-commercial features of the landscape have a criminogenic influence on robberies during all times of the day and the week. | * At-risk housing<br>* Cemeteries<br>* Churches<br>* Libraries<br>* Schools |
| | H 2.6. Illegal markets have a criminogenic influence on robberies during all times of the day and the week. | * Drug Charges<br>* Prostitution Charges |

To test Hypothesis 2.4, only light rail stops were included in the analysis.[7] To test Hypothesis 2.5, at-risk housing, cemeteries, churches, libraries, and schools were included to the group of non-commercial features. Lastly, to test Hypothesis 2.6, drug charges and prostitution charges were used as indicators of illegal markets.

*Findings*

**Model 0: "All-Time" Robberies**

As indicated with the Incidence Rate Ratios (IRR) and p-values in Table 8, out of twenty-three variables included in the analysis sixteen had a significant and positive (criminogenic) influence on street robberies while one variable, namely car dealers, unexpectedly had a significant but negative (crime reducing) influence ($p<0.05$) on CY 2010 all-time robberies. From the sixteen significant criminogenic variables, at-risk housing, banks, bars, churches, drug charges, grocery stores, hair and nail salons, liquor stores, pawn shops, retail stores, schools, sit-down restaurants, and take-out restaurants were significant at the $p<0.001$ level, whereas auto repair shops and laundries and drycleaners were significant at the $p<0.01$ level, and libraries were significant at the $p<0.05$ level. Overall, for the CY 2010 all-time robberies, a majority of the cash businesses (eleven out of fifteen), non-commercial features (four out of five) and illegal markets (drug charges) had a criminogenic spatial influence on street robberies, and light rail stations were found not to have a criminogenic influence on CY 2010 street robberies.

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[7] Bus stops were intentionally not included in the analysis as a transportation feature. In a preliminary analysis of this dataset including bus stops, risk values in RTM was disproportionately affected by the distance to bus stops because of the number and homogeneous distribution of bus stops in the study extent.

**Table 8. Results of Negative Binomial Regression Analysis for Model 0**

| | | | | | 95% CI | |
|---|---|---|---|---|---|---|
| **Cash Economies (Regular hours)** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Auto Repair Shops | 1.217 | 0.097 | 2.45 | 0.014 | 1.040 | 1.424 |
| Car Dealers | 0.788 | 0.090 | -2.10 | 0.036 | 0.630 | 0.984 |
| Car Washes | 1.012 | 0.175 | 0.07 | 0.947 | 0.720 | 1.421 |
| Hair & Nail Salons | 2.526 | 0.222 | 10.54 | 0.000 | 2.126 | 3.001 |
| Pawn Shops | 2.755 | 0.313 | 8.93 | 0.000 | 2.205 | 3.441 |
| Post Offices | 0.760 | 0.192 | -1.09 | 0.276 | 0.463 | 1.245 |
| Retail Stores | 1.931 | 0.196 | 6.48 | 0.000 | 1.583 | 2.357 |
| **Cash Economies (Extended hours)** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Banks | 1.627 | 0.176 | 4.51 | 0.000 | 1.317 | 2.011 |
| Gas Stations | 1.137 | 0.148 | 0.99 | 0.322 | 0.881 | 1.468 |
| Grocery Stores | 2.698 | 0.220 | 12.17 | 0.000 | 2.300 | 3.166 |
| Laundries & Drycleaners | 1.378 | 0.159 | 2.78 | 0.005 | 1.099 | 1.728 |
| Liquor Stores | 1.757 | 0.142 | 7.00 | 0.000 | 1.500 | 2.057 |
| Sit-down Restaurants | 2.064 | 0.174 | 8.61 | 0.000 | 1.750 | 2.434 |
| Take-out Restaurants | 2.201 | 0.208 | 8.35 | 0.000 | 1.829 | 2.649 |
| **Cash Economies (Late hours)** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Bars | 1.756 | 0.163 | 6.06 | 0.000 | 1.464 | 2.106 |
| **Transportation** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Light Rail Stops | 0.867 | 0.171 | -0.73 | 0.467 | 0.589 | 1.275 |
| **Non-commercial Features** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| At-risk Housing | 1.467 | 0.123 | 4.56 | 0.000 | 1.244 | 1.729 |
| Cemeteries | 0.728 | 0.263 | -0.88 | 0.381 | 0.358 | 1.480 |
| Churches | 2.029 | 0.157 | 9.09 | 0.000 | 1.738 | 2.355 |
| Libraries | 1.492 | 0.259 | 2.30 | 0.021 | 1.062 | 2.098 |
| Schools | 1.708 | 0.123 | 7.44 | 0.000 | 1.483 | 1.967 |
| **Illegal Markets** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Drug Charges | 3.101 | 0.363 | 9.66 | 0.000 | 2.464 | 3.901 |
| Prostitution Charges | 1.005 | 0.166 | 0.03 | 0.976 | 0.727 | 1.389 |

Based on these results it can be concluded that, as suggested by the literature, a variety of cash economies and non-commercial landscape, and drug markets exert criminogenic spatial influences on street robberies. With that being said, in Model 0, since the criminogenic spatial influences of these features were tested for all CY 2010 robberies without temporal groupings, features' criminogenic influences are expected to change within temporal models. In temporal models, with the weekly and hourly analysis of robberies and based on the social relevancy of included risk features, the variety and combination of criminogenic environment features in each time-nested model is expected to differ from Model 0. The detection of the criminogenic influence of churches on robberies in Newark supports the observation of the landscape features of crime hot spots for different study extents to identify potential landscape features that might have a criminogenic spatial influence on crime outcomes. The identification of the negative criminogenic spatial influence of car dealers in Model 0, if further backed up with the results from time-nested models, might suggest the protective spatial influence of these features on street robberies in Newark.

**Model 1: "Weekday Business Hours" Robberies**

Within all time-nested models, Model 1 "Weekday Business Hours" robberies had the greatest number of significant risk factors. With the exception of auto-repair shops and laundries and drycleaners, all features that had a criminogenic influence in Model 0, namely at-risk housing, banks, bars, churches, drug charges, grocery stores, hair and nail salons, libraries, liquor stores, pawn shops, retail stores, schools, take-out restaurants and sit-down restaurants, also had criminogenic influences in Model 1 (see Table 9).

For Model 1, Hypothesis 2.4 which suggested the insignificant criminogenic spatial influence of light rail stops on street robberies was supported by the results of the regression analysis (see Table 9). As illustrated in Table 9, similar to Model 0, car dealers had a negative influence on CY 2010 weekday business hours street robberies ($p<0.05$). Unsimilar to the findings from Model 0, in Model 1, banks and liquor stores had a significant criminogenic influence at a higher significance level ($p<0.05$, see Table 9).

As stated earlier with the sub-hypotheses for Hypothesis 2, cash economies that operate during regular business hours are expected to have a criminogenic influence during business hours, and non-commercial features and illegal markets are expected to have an overall criminogenic influence at all times. Although not all the landscape features tested for each hypothesis had a criminogenic spatial influence on CY 2010 weekday business hours robberies, the significant criminogenic influence of at-risk housing, banks, churches, grocery stores, hair and nail salons, libraries, liquor stores, pawn shops, retail stores, schools, sit-down restaurants, take-out restaurants, and drug charges supported the criminogenic influence of cash businesses, non-commercial features and illegal markets during business hours in Model 0, as suggested by Hypotheses 2.1, 2.3, 2.5, and 2.6. According to Hypothesis 2.2, bars with their relatively late hour of operation, are expected to exert their criminogenic influence at late hours, however, in Model 1, bars were observed to exert a criminogenic influence on business hours robberies. With that being said, with bars' relatively late operating hours, the strength of the criminogenic influence of bars in Model 1 is expected to be weaker than the rest of the cash businesses in Model 1.

**Table 9. Results of Negative Binomial Regression Analysis for Model 1**

| | | | | | 95% CI | |
|---|---|---|---|---|---|---|
| **Cash Economies (Regular hours)** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Auto Repair Shops | 0.916 | 0.132 | -0.61 | 0.544 | 0.690 | 1.216 |
| Car Dealers | 0.568 | 0.125 | -2.58 | 0.010 | 0.369 | 0.873 |
| Car Washes | 0.902 | 0.276 | -0.34 | 0.737 | 0.494 | 1.646 |
| Hair & Nail Salons | 2.478 | 0.358 | 6.28 | 0.000 | 1.867 | 3.290 |
| Pawn Shops | 2.679 | 0.492 | 5.36 | 0.000 | 1.869 | 3.840 |
| Post Offices | 0.732 | 0.323 | -0.71 | 0.480 | 0.309 | 1.738 |
| Retail Stores | 2.414 | 0.379 | 5.62 | 0.000 | 1.775 | 3.283 |
| **Cash Economies (Extended hours)** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Banks | 1.538 | 0.28 | 2.37 | 0.018 | 1.078 | 2.197 |
| Gas Stations | 0.850 | 0.207 | -0.67 | 0.505 | 0.528 | 1.370 |
| Grocery Stores | 2.526 | 0.344 | 6.81 | 0.000 | 1.935 | 3.298 |
| Laundries & Drycleaners | 0.874 | 0.197 | -0.60 | 0.549 | 0.562 | 1.358 |
| Liquor Stores | 1.398 | 0.197 | 2.37 | 0.018 | 1.060 | 1.844 |
| Sit-down Restaurants | 1.794 | 0.258 | 4.06 | 0.000 | 1.353 | 2.378 |
| Take-out Restaurants | 2.039 | 0.322 | 4.51 | 0.000 | 1.496 | 2.779 |
| **Cash Economies (Late hours)** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Bars | 1.767 | 0.271 | 3.71 | 0.000 | 1.308 | 2.387 |
| **Transportation** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Light Rail Stops | 0.979 | 0.314 | -0.07 | 0.947 | 0.522 | 1.836 |
| **Non-commercial Features** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| At-risk Housing | 1.972 | 0.241 | 5.57 | 0.000 | 1.553 | 2.505 |
| Cemeteries | 0.490 | 0.364 | -0.96 | 0.338 | 0.114 | 2.105 |
| Churches | 1.849 | 0.243 | 4.68 | 0.000 | 1.429 | 2.391 |
| Libraries | 1.754 | 0.477 | 2.07 | 0.039 | 1.030 | 2.988 |
| Schools | 1.793 | 0.216 | 4.86 | 0.000 | 1.417 | 2.270 |
| **Illegal Markets** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Drug Charges | 3.027 | 0.569 | 5.90 | 0.000 | 2.095 | 4.375 |
| Prostitution Charges | 0.810 | 0.247 | -0.69 | 0.488 | 0.446 | 1.471 |

**Model 2 "Weekday Happy Hours" Robberies**

As illustrated in Table 10, a new variable that was not significant in either Model 0 or Model 1, laundries and drycleaners, was identified to have a criminogenic influence on weekday happy hours robberies. Moreover, libraries that had a criminogenic influence in Model 0 and Model 1, lost that influence in Model 2. As suggested by Hypotheses 2.2 and 2.3, businesses with late work hours are expected to have a criminogenic spatial influences during late hours on weekdays and weekends. In accordance with this suggestion, laundries and drycleaners, bars, banks, grocery stores, liquor stores, sit-down restaurants, and take-out restaurants, all of which operate past regular business hours, exerted criminogenic spatial influences on street robberies in Model 2 (see Table 10). As can be seen in Table 10, from all cash economies with late hours, only gas stations did not have a criminogenic spatial influence in Model 2. Similar to Model 0 and Model 1, light rail stations did not have a significant criminogenic influence on street robberies in Model 2, either (see Table 10). Thus, Hypothesis 2.4 was also supported with the results from Model 2.

From the pool of cash economies that were assumed to have criminogenic spatial influences only during regular business hours, hair and nail salons, pawn shops, and retail stores were unexpectedly found to have criminogenic spatial influences on street robberies during weekday happy hours (see Table 10). As suggested with Hypotheses 2.5 and 2.6, at-risk housing, churches and schools— representing non-commercial features—and drug charges—representing illegal markets—exerted criminogenic influence on street robberies in Model 2.

**Table 10. Results of Negative Binomial Regression Analysis for Model 2**

| | | | | | 95% CI | |
|---|---|---|---|---|---|---|
| **Cash Economies (Regular hours)** | **IRR** | **Std.Err** | **z** | **p>\|z\|** | **Lower** | **Upper** |
| Auto Repair Shops | 1.239 | 0.165 | 1.61 | 0.108 | 0.954 | 1.608 |
| Car Dealers | 0.788 | 0.153 | -1.22 | 0.221 | 0.538 | 1.154 |
| Car Washes | 0.728 | 0.243 | -0.95 | 0.342 | 0.378 | 1.402 |
| Hair & Nail Salons | 2.410 | 0.341 | 6.21 | 0.000 | 1.825 | 3.181 |
| Pawn Shops | 2.314 | 0.430 | 4.52 | 0.000 | 1.608 | 3.331 |
| Post Offices | 1.172 | 0.422 | 0.44 | 0.660 | 0.579 | 2.372 |
| Retail Stores | 1.688 | 0.287 | 3.08 | 0.002 | 1.210 | 2.354 |
| **Cash Economies (Extended hours)** | **IRR** | **Std.Err** | **z** | **p>\|z\|** | **Lower** | **Upper** |
| Banks | 1.944 | 0.321 | 4.02 | 0.000 | 1.406 | 2.688 |
| Gas Stations | 0.993 | 0.227 | -0.03 | 0.975 | 0.635 | 1.553 |
| Grocery Stores | 2.843 | 0.367 | 8.08 | 0.000 | 2.207 | 3.663 |
| Laundries & Drycleaners | 1.873 | 0.320 | 3.67 | 0.000 | 1.340 | 2.617 |
| Liquor Stores | 1.836 | 0.240 | 4.65 | 0.000 | 1.421 | 2.371 |
| Sit-down Restaurants | 1.989 | 0.273 | 5.00 | 0.000 | 1.519 | 2.603 |
| Take-out Restaurants | 1.775 | 0.285 | 3.57 | 0.000 | 1.296 | 2.431 |
| **Cash Economies (Late hours)** | **IRR** | **Std.Err** | **z** | **p>\|z\|** | **Lower** | **Upper** |
| Bars | 1.718 | 0.260 | 3.57 | 0.000 | 1.277 | 2.312 |
| **Transportation** | **IRR** | **Std.Err** | **z** | **p>\|z\|** | **Lower** | **Upper** |
| Light Rail Stops | 0.682 | 0.254 | -1.03 | 0.304 | 0.329 | 1.414 |
| **Non-commercial Features** | **IRR** | **Std.Err** | **z** | **p>\|z\|** | **Lower** | **Upper** |
| At-risk Housing | 1.390 | 0.177 | 2.58 | 0.010 | 1.083 | 1.785 |
| Cemeteries | 0.518 | 0.378 | -0.90 | 0.368 | 0.124 | 2.169 |
| Churches | 1.754 | 0.229 | 4.31 | 0.000 | 1.358 | 2.264 |
| Libraries | 1.449 | 0.413 | 1.30 | 0.193 | 0.829 | 2.530 |
| Schools | 1.468 | 0.179 | 3.15 | 0.002 | 1.156 | 1.864 |
| **Illegal Markets** | **IRR** | **Std.Err** | **z** | **p>\|z\|** | **Lower** | **Upper** |
| Drug Charges | 2.832 | 0.521 | 5.66 | 0.000 | 1.975 | 4.063 |
| Prostitution Charges | 0.925 | 0.266 | -0.27 | 0.787 | 0.527 | 1.625 |

**Model 3 "Weekday Bedtime Hours" Robberies**

As illustrated in Table 11, thirteen out of twenty-three risk features included in the analysis were identified to have a criminogenic influence on weekday bedtime hours robberies. These criminogenic features in late hours had both similarities with and differences from the criminogenic features for weekday happy hours robberies. For instance, at-risk housing, churches, and schools, all of which represent the non-commercial features in the analysis, were identified to be criminogenic also in Model 3. Furthermore, commercial businesses namely banks, grocery stores, hair and nail salons, laundries and drycleaners, liquor stores, pawn shops, sit-down restaurants, and take-out restaurants, which were identified to be criminogenic in Model 2, were also identified to be criminogenic in Model 3. Similarly, drug charges, which have been a consistent criminogenic feature of street robberies in Models 0, 1, and 2, were also criminogenic for weekday bedtime hours robberies. On the other hand, bars, laundries and drycleaners, and retail stores which were criminogenic after business hours in Model 2, were not criminogenic in the later night hours in Model 3. Furthermore, auto repair shops and gas stations that were not significant for weekday business and happy hours were significant criminogenic factors for weekday bedtime hours.

