Using "Barriers" in Kernel Density Estimation to Improve the Predictive Accuracy of Crime Forecasts: A Case Study of Three Florida Cities

by

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TALBE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

Crime pattern analysis is a crucial component of many place-based policing strategies. Because crime does not occur randomly in space, crime pattern analysis aims to identify where it is most geographically concentrated (i.e., where it clusters). Areas of spatially clustered crime incident locations are referred to as crime hot spots, which can be visualized using crime hot spot maps. Identifying crime hot spots and allocating resources to those locations is a popular crime analysis technique used to reduce and prevent crime.

Many techniques can be used to identify crime hot spots. Point-pattern analysis, spatial ellipses, grid-based thematic mapping, and kernel density estimation (KDE) are a few of the most common methods used in crime pattern analysis. For example, KDE is used in crime hot spot mapping to create a continuous "crime risk" surface area across the digital landscape that represents an agency's entire jurisdiction. Crime hot spots can be easily identified on a KDE map as "high risk" using a graduated color ramp, where various shades of yellows, oranges, and reds represent the varying concentrations of crime. Chainey and colleagues (2008) suggest that KDE is a popular technique for identifying crime hot spots because it is visually impactful and can be used to produce reliable and accurate crime forecasts (see also, Chainey et al., 2002; Chainey & Ratcliffe, 2005; Eck et al., 2005; Williamson et al., 1999).

Although studies show that KDE is a prospective crime forecasting technique capable of outperforming other methods (Chainey & Ratcliffe, 2005; Eck et al., 2005), it is not without certain shortcomings that may limit its utility (Chainey et al., 2008, Levine, 2008). For example, KDE involves estimating a continuous crime surface area based on the known locations of discrete crime events. The distance between the center point of each grid cell that is overlaid on top of a study area during the analysis and each crime incident is measured. Then a mathematical formula is used to estimate crime intensity between them. Once complete, KDE maps show the intensity of crime concentration “smoothed” across the entire study area, including locations classified as “barriers” to crime. In this context, barriers are features on a digital map representing obstructions between locations of where crime has been recorded, and that may affect how density estimates are calculated.

In crime pattern analysis, barriers can be viewed as places where criminal incidents cannot occur in the physical environment. For example, an offender cannot commit a residential burglary in a park if there are no residential properties located within the park’s boundaries. Likewise, motor vehicle thefts cannot occur within the perimeter of a lake. In these examples, both the park and lake would be considered barriers to crime. Although barriers to a crime can be found throughout most jurisdictions, basic KDE does not consider them when a risk surface area is interpolated. Given the role crime pattern analysis plays in place-based policing and the widespread adoption of KDE as a hot spot mapping technique (Chainey et al., 2008), it is incumbent upon us to seek ways to improve this popular crime-fighting methodology. In response, the current study explored whether incorporating “barriers” into KDE can improve the predictive accuracy of crime forecasts.

Statement of Problem

Kernel density estimation (KDE) is one of the most popular crime hot spot mapping methods used to reduce and prevent crime. However, this technique does not consider where crime cannot occur within a study area when a crime risk surface is interpolated[1].Therefore, a knowledge gap exists as to how effective incorporating barriers into KDE analysis can be in producing more accurate prospective crime hot spot maps. Therefore, the current study investigated whether the predictive accuracy of crime forecasts based on KDE will improve when barriers to crime are incorporated into the analytic process.

Background of the Problem

Hot spot mapping leverages the power of Geographical Information Systems (GIS), which can be defined as “a branch of information technology that involves collecting, storing, manipulating, analyzing, managing, and presenting geospatially referenced data” (Rennison & Hart, 2018 p. 315). Crime analysts use GIS to create hot spot maps by integrating diverse data sets into their spatial analysis applications, producing a better understanding of crime patterns. In addition to crime incident location data, geospatially referenced data pertaining to the locations of crime attractors and generators such as liquor stores, schools, parking garages, and ATMs can also be included in crime pattern analysis to enhance and improve forecasting results and crime control efforts. GIS also allows the dissemination of hot spot maps to the public through open cloud-based online open data portals.

GIS provides the foundation for predictive policing and prospective hot spot mapping methods. As noted previously, the KDE process involves the visual presentation of discrete crime points, “smoothed” over an entire study area, creating a continuous crime-risk surface. To facilitate

[1] Typically, the interpolated surface area is cropped to the study area’s boundary. This cropping gives the impression to anyone looking at a KDE map that the interpolation was bounded by the study area’s edges; but this is not what happens during the KDE analysis.

this process, parameters must be defined before the KDE interpolation procedure is run in a GIS application. These parameters include the kernel function, bandwidth, and grid cell size (Hart & Zandbergen, 2014).

Parameters play a decisive role in crime hot spot mapping because they can impact results, including how well a prospective hot spot map accurately predicts where crime will occur in the future (Chainey et al., 2008; Hart & Zandergen, 2014). Existing studies have examined the influence that parameter settings can have on the predictive accuracy of KDE maps and provide guidance to researchers and practitioners on how to improve our understanding of crime patterns and crime-fighting efforts (see, for example Hart & Zandergen, 2014). Although these studies offer suggestions on optimizing parameter settings, no known research has examined how barriers to crime found in the natural environment might impact the production of prospective hot spot maps like those produced from KDE. Barriers might impact the calculation of crime density by either increasing the distance between features or excluding a feature from the calculation. In either situation, crime density calculations may be impacted significantly. In response, this study examined whether the natural barriers found throughout the physical landscape significantly affect the predictive accuracy of prospective hot spot maps. When complete, findings from the current study could improve law enforcement crime reduction efforts and contribute to future theoretical applications of crime pattern analysis.

Purpose of Study

Previous research has revealed that prospective hot spot maps produced from KDE can be used to accurately and reliably forecast where crime will occur in the future (Chainey & Ratcliffe, 2005; Eck et al, 2005). Prior research has also demonstrated these findings across different study areas and different types of crime (Chainey et al., 2008; Eck et al, 2005). However, it is unknown whether including barriers in spatial interpolation methods can improve crime predictions. Considering this shortcoming in the current literature, the purpose of the current study was to examine whether including barriers in the spatial analysis of crime hot spots can improve crime predictions.

Ultimately, the purpose of this study was twofold. First, findings from the current study can be used to assist practitioners, including crime analysts, who support law enforcement efforts to prevent and reduce crime through implementing strategies that incorporate spatial patterns analysis of crime incident locations. If the techniques that crime analysts use can be improved, then efforts to make communities safer could be more successful. Second, findings from the study can advance our theoretical understanding of crime within the field of environmental criminology (Brantingham & Brantingham, 1981; Cohen & Felson, 1979; Cornish & Clarke, 1987). For example, by studying the influence of barriers on crime pattern analysis, academics can further develop theoretical explanations for why certain places are crime generators or attractors because measures of crime intensity around them could be improved when barriers are considered. Comprehensively, the current research was intended to yield results that can contribute to the further practical and academic understanding of crime pattern analysis in general and prospective crime hot spot analysis in particular.

Theoretical Framework

The current study was guided primarily by theories found in the existing environmental criminology literature (Brantingham & Brantingham, 2013; Brantingham et al., 2016). Environmental criminology examines crime, criminality, and victimization as they relate to distinct places and how individuals and organizations shape their activities by place-based or environmental factors (Bottoms & Wiles, 1997). Environmental criminologists argue that crime patterns can be explained by three well-established lines of empirical inquiry: routine activities theory (Cohen & Felson, 1979), rational choice theory (Clarke & Cornish, 1985), and the geometry of crime (Brantingham & Brantingham, 1995).

The original premise of routine activities theory conceptualized criminal opportunities as the result of three necessary elements converging in space and time: a motivated offender, suitable target, and lack of capable guardianship (Cohen & Felson, 1979). Cohen and Felson (1979) further argued that the lack of any one of these elements would be sufficient to prevent the successful completion of a predatory crime, which may lead to significant decreases in crime rates. A decade later, Sherman and colleagues (1989) expanded these ideas by suggesting that crime rates are not only affected by the absolute size of the supply of offenders, targets, or guardianship, but by factors influencing the frequency of their concurrence in space and time. More recently, Braga and colleagues' (2017) comprehensive review of existing place-based research shows that motivated offenders and suitable targets converge at specific microspatial places more frequently than others. Therefore, any structural change in the physical environment that impacts individuals' routine activity patterns – including barriers to crime – could influence overall crime rates.

Historically, a considerable amount of research in criminology has focused on offenders and their decision-making process (Sherman, Gottfredson, Mackenzie, & Eck, 1997). Although the focus is still on decision-making, environmental criminology focuses on the built environment and how it can impact human behavior, including criminal offending. In other words, if we change things in our environment that a potential offender might observe or interact with, we can change their behavior. Identifying where crime concentrates and understanding that we can change the environment and the behavior of potential offenders creates opportunities for reducing crime.

Clark and Cornish (1985) developed a line of scholarship relevant to the current study that focuses on the rational choices potential offenders make.

The underlying premise of rational choice theory is that humans are designed to act out of self-interest, making decisions and choices that will maximize the benefits of their present situations, while minimizing the costs (Clarke & Cornish, 1985). Studies in environmental criminology have continued to broaden this premise by demonstrating that offenders are active decision-makers who use environmental cues to make calculated and purposive decisions about their engagement in specific crimes (Johnson, 2017). Clarke and Cornish's (1985) basic argument are that the weighting of costs and benefits is not only a sign that one's action to commit crime is purposive and deliberate, but also rational and open to being influenced by the environment.

The geometry of crime represents another criminological theory associated with environmental criminology (Brantingham & Brantingham, 1995) and used to develop the current research. According to this perspective, knowing the "places" where we spend most of our time (i.e., activity nodes), the pathways between and around them, and the environmental backcloth are the keys to explaining crime patterns (Brantingham et al., 2016). Each of these elements are associated with aspects of both routine activities theory and rational choice theory discussed previously. For example, how we move through our environment during our everyday routine activities can be restricted by the nature of our local road networks (i.e., pathway) and transportation hubs (i.e., activity nodes) (Brantingham et al., 2016). These restrictions of our daily movement can compromise our movement patterns, which can either create criminal opportunities or reduce them.

Finally, crime pattern theory is what Brantingham and colleagues (2016) refer to as a meta-theory. It serves as an umbrella theory over routine activities theory, rational choice theory, and the geometry of crime, which collectively define environmental criminology. In other words, crime pattern theory provides a theoretical framework of environmental characteristics, offender perception, and movements to explain the spatially patterned nature of crime (Wortley & Townsley, 2017). Crime pattern theory emphasizes the importance of locations and how and why these locations are typically chosen by offenders (Weisburd, 2015).

In summary, environmental criminology provided the theoretical framework that guided the present study. This broad framework was built upon the foundations of routine activities theory (Cohen & Felson, 1979), rational choice theory (Cornish & Clark, 1985), and the geometry of crime (Brantingham & Brantingham, 1993) to explain why crime concentrates in microgeographic places, which has been formally recognized recently by the law of crime concentration (Weisburd, 2015).

Definition of Terms & List of Abbreviations

This section provides definitions of technical terms, abbreviations, and professional jargon that were used throughout the study.

Terms

Bandwidth: the “spread” of the kernel function used to estimate grid-cell density (Chainey, 2013).

Bandwidth of percentages: “a specific cumulative proportion of crime, such as 25 or 50% of crime in a city” (Weisburd, 2015, p. 133).

Barriers: alters the influence of a feature while calculating kernel density for a cell in the output raster (ESRI, 2019).

Crime analysis: the process of reviewing raw data with the goal of identifying and analyzing a pattern of crimes that the analyst believes is committed by the same person or persons (Wortley & Townsley, 2016).

Crime attractors: particular places, areas, neighborhood, districts which create known criminal opportunities to which intending criminal offenders are attracted because of the known opportunity (Brantingham et al., 2016).

Crime generators: particular nodal areas to which large numbers of people are attracted for reasons unrelated to any particular level of criminal motivation (Brantingham et al., 2016).

Crime hot spots: a significantly higher than average concentration of crime events within the study area (Hart & Zandbergen, 2013).

Crime pattern theory: a meta-theory that integrates the three main theoretical perspectives within environmental criminology (routine activity theory, rational choice theory, and geometry of crime) (Brantingham et al., 2016).

Grid cell: the coordinates referring to the centroid of the cell (Chainey, 2013)

Interpolation: a technique for generalizing incident locations to an entire area (Hart & Zandbergen, 2014).

Kernel density estimation (KDE): a popular technique for identifying crime hot spots by smoothing the curve of the data (Chainey & Ratcliffe, 2005).

Kernel function: a function that takes as its inputs vectors in the original space and returns the dot product of the vectors in the feature space (Chainey et al., 2008).

Kernel smoothing: a method that generates a map of density values from the point event data (Williamson et al., 1999).

Pattern: recognizable inter-connectivity among objects, rules, and processes (Wortley & Townsley, 2017).

Predictive accuracy: a ratio measure comprising a numerator of the proportion of crime events falling within the mission grids for each district and a denominator of the percentage of the relevant police district covered by the mission grid (Chainey et al. 2008; Eck et al., 2005)

Predictive Accuracy Index (PAI): a method for the objective evaluation of hot spot methods (Chainey et al., 2008).

Prospective hot spot mapping: an analytical technique that is used to help identify where to target police and crime reduction resources (Chainey et al., 2008).

Recapture Rate Index (RRI): The index calculated by dividing the ratio of hotspot crime counts by the ratio of the total number of crimes for each year (Levine, 2008).

Abbreviations

CPTED: Crime prevention through environmental design

FBI: Federal Bureau of Investigation

GIS: geographical information system

KDE: kernel density estimation

PAI: predictive accuracy index

RRI: recapture rate index

RAT: Routine Activity Theory

SCP: Situational crime prevention

UCR: Uniform Crime Reporting Program

Hypotheses

The present study tested a research hypothesis related to how barriers may influence prospective crime hot spot mapping results that are produced from kernel density estimation

(KDE). The research hypothesis stated below was assessed for both violent and property crimes, using data from three Florida cities as case studies.

H_0: The predictive accuracy of prospective crime hot spot maps that are produced using kernel density estimation will not be affected by the inclusion of barriers in the interpolation process.

H_1: The predictive accuracy of prospective crime hot spot maps that are produced using kernel density estimation will be higher for those that include barriers in the interpolation process than those that do not.

Significance of the Investigation

As noted previously, the study is significant due to its potential impact on both research and practice. The long-term goal of this research was to develop and provide a better understanding of crime hot spot prediction through formalized use of barriers in kernel density estimation (KDE). The study's objective was to produce a comprehensive literature review, including current "best practices" in relation to the KDE application and parameters setting. This review also outlined a conceptual framework for more predictively accurate hot spot maps by incorporating known barriers in the interpolation process. Results of this study are valuable to criminologists' efforts to develop criminological theory within the place-based framework and to practitioners' efforts to better understand where crime clusters and to develop strategies that improve crime reduction and prevention efforts.

CHAPTER 2

LITERATURE REVIEW

The literature review that follows examines the existing research relevant to the present study. It begins with the theoretical bases for the current research – the positivist perspective – that inform crime hot spot methods and placed-based crime prevention strategies. It continues with a discussion of theories recognized as early influences of the place-based perspective on crime. Literature that has shaped our contemporary understanding of place-based interventions and crime hot spots is also described. The chapter concludes with a summary of theories that emphasizes the links between hot spot mapping and the need for examining whether barriers to crime should be considered in kernel density estimation techniques.

Positivism

The present study is based on the positivist school of criminological thought. Positivists believe that measurement, objectivity, and causality of reality exist apart from the perceptions of those who observe it. Positivist criminology is where we stopped focusing on the criminal man (e.g., born criminals) and began focusing on external factors (e.g., the environment) that could influence crime. In other words, unlike the classical school of criminology, the positivist school of criminology assumes that criminal behavior occurs because individuals can make rational choices based on free will and the causes of crime are outside the offender's control.

Positivist criminology uses empirical research methods based on logic and scientific reasoning to identify what causes criminality, instead of identifying the behaviors of criminals. Existing research from the positivist school links various factors external to the individual to criminal offending, including poverty, residential mobility, and exposure to the deviant structure. Others in the positivist school of criminology have focused their attention on the built environment.

Subsequently, to understand what causes criminality, and spatial patterns of crime events, we can turn to some of the more well-known positivist theories, such as social disorganization theory, lifestyle theories of victimization and offending, and theories that fall within the environmental criminology perspective.