The significant criminogenic influence of bars, drug charges, at-risk housing, churches and schools supported Hypotheses 2.2, 2.3, 2.5, and 2.6, similar to the findings of Model 1 and Model 2. The statistical insignificance of light rail stops in Model 3, supported Hypothesis 2.4 for weekday bedtime robberies.

**Table 11. Results of Negative Binomial Regression Analysis for Model 3**

| | | | | | 95% CI | |
|---|---|---|---|---|---|---|
| **Cash Economies (Regular hours)** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Auto Repair Shops | 2.122 | 0.474 | 3.37 | 0.001 | 1.369 | 3.288 |
| Car Dealers | 1.182 | 0.376 | 0.53 | 0.598 | 0.634 | 2.203 |
| Car Washes | 1.736 | 0.758 | 1.26 | 0.207 | 0.737 | 4.085 |
| Hair & Nail Salons | 1.976 | 0.549 | 2.45 | 0.014 | 1.146 | 3.408 |
| Pawn Shops | 2.448 | 0.819 | 2.67 | 0.007 | 1.270 | 4.717 |
| Post Offices | 0.490 | 0.498 | -0.70 | 0.482 | 0.067 | 3.587 |
| Retail Stores | 1.484 | 0.491 | 1.19 | 0.233 | 0.776 | 2.838 |
| **Cash Economies (Extended hours)** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Banks | 2.056 | 0.619 | 2.40 | 0.017 | 1.140 | 3.708 |
| Gas Stations | 2.133 | 0.685 | 2.36 | 0.018 | 1.136 | 4.003 |
| Grocery Stores | 2.137 | 0.550 | 2.95 | 0.003 | 1.291 | 3.538 |
| Laundries & Drycleaners | 1.819 | 0.582 | 1.87 | 0.062 | 0.971 | 3.407 |
| Liquor Stores | 2.606 | 0.595 | 4.19 | 0.000 | 1.666 | 4.078 |
| Sit-down Restaurants | 2.624 | 0.630 | 4.02 | 0.000 | 1.639 | 4.200 |
| Take-out Restaurants | 2.903 | 0.750 | 4.13 | 0.000 | 1.750 | 4.815 |
| **Cash Economies (Late hours)** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Bars | 1.317 | 0.405 | 0.90 | 0.370 | 0.721 | 2.408 |
| **Transportation** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Light Rail Stops | 0.322 | 0.326 | -1.12 | 0.263 | 0.044 | 2.340 |
| **Non-commercial Features** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| At-risk Housing | 2.122 | 0.474 | 3.37 | 0.001 | 1.369 | 3.288 |
| Cemeteries | 2.013 | 1.497 | 0.94 | 0.347 | 0.469 | 8.647 |
| Churches | 1.819 | 0.440 | 2.47 | 0.013 | 1.132 | 2.924 |
| Libraries | 1.477 | 0.778 | 0.74 | 0.459 | 0.526 | 4.147 |
| Schools | 1.692 | 0.380 | 2.34 | 0.019 | 1.090 | 2.629 |
| **Illegal Markets** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Drug Charges | 4.073 | 1.208 | 4.74 | 0.000 | 2.278 | 7.283 |
| Prostitution Charges | 1.840 | 0.749 | 1.50 | 0.134 | 0.828 | 4.087 |

Similar to the discussion for certain cash businesses in Model 2, the statistically significant criminogenic influences of auto-repair shops, gas stations, grocery stores, hair and nail salons, liquor stores, pawn shops, sit-down restaurants, and take-out restaurants after their operating hours indicated a different crime generating condition around these features than their social relevancy during regular business hours.

**Model 4 "Weekend Business Hours" Robberies**

Among all models, Model 4 Weekend Business Hours robberies was the model with the fewest significant criminogenic risk factors. More importantly, despite covering the same time period with Model 1 "Weekday Business Hours" robberies, the number and combination of criminogenic risk factors for Model 4 were different than in Model 1. As can be seen in Table 12, the significant criminogenic features were either the non-commercial features that were expected to have a round-the clock criminogenic influence (namely at-risk housing, churches, and schools) or the cash businesses that have regular and late business hours (namely grocery stores, hair an nail salons, pawn shops, sit-down restaurants, and take-out restaurants). Surprisingly drug charges which had a significant criminogenic influence on street robberies in Model 0, Model 1, Model 2, and Model 3 did not have a criminogenic influence on weekend business hours robberies. The significance of non-commercial businesses and commercial businesses in Model 4, supported Hypotheses 2.1, 2.3, 2.5. The insignificance of drug charges refuted hypothesis 2.6, and the insignificance of light rail stops supported Hypothesis 2.4 for weekend business hours robberies.

**Table 12. Results of Negative Binomial Regression Analysis for Model 4**

| | | | | | 95% CI | |
|---|---|---|---|---|---|---|
| **Cash Economies (Regular hours)** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Auto Repair Shops | 1.039 | 0.234 | 0.17 | 0.865 | 0.668 | 1.615 |
| Car Dealers | 0.773 | 0.247 | -0.81 | 0.420 | 0.413 | 1.447 |
| Car Washes | 1.501 | 0.596 | 1.02 | 0.307 | 0.689 | 3.270 |
| Hair & Nail Salons | 2.340 | 0.530 | 3.75 | 0.000 | 1.501 | 3.649 |
| Pawn Shops | 1.668 | 0.341 | 2.50 | 0.012 | 1.117 | 2.492 |
| Post Offices | 0.365 | 0.369 | -1.00 | 0.318 | 0.050 | 2.641 |
| Retail Stores | 1.403 | 0.406 | 1.17 | 0.243 | 0.795 | 2.475 |
| **Cash Economies (Extended hours)** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Banks | 1.589 | 0.448 | 1.64 | 0.100 | 0.915 | 2.760 |
| Gas Stations | 1.394 | 0.449 | 1.03 | 0.303 | 0.741 | 2.622 |
| Grocery Stores | 2.438 | 0.520 | 4.18 | 0.000 | 1.605 | 3.702 |
| Laundries & Drycleaners | 1.189 | 0.382 | 0.54 | 0.590 | 0.633 | 2.233 |
| Liquor Stores | 1.363 | 0.308 | 1.37 | 0.169 | 0.876 | 2.121 |
| Sit-down Restaurants | 1.866 | 0.416 | 2.80 | 0.005 | 1.205 | 2.889 |
| Take-out Restaurants | 2.014 | 0.495 | 2.85 | 0.004 | 1.244 | 3.260 |
| **Cash Economies (Late hours)** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Bars | 1.373 | 0.357 | 1.22 | 0.224 | 0.824 | 2.286 |
| **Transportation** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Light Rail Stops | 1.769 | 0.705 | 1.43 | 0.152 | 0.810 | 3.865 |
| **Non-commercial Features** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| At-risk Housing | 2.163 | 0.414 | 4.03 | 0.000 | 1.487 | 3.147 |
| Cemeteries | 0.742 | 0.753 | -0.29 | 0.769 | 0.102 | 5.423 |
| Churches | 2.020 | 0.410 | 3.46 | 0.001 | 1.357 | 3.008 |
| Libraries | 0.812 | 0.480 | -0.35 | 0.725 | 0.255 | 2.588 |
| Schools | 1.942 | 0.368 | 3.50 | 0.000 | 1.338 | 2.816 |
| **Illegal Markets** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Drug Charges | 1.644 | 0.582 | 1.40 | 0.160 | 0.821 | 3.291 |
| Prostitution Charges | 0.557 | 0.329 | -0.99 | 0.321 | 0.176 | 1.770 |

**Model 5 “Weekend Happy Hours” Robberies**

Model 5 “Weekend Happy Hours” and Model 2 “Weekday Happy Hours” had twelve criminogenic features in common: at-risk housing, bars, churches, drug charges, grocery stores, hair and nail salons, liquor stores, pawn shops, retail stores, schools, sit-down restaurants, and take-out restaurants (see Table 10 and Table 13).

The main difference between these two models was the lacking criminogenic influences of banks, laundries and drycleaners, and the added criminogenic influence of auto repair shops on street robberies during weekend happy hours in comparison to weekday happy hours. The significance of bars, grocery stores, liquor shops, sit-down restaurants, and take-out restaurants as commercial businesses with late operating hours supported Hypotheses 2.2, whereas the reemerging significance of drug charges supported Hypothesis 2.6 for Model 5. The light rail stops, as expected, did not exert a criminogenic influence on Model 5 street robberies. Thus, Hypothesis 2.4 was supported for weekend happy hours robberies. The repeated criminogenic influence of at-risk housing, churches, and schools supported hypothesis 2.5 for Model 5. Lastly, similar to Model 2, certain cash economies exerted criminogenic influences on weekend happy hours robberies after their operating hours.

**Table 13. Results of Negative Binomial Regression Analysis for Model 5**

| | | | | | 95% CI | |
|---|---|---|---|---|---|---|
| **Cash Economies (Regular hours)** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Auto Repair Shops | 1.355 | 0.209 | 1.97 | 0.049 | 1.002 | 1.834 |
| Car Dealers | 1.084 | 0.223 | 0.39 | 0.696 | 0.724 | 1.622 |
| Car Washes | 0.747 | 0.294 | -0.74 | 0.459 | 0.345 | 1.617 |
| Hair & Nail Salons | 3.120 | 0.485 | 7.31 | 0.000 | 2.300 | 4.232 |
| Pawn Shops | 3.507 | 0.660 | 6.66 | 0.000 | 2.425 | 5.073 |
| Post Offices | 0.756 | 0.391 | -0.54 | 0.589 | 0.274 | 2.086 |
| Retail Stores | 1.996 | 0.377 | 3.66 | 0.000 | 1.378 | 2.891 |
| **Cash Economies (Extended hours)** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Banks | 1.451 | 0.311 | 1.74 | 0.082 | 0.954 | 2.208 |
| Gas Stations | 1.362 | 0.326 | 1.29 | 0.196 | 0.853 | 2.176 |
| Grocery Stores | 2.990 | 0.450 | 7.29 | 0.000 | 2.228 | 4.014 |
| Laundries & Drycleaners | 1.347 | 0.303 | 1.32 | 0.186 | 0.866 | 2.094 |
| Liquor Stores | 2.064 | 0.310 | 4.83 | 0.000 | 1.538 | 2.771 |
| Sit-down Restaurants | 2.370 | 0.367 | 5.57 | 0.000 | 1.750 | 3.211 |
| Take-out Restaurants | 2.582 | 0.436 | 5.62 | 0.000 | 1.855 | 3.594 |
| **Cash Economies (Late hours)** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Bars | 1.905 | 0.329 | 3.73 | 0.000 | 1.358 | 2.673 |
| **Transportation** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Light Rail Stops | 0.497 | 0.255 | -1.36 | 0.173 | 0.182 | 1.358 |
| **Non-commercial Features** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| At-risk Housing | 1.985 | 0.281 | 4.83 | 0.000 | 1.503 | 2.621 |
| Cemeteries | 0.761 | 0.555 | -0.37 | 0.708 | 0.182 | 3.178 |
| Churches | 2.743 | 0.389 | 7.12 | 0.000 | 2.078 | 3.622 |
| Libraries | 1.414 | 0.479 | 1.02 | 0.306 | 0.728 | 2.746 |
| Schools | 1.820 | 0.255 | 4.28 | 0.000 | 1.383 | 2.395 |
| **Illegal Markets** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Drug Charges | 4.187 | 0.784 | 7.64 | 0.000 | 2.900 | 6.044 |
| Prostitution Charges | 1.073 | 0.344 | 0.22 | 0.827 | 0.572 | 2.010 |

**Model 6 “Weekend Bedtime Hours Robberies”**

Model 6 “Weekend Business Hours” was the model with the second fewest amount of significant criminogenic risk factors.

**Table 14. Results of Negative Binomial Regression Analysis for Model 6**

| | | | | | 95% CI | |
|---|---|---|---|---|---|---|
| **Cash Economies (Regular hours)** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Auto Repair Shops | 1.644 | 0.431 | 1.89 | 0.058 | 0.983 | 2.750 |
| Car Dealers | 0.542 | 0.257 | -1.29 | 0.196 | 0.214 | 1.372 |
| Car Washes | 2.088 | 0.953 | 1.61 | 0.107 | 0.853 | 5.107 |
| Hair & Nail Salons | 2.453 | 0.719 | 3.06 | 0.002 | 1.381 | 4.359 |
| Pawn Shops | 3.306 | 1.129 | 3.50 | 0.000 | 1.693 | 6.458 |
| Post Offices | 4.920 | 0.001 | -0.01 | 0.989 | 0.000 | 0.000 |
| Retail Stores | 2.004 | 0.671 | 2.08 | 0.038 | 1.040 | 3.862 |
| **Cash Economies (Extended hours)** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Banks | 0.787 | 0.376 | -0.50 | 0.616 | 0.308 | 2.008 |
| Gas Stations | 0.978 | 0.470 | -0.05 | 0.962 | 0.381 | 2.509 |
| Grocery Stores | 3.257 | 0.853 | 4.51 | 0.000 | 1.949 | 5.443 |
| Laundries & Drycleaners | 1.592 | 0.597 | 1.24 | 0.215 | 0.763 | 3.322 |
| Liquor Stores | 2.157 | 0.569 | 2.92 | 0.004 | 1.287 | 3.616 |
| Sit-down Restaurants | 2.473 | 0.673 | 3.33 | 0.001 | 1.451 | 4.215 |
| Take-out Restaurants | 3.418 | 0.952 | 4.41 | 0.000 | 1.980 | 5.901 |
| **Cash Economies (Late hours)** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Bars | 2.613 | 0.737 | 3.41 | 0.001 | 1.504 | 4.541 |
| **Transportation** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Light Rail Stops | 1.595 | 0.869 | 0.86 | 0.391 | 0.548 | 4.638 |
| **Non-commercial Features** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| At-risk Housing | 2.288 | 0.564 | 3.36 | 0.001 | 1.411 | 3.711 |
| Cemeteries | 1.183 | 1.247 | 0.16 | 0.873 | 0.150 | 9.334 |
| Churches | 2.471 | 0.631 | 3.55 | 0.000 | 1.499 | 4.075 |
| Libraries | 1.769 | 0.968 | 1.04 | 0.298 | 0.605 | 5.172 |
| Schools | 1.811 | 0.449 | 2.39 | 0.017 | 1.114 | 2.943 |
| **Illegal Markets** | **IRR** | **Std.Err** | **z** | **p>│z│** | **Lower** | **Upper** |
| Drug Charges | 2.741 | 1.054 | 2.62 | 0.009 | 1.290 | 5.823 |
| Prostitution Charges | 1.874 | 0.851 | 1.38 | 0.166 | 0.770 | 4.561 |

As set forth by Hypotheses 2.2, 2.5, and 2.6, bars representing the businesses with the latest starting operating hours; at-risk housing, churches, and schools representing non-commercial features; and drug charges representing illegal markets had criminogenic influences on weekend robberies at late hours. As illustrated in Table 14, similar to Model 3, some cash businesses (namely grocery stores, hair and nail salons, liquor stores, pawn shops, retail stores, sit-down restaurants and take-out restaurants) had spatial criminogenic influences on weekend bedtime hours robberies after their operating hours. The main difference between Model 3 and Model 6 robberies was the lacking criminogenic influences of auto repair shops, banks, and gas stations, and the added criminogenic influences of bars and retail shops on street robberies during weekend bedtime hours in comparison to weekday bedtime hours.

*Summary*

As illustrated in Table 15, it was shown that the criminogenic influences of land use features change in different time models. Nested weekday and weekend time models provided more insight into the dynamic nature of land use features' criminogenic spatial influences. As illustrated in Table 15, hair and nail salons, pawn shops, grocery stores, sit-down and take-out restaurants, at-risk housing, churches, and schools were the only features that had a criminogenic influence in the base model (Model 0) and in all time-nested models (Models 1-6). Compared to the time-nested models the base model had the highest number of criminogenic features. In comparison to all models, weekend business hours model has the lowest number of significant correlates, and overall weekend models had less criminogenic features. Light rail stops did not have a criminogenic spatial influence in either Model 0 or time-nested models 1-6.

**Table 15. Significant Correlates of 2010 Street Robberies in Models 0-6**

| | Model 0 All-time | Model 1 Weekday Business Hours | Model 2 Weekday Happy Hours | Model 3 Weekday Bedtime Hours | Model 4 Weekend Business Hours | Model 5 Weekend Happy Hours | Model 6 Weekend Bedtime Hours |
|---|---|---|---|---|---|---|---|
| | IRR | IRR | IRR | IRR | IRR | IRR | IRR |
| **Cash Economies (Regular hours)** | | | | | | | |
| Auto Repair Shops | 1.217* | -- | -- | 2.122*** | -- | 1.355* | -- |
| Car Dealers | 0.788* | 0.568** | -- | -- | -- | -- | -- |
| Car Washes | -- | -- | -- | -- | -- | -- | -- |
| Hair & Nail Salons | 2.526*** | 2.478*** | 2.410*** | 1.976* | 2.340*** | 3.120*** | 2.453*** |
| Pawn Shops | 2.775*** | 2.679*** | 2.314*** | 2.448** | 1.668* | 3.507*** | 3.306*** |
| Post Offices | -- | -- | -- | -- | -- | -- | -- |
| Retail Stores | 1.931*** | 2.414*** | 1.688** | -- | -- | 1.996*** | 2.004* |
| **Cash Economies (Extended hours)** | | | | | | | |
| Banks | 1.627*** | 1.538* | 1.944*** | 2.056* | -- | -- | -- |
| Gas Stations | -- | -- | -- | 2.133* | -- | -- | -- |
| Grocery Stores | 2.698*** | 2.526*** | 2.843*** | 2.137** | 2.438*** | 2.990*** | 3.257*** |
| Laundries & Drycleaners | 1.378** | -- | 1.873*** | -- | -- | -- | -- |
| Liquor Stores | 1.757*** | 1.398* | 1.836*** | 2.606*** | -- | 2.064*** | 2.157** |
| Sit-down Restaurants | 2.064*** | 1.794*** | 1.989*** | 2.624*** | 1.866** | 2.370*** | 2.473*** |
| Take-out Restaurants | 2.201*** | 2.039*** | 1.775*** | 2.903*** | 2.014** | 2.582*** | 3.418*** |
| **Cash Economies (Late hours)** | | | | | | | |
| Bars | 1.756*** | 1.767*** | 1.718*** | -- | -- | 1.905*** | 2.613*** |
| **Transportation** | | | | | | | |
| Light Rail Stops | -- | -- | -- | -- | -- | -- | -- |
| **Non-commercial Features** | | | | | | | |
| At-risk Housing | 1.467*** | 1.972*** | 1.390** | 2.122*** | 2.163*** | 1.985*** | 2.288*** |
| Cemeteries | -- | -- | -- | -- | -- | -- | -- |
| Churches | 2.029*** | 1.849*** | 1.754*** | 1.819* | 2.020*** | 2.743*** | 2.471*** |
| Libraries | 1.492* | 1.754* | -- | -- | -- | -- | -- |
| Schools | 1.708*** | 1.793*** | 1.468** | 1.692* | 1.942*** | 1.820*** | 1.811* |
| **Illegal Markets** | | | | | | | |
| Drug Charges | 3.101*** | 3.027*** | 2.832*** | 4.073*** | -- | 4.187*** | 2.741** |
| Prostitution Charges | -- | -- | -- | -- | -- | -- | -- |

*p≤0.05, **p≤0.01, ***p≤0.001

## 3.3. Testing Hypothesis #3: Do weights of the criminogenic spatial influence of landscape features for street robberies vary temporally?

*Calculating the Relative Spatial Influence and Weight of Each Criminogenic Risk Factor*

The Relative Spatial Influence (RSI) and weight of each criminogenic risk factor in all models were calculated following the weighting steps in RTM suggested by Kennedy and Caplan (2011). First, using the "RSI Calculation" tool in RTM toolbox, the reclassified risk map layers were transformed into point features for each risk map layer in each time model. Then, the study extent cells that intersect with risky cells were selected, and the number of robbery outcomes in risky cells were identified. Following that, the relative spatial influence (RSI) value was computed by dividing the number of outcome events with the number of risky cells for each risk factor in each time model. Finally, the weights of risk factors were computed by dividing the RSI value of each risk factor in each time model with the smallest RSI value in each time model.

*Findings*

**Model 0 "All Time" Robberies**

Table 16 shows the results of the RSI and weight calculations for Model 0. In Model 0, drug charges, representing the illegal markets, had the strongest criminogenic spatial influence on CY 2010 all-time robberies. Among cash businesses which had significant criminogenic spatial influences on all CY 2010 robberies, pawn shops, grocery stores, hair and nail salons, and take-out restaurants had a stronger criminogenic influence than sit-down restaurants, retail stores, bars, liquor stores, banks, laundries and drycleaners. Among all significant risk features, auto-repair shops had the weakest criminogenic spatial influence. As explained earlier, non-commercial features have been consistent predictors of street robberies in all time models. However, as illustrated in Table 16, when compared to illegal markets and cash businesses, these features had relatively weaker criminogenic influences.

**Table 16. RSI and Weight of Criminogenic Features in Model 0***

| Feature | Number of selected outcome events | Number of selected cells | RSI | Weight |
|---|---|---|---|---|
| At-risk Housing | 231 | 2936 | 0.079 | 1.157 |
| Auto Repair Shops | 299 | 4375 | 0.068 | 1.000 |
| Banks | 156 | 1717 | 0.091 | 1.336 |
| Bars | 225 | 2371 | 0.095 | 1.396 |
| Churches | 367 | 3647 | 0.101 | 1.480 |
| Drug Charges | 162 | 978 | 0.166 | **2.436** |
| Grocery Stores | 340 | 2605 | 0.131 | 1.919 |
| Hair & Nail Salons | 281 | 2202 | 0.128 | 1.877 |
| Laundries & Drycleaners | 128 | 1628 | 0.079 | 1.156 |
| Libraries | 55 | 637 | 0.086 | 1.270 |
| Liquor Stores | 321 | 3511 | 0.091 | 1.345 |
| Pawn Shops | 166 | 1124 | 0.148 | 2.172 |
| Retail Stores | 188 | 1791 | 0.105 | 1.544 |
| Schools | 452 | 5329 | 0.085 | 1.247 |
| Sit-down Restaurants | 297 | 2804 | 0.106 | 1.558 |
| Take-out Restaurants | 230 | 1984 | 0.116 | 1.705 |

* The highlighted weight in each model signifies the strongest criminogenic influence in the model

**Model 1 "Weekday Business Hours" Robberies**

Table 17 shows the results of the RSI and weight calculations for Model 1. The weight of the criminogenic features for the weekday business hours were quite similar to the weights identified for Model 0's significant risk factors. For instance, in Model 1, drug charges had the strongest criminogenic influence representing illegal markets. Furthermore, the cash businesses of pawn shops, grocery stores, and hair and nail salons were in the top five features with the strongest criminogenic influences. Moreover, similar to Model 0, non-commercial features had weaker criminogenic influences compared to illegal markets and a majority of cash businesses. In Model 1, liquor stores had the weakest criminogenic influence.

**Table 17. RSI and Weight of Criminogenic Features in Model 1**

| Feature | Number of selected outcome events | Number of selected cells | RSI | Weight |
|---|---|---|---|---|
| At-risk Housing | 79 | 2936 | 0.027 | 1.170 |
| Banks | 44 | 1717 | 0.026 | 1.114 |
| Bars | 67 | 2371 | 0.028 | 1.229 |
| Churches | 102 | 3647 | 0.028 | 1.216 |
| Drug Charges | 47 | 978 | 0.048 | **2.089** |
| Grocery Stores | 96 | 2605 | 0.037 | 1.602 |
| Hair & Nail Salons | 82 | 2202 | 0.037 | 1.619 |
| Libraries | 19 | 637 | 0.030 | 1.297 |
| Liquor Stores | 80 | 3511 | 0.023 | 1.000 |
| Pawn Shops | 48 | 1124 | 0.043 | 1.857 |
| Retail Stores | 67 | 1791 | 0.037 | 1.626 |
| Schools | 138 | 5329 | 0.026 | 1.126 |
| Sit-down Restaurants | 79 | 2804 | 0.028 | 1.225 |
| Take-out Restaurants | 64 | 1984 | 0.032 | 1.403 |

Despite the unexpected criminogenic influence of bars during weekday business hours, compared to other cash businesses with earlier business hours, bars during weekday business hours were observed to exert a mediocre criminogenic influence. Moreover, retail stores that had a weaker criminogenic influence in Model 0 had a stronger criminogenic influence in Model 1.

**Model 2 “Weekday Happy Hours” Robberies**

Table 18 shows the results of the RSI and weight calculations for Model 2. Similar to Model 0 and Model 1, drug charges, grocery stores, pawn shops, and hair and nail salons had the strongest criminogenic influence in Model 2. As indicated earlier, the significance of pawn shops and hair and nail salons after their regular hours has been unexpected. Adding to that finding, the further identification of the strong criminogenic influence of these features supported the earlier suggestion on the changing social relevancy of features at later hours.

Moreover, in Model 2, banks which had a moderate criminogenic effect for all time robberies and weekday business robberies had one of the strongest criminogenic influences on weekday happy hours robberies. The identification of churches, schools and at-risk housing as the criminogenic features with the weakest spatial influence further supported the relatively less significant criminogenic spatial influences of non-commercial features of the landscape on street robberies compared to illegal markets and cash economies.

**Table 18. RSI and Weight of Criminogenic Features in Model 2**

| Feature | Number of selected outcome events | Number of selected cells | RSI | Weight |
|---|---|---|---|---|
| At-risk Housing | 55 | 2936 | 0.019 | 1.000 |
| Banks | 51 | 1717 | 0.030 | 1.563 |
| Bars | 62 | 2371 | 0.026 | 1.376 |
| Churches | 93 | 3647 | 0.026 | 1.342 |
| Drug Charges | 42 | 978 | 0.043 | **2.260** |
| Grocery Stores | 99 | 2605 | 0.038 | 2.000 |
| Hair & Nail Salons | 76 | 2202 | 0.035 | 1.817 |
| Laundries & Drycleaners | 47 | 1628 | 0.029 | 1.519 |
| Liquor Stores | 93 | 3511 | 0.026 | 1.394 |
| Pawn Shops | 40 | 1124 | 0.036 | 1.873 |
| Retail Stores | 47 | 1791 | 0.026 | 1.381 |
| Schools | 115 | 5329 | 0.022 | 1.136 |
| Sit-down Restaurants | 81 | 2804 | 0.029 | 1.520 |
| Take-out Restaurants | 54 | 1984 | 0.027 | 1.433 |

**Model 3 "Weekday Bedtime Hours" Robberies**

Table 19 shows the results of the RSI and weight calculations for Model 3. For weekday bedtime hours robberies, drug charges, take-out restaurants, pawn shops, sit-down restaurants and liquor stores had the strongest criminogenic influences. Solely looking at the ratios of the strongest risk factor to the weakest risk factor in models 0-3, drug charges exerted the strongest influence in Model 3 with a weight of 3. Liquor stores, sit-down restaurants, and take-out restaurants, all of which had a moderate criminogenic influence in Model 1 (see Table 17), transformed into relatively more criminogenic features for weekday bedtime hours robberies. At-risk housing, churches, and schools, though significant, continued to exert the weakest criminogenic influence in Model 3, compared to cash businesses and illegal markets.

**Table 19. RSI and Weight of Criminogenic Features in Model 3**

| Feature | Number of selected outcome events | Number of selected cells | RSI | Weight |
|---|---|---|---|---|
| At-risk Housing | 16 | 2936 | 0.005 | 1.000 |
| Auto Repair Shops | 32 | 4375 | 0.007 | 1.463 |
| Banks | 14 | 1717 | 0.008 | 1.631 |
| Churches | 25 | 3647 | 0.007 | 1.371 |
| Drug Charges | 15 | 978 | 0.015 | **3.067** |
| Gas Stations | 12 | 1405 | 0.009 | 1.708 |
| Grocery Stores | 21 | 2605 | 0.008 | 1.612 |
| Hair & Nail Salons | 17 | 2202 | 0.008 | 1.544 |
| Liquor Stores | 31 | 3511 | 0.009 | 1.766 |
| Pawn Shops | 11 | 1124 | 0.010 | 1.957 |
| Schools | 33 | 5329 | 0.006 | 1.239 |
| Sit-down Restaurants | 26 | 2804 | 0.009 | 1.854 |
| Take-out Restaurants | 21 | 1984 | 0.011 | 2.117 |

**Model 4 "Weekend Business Hours" Robberies**

Table 20 shows the results of the RSI and weight calculations for Model 4. Unlike Model 1 "Weekday Business Hours" robberies, pawn shops had the strongest criminogenic influence on Model 4 "Weekend Business Hours" robberies. Similar to findings from Model 1, grocery stores and hair and nail salons had strong criminogenic influences on Model 4 street robberies. Furthermore, at-risk housing's, schools', and churches' criminogenic influences were statistically significant, albeit weak.

**Table 20. RSI and Weight of Criminogenic Features in Model 4**

| Feature | Number of selected outcome events | Number of selected cells | RSI | Weight |
|---|---|---|---|---|
| At-risk Housing | 27 | 2936 | 0.009 | 1.022 |
| Churches | 36 | 3647 | 0.010 | 1.097 |
| Grocery Stores | 31 | 2605 | 0.012 | 1.322 |
| Hair & Nail Salons | 26 | 2202 | 0.012 | 1.312 |
| Pawn Shops | 16 | 1124 | 0.014 | **1.582** |
| Schools | 48 | 5329 | 0.009 | 1.000 |
| Sit-down Restaurants | 27 | 2804 | 0.010 | 1.070 |
| Take-out Restaurants | 21 | 1984 | 0.011 | 1.176 |

**Model 5 "Weekend Happy Hours" Robberies**

Table 21 shows the results of the RSI and weight calculations for Model 5.