Social Disorganization Theory

Social disorganization theory plays a vital role in crime and places literature and emerged from research conducted in Chicago by Shaw and McKay (1942). Using spatial maps, Shaw and McKay (1942) discovered that crime rates were not evenly distributed across the city; instead, crime was concentrated within particular areas. They also found that crime remained relatively stable within different areas despite population changes. The observations of Shaw and McKay's (1942) study demonstrated that crime was likely a function of neighborhood mobility and not necessarily a function of the individuals that resided within neighborhoods. In other words, a person's physical and social environments were primarily responsible for the criminogenic behavioral choices made by those in their neighborhoods. To better understand this concept, subsequent studies focused on areas that experienced rapid social and economic structural changes to understand why the characteristics of various neighborhoods accounted for the concentration of crime (Sampson & Groves, 1989; Sherman et al., 1989)

Social disorganization theory asserts three fundamental components for increased crime rates: low economic status, residential mobility, and ethnic heterogeneity (Sampson & Groves, 1989). For example, areas with low socioeconomic status (SES) or poverty that are socially or physically isolated from established neighborhoods encourage the growth of crime in those regions. The low SES and the structural characteristics of residential mobility and ethnic heterogeneity also inhibit a community from maintaining informal social control (Sampson &

Groves, 1989). For example, Sampson and colleagues' (1997) analysis of social cohesion and its link to violence in Chicago, Illinois demonstrated that neighborhoods with poor structural characteristics were related to increased criminal behavior. Furthermore, they contended that a lack of social capital created an absence of collective efficacy in neighborhoods, which could lead to increased neighborhood crime. Sampson (1985) defines collective efficacy as the process of converting social ties or drawing upon social capital among neighborhood residents to achieve specific tasks. These "tasks" commonly include public order, political demands, regulation of crime, violence, and delinquency (Sampson, 1985). The shared belief in the capabilities to organize and execute the courses of action required to produce levels of success within these specific tasks is what allows for social control. In short, previous research shows that the inability of a neighborhood to maintain social control is linked to high-crime neighborhoods. From a place-based perspective, this absence of control and high levels of neighborhood disorganization eventually lead to instability, thus creating opportunities for crime. Subsequently, the concept of collective efficacy in social disorganization theory helps to provide a strong theoretical foundation for understanding the interactive coordination of a neighborhood's routine transactions (Shaw & McKay, 1924).

Sampson and colleagues' (1997) comprehensive study of Chicago neighborhoods demonstrated the role that neighborhood social processes, such as social control, played in preventing crime. Along with the work of Shaw and McKay (1924), the work of Sampson and colleagues (1997) provides insight into the understanding of crime from the social disorganization theory perspective and the spatial distribution of crime. However, these studies were conducted at a macro-level scale (i.e., neighborhoods). As a result, conclusions about crime, based on social disorganization theory, sparked researchers' interest in analyzing data to understand how social structure influences crime, but at smaller units of analysis.

For example, Weisburd and colleagues (2012) studied social disorganization in Seattle, using street segments. This study mainly argued for social interventions on the micro-level to increase social controls in crime hot spots to reduce crime. Weisburd and colleagues (2012) argued that residents could improve public order or control crime collectively, by increasing collective efficacy in specific locations within the larger social environment, which they described as communities or neighborhoods. However, the decrease in social controls in Seattle during the 1990's coincided with a significant crime decline, suggesting that the concentration of crime typically changed little in terms of criminal activities and that some areas even experienced sustained crime waves. Regardless, Weisburd and colleagues' (2012) study reinforced the significance of looking more closely at crime at small geographic units of analysis and revitalized interest in integrating components of routine activities theory – which is discussed below in greater detail – and social disorganization theory as a branch of criminological inquiry.

Since social disorganization and routine activities theory developed, efforts have been made to integrate the two ways of thinking about crime. For example, research by Gottfredson, McNeil, and Gottfredson (1991) as well as by Smith, Frazee, and Davison (2000) showed promise. However, their studies were less interesting to place-based researchers because neither focused on the spatial patterns of crime, nor used spatial analysis methods to identify specific crime patterns. Recently, however, Andresen (2017) used spatial regression models to demonstrate that social disorganization theory and routine activities theory could be integrated successfully to explain criminal activity. His study included typical measures of social disorganization theory like ethnic heterogeneity, unemployment, and residential tenure, but they were recorded at the census tract level. As a result, the utility of these findings for place-based crime-fighting initiatives are noteworthy but limited. Although others continue to develop scholarship around the integration of routine activities and social disorganization theories (Jones & Pridemore, 2019), another promising line of research for understanding crime and place emerged from early lifestyle theories of victimization and offending.

Lifestyle Theories of Victimization and Offending

Understanding opportunities for crime is crucial to comprehending the variability of crime at micro-places. From this perspective, crime is contingent on two primary things: potential offenders who are ready and able to engage in a criminal activity and the environmental conditions in which potential offenders are situated, which impacts their decision-making process. Some scholars in this area focused their research on the interplay between criminal opportunities and the environment, emphasizing how individual lifestyles correlate with victimization and offending (Hindelang, Gottfredson, & Garafalo, 1978).

Early lifestyle theories suggested that the more one is exposed to criminogenic environments, the greater the likelihood they will engage in criminal activity or becoming a crime victim (Garofalo, 1987; Gottfredson, 1981; Hindelang et al., 1978; Meier & Miethe, 1993). Although demographic characteristics including age, gender, marital status, family income, and race were incorporated into early lifestyle research, societal characteristics from which role expectations and structural constraints developed were considered paramount (Hindelang et al., 1978). In this context, role expectations are viewed as the traits or behaviors that society considered “appropriate” for an individual (i.e., someone under 21 years of age not consuming alcohol), whereas structural constraints are the various social and cultural factors limiting an individual’s decision-making process (i.e., not engaging in criminal activity if it meant risking a well-paying job). In short, structural constraints limit behavioral choices, thereby affecting role expectations, leading to varying lifestyles. This difference in lifestyles accounts for variations in criminogenic exposure, both in direct exposure and vicarious exposure of individuals with similar lifestyles (Hindelang et al., 1978). As academic interest in explaining crime through the lifestyle perspective developed, scholars began focusing more intently on the link between the everyday routine activities of crime victims (Cohen & Felson, 1979).

Routine Activities Theory

Cohen and Felson's (1979) routine activities theory argues that for crime to take place, there must be a motivated offender, a suitable target, and the absence of capable guardians. The initial focus of routine activities theory was on persons rather than events, suggesting that crime was a function of significant changes in the basic framework of society and that high crime rates in the contemporary world are relatively inevitable (Cohen & Felson, 1979).

Since its initial introduction, the proposition of routine activities theory has shifted, emphasizing the socio-physical world rather than the social world devoid of its physical structure to explain crime (Wortley & Townsley, 2017). Consequently, from this theoretical perspective, we now view crime as events that require a physical convergence of the three elements to crime and that the intersection of these elements is not only guided by our everyday routine activities, but by the environment in which they take place (Felson & Eckert, 2016).

While routine activities theory establishes that opportunities for crime stem from the convergence of offenders and criminal targets, accounting for factors that influence their convergence is essential to understanding the spatial distribution of crime (Ratcliffe, 2015; Sherman et al., 1989). Research conducted by Lemieux and Felson (2012), for example, examined how exposure to risk of violent victimization is best understood by looking at where people are, what they do while in those places, and how long they remain in these areas. When time-based victimization rates are based on these factors, the researchers conclude, different patterns of victimization emerge. Furthermore, research by Weisburd (2015) and Ratcliffe (2006) not only show that crime clusters, but that clusters shift significantly by hour of day and day of week, providing evidence that opportunities to commit crime also varies. On that premise, without the concurrence of opportunities, offenders and targets would be less likely to cross paths and the likelihood of crime would decrease (Cohen & Felson, 1979).

Both criminals and non-criminals move throughout space and time, and the street segments they travel serve as the central pathway for movement, which increases the probability of their interaction. Brantingham and Brantingham (1981) propose that offenders search for criminal opportunities within the spatial and temporal geographic places (i.e., activity spaces) in which offenders carry out their routine activities. Therefore, routine activities theory can inform us about where there may be overlap in the activity spaces of offender and targets in concurrence with the third necessary element of a crime – an absent guardian – and the probability of a crime occurring (Cohen & Felson, 1979; Sherman et al., 1989). Even though the theory suggests that the source of these overlapping movements can be legitimate activities unrelated to crime, it still suggests little about how these elements converge in time and space. The theory also does not address the decision-making process undertaken by offenders when their paths cross with suitable targets, which is the focus of rational choice theory (Cornish & Clark, 1987).

Rational Choice Theory

Rational choice theory suggests that offenders make rational choices, choosing targets that offer a low risk of apprehension and a high likelihood of reward. At the core of this theory are the concepts of choice and decision making and that the success in committing crime drives the development of criminal lifestyles (Cornish & Clarke, 1987). Although the theoretical emphasis on the perceived cost and benefits is central to the rational choice framework, it has evolved into a more complex perspective that considers that rational choices are situationally (i.e., spatially and temporally) crime specific.

Specific offenses bring particular benefit to offenders and are committed with individual motives in mind (Clarke & Cornish, 2008). Furthermore, even within the narrow confines of a single crime, what motivates one offender may not be the same for another. Therefore, each involvement or continuance in crime activity needs separate explanations because involvement decisions are multistage and multi-factored, extending over long time periods. In short, people make rational decisions based on how they expect the choices to increase their benefits and lower their costs. Subsequently, a well-protected target for crime may be less likely to be victimized because a rational offender may decide that it is too risky or requires too much effort to commit. As a result, according to rational choice theory, a reasoning criminal would commit a crime after deliberating their gains and losses, considering the elements that minimize their risks, time, place, and other situational factors.