**Table 21. RSI and Weight of Criminogenic Features in Model 5**

| Feature | Number of selected outcome events | Number of selected cells | RSI | Weight |
|---|---|---|---|---|
| At-risk Housing | 43 | 2936 | 0.015 | 1.046 |
| Auto Repair Shops | 62 | 4375 | 0.014 | 1.000 |
| Bars | 46 | 2371 | 0.019 | 1.386 |
| Churches | 86 | 3647 | 0.024 | 1.684 |
| Drug Charges | 40 | 978 | 0.041 | **2.921** |
| Grocery Stores | 70 | 2605 | 0.027 | 1.919 |
| Hair & Nail Salons | 63 | 2202 | 0.029 | 2.044 |
| Liquor Stores | 69 | 3511 | 0.020 | 1.404 |
| Pawn Shops | 39 | 1124 | 0.035 | 2.478 |
| Retail Stores | 37 | 1791 | 0.021 | 1.476 |
| Schools | 90 | 5329 | 0.017 | 1.206 |
| Sit-down Restaurants | 63 | 2804 | 0.022 | 1.605 |
| Take-out Restaurants | 50 | 1984 | 0.025 | 1.800 |

In Model 5 "Weekend Happy Hours" robberies, drug charges again had the strongest criminogenic influence followed by pawn shops, hair and nail salons, and grocery stores. However, in Model 5, take-out restaurants and churches had relatively stronger criminogenic influences when compared to their weaker criminogenic influences in Model 2. On the other hand, at-risk housing and schools continued exerting weak criminogenic influences in Model 5.

### Model 6 "Weekend Bedtime Hours" Robberies

Table 22 shows the results of the RSI and weight calculations for Model 6. Although drug charges had a strong criminogenic influence on weekend bedtime robberies, they did not have a criminogenic influence as strong as pawn shops.

**Table 22. RSI and Weight of Criminogenic Features in Model 6**

| Feature | Number of selected outcome events | Number of selected cells | RSI | Weight |
|---|---|---|---|---|
| At-risk Housing | 11 | 2936 | 0.004 | 1.000 |
| Bars | 19 | 2371 | 0.008 | 2.003 |
| Churches | 26 | 3647 | 0.007 | 1.782 |
| Drug Charges | 9 | 978 | 0.009 | 2.301 |
| Grocery Stores | 24 | 2605 | 0.009 | 2.303 |
| Hair & Nail Salons | 17 | 2202 | 0.008 | 1.930 |
| Liquor Stores | 23 | 3511 | 0.007 | 1.638 |
| Pawn Shops | 12 | 1124 | 0.011 | **2.669** |
| Retail Stores | 12 | 1791 | 0.007 | 1.675 |
| Schools | 29 | 5329 | 0.005 | 1.360 |
| Sit-down Restaurants | 21 | 2804 | 0.007 | 1.872 |
| Take-out Restaurants | 20 | 1984 | 0.010 | 2.520 |

Take-out restaurant, which had the second strongest criminogenic influence on Model 3 “Weekday Bedtime Hours” robberies, continued to exert a similar influence on also Model 6 “Weekend Bedtime Hours” robberies. Bars that did not have a strong criminogenic influence in the other time-nested models, exerted a strong criminogenic influence in Model 6.

*Summary*

As explained earlier, in Models 0-6, several landscape features have been identified to have criminogenic influences on street robberies at different times. Despite the variety and combination of features in different time models, the exploration of the weights of features in relation to one another revealed distinctive trends that held true among a majority of the models (see Table 23). For instance, with the exception of Model 4 Weekend Business Hours robberies, drug charges exerted either the strongest or a very strong criminogenic influence on street robberies in the base model and the remaining time-nested models. Similarly, pawn shops which had a round-the-clock criminogenic influence on street robberies, also exerted either the strongest or a very strong criminogenic influence in different time models. At-risk housing, churches, and schools, on the other hand, all of which exerted a round-the-clock criminogenic influence on street robberies similar to pawn shops, exerted either the weakest or very weak criminogenic influences on street robberies in comparison to other features. In addition to these general trends, in different models a variety of cash businesses with regular and extended hours (i.e., grocery stores, hair and nail salons, retail stores, take-out restaurants, sit-down restaurants) exerted strong criminogenic influences on street robberies.

**Table 23. Weight of Significant Risk Features in Models 0-6**

| | Model 0 All-time | Model 1 Weekday Business Hours | Model 2 Weekday Happy Hours | Model 3 Weekday Bedtime Hours | Model 4 Weekend Business Hours | Model 5 Weekend Happy Hours | Model 6 Weekend Bedtime Hours |
|---|---|---|---|---|---|---|---|
| | Weight | Weight | Weight | Weight | Weight | Weight | Weight |
| **Cash Economies (Regular hours)** | | | | | | | |
| Auto Repair Shops | 1.000 | -- | -- | 1.463 | -- | 1.000 | -- |
| Car Dealers | -- | -- | -- | -- | -- | -- | -- |
| Car Washes | -- | -- | -- | -- | -- | -- | -- |
| Hair & Nail Salons | 1.877 | 1.619 | 1.817 | 1.544 | 1.312 | 2.044 | 1.930 |
| Pawn Shops | 2.172 | 1.857 | 1.873 | 1.957 | **1.582** | 2.478 | **2.669** |
| Post Offices | -- | -- | -- | -- | -- | -- | -- |
| Retail Stores | 1.544 | 1.626 | 1.381 | -- | -- | 1.476 | 1.675 |
| **Cash Economies (Extended hours)** | | | | | | | |
| Banks | 1.336 | 1.114 | 1.563 | 1.631 | -- | -- | -- |
| Gas Stations | -- | -- | -- | 1.71 | -- | -- | -- |
| Grocery Stores | 1.919 | 1.602 | 2 | 1.322 | 1.322 | 1.919 | 2.303 |
| Laundries & Drycleaners | 1.156 | -- | 1.519 | -- | -- | -- | -- |
| Liquor Stores | 1.345 | 1.345 | 1.394 | 1.766 | -- | 1.404 | 1.638 |
| Sit-down Restaurants | 1.558 | 1.225 | 1.520 | 1.854 | 1.070 | 1.605 | 1.872 |
| Take-out Restaurants | 1.705 | 1.403 | 1.433 | 2.117 | 1.176 | 1.800 | 2.520 |
| **Cash Economies (Late hours)** | | | | | | | |
| Bars | 1.396 | 1.229 | 1.376 | -- | -- | 1.386 | 2.003 |
| **Transportation** | | | | | | | |
| Light Rail Stops | -- | -- | -- | -- | -- | -- | -- |
| **Non-commercial Features** | | | | | | | |
| At-risk Housing | 1.157 | 1.170 | 1.000 | 1.000 | 1.022 | 1.046 | 1.000 |
| Cemeteries | -- | -- | -- | -- | -- | -- | -- |
| Churches | 1.48 | 1.216 | 1.342 | 1.371 | 1.097 | 1.684 | 1.782 |
| Libraries | 1.270 | 1.297 | -- | -- | -- | -- | -- |
| Schools | 1.247 | 1.126 | 1.136 | 1.239 | 1.000 | 1.000 | 1.360 |
| **Illegal Markets** | | | | | | | |
| Drug Charges | **2.436** | **2.089** | **2.260** | **3.067** | -- | **2.921** | 2.301 |
| Prostitution Charges | -- | -- | -- | -- | -- | -- | -- |

# CHAPTER 4: THE COMBINED TEMPORAL CRIMINOGENIC INFLUENCES OF LANDSCAPE FEATURES ON STREET ROBBERIES

In this dissertation, the analysis of the individual criminogenic spatial influences of landscape features on street robberies has demonstrated the dynamic nature of the criminogenic spatial influences of illegal markets, cash businesses, and non-commercial features. The findings not only proved that the criminogenic features are different at different times of the day and different days of the week, but also the extent and the strength of these criminogenic influences vary within and between time periods and features. In this chapter, the combined temporal criminogenic influences of landscape features on street robberies are tested by exploring if street robberies emerge at places where there is high vulnerability based on the combined spatial influence of criminogenic features at different times of the day and different days of the week.

## 4.1. Testing Hypothesis #4 and #5: Do street robberies emerge at risky places of combined criminogenic influences at different times of the day and different days of the week?

*Producing Composite Risk Terrain Maps with the Weighted Risk Map Layers and Testing the Statistical Significance of the Models*

To test hypotheses #4 and #5, a composite risk map was created for each model by summing the weighted risk values of significant risk factors identified in Chapter 3 for each model using the weighted sum tool in ArcMap. To control for the interaction effect of the clustered robberies, as identified with the Global Moran's I test earlier, a spatial weight was created for each robbery in Model 0, Model 1, Model 2, Model 5, and Model 6, using the “Generate Spatial Weights Matrix” function in ArcMap. The spatial weight variable was joined to the robbery layer using the “Join Attributes From a Table” function in ArcMap. Following that, the raster composite risk map was converted to a vector composite vulnerability map by using the “Convert Raster Layer to Vector Grid” function in the RTM Toolbox. After that, the locations of robberies were joined to the vector composite risk map by using the “Join Count of Outcome Event to Vector Grid” function in RTM toolbox. After joining these two layers, a new field was created in the attribute table of the vector composite risk map using the “Add Field” function in ArcMap. Then, using the “Field Calculator” function in the attribute table, the spatial lag value was calculated by multiplying the spatial weight value with the robbery count value. Following that, the attribute table of the resulting layer with the fields of robbery count, spatial lag, and composite vulnerability value was exported to STATA to run a negative binomial regression analysis. The results from the negative binomial regression analysis was used to measure the extent to which the composite risk value explains the variance in robbery count controlling for spatial autocorrelation. This process was repeated for each time model.

*Findings*

**Model 0 “All-time” Robberies**

Figure 6 displays the Model 0 “All-time” robberies risk terrain map.

**Figure 6. Risk Terrain Map with CY 2010 All-time Robberies**

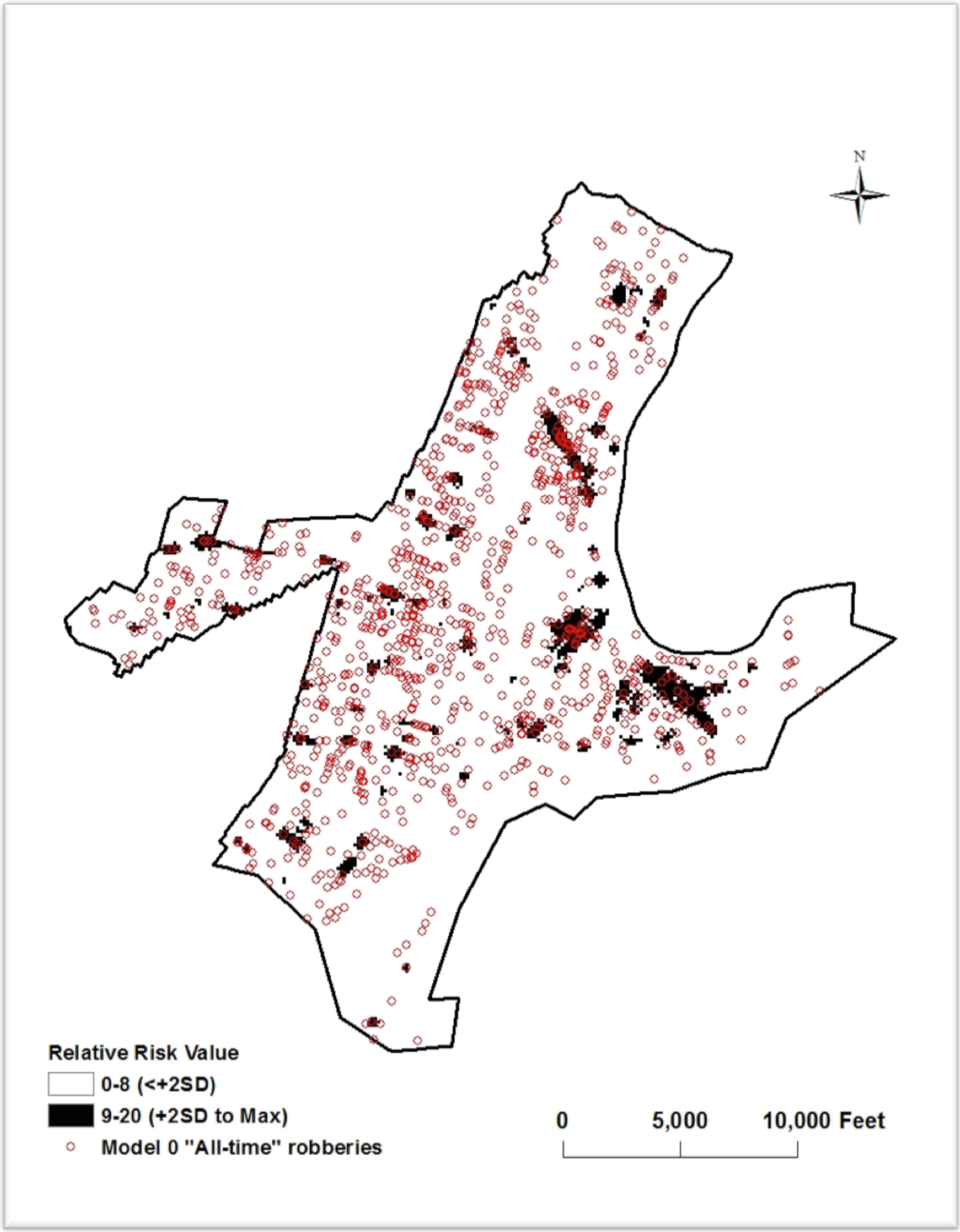

**Table 24. Negative Binomial Regression Results for Model 0 Risk Terrain Forecasting**

| Variable | IRR | Std.Err | z | p>\|z\| | 95% CI Lower | 95% CI Upper |
|---|---|---|---|---|---|---|
| Risk Value (0-20) | 1.112 | 0.010 | 12.40 | 0.000 | 1.094 | 1.131 |
| Spatial Lag | 21.474 | 6.215 | 10.60 | 0.000 | 12.178 | 37.868 |
| Constant | 0.027 | 0.001 | 69.03 | 0.000 | 0.024 | 0.030 |

Pseudo $R^2$=0.19

Table 24 shows the results of a negative binomial regression analysis with "Risk Value" and "Spatial Lag" as the independent variables and the count of CY 2010 "All-time" street robberies as the dependent variable. As illustrated by the Incidence Rate Ratio (IRR) in Table 24, for every unit increase in risk, CY 2010's street robbery counts is expected to increase by 11% ($p<0.001$). The significance of a spatial lag variable in this statistical testing further suggests that, controlling for other predictors, the emergence of CY 2010 all-time street robberies at one place is also a good indicator for all-time street robberies at neighboring places. Lastly, the statistical significance of the constant suggests that there is unaccounted variance in the regression, which is unaccounted for by the risk value and the spatial lag predictors.

In linear regression analysis, the $R^2$ is used to interpret the total variation in the regression model that is accounted for by the independent variables included in the model. However the $R^2$ result in negative binomial regression analysis does not compare to the $R^2$ in linear regression, and is called pseudo $R^2$. In statistics this parameter is suggested to be used with caution (IDRE, n.d.). With that being said, a particular type of pseudo- $R^2$ can be compared to another pseudo- $R^2$ of the same type (Long and Freese, 2006). In Model 0, the pseudo $R^2$ is 0.19.

**Model 1 "Weekday Business Hours" Robberies**

Figure 7 displays the Model 1 "Weekday Business Hours" robberies risk terrain map.

**Figure 7. Risk Terrain Map with CY 2010 Weekday Business Hours Robberies**

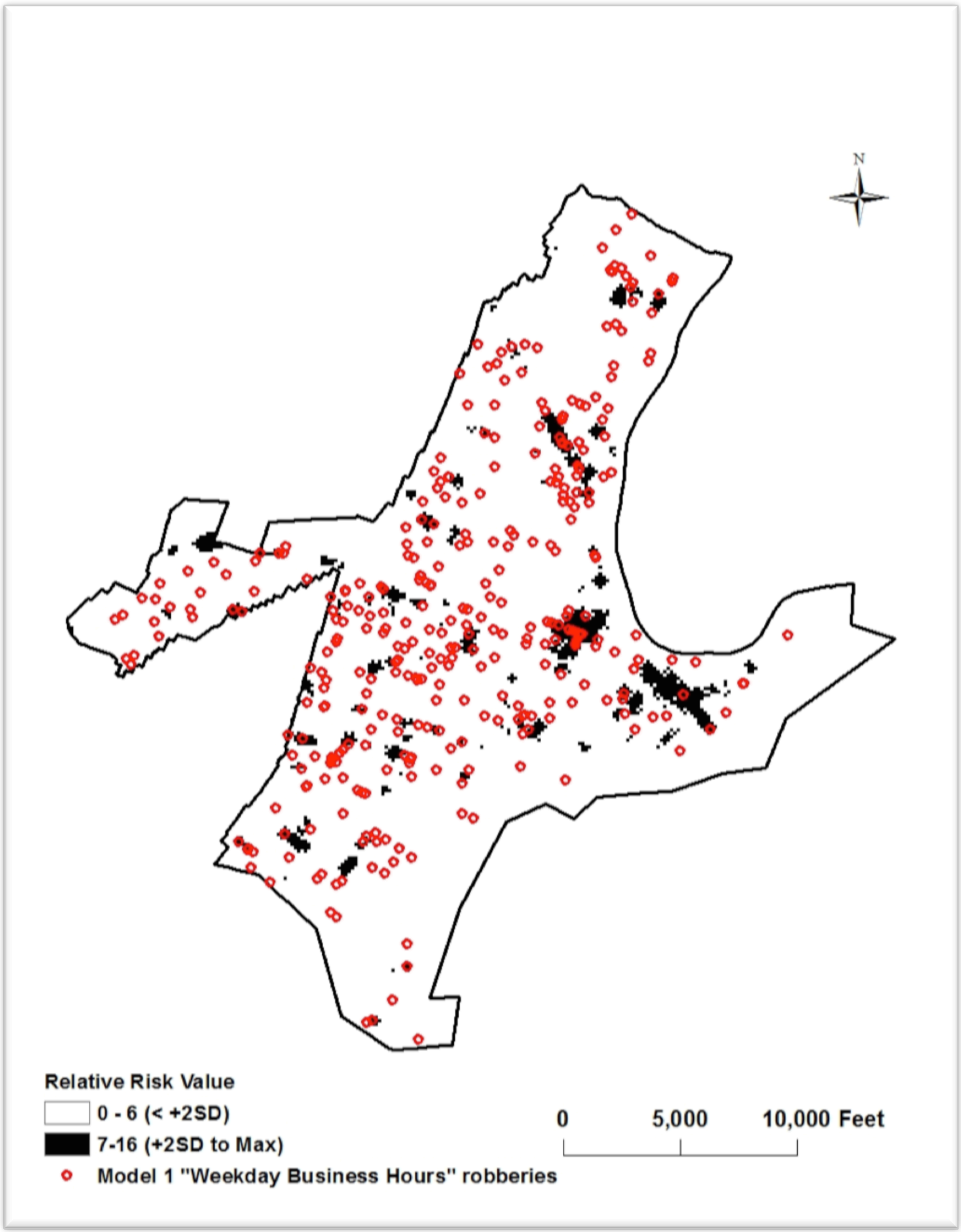

**Table 25. Negative Binomial Regression Results for Model 1 Risk Terrain Forecasting**

| Variable | IRR | Std.Err | z | p>\|z\| | 95% CI Lower | 95% CI Upper |
|---|---|---|---|---|---|---|
| Risk Value (0-16) | 1.125 | 0.029 | 4.52 | 0.000 | 1.069 | 1.184 |
| Spatial Lag | 6.89 | 1.270 | 13.50 | 0.000 | 1.840 | 2.580 |
| Constant | 0.004 | 0.001 | 40.82 | 0.000 | 0.003 | 0.005 |

Pseudo $R^2$: 0.30

Table 25 shows the results of a negative binomial regression analysis with "Risk Value" and "Spatial Lag" as the independent variables and the count of CY 2010 "Weekday Business Hours" street robberies as the dependent variable. As illustrated by the IRR in Table 25, for every unit increase in risk, CY 2010 weekday business hours street robbery counts is expected to increase by 13% ($p<0.001$). Similar to Model 0, the significance of the spatial lag variable in Model 1 suggests that, controlling for other predictors, the emergence of CY 2010 weekday business hours street robberies at one place is also a good indicator for other weekday business hours street robberies at neighboring places. Lastly, the statistical significance of the constant suggests that there is unaccounted variance in the regression, which is unaccounted for by the risk value and the spatial lag predictors in Model 1. In Model 1, the pseudo $R^2$ is 0.30.

**Model 2 "Weekday Happy Hours" Robberies**

Figure 8 displays the Model 2 "Weekday Happy Hours" robberies risk terrain map.

**Figure 8. Risk Terrain Map with CY 2010 Weekday Happy Hours Robberies**

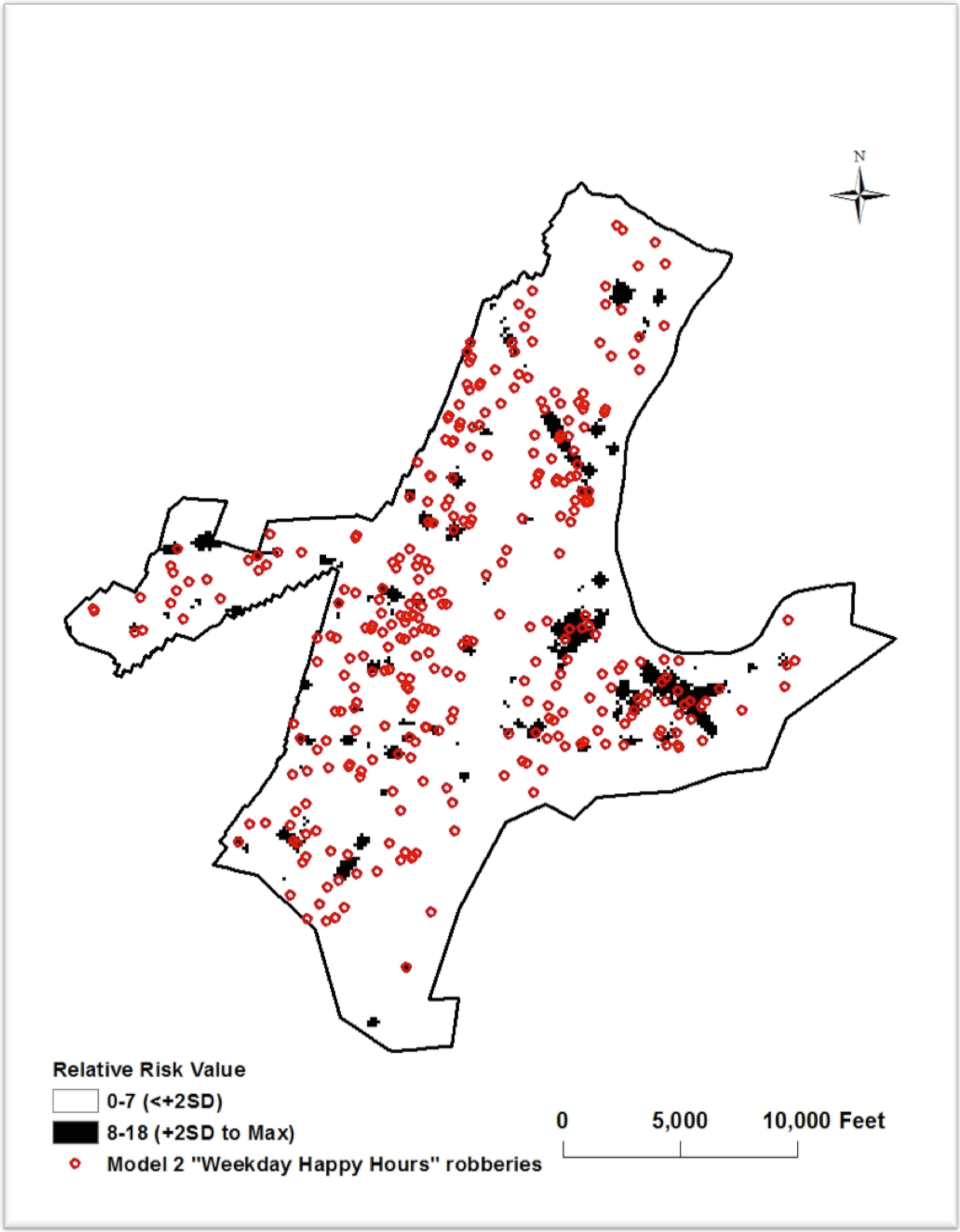

**Table 26. Negative Binomial Regression Results for Model 2 Risk Terrain Forecasting**

| Variable | IRR | Std.Err | z | p>│z│ | 95% CI Lower | 95% CI Upper |
|---|---|---|---|---|---|---|
| Risk Value (0-18) | 1.083 | 0.027 | 3.15 | 0.002 | 1.030 | 1.137 |
| Spatial Lag | 2.64 | 3.740 | 18.59 | 0.000 | 1.650 | 4.230 |
| Constant | 0.003 | 0.001 | -39.43 | 0.000 | 0.002 | 0.004 |

Pseudo $R^2$: 0.37

Table 26 shows the results of a negative binomial regression analysis with “Risk Value” and “Spatial Lag” as the independent variables and the count of CY 2010 “Weekday Happy Hours” street robberies as the dependent variable. As illustrated by the IRR in Table 26, for every unit increase in risk, CY 2010 weekday happy hours street robbery counts is expected to increase by 8% ($p<0.001$). Similar to Model 0 and 1, the significance of the spatial lag variable in Model 1 suggests that, controlling for other predictors, the emergence of CY 2010 weekday happy hours street robberies at one place is also a good indicator for other weekday happy hours street robberies at neighboring places. Lastly, the statistical significance of the constant suggests that there is unaccounted variance in the regression, which is unaccounted for by the risk value and the spatial lag predictors in Model 2. In Model 2, the pseudo $R^2$ is 0.37.

**Model 3 “Weekday Bedtime Hours” Robberies**

Figure 9 displays the Model 3 “Weekday Bedtime Hours” robberies risk terrain map.

**Figure 9. Risk Terrain Map with CY 2010 Weekday Bedtime Hours Robberies**

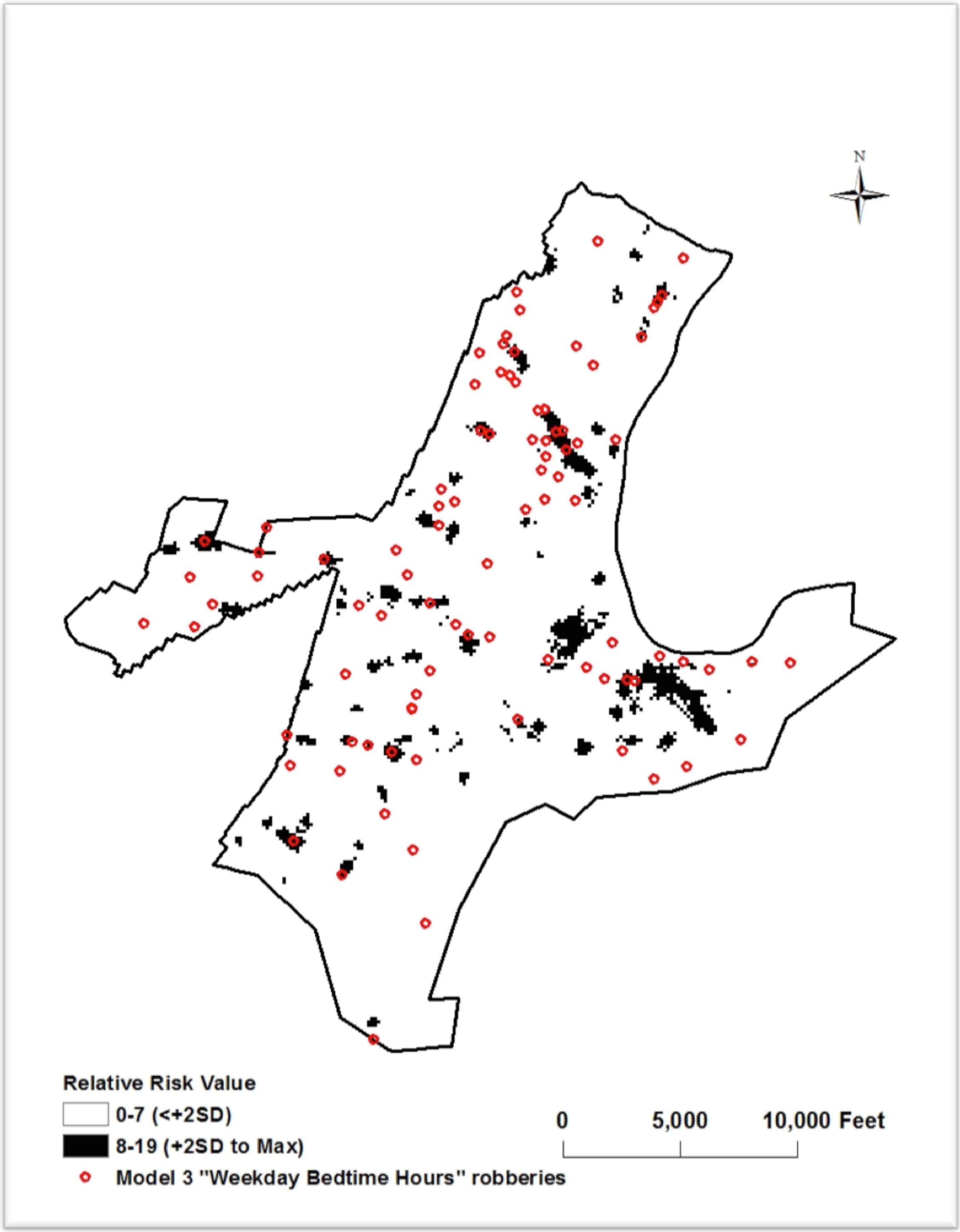

**Table 27. Negative Binomial Regression Results for Model 3 Risk Terrain Forecasting**

| Variable | IRR | Std.Err | z | p>│z│ | 95% CI Lower | Upper |
|---|---|---|---|---|---|---|
| Risk Value (0-19) | 1.198 | 0.053 | 7.28 | 0.000 | 1.141 | 1.258 |
| Constant | 0.002 | 0.004 | -37.78 | 0.000 | 0.002 | 0.003 |

Pseudo $R^2$: 0.04

Table 27 shows the results of a negative binomial regression analysis with "Risk Value" as the independent variable and the count of CY 2010 "Weekday Bedtime Hours" street robberies as the dependent variable. In this model, the spatial lag was not included in the analysis as an independent variable because, as indicated earlier with the results of the Moran's I statistics, the distribution of street robberies at weekday bedtime hours were found to be spatially uncorrelated. As illustrated by the Incidence Rate Ratio (IRR) in Table 27, for every unit increase in risk, CY 2010 weekday bedtime hours street robbery counts is expected to increase by 20% ($p<0.001$). The statistical significance of the constant suggests that there is unaccounted variance in the regression, which is unaccounted for by the risk value in Model 3. In Model 3, the pseudo $R^2$ is 0.04.