Research into rational choice theory has also drawn interest and focus on the ecological setting of offenses and their targets. Choices about settings and targets have been shown to be related to environmental cues of risk, reward, and effort (Clarke & Cornish, 1985). For example, Clarke and Mayhew (1988) studied gas suicides in Britain from 1963 to 1975 to determine the influence of environmental settings on behavior. The researchers observed a significant decline in suicides during a time when suicide was increasing in most other European countries, which was a result of the progressive removal of carbon monoxide from domestic gas in England and Wales. Suicide by domestic gas, which accounted for 50% of the deaths at the start of the period, was virtually eliminated by the end of the period simply by removing access to a means of death. Specifically, they showed that blocking the opportunity to commit suicide by changing the environment reduced a deeply motivated act such as suicide.

Existing research also generally shows that changes to the environment can have a “net-positive” effect on crime, meaning that crime can be reduced without simply displacing it to other areas. Some research shows that changing the environment to decrease the opportunities for crime can also have a “diffusion of benefit” effect (Barr & Pease, 1990). In this context, displacement refers to the relocation of crime from one place, time, target, offense, or tactic to another due to crime prevention initiatives (Guertte, 2009), whereas crime diffusion refers to the reduction of crime in areas that are close to crime prevention efforts but not targeted by the intervention specifically (Clarke & Weisburd, 1999). While some researchers focused on the relationship between the routine activities of everyday life and criminal victimization and offenders’ decision-making process to explain crime patterns, others focus more intently on the link between the structure of the physical environment and how people move through and the crime patterns that emerge from this kind of place-based interaction.

The Geometry of Crime

The geometry of crime emerged from the work of Brantingham and Brantingham (1981, 1993, 2016) with the aim of understanding and explaining crime patterns. Their approach to understanding crime incorporated elements of environmental psychology, transportation research, and research from the field of criminology and many new concepts emerged from the geometry of crime theory. These concepts not only help us better understand how we move through the physical world and the relationship between our movements and criminal opportunities, but how crime patterns emerge from our spatial behavior. These concepts include activity nodes, activity space, pathways and activity space, awareness space, and the environmental backcloth. Since its introduction, place-based researchers have studied how these concepts help us understand and explain where crime occurs at a micro-geographic level.

According to the geometry of crime theory, people spend most of their day at certain locations, engaging in non-criminal activity (Brantingham & Brantingham, 1981, 1993, 2016). These locations are common to most people and include their home residence, friends' or relatives' homes, and where they go to school or work. Other places where people spend most of their time outside of these places include parks, entertainment centers, malls and shopping centers, sporting venues, and public transportation nodes.

Hart and Miethe's (2014) research on robbery environments suggests that they are defined by the spatial interaction of several different activity nodes (e.g., bus stops, convenience stores, gas stations, parking garages, and ATMs) in close proximity (i.e., 1,000ft) to each other. Similarly, Rice and Smith (2002) analyzed crime patterns and found that bars, gas stations, and hotels interacted to generate circumstances favorable to automobile theft. In summary, activity nodes represent the places where people engage in their frequent or daily legitimate activities and existing research demonstrates how they can be linked to crime patterns (Johnson, 2017).

People move along pathways that connect activity nodes (Brantingham & Brantingham, 1993). Although paths can represent any transportation network, the most common routes people take between nodes are along street networks. Collectively, activity nodes and the pathways that connect them define an individual's activity space (Brantingham et al., 2016). In a recent study conducted in Brisbane, Australia, Hart and colleagues (2018) measured the spatial movement patterns of nearly 1,000 study participants' daily trips, using cellphone data recorded over a 1-month period. They found that participants' movement within their activity spaces varied considerably. Moreover, most participants' activity spaces – around 75% – overlapped, which illustrated the convergence of potential victims and offenders in space and time, which Felson and Eckert (2016) argue is key to understanding crime patterns from a routine activities' perspective. According to the geometry of crime theory, the regular routes that overlap potential offenders and victims are referred to as pathways. Movement between nodes along pathways can create patterns of repetitive travel and subsequently, opportunities for crime to concentrate into identifiable patterns.

Awareness space and environmental backcloth are two additional terms described in the geometry of crime theory (Brantingham & Brantingham, 1981, 1993, 2016). Awareness space are areas of the built environment that are within "visual range" of an individual's activity space, whereas the environmental backcloth is defined by the social, economic, political, and physical dimensions of the movements of our everyday routine activities (Brantingham & Brantingham, 1993). Caccato and Uittenbogaard (2013) examined changes in everyday movements of transit station passengers in Stockholm, Sweden. They found that crime patterns were linked to variations in passenger volume across different time periods (i.e., evening, night, holiday, and weekends) at different transit nodes. They also discovered that stations' environmental attributes affected levels of crime at different times, which supported the notion that the environmental backcloth is linked to crime patterns. Similar studies in the UK (e.g., Armitage, 2007; Hillier, 2004) and the US (Groff & LaVigne, 2001; Rossmo & Fang, 2012) using street segments as micro-level units of analyses have produced similar findings. To date, however, no known study has assessed whether barriers to movement through an individual's activity space or that define the environmental backcloth can impact crime patterns in a way that influence prospective forecasts.

Crime Pattern Theory

Over the past few decades, ideas found in rational choice theory (Clarke & Cornish, 1987), routine activities theory, (Cohen & Felson, 1979), and the geometry of crime theory (Brantingham & Brantingham, 1993) have been integrated into a single meta-theory: crime pattern theory (Brantingham & Brantingham, 2013). According to crime pattern theory, criminals have normal spatio-temporal movement patterns that are like that of non-criminals and researchers have used crime patterns to draw more attention to the geographical distribution of crime to reduce and prevent crime.

For instance, studies have shown that an offender's journey to crime is typically very short because the most probable areas for a criminal to commit a crime are within one or two miles of their everyday activities and awareness spaces (Rossmo, 2000; Rossmo & Rombouts, 2016). Journey-to-crime patterns have been shown to vary by crime type (Townsley & Sidebottom, 2010) and law enforcement agencies have applied this idea to geographically profile serial offenders. However, existing research is divided as to whether geographic profiling strategies proposed by Rossmo (2000), and others consistently outperform other spatial analytic strategies (Snook, Zito, Bennell, & Taylor, 2005).

Despite definitive conclusions about geographic profiling, it is widely accepted that crime incident locations are not distributed randomly across an agency's jurisdictions; they cluster geographically. In research aimed at understanding crime patterns, microspatial units of analysis have received considerable attention by researchers because they can best inform place-based policing strategies. For example, examinations of small geographic units of analysis help us better understand why crime occurs at specific places, rather than focusing on the specific type of people who commit crime (Weisburd, 2015). Weisburd and colleagues (2012) found that about 60% of calls for service in Seattle were attributed to about 5% of the street segments examined. Similarly, Braga and colleagues (2012) found that 8% of Boston's Street segments and intersections accounted for 50% of reported robberies. Overall, studies conducted at small spatial units of analysis and informed by crime pattern theory enforce the growing idea that most of the crime is happening in more concentrated areas. They also demonstrate the importance of using micro-geographic spatial units of analysis when studying crime and place and identifying crime hot spots.

Law of Crime Concentration

The law of crime concentration asserts that for a fixed measure of crime at a microgeographic unit, the concentration of crime will fall within a narrow bandwidth of percentages for a defined cumulative proportion of crime (Andresen et al., 2017). In other words, crime concentration is so regular that a given percentage of the worst crime-afflicted places will account for a fixed percentage of all crime in most cities (Weisburd, 2015). Recent research has also shown that these crime patterns may remain stable over long-time spans (Weisburd, 2015; Braga et al., 2012; Wortley & Townsley, 2016).

Our empirical knowledge about high-crime locations has guided place-based prevention strategies, by focusing police resources on persistent problematic places (Braga et al., 2017). Given that crime is not randomly distributed across space and time, efforts to reduce and prevent crime have focused on the most crime-conducive area within the environment, often implementing strategies associated with Crime Prevention Through Environmental Design (CPTED) and Situational Crime Prevention (SCP) strategies.

Crime Prevention Through Environmental Design (CPTED)

The basis of Crime Prevention Through Environmental Design (CPTED) is that intentional or legitimate urban design and efficient use of the built environment can reduce the incidence and fear of crime, and in turn, improve the quality of a neighborhood (Jeffery, 1977). This design philosophy is the basis of environmental criminology and place-based research. The CPTED philosophy also informs law enforcement efforts to reduce and prevent crime by focusing on the neighborhood structure and urban development (Moffat, 1995). In short, as a placed-based prevention strategy, CPTED focuses on conditions of the physical and social environment and the opportunities provided by the conditions created to assess the threats and crime vulnerabilities.

Initial CPTED studies were primarily based on observations of the built environment that identified associations between specific design features and recorded crime rates (Jeffery, 1971; Moffat, 1983; Newman, 1972;). Newman (1972) argued that defensible space is fundamental to CPTED, which he defined as residential environments whose physical landscape – built into the layout and site plan – functions to allow residents to become the key agents of insuring security or unrestricted pedestrian movement. Newman (1972) argued that defensible space is made up of a range of mechanisms that are both real (e.g., fences or designs that define and delineates between private, semi-private, and public spaces) and symbolic (e.g., signage) barriers. In this context, barriers are defined as areas of influence that improve opportunities for surveillance (Cozen, Saville, & Hillier, 2005). These design elements act independently and in combination to help promote a sense of ownership and collective efficacy of residents to secure and maintain safe, productive, and well-maintained neighborhoods (Newman, 1972).