**Model 4 "Weekend Business Hours" Robberies**

Figure 10 displays the Model 4 "Weekend Business Hours" robberies risk terrain map. Table 28 shows the results of a negative binomial regression analysis with "Risk Value" as the independent variable and the count of CY 2010 "Weekend Business Hours" street robberies as the dependent variable.

**Figure 10. Risk Terrain Map with CY 2010 Weekend Business Hours Robberies**

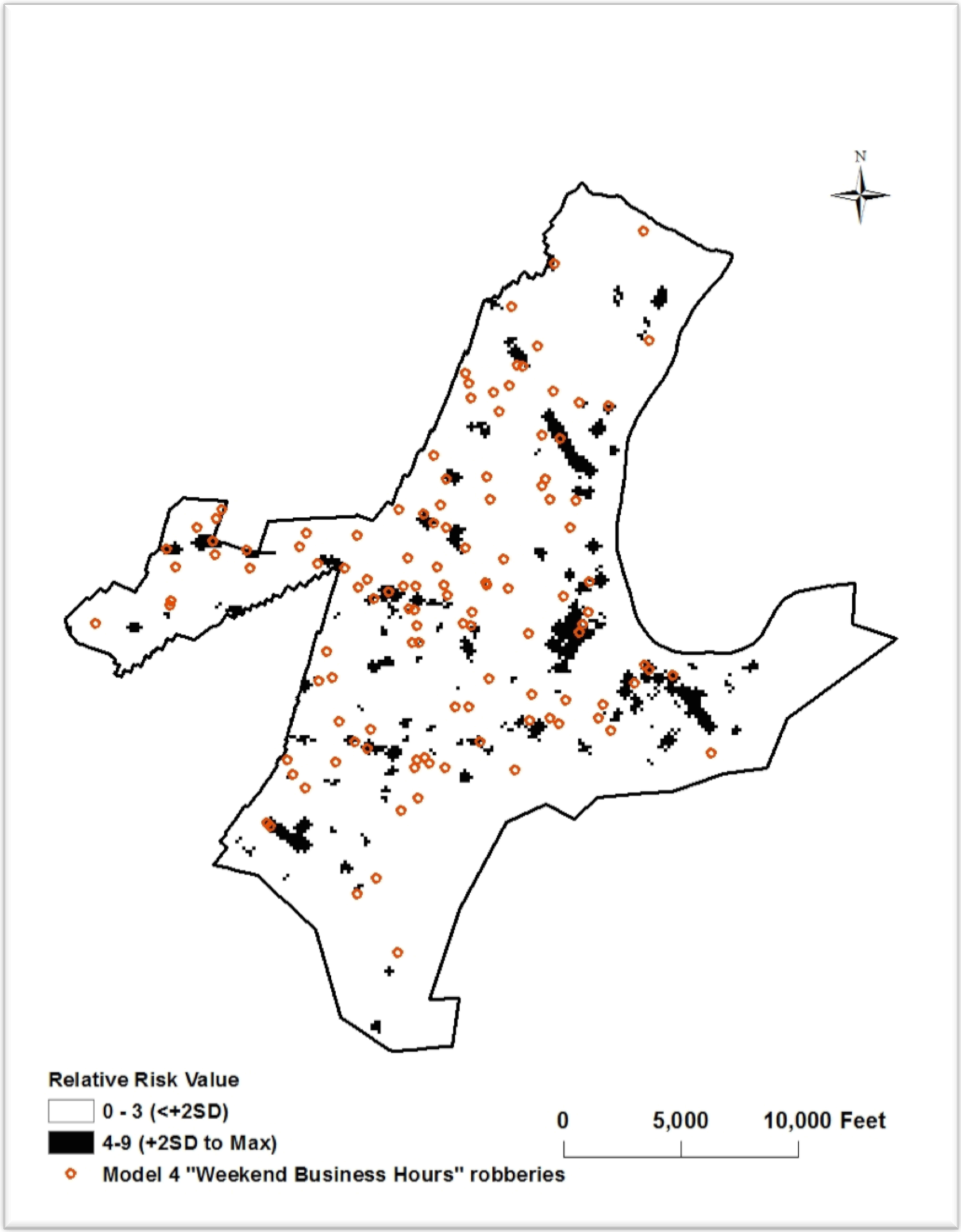

**Table 28. Negative Binomial Regression Results for Model 4 Risk Terrain Forecasting**

| Variable | IRR | Std.Err | z | p>│z│ | 95% CI Lower | 95% CI Upper |
|---|---|---|---|---|---|---|
| Risk Value (0-9.5) | 1.322 | 0.057 | 6.44 | 0.000 | 1.215 | 1.440 |
| Constant | 0.004 | 0.001 | -43.41 | 0.000 | 0.003 | 0.005 |

Pseudo $R^2$: 0.02

In Model 4, similar to Model 3, the spatial lag was not included in the analysis as an independent variable because the distribution of street robberies at weekend business hours were found to be spatially uncorrelated with the Moran's I analysis. As illustrated by the IRR in Table 28, for every unit increase in risk, CY 2010 weekend business hours street robbery counts is expected to increase by 32% ($p<0.001$). The statistical significance of the constant suggests that there is unaccounted variance in the regression, which is unaccounted for by the risk value in Model 4. In Model 4, the pseudo $R^2$ is 0.02.

**Model 5 "Weekend Happy Hours" Robberies**

Figure 11 displays the Model 5 "Weekend Happy Hours" robberies risk terrain map. Table 29 shows the results of a negative binomial regression analysis with "Risk Value" and "Spatial Lag" as the independent variables and the count of CY 2010 "Weekend Happy Hours" street robberies as the dependent variable.

**Figure 11. Risk Terrain Map with CY 2010 Weekend Happy Hours Robberies**

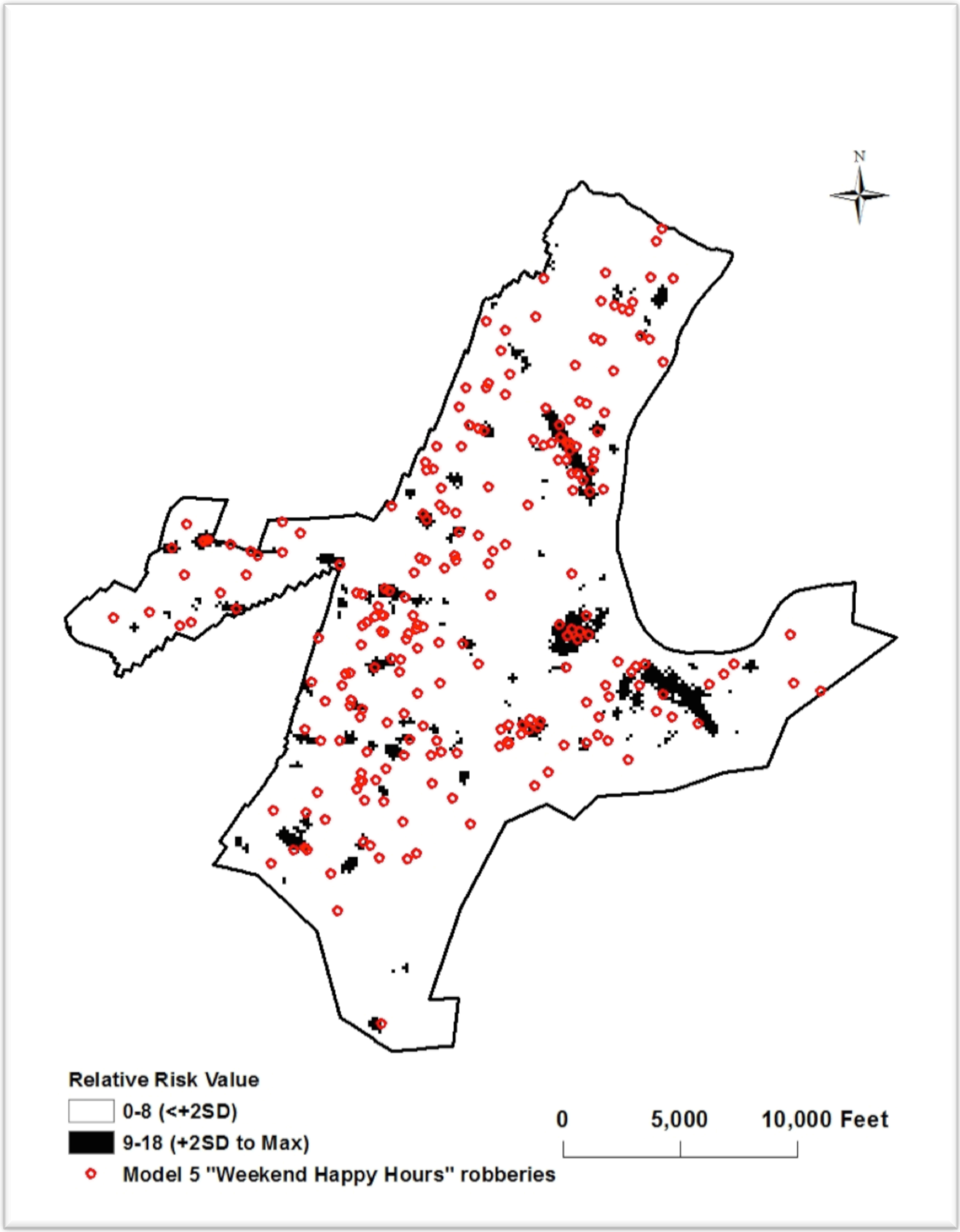

**Table 29. Negative Binomial Regression Results for Model 5 Risk Terrain Forecasting**

| Variable | IRR | Std.Err | z | p>│z│ | 95% CI Lower | 95% CI Upper |
|---|---|---|---|---|---|---|
| Risk Value (0-19) | 1.070 | 0.032 | 2.23 | 0.025 | 1.008 | 1.135 |
| Spatial Lag | 2.090 | 5.620 | 16.52 | 0.000 | 1.070 | 4.080 |
| Constant | 0.002 | 0.000 | -34.96 | 0.000 | 0.002 | 0.003 |

Pseudo $R^2$: 0.40

As illustrated by the IRR in Table 29, for every unit increase in risk, CY 2010 weekday business hours street robbery counts is expected to increase by 7% ($p<0.05$). The significance of the spatial lag variable in Model 5 suggests that, controlling for other predictors, the emergence of CY 2010 weekend happy hours street robberies at one place is also a good indicator for other weekend happy hours street robberies at neighboring places. Lastly, the statistical significance of the constant suggests that there is unaccounted variance in the regression, which is unaccounted for by the risk value and the spatial lag predictors in Model 5. In Model 5, the pseudo $R^2$ is 0.40.

**Model 6 "Weekend Bedtime Hours" Robberies**

Figure 12 displays the Model 6 "Weekend Bedtime Hours" robberies risk terrain map. Table 30 shows the results of a negative binomial regression analysis with "Risk Value" and "Spatial Lag" as the independent variables and the count of CY 2010 "Weekend Bedtime Hours" street robberies as the dependent variable.

**Figure 12. Risk Terrain Map with CY 2010 Weekend Bedtime Hours Robberies**

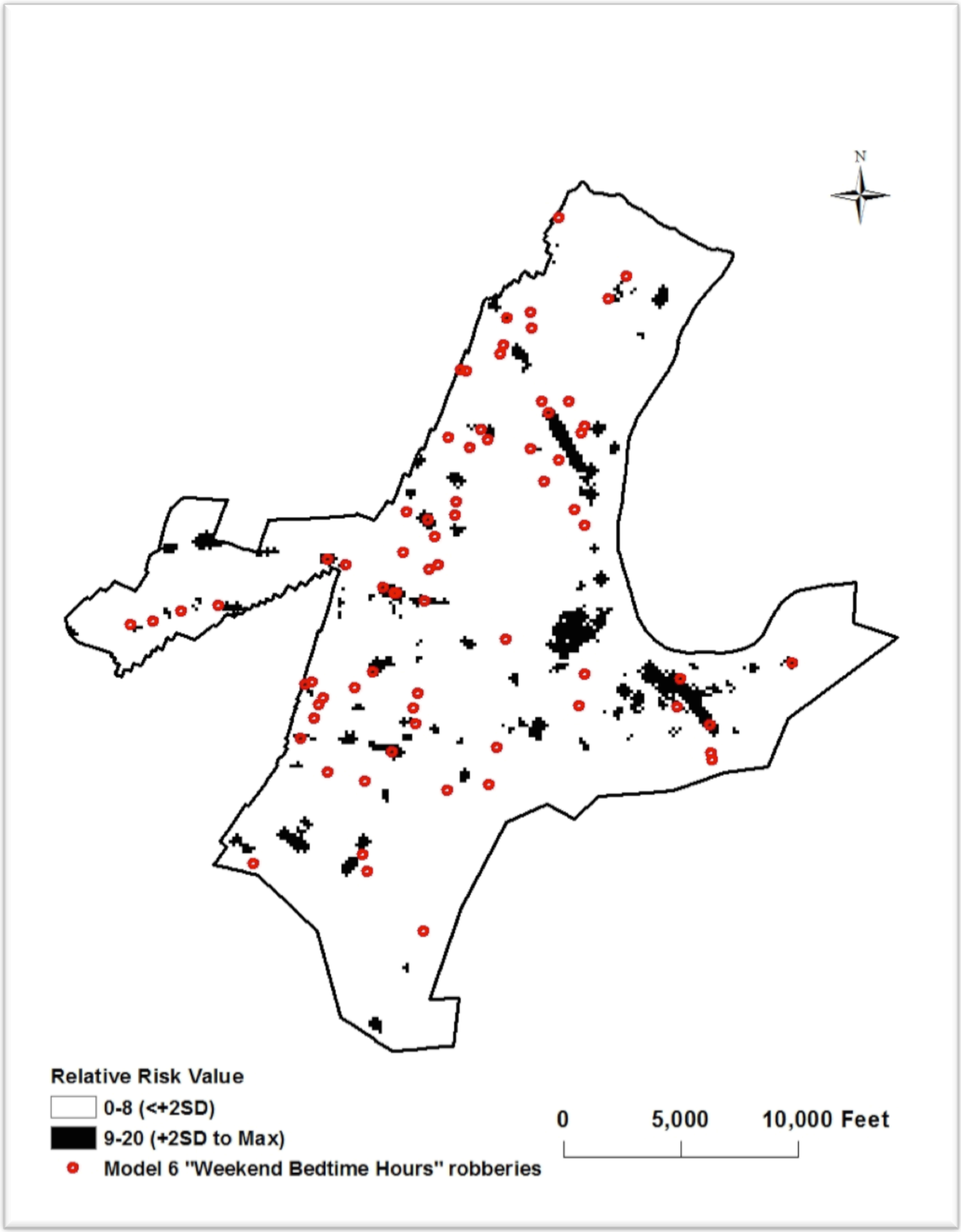

**Table 30. Negative Binomial Regression Results for Model 6 Risk Terrain Forecasting**

| Variable | IRR | Std.Err | z | p>│z│ | 95% CI Lower | 95% CI Upper |
|---|---|---|---|---|---|---|
| Risk Value (0-20) | 1.149 | 0.047 | 3.36 | 0.001 | 1.060 | 1.246 |
| Spatial Lag | 4.100 | 9.860 | 10.16 | 0.000 | 3.670 | 4.580 |
| Constant | 0.000 | 0.000 | -22.37 | 0.000 | 0.000 | 0.001 |

Pseudo $R^2$: 0.51

As illustrated by the IRR in Table 30, for every unit increase in risk, CY 2010 weekend bedtime street robbery counts is expected to increase by 15% ($p<0.001$). The significance of the spatial lag variable in Model 6 suggests that, controlling for other predictors, the emergence of CY 2010 weekend bedtime hours street robberies at one place is also a good indicator for other weekend bedtime hours street robberies at neighboring places. Lastly, the statistical significance of the constant suggests that there is unaccounted variance in the regression which is unaccounted for by the risk value and the spatial lag predictors in Model 6. In Model 6, the pseudo $R^2$ is 0.51.