Following on Newman's work, Moffat (1983) proposed six characteristics that better defined defensible spaces. They include territoriality, surveillance that is natural (e.g., resident's self-surveillance), formal (e.g., police patrols) or mechanical (e.g., street lighting and CCTV), access control, image/maintenance, activity program support, and target hardening (Moffat, 1983). According to Moffat (1983), these distinct elements of defensible space are not independent of one another. Rather, they act congruently to define acceptable patterns of usage and ownership of a place and to promote opportunities to reduce crime (Cozen et al., 2005). For example, the physical design of a built environment may support informal or natural surveillance opportunities, which can increase the risk to potential offenders of apprehension. Reynald's (2009) research in The Hague and Moir and colleagues' (2019) study in Brisbane demonstrated how many of Moffat's (1983) characteristics of defensible space are linked to active guardianship. Both studies showed that as defensible space increased, active guardianship also increased, which was linked to decreased crime.

Strategies to control access have also been shown to reduce vehicle thefts, prevent bank robberies, and lower shoplifting through increased presence of formal guardianship. Mechanical surveillance such as CCTV has been shown to also reduce fear of crime significantly. For example, Ratcliff and colleagues (2009) studied the impact that CCTVs had on crime in Philadelphia and found that they reduced crime in some areas as much as 13%. More recently, Lim and Wilcox (2017) found that CCTVs were most effective at reducing crime in residential areas and that the diffusion of benefit for having CCTVs far exceeded the displacement of crime. In summary, clearly defining boundaries and creating and maintaining a positive "image" through the use of mechanical surveillance can affect offender's behavior in a way that can discourage criminal offending (Cozen et al., 2005). Although CPTED is useful in broadly understanding the effects of environmental design on crime, a new approach that focuses more on the specific target of the crime has emerged in recent years. This approach focuses on people, places, or objects of crime and is referred to as situational crime prevention.

Situational Crime Prevention (SCP)

Situational crime prevention (SCP) is a primary prevention measure directed at stopping crime and crime-related problems before they occur. SCP represents a micro-level development of an environmental perspective to crime fighting, focusing on the nature of the environment and its potential for criminal acts (Clarke, 1995). To prevent crime and the opportunities that facilitate it, SCP strategies are designed to manipulate the environment and increase the associated risks and efforts to commit an offense, thereby reducing opportunities and incidents.

Theoretically, SCP emphasizes that crime and criminal involvement are a function of the reality of a practical or attractive opportunity to commit a crime. As a result, fundamentally, it aims to portray criminal activity to reasoning criminals as riskier and less rewarding in the hopes of reducing criminal events. SCP offers a comprehensive set of techniques for operationalizing crime prevention, grounded in the concepts of routine activity (Cohen & Felson, 1979), crime pattern analysis (Brantingham & Brantingham, 1993), and rational choice theory (Clarke & Cornish, 1985). Although routine activities theory and crime pattern theory are important to the structure of SCP, it was the development in the rational choice perspective of the “crime script” that formulated the underpinning of this model (Clarke & Cornish, 1985).

The crime script constitutes that the crime event does not occur at a single point in time and space; rather, it may take days or even weeks to achieve, and activity can occur at various locations. For example, a burglary may start with the offender researching likely targets and gathering the necessary tools possible days before and end with the offender trying to dispose of or sell the stolen items days after the event. The notion of there being dozens of individual steps between the start and end of a crime event asserts that there is not just one decision point at which rational choices are made, and each point offers an opportunity for intervention (Cornish, 1994).

Considerable researcher attention has been paid in recent years to the use of crime scripts to better understand the offending process and to develop SCP-based strategies to prevent crime (Leclerc, 2014). For example, Beauregard and colleagues (2007) examined the hunting process scripts of over 300 serial sex offenders to identify both the behavioral and geographical aspects of these incidents. They identified and defined three distinct hunting styles sex offenders use and proposed specific crime prevention strategies based on their findings that were rooted in situational crime prevention. Similarly, Osborne and Capellan (2017) applied crime script analysis to active shooter events and a rational choice theoretical perspective. They found distinct planning, execution, and conclusion stages during these events and proposed situational crime prevention strategies based on the shooting typologies they identified.

As opportunities for intervention have been identified, they have been incorporated into an original table of SCP techniques developed by Clarke (1995). These techniques initially involved three strategies – reducing rewards, increasing risks, and increasing efforts – and yielded 12 prevention techniques (Clarke, 1995). Despite the broad assumptions of this technique, Cornish and Clarke (2003) found that there were situations in which called for the expansion of these decision factors to include mechanisms involving excuse and provocation. This expansion yielded 25 techniques of situational prevention. Figure 1 presents the most recent list of strategies and techniques. Many of the SCP strategies and CPTED approaches have been evaluated in place-based research and facilitated the development of a division of criminology known as environmental criminology.

Figure 1

Twenty-Five Techniques of Situational Crime Prevention

Increase the Effort	Increase the Risks	Reduce the Reward	Reduce Provocations	Remove Excuses
1. Target hardening: Steering • Anti-robbery screens • Tamper-proof packaging	6. Extended guardianship: • Take routine precautions • Carry phone	11. Conceal targets: • Off-street parking • Gender-neutral phone directories	16. Reduce frustration and stress: • Efficient queues and polite service • Expanded seating • Smoothing music/lights	21. Set rules: • Rental agreements • Hotel registrations
2. Control access to facilities: • Entry phones • Baggage screening	7. Assist natural surveillance: • Improve lighting • Defensible space design	12. Remove targets: • Removable car radios • Women's refuges	17. Avoid • Separate enclosures for rival soccer fans • Reduce crowding in bars • Fixed cab fares	22. Post instructions: • "No Parking" • "Private Property"
3. Screen exits: • Tickets needed for exit • Electronic merchandis e tags	8. Reduce • Taxi cab IDs • School uniforms • "How's my driving?" stickers	13. Identify property: • Property marking • Cattle branding • Vehicle parts marking	18. Reduce • Controls on violent pornography • Prohibit racial slurs	23. Alert conscience: • Roadside speed display boards • Signatures for customs declarations
4. Deflect offenders: • Street closures • Disperse pubs	9. Utilize place managers: • Two clerks at convenience stores • Reward vigilance	14. Disrupt markets: • Monitor pawn shops • Controls on classified ads • License street vendors	19. Neutralize peer • "It's OK to say, 'No.'" • "Idiots drive drunk."	24. Assist compliance: • Easy library checkout • Public lavatories • Trash cans
5. Control tools/weapons: • Disabling stolen cell phones • Restrict spray paint sales to juveniles	10. Strengthen formal • Burglar alarms • Security guards	15. Deny benefits: • Ink merchandis e tags • Graffiti cleaning • Speed bumps	20. Discourage imitation: • Rapid repair of vandalism • Censor details of MO	25. Control drugs and alcohol: • Breathalyzers in bars • Alcohol-free events

Adapted from Cornish & Clarke (2003, p. 90).

Environmental Criminology

Environmental criminology is defined as the study of crime, criminality, and victimization as they relate to specific places and the way that individuals and organizations shape their activities by placed-based or environmental factors (Bottoms & Wiles, 1997). According to this perspective, "criminal events must be understood as confluences of offenders, victims or criminal targets and laws in specific settings at particular times and places" (Brantingham & Brantingham, 1991, p. 2). Since the spatial distribution of offenses and offenders throughout a city is not random and some places experience disproportionate amounts of crime, environmental criminology provides the theoretical foundation for placed-based policing strategies. These approaches concentrate on the crime patterns and how placed-based interventions can influence offenders' behavior. Hot spot policing is one of the most used place-based policing strategies.

Hot Spot Policing

Using official police data in Minneapolis, Minnesota, Sherman and colleagues (1989) observed that a relatively small proportion of crime "hot spots" accounted for a relatively large proportion of all calls for service. Their research marked one of the first contemporary observations empirically supporting the idea that crime is not distributed randomly in space and is viewed by many as the catalysts for studying crime and place within criminology. Sherman and colleagues' (1989) observations led to the Minneapolis Hot Spots Patrol Experiment, which explored whether proactively policing crime hot spots with preventative patrols would be an effective approach to fighting crime (Sherman & Weisburd, 1995). Results of Sherman and Weisburd's (1995) study revealed a significant reduction in calls for service for the hot spots treatment group that received police patrols (i.e., between 6% - 13%), compared to the control hot spots. Since these two hallmark studies, researchers have developed methods of different hot spot policing strategies, including predictive policing, which is based on forecasting or predicting future crime hot spots, given on the known locations of where crime has occurred in the past (Braga, Papachirstos, & Hureau, 2014).

Predictive Policing

Existing research indicates that the predictive policing techniques have considerable advantages over more traditional crime-fighting methods and might prove particularly useful in more effectively and efficiently deploying police resources. For example, Bowers, Johnson, and Pease (2004) used prospective hot spot mapping techniques to show how future burglary incidents in Merseyside, England could be accurately predicted, based on where incidents occurred in the past. Between 62%-64% of all incidents were successfully forecast within a 1-week prediction period. Mohler and colleagues (2015) conducted a randomized control experiment on predictive policing methods used in California cities and found that they could reduce incidents by as much as 4.3 fewer crimes per week, or an average reduction of 7.4% in the total crime volume across the study area. Finally, Braga and colleagues' (2012) systematic review of hot spot policing research revealed that although not every study found in the literature significantly reduced crime, 80% demonstrated a significant decline in crime. Overall, the body of literature on predictive policing suggests it can be an effective place-based approach to fighting crime.

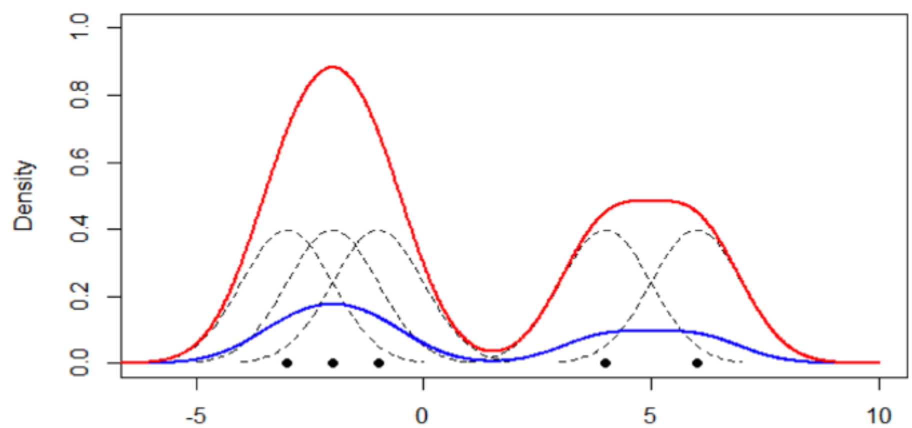
Existing research shows that there are different predictive policing methods that law enforcement used to forecast crime. For example, VanPatten and colleagues (2009) evaluated the ability of multiple prospective mapping methods to predict street robberies in Roanoke, Virginia. The researchers examined the forecasting performance of spatial and temporal analysis of crime (STAC), nearest neighbor hierarchal clustering (NNH), and kernel density estimation (KDE), using Chainey and colleagues' (2008) Predictive Accuracy Index (PAI). Results showed that they all produced forecasts that tended to converge on the same areas of the city, indicating good overall agreement among the different techniques. Kennedy and colleagues' (2015) analysis demonstrates that Risk Terrain Modeling (RTM) can be an effective prospective hot spot mapping technique that can inform place-based strategies to significantly reduce crime (see also, Caplan & Kennedy, 2016). Although there is no consensus about which prospective mapping method consistently outperforms all others. Chainey (2005) used street robbery and residential burglary data from London, England and found that KDE was "more than just a method that presents an attractive map of crime but is a more robust technique suited to understanding spatial patterns of crime hot spots" (p. 33). Similar findings have been observed by Hart and Zandbergen (2014) and by Chainey and colleagues (2008). Today, KDE is one of the most popular spatial analysis techniques used to create hot spot maps, which are used to proactively fight crime.

Kernel Density Estimation (KDE)

Kernel density estimation (KDE) – also referred to as kernel density interpolation – is a popular non-parametric spatial statistics method used in prospective hot spot mapping. KDE allows researchers and analysts to create a continuous "risk surface" across an entire study area from a set of discrete points that represent the known locations of crime incidents (Rosenblatt, 1956; Silverman, 1986). KDE can be thought of as a method that converts discrete data into a theoretical distribution, like the example shown in Figure 2. Given the utility of KDE in place-based criminology, many regard it as the most suitable spatial analysis technique for visualizing crime data (Chainey et al., 2002; Chainey & Ratcliffe, 2005; Eck et al., 2005; McGuire & Williamson, 1999; Williamson et al., 1999, 2001).

Figure 2

Example of One-Dimensional (Univariate) Kernel Density Estimation.



Source: "*Kernels and Density Estimation. The Geographic Information Science & Technology Body of Knowledge (1st Quarter 2020 Edition),* John P. Wilson (ed.)," by Yin, P. (2020).

The process of using KDE to convert discrete crime locations into a continuous crime risk is straightforward. It begins with using a geographical information systems (GIS) software application (i.e., ArcMap) to create a data layer containing the spatial locations of known crime incidents. Next, a two-dimensional lattice network or grid network of equally sized cells is created that covers an entire extent of crime locations. Then a density estimate is calculated based on a mathematical formula that considers the spatial location of incidents, relative to the center of the grid cells that fall within a specified search radius. Finally, the density estimates for each cell are weighted based on the specific interpolation method (i.e., kernel function) that is used in the estimation process. Once a data layer visualizing the study area is added to the risk surface layer created by KDE, the location of crime hot spots can easily be identified.

Defining parameters (i.e., grid cell size, interpolation method, and bandwidth) is a key step in the KDE process and the impact that parameter settings have on the predictive accuracy of prospective hot spot maps are well documented in the current literature. For example, Chainey and

Ratcliffe (2005) suggest that grid cell size should be equal to approximately the extent of the shorter side of a study area divided by 150. Others suggest that the physical terrain should guide decisions concerning grid cell size, suggesting that grid cells should be between one-half and one-third the length of the average blockface found in a study area (Caplan, Kennedy, & Baughman, 2012; Caplan, Kennedy, & Miller, 2011). Furthermore, Hart and Zandbergen (2014) argue both the interpolation method and bandwidth can impact predictive accuracy, but that the magnitude of effect is crime-type dependent. Table 1 shows the recommended KDE parameter settings for analysis of aggravated assault, robbery, commercial burglary, and motor vehicle theft.

Table 1.

KDE Parameter Settings for Analysis

	Highest score		
Crime type	HR	PAI	RRI
Aggravated assault	RTM/T/0.25	RTM/T/0.25	RTM/U/0.50
Robbery	RTM/T/0.50	RTM/Q/0.25	250/Q/1
Commercial burglary	150/T/0.25	250/Q/0.25	150/N/1
Motor vehicle theft	RTM/T/0.25	RTM/Q/0.25	150/U/0.50

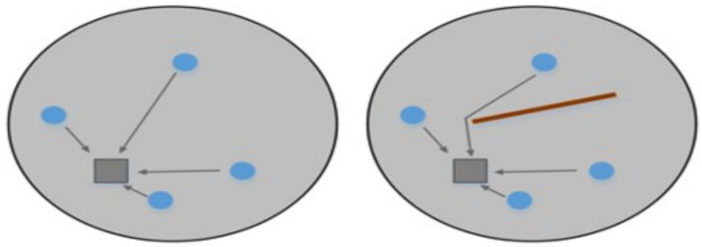
Notes: HR = Hit rate; PAI = Predictive accuracy index; RRI = Recapture rate index. The three parameters reported include the number of columns (150 = 150 columns; 250 = 250 columns; and RTM = average streetline segment divided by 0.33), the density function (N = normal; Q = quartic; T = Triangular; and U = uniform), and the search radius (0.25 = 1/4 mile; 0.50 = 1/2 mile, and 1 = 1 mile). Source: Hart & Zandbergen (2014).

Despite the guidance provided by the literature regarding KDE parameter settings, far less is known about other aspects of the interpolation process. As noted previously, KDE creates a continuous risk surface area across the ***entire*** extent of the study area. However, there are certain places within most jurisdictions where crime cannot occur. For example, a residential burglary cannot occur on a commercial property; a motor vehicle theft cannot occur in a lake. In this context, the commercial property and lake are geographic domains that are “barriers” to crime (Yuan & Hornsby, 2019). To date, no known study has attempted to examine the impact that barriers to crime might have on the predictive accuracy of prospective hot spot maps. The present study begins to address this shortcoming in the literature.

Physical Barriers to Crime. In a geographical information systems (GIS) software application, a physical barrier to crime is a geographical domain that can be used to alter the influence of kernel density estimation (KDE) calculations. Some GIS software application enable different types of barriers to be incorporated into the KDE process. For example, in ArcMap (ESRI, 2019), barriers can be defined as a polyline (i.e., a street) or a polygon (i.e., a lake or commercial parcel) feature layer that is included in the spatial interpolation process, which might affect density calculations in two specific ways. First, they may increase the distance between a crime incident location and the center of the grid cell. Second, they might result in the exclusion of a feature from the density calculation entirely. Figure 3 illustrates how a barrier to crime, depicted as a polyline feature class, could affect the calculation of a kernel density estimation. Including physical barriers to crime in the KDE process might affect the predictive accuracy of a prospective hot spot map.