*Summary*

As discussed earlier, in every street robbery risk terrain model, street robberies were observed to be more likely to occur at places that were identified to be high risk by the combined criminogenic spatial influences of landscape features. Based on the IRRS, with the exception of risk terrain models for happy hour robberies, time nested models have outperformed the base model in their predictive power. Table 31 illustrates the number of street robberies in the cells deemed to be risky by the RTM analysis.

**Table 31. Number and Likelihood of Robberies at Risky Places**

| | # of High Risk Cells* (Risk value ≥ +2SD from the mean) | % of Robberies at High Risk Cells | The Likelihood of Robbery at the Riskiest Cell (The cell with the highest risk value) |
|---|---|---|---|
| Model 0 "All-time" | 1377 | 19% | 210% |
| Model 1 "Weekday Business Hours" | 1531 | 20% | 208% |
| Model 2 "Weekday Happy Hours" | 1635 | 20% | 144% |
| Model 3 "Weekday Bedtime Hours" | 1743 | 25% | 380% |
| Model 4 "Weekend Business Hours" | 1931 | 19% | 304% |
| Model 5 "Weekend Happy Hours" | 1223 | 20% | 133% |
| Model 6 "Weekend Bedtime Hours" | 1484 | 27% | 300% |

* The study extent is comprised of 21,931 cells.

As illustrated in Table 31, the high risk cells made up 6%-9% of all cells in the Newark study extent in different models. In the time nested models, highest risk cells contained at least the same percentage or a higher percentage of street robberies in comparison to Model 0. Specifically in late night robberies models, the highest risk cells accounted for at least 25% of all robberies.

In Model 0, at the riskiest cell, the robbery likelihood was observed to increase by 210%. When robberies were analyzed according to the different times of the day and the week, this likelihood was observed to increase one-fold for weekday bedtime hours robberies and weekend business hours and bedtime hours robberies. Overall in all models including Model 0, the places identified to be high risk by the respective risk terrain models were observed to have a higher likelihood for street robberies and time-nested models have proven to have at least the same or better predictive power than the non-time nested model.

# CHAPTER 5: OVERVIEW AND DISCUSSION OF FINDINGS

Even though many scholars acknowledge that temporal rhythms influence crime outcomes, this influence has not been fully integrated into the micro-level studies of crime, or the contextual analysis of crime events. This dissertation is the first study that brings together several strengths of contemporary contextual crime analysis studies to study the spatiotemporally dynamic criminogenic influences of several landscape features on street robbery outcomes. Street robbery, in the study extent of Newark, NJ, is a high frequency crime that affects the urban landscape at all times of the day and all days of the week. As discussed earlier, a variety of landscape features, classified under the umbrella of cash economies, illegal markets, and non-commercial features, were identified by the literature to have criminogenic spatial influences on street robberies in different study extents. The aim of the first research question of this dissertation was to explore the nature of the change in the individual criminogenic influences of these landscape features at different times of the day and different days of the week. The aim of the second research question was to synthesize the information from the findings of the first research question to ascertain crimes emerge at places that are under the combined dynamic spatiotemporal criminogenic influences of several landscape features. The answers to these research questions have several implications for criminological theory and the fields of risk assessment, crime prevention and urban planning, which are discussed in detail in the Conclusion.

In the Conceptual Framework three hypotheses were formulated to answer the first research question:

- *H1: The spatial extents of the criminogenic influence of landscape features on street robberies are different from one another at different times of the day and different days of the week.*
- *H2: The criminogenic landscape features for street robberies are different at different times of the day and different days of the week.*
- *H3: The weights of the criminogenic spatial influences of landscape features on street robberies are different from one another at different times of the day and different days of the week.*

The key findings of the analysis in Chapter 3 suggested that the criminogenic features are different for different time models, and the extent and weight of their criminogenic influences vary between and within time nested models. Moreover the criminogenic influences of landscape features in time-nested models 1-6 were different than of Model 0's—the model with no daily or hourly robbery classification. Overall, these findings supported Hypotheses 1-3.

The testing of the sub-hypotheses of Hypothesis #2 yielded expected and unexpected findings on the criminogenic influences of the same landscape features at different times of the day and different days of the week. The significant criminogenic influences of cash businesses operating during regular business hours in Model 1 and Model 4 supported Hypothesis 2.1 for these models. The significant criminogenic influences of cash businesses with regular and late hours in models 1-6 supported Hypothesis 2.3 for these models, and the significant criminogenic influence of bars in Model 2, Model 5, and Model 6 supported Hypothesis 2.2 for these models. The lack of criminogenic influence of light rail stops in all models supported Hypothesis 2.4. The criminogenic spatial influences of non-commercial features in models 1-6, supported Hypothesis 2.5 in these models. The criminogenic spatial influence of drug charges in models 1, 2, 3, 5, and 6, supported Hypothesis 2.6 for these models. Last, but not least, the detection of the highest number of significant criminogenic risk factors in Model 0, compared to the time-nested models, supported hypothesis 2.7. In addition to these expected findings, some cash businesses had unexpected criminogenic influences well after their operation hours, and car dealers had an unexpected negative (protective) spatial influence in Model 0 and Model 1. At-risk housing, schools, and churches representing non-commercial features of the landscape, and grocery stores, hair and nail salons, pawn shops, sit-down restaurants, and take-out restaurants representing cash businesses, were the only features that had criminogenic influences on street robberies in all time-nested models and Model 0.

The significant criminogenic influences of cash businesses during operating hours, as also supported by the extensive literature covered in the Conceptual Framework, can be attributed to the frequenting of these places and their immediate environments by potential targets rich in cash and valuables during regular operating hours. In the literature, the lacking criminogenic spatial influence of rail stations on robberies was attributed to many factors such as the gentrification along rail lines, more public and private investment, landscape maintenance, and increased surveillance measures in and around the rail stations (Poister, 1996). In Newark, the light-rail system is comprised of the Newark City Subway line and the Broad Street extension which are regulated by New Jersey Transit. The Broad Street extension started operating in 2006 and mainly serves as a connection line between the two major commuter rail terminals, Newark Penn Station and Broad Street Station, which are heavily patrolled by NJ Transit Police. The Broad Street extension provides service for commuters to and from offices along the line, providing close access to office buildings in the immediate vicinity. The ridership on this line is less when compared to the Newark City line, and there are less cash businesses along this extension compared to the City Subway line. The City Subway line, on the other hand, though intersecting with the major thoroughfares in the City, runs through relatively better maintained blue-collar neighborhoods in Newark. These conditions, coupled with the surveillance and patrolling activities by the NJ Transit Police department in the light rail stations can arguably contribute to the lacking criminogenic influence of light rail stations on street robberies in Newark.

Public housing has been cited several times as a criminogenic feature for different crime outcomes in different studies. As such, the round-the-clock criminogenic spatial influence might be unsurprising for most. The round-the clock criminogenic spatial influences of churches, schools, grocery stores, pawn shops, sit-down restaurants, and take-out restaurants well after their regular hours and days of operation, on the other hand, can and should raise questions such as why these features continue attracting crimes at odd hours and days, when they are not open. The attempts to answer this and similar questions set the basis for a much needed discussion in crime and place literature on the changing social relevancies of the features and immediate surroundings of features at different times, and the effect of these relevancies on street crime such as street robberies. Most micro-level contextual studies of crime events identify certain features as criminogenic for a study extent at all times, labeling these features as criminogenic because of the ways they pull crimes and criminals. As indicated earlier, one of the most popular ways to explain the criminogenity of landscape features is to classify the features as crime attractors or crime generators from the get-go. As discussed in the Conceptual Framework some features are presumed to be crime generators because of the high number of people using these features as nodes in their daily routines, whereas some features are presumed to be crime attractors because they provide known crime opportunities at places, such as having many attractive targets or having a reputation as a tumultuous environment. Most studies assume these abstract qualities without exploring how these qualities can change in relation to daily rhythms. For instance, illegal markets, cash businesses, and schools are commonly assumed to be crime attractors for street robberies because these features provide attractive targets for potential robbers (Bernasco and Block, 2009). However, when thought in relation to the operation hours of such features, the conditions that pull offenders to these locations can change at different times of the day. When compared to illegal markets, cash businesses and schools are expected to attract people at different and more limited hours to their locations. As such, a feature can be pulling crime and criminals as either a crime generator and crime attractor or both, depending on the social relevancy of that feature at different times. Based on this conclusion, one can suggest studying the criminogenic influences of these features without thinking about the dynamics leading to the criminogenic influence of the features. This can hinder crime analysis and prevention because the identification of the spatiotemporal dynamics that affect the criminogenic influence of a landscape feature in daily routines can serve as a starting point for deciding how to untangle the local crime problem. The identification of the reasons why certain features and the immediate surroundings of a feature pull crimes and criminals at different times can aid in deciding what measures and which actors to involve in responding to the crime problem at hand.

Solely looking at the criminogenic features in each time model, one can conclude that too many landscape features have criminogenic spatial influences on street robberies. Thus, contextual robbery analysis is not practical. However, a closer look at the criminogenic features with particular attention given to the RSI values and weights of the features reveal that only a handful landscape features contribute the strongest to the street robbery risk at micro places in Newark. For instance, in different time models, pawn shops, grocery stores, hair and nail restaurants, retail stores, and take-out restaurants—which appeared in the top three as the strongest cash business predictors of street robberies (see Chapter 3). On the other hand, at-risk housing, auto repair shops, bars, churches, and schools—all of which were significant in one or more of the time-nested models—were found to have very weak criminogenic influence on street robberies (see Chapter 3). With the exception of Model 4 “Weekend Business Hours” robberies and Model 6 “Weekend Bedtime Hours” robberies, the feature of drug charges was the strongest predictor in all models. The potential victims frequenting drug market areas during early hours or later hours on the weekdays and the weekends can become more vulnerable to street robberies.

Everything considered, four key findings from the test of Hypothesis 2 can be used to shape the response to the street robbery problem in the short-term: 1) The combination of criminogenic features and the extent and the weights of their criminogenic influences change in each time-model; 2) Drug charges representing the illegal markets and the surroundings of pawn shops, grocery stores, take-out restaurants, and hair and nail salons representing cash businesses exert the most consistent and the strongest criminogenic influences on street robberies in all time models; 3) At-risk housing, churches, school, and libraries representing non-commercial features exert significant albeit weak criminogenic influences on street robberies; and 4) Time-nested models 1-6 had a smaller number of significant risk factors, especially on the weekend, which can be attributed to the increased significance of independent variables in analysis with bigger sample sizes. These four considerations and their policy implications will be discussed more in detail in the Conclusion.

In the Conceptual Framework two hypotheses were formulated to answer the second research question as below:

- *H4: Street robberies emerge at places when there is high risk based on the combined spatial influence of criminogenic features of a landscape at different times of the day and different days of the week.*
- *H5: Robbery forecasting model with no time-of-the-day and day-of-the week cycles has a weaker prediction power than forecasting models with time cycles.*

The key findings of the analysis in "Chapter 4" suggested that the increase in the count of street robberies in all models were in parallel with the increase in the composite risk exerted by the criminogenic landscape features in these models. Moreover looking at the IRR values, with the exception of Models 2 and 5, the time-nested models 1-6 were found to have a stronger predictive power over Model 0 with no time-of the day and day-of-the week distinctions. When IRR values were taken into consideration, Models 2 and Model 5 had slightly lower IRR values than Model

0. Overall, these findings supported Hypotheses 4 in all time models and Hypothesis 5 for models 1, 3, 4, and 6. The emergence of robberies at places that are under the simultaneous criminogenic influences of multiple factors is not surprising as the conflation of multiple risk components for a riskier situation makes intuitive sense and is well supported by risk assessment studies in and out of criminology. The increased goodness of fit of the time nested models 1-6, in comparison to Model 0, can be explained by theoretically meaningful allocation of the street robberies in time-nested models in smaller counts.

# CHAPTER 6: CONCLUSION

As indicated earlier the identification of the varying criminogenic influences of landscape features on street robberies and the spatiotemporal dynamics that affect the criminogenity of these features can determine the avenues of response which might include a variety of actions and actors. Based on this suggestion, this chapter discusses the implications of these findings for environmental criminology, risk assessment, crime prevention, and future research.

## 6.1. Implications for Environmental Criminology

Although this dissertation specifically focused on street robberies, the findings from the study support past research findings on criminogenic features in micro places. This dissertation makes a unique contribution to the crime and place literature by considering the temporal aspect of individual and combined criminogenic spatial influences of land use features on street robbery outcomes.

In a variety of studies, specific features of the built environment and illegal markets have been identified to have a criminogenic spatial influence on different crime outcomes. In conformity with these studies, the findings of this dissertation also identified the spatial influence of several land use features as important risk factors for street robbery outcomes. Recent research has also suggested that places that appear to be high risk for crimes based on the combined criminogenic influence of different features of the landscape are also places where crimes occur the most (e.g., Caplan, 2011; Kennedy et al., 2011). In conformity with this research, the results of this dissertation also indicated that micro places under the combined criminogenic spatial influence of street robbery risk factors are more likely places for street robberies than places that are not under such an influence. The findings of this dissertation also support Ratcliffe's (2012) suggestion about the varying extent of the criminogenic spatial influence of criminogenic land use features. The land use features that were found to have an important criminogenic spatial influence on CY 2010 street robberies in the nonnested and time-nested models were observed to reach their maximum criminogenic influence at different distances ranging between one-half block (145 feet) and three blocks (870 feet).

Moreover, as suggested by Caplan and Kennedy (2010), among different criminogenic features, some were identified to have a stronger criminogenic spatial influence than others. The findings of this dissertation augment the previous research on the criminality of micro places by showing that the extent and weight of the individual criminogenic spatial influences of land use features on crime outcomes changes across time periods. By showing this, the results of this dissertation also makes more room in environmental criminology for testing of the basic assumption of time geography: human activities (including criminal acts) are limited by the temporal and spatial constraints exerted on these activities (Miller, 2004).

The findings from this dissertation contribute to the discussion on the concept of environmental backcloth (Brantingham and Brantingham, 1981) in environmental criminology. The concept of environmental backcloth, and the terms crime generators and crime attractors, have been widely used in micro geographical level studies of street crimes, including street robberies. However, despite Brantingham and Brantingham's (1981, 1995) original discussion of the criminogenic influences of landscape features (crime generators and crime attractors) with varying spatiotemporal potentials within a dynamic environmental backcloth, various studies have operationalized the criminogenic influences of landscape features uniformly.