Figure 3

Distance Calculation Between a Cell and an Input Point Figure.

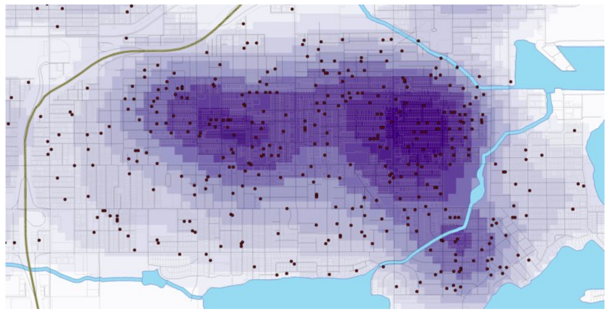


Note: Kernel density without a barrier is on the left; Kernel density with a barrier depicted as the red polyline is on the right. Source: https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/how-kernel-density-works.htm.

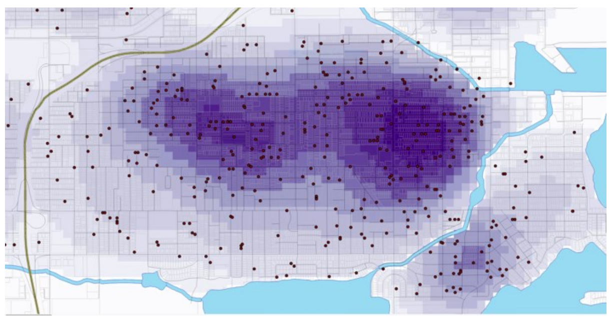
Including physical barriers to crime in kernel density calculations could provide more realistic and accurate prospective crime hot spot maps in some situations, compared to calculations made without them. For example, Figure 4 illustrates a kernel density estimation produced from the discrete locations of burglaries in south Saint Petersburg, Florida (ESRI, 2019). The left panel (1) shows the kernel density estimation without a water barrier (i.e., geographic domains where a burglary cannot occur), whereas the right panel (2) shows the density estimations with a water barrier on both sides of the area. In this example, incorporating waterways as barriers to residential burglaries produced calculations that provide a much better estimation of burglary hot spots.

Figure 4

Examples of Kernel Density Estimation of Burglary Risk



(1)



(2)

Note: The two images above show KDE output for burglary risk in a southern area of St. Peterburg, Florida. Image 1 shows results of KDE that do not include barriers in the analysis, whereas Image 2 defined waterways as a barrier to crime.

Summary

The current study applied a positivist view to understanding crime patterns that is informed by the environmental criminology perspective – a theoretical perspective that integrates some of the most longstanding and researched theories of victimization and offending found in our discipline (i.e., routine activities theory, rational choice theory, the geometry of crime, and crime pattern theory). The present investigation sought to address a gap in the crime pattern literature that relates to prospective crime hot spot mapping – a popular place-based approach to fighting crime. The current study tested whether the predictive accuracy of prospective hot spot maps that are created by kernel density estimation (KDE) are improved when physical barriers to crime are incorporated into the analytic process. The next chapter describes the data, measures, and methods that were used to undertake the current study.

CHAPTER 3

METHODOLOGY

The current study used geographic information systems (GIS) and various crime analysis and mapping techniques to test the research hypotheses presented in chapter 1. The current chapter will build on this foundation and present a description of the research design, followed by a discussion of the sampling procedures, data and measures, and analytic techniques that were used to answer the research question.

Research Design

Secondary data analysis is the primary research methodology used in the study. This type of methodology is defined as one that "…involves the reanalysis of data collected by someone else, for some other purpose, to answer a new research question or to test a new research hypothesis" (Rennison & Hart, 2018, p. 277). The study analyzed administrative data collected from three Florida law enforcement agencies that contain the geographic locations of recorded crime incidents. Administrative data on the geographic locations of various environmental barriers to crime were also incorporated into the crime hot spot analysis. These data were obtained from local governments within the law enforcement agencies' jurisdictions that oversee publicly available GIS data. Although there are several benefits to using secondary data as a research methodology, it is not without limitations.

There are two primary advantages to using secondary data analysis for the investigation. First, administrative data that were collected for this study are available online. Therefore, the data collection phase of this project was much faster than if alternative methods like survey research or a quasi-experimental design were employed. Second, administrative data that were used in the study are available to the public at no cost. Having access to free data kept the overall cost of the project very low, relative to other methodologies. In short, secondary data analysis offered the most efficient and inexpensive research design capable of answering the research question[2].

There are certain limitations to secondary data analysis that also must be acknowledged. First, secondary data may not be able to address the specific research question associated with an investigation. However, the administrative data that were used in the study contained sufficient information about when and where a crime incident occurred, the type of incident that was recorded, and the location of various barriers to crime to answer the present research question. Second, secondary data may not code variables or have response categories that an investigator needs to answer his or her research question. However, administrative data that were used in the current research have sufficient detail about the day, time, type of crime, and location and type of barriers to crime that support the type of analysis necessary to answer the research hypotheses. Finally, if a researcher is not involved with the collection of the original data, they may not have a full understanding of the data's strengths and weaknesses. To guard against this potential shortcoming, particular attention was paid to the quality of geocoding associated with both the crime incident locations and barriers to crime. Furthermore, information about a crime incident's uniform crime reporting (UCR) program's categorization were used to assure data consistency across crime types and jurisdictions that were analyzed in the current study.

Sampling Procedure

Purposive sampling was used to collect data needed for the present research. Purposive sampling, also known as selective or subjective sampling, is a non-probability sampling method

[2] Because the current study involved analyzing crime incident locations and not human subjects (i.e., victims or offenders), UT's IRB does not require the submission of an IRB application.

that involves selecting a sample of elements based on a particular characteristic of the unit of analysis. This sampling approach allowed for an adequate sample size but does not permit the current findings to be generalized to all agencies or across all crime types.

Data Collection and Analysis

In the present study, crime incidents were the unit of analysis. Data were collected on street robberies (*N* = 1,477), residential burglaries (*N* = 5,386), and motor vehicle thefts (*N* = 7,166) that occurred and were recorded between January 1, 2019, and December 31, 2020, within the Gainesville Police Department's, Orlando Police Department's, and the St. Petersburg Police Department's jurisdictions. These agencies differ in terms of size, population served, and volume of recorded crime. For example, according to recent figures from the Bureau of Justice Statistic's Law Enforcement Management and Administrative Statistics data (LEMAS; BJS, 2016), Gainesville Police Department serves a population about half the size of Orlando and St. Petersburg Police Departments. The agencies also differ in the number of full-time sworn personnel they employ. Orlando Police Department has more than 740 full-time sworn officers, St. Petersburg Police Department has more than 530, but Gainesville Police Department has less than 300, according to the LEMAS data. Analyzing data from diverse law enforcement agencies provided an opportunity to assess the robustness of the findings generated from the current study related to whether barriers impact the predictive accuracy of crime forecasts.

Crime Incidents

The types of crimes that were analyzed in the study were chosen because past research shows that they typically cluster in crime hot spots (Ratcliffe, 2006; Weisburd, 2015). They are also incidents that many agencies focus on when developing crime reduction and prevention efforts because they not only have a direct impact on crime victims, but an adverse impact of the broader community. Furthermore, they are crimes that occur with enough frequency in most jurisdictions that makes it possible to conduct analysis of the potential impact that barriers may have on crime forecasting accuracy. Finally, any reduction in these types of incidents as a function of improved forecasting methods could result in a significant reduction of an agency's overall recorded crime rates.

Street robbery. According to the FBI's Uniform Crime Reporting (UCR) Program, robbery is defined as "the taking or attempting to take anything of value 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" (FBI, 2004). In the study, personal robbery or "street robbery" – regardless of whether a weapon was used – were included in the analysis. Bank robbery, burglaries involving battery, carjacking, commercial robbery, and home invasion are crimes that some jurisdictions classify as robbery, but these incidents were not included in the research.

Residential burglary. According to the UCR Program definition, burglary involves the "unlawful entry of a structure to commit a felony or theft" (FBI, 2004). There are three subclassifications of burglary in the UCR Program: forcible entry, unlawful entry where no force is used, and attempted forcible entry. Furthermore, the UCR definition of "structure" includes an apartment, barn, house trailer or houseboat when used as a permanent dwelling, office, railroad car (but not automobile), stable, and vessel (i.e., ship). Although burglaries where the structure is a commercial property were not included in the analysis, commercial properties were used as a barrier to residential burglaries in the hot spot and forecasting analysis.