This study brought together the concept of environmental backcloth with the time geography (Hägerstrand, 1970) and risky places (Kennedy and Caplan, 2012) frameworks to highlight the spatiotemporally dynamic nature of criminogenic influences of landscape features. The methods used in this study made it possible to identify the significant criminogenic risk factors for street robberies at different times of the day and different days of the week. While the results supported the established findings from previous research that certain illegal markets, cash businesses, and non-commercial features have criminogenic spatial influences on street robberies, the in-depth analysis of the ways in which these risk factors influence street robberies made it possible to evidence the overemphasized and underemphasized importance of certain landscape features in literature, for the study extent of Newark, NJ.

In summary, for this study's extent of Newark, NJ, the findings contributed to the discussion of environmental backcloth by showing that:

1. The criminogenic features for street robberies can be different at different times of the day and different days of the week.
2. The extents of the spatial influences of different cash businesses, illegal markets, and non-commercial businesses can be different from one another in the same time period or in different time periods.
3. The extents of the spatial influence of the same feature can be different at different times of the day and different days of the week.

4. Despite the number of significant risk factors identified for street robberies in each time period, some have stronger criminogenic influences than others.
5. Some landscape features uniformly identified as crime generators or crime attractors can attract street robberies for different reasons at different time periods, within or outside their operation hours. When the social relevancy of a particular landscape feature is not enough to explain the criminogenity of this feature at an unexpected time or day, some other mechanisms such as changing travel patterns can be used to explain these criminogenic influences.
6. Some landscape features can have a protective influence over street robberies.
7. When the combined extent and weight of the criminogenic influences of several landscape features at a place is taken into consideration, it can be easier to identify the riskiest places for street robberies.

### 6.2. Implications for Risk Assessment

The methodology used in this study can be used for the micro-level analysis of the risk for street robberies and other crimes and disorder at the micro level. Furthermore, the methodology used in this study can be adapted for different study extents and different temporal cycles. Overall, the findings of this study suggest that the consideration of the temporal changes in the extents and weights of the individual criminogenic influences of illegal markets, cash businesses, and non-commercial features, and the combined criminogenic spatial influence of several features at places, might be a more precise methodology for micro-geographical level crime risk assessment. Despite the acknowledgement of the dynamic nature of criminogenic influences of landscape features in a few studies, most studies neglect the dynamic nature of contextual crime risk in the time-space continuum. The following paragraphs explain how and in what capacity the findings of this study can contribute to the current risk assessment methodologies.

The first contribution of this study to risk assessment comes from the method used to identify the pool of risk factors to be included in the risk assessment analysis. At the initial stage of risk assessment, researchers can decide on which risk factors to include in the analysis including, but not limited to, practitioner knowledge, literature review, and meta-analysis etc. (Caplan and Kennedy, 2010). As indicated earlier, Caplan (2011) suggested that empirically and theoretically grounded risk factors are key to producing robust risk prediction models in risk assessment. In this study, the pool of criminogenic landscape features to be included in the analysis were decided after a careful review of previous research on street robberies and observation of landscape features at sample hot spots for 2010 street robberies in Newark using Google Earth. The observation of the street robbery hot spots in Newark not only confirmed the presence of all criminogenic landscape features identified by previous robbery research, but also identified five additional landscape features (auto repair shops, car dealerships, car washes, cemeteries, and churches) in the Newark street robbery hot spots. Of these five additional features, auto repair shops and churches were identified to have a significant criminogenic influence on CY 2010 robberies in different time models and surprisingly car dealers, despite being observed in the hot spots of robberies, were observed to exert a protective influence on Model 0 and Model 1 street robberies in the study extent. The ground-truthing of past research findings for other study extents, as was done in this dissertation, might help crime analysts to determine which risk factors to include in their prediction models or help them identify new risk factors or even protective factors particular to their study extent. The ground-truthing using Google Earth imagery might not be the most convenient way to collect risk data in all research projects. However, with the proper technological tools and analytical abilities to collect, sort, and analyze data, data sources other than traditional crime data (such as citizen input, social media and news, crowdsourcing) might be incorporated into risk assessment for unwanted outcomes including but not limited to crime.

The second contribution of this study to risk assessment comes from the in-depth analysis of the extent and weight of the individual spatial criminogenic influences of landscape features at particular time-periods in synch with the daily rhythms of human activity, and the evaluation of the combined criminogenic influences of said factors at micro places. In crime analysis, this kind of intelligence can be adapted to the needs of police departments to model the risk of any crime type in different study extents and in different spatiotemporal units of analysis. As stated in the previous paragraph, with the appropriate technology to collect, sort, filter and analyze such data, more robust crime risk assessment models can be built in accordance with the spatial extent and weight of the criminogenic risk factors for different time periods. One of the main requirements of such an analysis is the standardized collection and sorting of the outcomes of interest (any type of crime or disorder variable) with the time and day data of the incidents in a user friendly format.

The third contribution of this study comes from the high pseudo $R^2$ values achieved in the time nested models. According to Weisburd and Piquero (2008) criminological work typically leaves 80-90% of the variance in crime unexplained. In this dissertation, similar to Weisburd and Piquero’s conclusion, an a-temporal street robbery forecasting model

(Model 0 “All-time Robberies”) has been successful in explaining around 20% of the variance in street robberies, whereas in four out of six time-nested models, the variance explained changed between 30% and 51%. Since the operationalization and weighting processes for all models were the same, the increase in the explained variance can be attributed to the sub-classification of robbery incidents into meaningful temporal groupings. These results necessitate the study of space-time interaction of criminal opportunities at micro places.

Last, but not least, the findings of this study have particular implications for the RTM methodology used to complete this analysis. As noted earlier, in their proof of concept of RTM, Caplan et al. (2011) suggested the extension of RTM for the testing of different crime types using different operationalization methods. This dissertation for the first time identified the extent and weights of the criminogenic spatial influences of landscape features at different times of the day and different days of the week using the steps of RTM, and used this information to produce temporal risk terrain models to represent daily and weekly rhythms. Coupled with the risky places framework (Kennedy and Caplan, 2012), RTM acknowledges that a crime risk assessment methodology will be limited in explanatory power if the continuous dynamic value of contextual crime risk over time and space is not taken into consideration. The findings of this study provide the proof of concept for this assertion by showing that the spatial extents and weights of the criminogenic landscape features not only differ from one another, they also change over different time periods. With the new utility “RTMDx” developed by the Rutgers Center on Public Security to automate the steps of RTM, the temporal risk terrain models produced with customized spatial extents and weights of the most significant risk factors can be turned into actionable intelligence by police departments on a continuous basis more efficiently.

### 6.3. Implications for Crime Prevention

The findings of this study showed that that not all criminogenic landscape features identified in the research literature are criminogenic for the study extent of Newark, and when certain features have criminogenic spatial influences, the extent and weight of their influence can vary at different times. The findings of the study also showed that the combined criminogenic influences of landscape features affect the robbery risk significantly. Based on these findings, focusing on spatiotemporal crime prevention programs is suggested as the most efficient way to target street robberies. As indicated earlier in the Conceptual Framework, random patrol by itself has been proven to be an ineffective crime prevention strategy. Especially in urban cities like Newark with high frequencies of street crimes and a large geography to cover, the police departments are in desperate need of accurate and on-the-fly intelligence to channel enforcement efforts with limited personnel, limited technology, and limited resources. As such, the prevention of street crimes including street robberies requires knowing which micro places are the riskiest for the crime problem at hand for what reasons, and tailoring the crime prevention efforts to the specific needs at problem places. In that particular regard, following the principles of Problem Oriented Policing (POP) might be the optimum strategy while using the intelligence produced with a methodology similar to this study's methodology.

POP is an approach to policing in which specific crime and disorder problems are addressed with systematic identification of crime problems, continuous analysis of the factors contributing to the problem, and customized responses to the problem by not only the criminal justice system, but also other stakeholders that can have a control over the problem (Goldstein, 2001). However, as suggested by Mazerolle (2001), to effectively implement POP responses, the police departments should overcome barriers such as the lack of methodologies and IT capability to produce meaningful intelligence. Mazerolle (2001) further suggests the need for effective management of the crime problems, involving the right parties in crime prevention efforts. The methodology of this study, coupled with the findings, is believed to provide the necessary means to overcome these barriers. The methodology used in this study to identify the extent and weight of the significant criminogenic influences of landscape features at different times can be used to identify the strongest individual criminogenic influences of certain risk factors and the overall combined criminogenic influences of landscape features at micro places. As evidenced by the findings of this study, the criminogenic influences of landscape features are transient across space and time. The evaluation of the transient criminological influences at micro places with a program such as RTMDx can optimize the analysis phase of POP. The information on the most risky features and most risky places—based on the individual and combined criminogenic influences of the landscape features—can be used to target the most criminogenic places, the most criminogenic features, and the most criminogenic times by three different venues of intervention:

**1. Directed patrol informed by spatiotemporal risk assessment**

As evidenced by the findings of this study, certain places and certain features pose a higher risk for street robberies at different times of the day and different days of the week. For patrolling purposes, this information can be used to identify the highest risk places for street robberies at different times and direct patrolling activities. The identification of the riskiest features and riskiest places does not mean the termination of patrolling activity in no-risk or low-risk places, but rather deployment of targeted patrols to higher risk places. As evidenced by the strong and consistent criminogenic influences of few cash businesses and drug activity areas in this study, with such deployment strategies, the majority of the street robbery problem can be addressed by focusing on few significant risk factors.

**2. Urban planning and CPTED**

In addition to increased patrolling at the risky places, the strategies of Crime Prevention Through Environmental Design (CPTED) can be used to increase surveillance and to remove opportunities to commit crimes at risky places. These strategies can include but are not limited to natural strategies such as city planning or landscape maintenance strategies to control access to risky places, organized strategies such as private security in or in the immediate vicinity of the most problematic features, and mechanical strategies such as cameras or lighting that increase the chances of detection of potential offenders.

**3. Transfer of crime prevention responsibility to third-parties**

For the most criminogenic cash businesses (e.g., grocery stores, pawn shops, take-out restaurants, hair and nail salons, in this study), crime outcomes can be reduced by introducing control measures that mandate businesses take appropriate steps to prevent the problem (Scott, 2005). The cooperation of such third-parties can be established either voluntarily or via regulations and ordinances. A recent example of such an approach in

Newark is a 2012 business ordinance that dictates a curfew for restaurants and shops in high-crime areas (Adarlo, 2012). Such curfews can be extended to high-crime-risk areas in other jurisdictions identified by the spatiotemporal approach used in this dissertation. Furthermore, non-place-based interventions can include empowering the residents in the most risky environments and focusing on deterrence of high-risk offenders through violence-reduction programs that target areas that high-risk offenders are likely to frequent.

### 6.4. Avenues for Future Research and Concluding Remarks

This study provided detailed insight into the criminogenic spatial influence of landscape features. As suggested by the findings, the extent and weight of the criminogenic spatial influences of landscape features on street robberies vary across features and times. Moreover, micro places that are exposed to the simultaneous criminogenic spatial influence of multiple landscape features are more vulnerable to street robbery risk. The findings on the extent, weight, and temporality of the spatial criminogenic influences of landscape features are intended to provide the framework for a robust methodology for the observation of the environmental backcloth of crime events. Assessment of crime risk in any geography requires an analytical approach that is backed by previous research and theory, and that is tailored to represent its own spatiotemporal study extent. This section summarizes the key issues that can be explored as a follow-up to the findings of this study.

One way to establish the generalizability of a study's findings is to replicate the study for different study extents and different outcomes. Based on the dynamic nature of the extent and weight of criminogenic spatial influences of landscape features on street robbery outcomes at different times, the criminogenic spatial influences of landscape features are expected to differ across different study extents and for different crimes. The extent of the criminogenic spatial influence of a landscape feature might not only be different at different times; such an extent might also be different in different cities or areas. Following the same logic, the extent and weight of the criminogenic spatial influences of landscape features are also expected to change for different crime types (e.g., shootings and aggravated assaults). In the study extent of the City of Newark, in addition to the known correlates of street robberies, auto repair shops and churches were identified as having a criminogenic spatial influences on street robberies at different times. Based on these findings, future studies on other study extents and for other crime outcomes might reveal criminogenic and protective landscape features that are specific to their study extents or crime outcomes.

Another potential area for future research is the joint use of event and context based analysis to explore the simultaneous criminogenic influences of environmental features and past crime incidents on future robbery outcomes. As suggested by Kennedy and Caplan (2012, p.3) in their brief on a theory of risky places, crime risk comes from the "increased vulnerability tied to features in the environment" and increases with the "exposure that derives from crime incidents". This dissertation, testing the individual and combined criminogenic influences of landscape features at different times have proved the first and second hypotheses of the risky places approach that different places at different times are more riskier for street robberies based on the individual and combined criminogenic influences of landscape features. In the future, this dissertation study can be expanded upon by exploring the spatial influence of past crime incidents on street robbery outcomes alongside the testing of the criminogenic influences of landscape features.

According to the results of this study, the dynamic criminogenic influences of different landscape features at different times, and specifically the criminogenic spatial influence of certain landscape features outside of their regular hours of operation, necessitate the in-depth study of the criminogenic spatial influences of these features outside their regular operating hours. This type of unexpected criminogenic influences might be explored in different study extents for different landscape features.

In addition to the question of how crimes occur, one can also question, why crimes do not occur at certain geographies. The risk of undesired criminal and disorderly behavior and how to protect against it has long been a hot topic in criminology, with a specific emphasis on the onset of juvenile delinquency and the recidivism of ex-offenders. The risk-protection assessment approach that has been employed for more than two decades in the field of criminal behavior forecasting has not been adapted to the studies of crime and place. Although analyzing why crimes emerge at certain locations in relation to the spatial influence of past crimes and land features has been popular in both event- and context-dependent analyses, no studies to date have analyzed why crimes do not emerge at places identified to be highly vulnerable to risk—whether in relation to events, context, or both. As shown by the findings of this dissertation, a landscape feature can acquire or lose its criminogenic spatial influence at different times of the day and on different days of the week. As further exemplified by the negative (protective) spatial influence of car dealers on street robberies, some landscape features might also have protective influences on crime outcomes. Based on these findings, future research can explore whether and how landscape features exert a protective spatial influence against crime events at different times in the presence of multiple criminogenic landscape features.

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Teaching Assistant, School of Criminal Justice
Rutgers University (2008-2011)

Research Assistant, Rutgers Center for Public Security
Rutgers University (2010-2012)

Research Director, Rutgers Center for Public Security
Rutgers University (2012-2013)

Research Associate I, Justice Police Center
The Urban Institute (August 2014 – Present)

**List of Publications**

Kennedy, L.W., Irvin-Erickson Y., and Kennedy, A.R., "Translational Criminology and Counterterrorism: Global Threats and Local Responses", 2014, NY: Springer.

Kennedy, L.W., Gaziarifoglu Y., and Caplan, J.M., "Analyzing and Visualizing Worldwide Spatial Data: An Application of Risk Terrain Modeling", 2012, Newark, NJ: Rutgers Center on Public Security.

Kennedy, L.W., and Gaziarifoglu, Y. “Applying RTM to Street Robberies” in Joel M. Caplan and Leslie W. Kennedy, Risk Terrain Modeling Compendium, 2011, Newark, NJ: Rutgers Center on Public Security.

Kennedy, L.W., Marteache, N., and Gaziarifoglu, Y., “Global Risk Assessment: The Search for a Common Methodology” in Kennedy, Leslie W. and Ed McGarrell, Risk in Crime and Terrorism: Issues in Criminology and Criminal Justice, 2011, NY: Routledge.