Motor vehicle theft. According to the UCR Program definition, motor vehicle thefts involve the theft or attempted theft of a motor vehicle (FBI, 2004). In this context, motor vehicles are defined as any a self-propelled vehicle that runs on land surfaces and not on rails. According to the FBI, sport utility vehicles, automobiles, trucks, buses, motorcycles, motor scooters, all-terrain vehicles, and snowmobiles are included in the definition of a motor vehicle. However, farm equipment, bulldozers, airplanes, construction equipment, or watercraft such as motorboats, sailboats, houseboats, or jet skis are not included in this crime. Table 2 provides descriptive statistics for agency characteristics and their reported crime information for the crime types for the incidents analyzed in the current study.

Table 2
Descriptive Statistics for Agency Characteristics and Reported Crime within their Jurisdictions, 2019-2020

	Agency Characteristics				Incident Characteristics ($N = 24$)		
Locations/ Crime Types	FTS	Budget (M$)	Population served	Size (mi^2)	Min	Max	*M*
St. Petersburg	537	$105.00	260,999	60.90			
Burglary					74	151	102.46
MVT					66	130	92.42
Robbery					10	25	17.71
Orlando	743	$133.02	277,173	106.00			
Burglary					64	133	93.54
MVT					138	246	180.95
Robbery					12	47	33.08
Gainesville	290	$34.52	131,591	37.00			
Burglary					14	39	28.46
MVT					33	72	25.21
Robbery					14	36	10.75

Note: Agency characteristic data from FY2016 (BJS, 2016). Incident characteristics are based on a total of 24 60-day intervals of data.

Barriers

The focus of the study is on whether physical barriers to crime found in the environment will affect the predictive accuracy of crime forecasts. Although not an exhaustive list, the study considered three specific types of barriers to crime, including waterways, parks, and commercial properties.

Waterways. In the study, waterways were included as a geographical barrier that could alter the influence of crime hot spots, based on kernel density estimation (KDE) calculations. Additionally, in the study, waterways included rivers, canals, ponds, lakes, bays, or gulfs that are defined in the geographic data and provided by the administrative authority in each jurisdiction who oversee the publicly available GIS data.

Parks. Municipal parks were also included in the analysis as geographic barriers to crime. In the study, parks are conceptually defined as areas within each agency's jurisdiction that has been zoned or otherwise designated by municipal code or county ordinance as a public park for the purpose of recreational activity.

Commercial properties. Commercial properties were included in the analysis of household burglary hotspots and are defined as any property that is zoned or used solely for business purposes, based on the municipal code or county ordinance in each of the three jurisdictions that were examined.

Hot Spots

As discussed in chapter 1, crime hot spots were calculated for the study using kernel density estimation (KDE). Density estimates were calculated based on a mathematical formula that considers the spatial location of each crime incident, relative to the center of grid cells that fall within a specified search radius, using the following formula:

$$f(x, y) = \frac{1}{nh^2} \sum_{i=1}^{n} k\left(\frac{d_i}{h}\right)$$

Where $f(x,y)$ is the hot spot density value at a specific location (x,y), n is the specific number of discrete crime incident locations, h is the bandwidth or search radius parameter set prior to the analysis, d_i is the physical distance between incident i and location (x,y). and k is the parameter setting for the specific density function used in the analysis, which is also referred to as the kernel function. In the study, hot spots are defined as grid cells that have interpolated risk value that are significantly higher than the average risk value for the entire interpolated surface area (i.e., $\bar{X}$ + 1.96[*SD*]). KDE hot spots maps that were created in the study using default parameter settings in ArcMap 10.8. The default bandwidth or search radius was calculated using the following formula:

$$Search\ Radius = 0.9 * \min\left(SD, \sqrt{\frac{1}{\ln(2)}} * D_m\right) * n^{-0.2}$$

where D*m* is the (weighted) median distance from (weighted) mean center; *n* is the number of incidents; and *SD* is the standard distance. The default kernel (i.e., quartic) function was also used[3].

Predictive Accuracy

Hit rate. In the study, hit rates were one way in which predictive accuracy was measured. A hit rate is simply the percentage of all crimes that occur in the future that are located within hot spots created from historic crime data. Hit rates are a popular approach to determining predictive accuracy because they are easy to understand, but their primary shortcoming is that they are strongly influenced by the size of the study area and the number of crimes observed in the time interval after the hot spot map is created. Given this limitation, the quality of predictions was also measured with the PAI.

PAI. Chainey and colleagues (2008) developed the PAI, which is the ratio of a hit rate to an area percentage, or the percentage of the study area that is defined as a hot spot. It is given by the following equation:

$$PAI = \frac{\left(\frac{n_h}{N_c}\right)}{\left(\frac{a_h}{A_s}\right)} = \frac{Hit\ Rate}{Area\ Percentage}$$

[3] For more details on ArcMap default settings for KDE, see https://desktop.arcgis.com/en/arcmap/latest/tools/spatial-analyst-toolbox/how-kernel-density-works.htm

where n_h is the number of future crimes that fall within areas of a jurisdiction defined as a predicted hot spot, N_c is the total number of future crimes, a_h is the area of a jurisdiction that is defined as a hot spot, and A_s is the area of the entire jurisdiction. Higher PAI scores indicate greater predictive accuracy.

RRI. Developed by Ned Levine in 2008 in response to his perceived shortcomings of the PAI, the RRI were also used in the study as a measure of predictive accuracy. The RRI compares a predicted hot spot density (i.e., PAI_p) to a historical hot spot density (i.e., PAI_h). In other words, the RRI is a ratio of $PAI_p{:}PAI_h$ and is intended to better measure the reliability of hot spot predictions (Levine, 2008). The Higher the RRI values, the greater the predictive consistency or reliability.

Analytic Technique

Hit rates, PAIs, and RRIs were calculated for each crime hot spot map, at 1-month intervals, for each jurisdiction, over a 2-year timeframe (i.e., January 1, 2019, through December 31, 2020). This resulted in 24 groups of crime data, for each crime type and jurisdiction, for which crime hot spot maps were create using KDE. Hit rate, PAI, and RRI calculations were based on KDE hot spot maps created with and without barriers. Subsequently, the hypothesis tests presented in the next chapter are based on analysis of the aggregated crime data, not the individual incidents. The rank-ordered distributions of each predictive accuracy measure for maps created with and without barriers were compared and differences tested using a Wilcoxon signed-ranked test at the $p < .05$ level of significance. The next chapter presents results of these tests.

CHAPTER 4

RESULTS

KDE crime hot spot maps with and without barriers were created for three types of crime (i.e., residential burglary, motor vehicle theft, and robbery) in three law enforcement jurisdictions (i.e., St. Petersburg Police Department, Orlando Police Department, and Gainesville Police Department). Three predictive accuracy measures (i.e., hit rate, PAI, and RRI) were calculated and compared across both types of KDE maps. Table 3 presents descriptive statistics for each type of predictive accuracy measure, by each crime type and jurisdiction for KDE hot spot maps created with and without barriers.

Table 3

Descriptive Statistics for Different Predictive Accuracy Measures

Locations/	Hit Rate			PAI			RRI		
Crime Types	Min	Max	*Mdn*	Min	Max	*Mdn*	Min	Max	*Mdn*
KDE Maps Created with Barriers									
All locations	0.10	0.77	0.47	0.92	19.19	2.95	0.09	6.12	1.02
St. Petersburg	0.38	0.75	0.54	1.14	5.37	2.15	0.42	2.61	0.98
Burglary	0.38	0.64	0.50	1.14	3.3	1.89	0.45	2.27	0.98
MVT	0.41	0.60	0.55	1.31	2.92	2.07	0.51	1.83	0.99
Robbery	0.45	0.75	0.59	1.92	5.37	3.56	0.42	2.61	0.96
Orlando	0.17	0.77	0.50	0.92	2.87	3.24	0.13	5.71	1.11
Burglary	0.30	0.62	0.52	1.68	4.53	2.85	0.52	1.79	1.08
MVT	0.34	0.55	0.46	1.66	5.92	3.18	0.38	2.24	1.20
Robbery	0.17	0.77	0.54	0.92	19.19	4.94	0.13	5.71	1.01
Gainesville	0.10	0.70	0.31	1.09	14.98	3.18	0.09	6.12	0.98
Burglary	0.10	0.60	0.33	1.12	5.86	3.42	0.31	2.62	0.95
MVT	0.15	0.55	0.30	1.25	7.68	3.04	0.25	6.12	1.04
Robbery	0.11	0.70	0.31	1.09	14.88	0.86	0.09	5.86	0.86
KDE Maps Created without Barriers									
All locations	0.00	0.69	0.36	0.00	27.12	3.02	0.00	10.48	0.99
St. Petersburg	0.38	0.69	0.55	1.08	4.88	2.15	0.45	2.54	1.04
Burglary	0.38	0.65	0.54	1.08	3.08	2.03	0.46	2.54	1.08
MVT	0.42	0.59	0.55	1.28	2.86	2.02	0.45	1.59	0.95
Robbery	0.44	0.69	0.59	1.78	4.88	3.62	0.46	2.07	1.09

Table 3 (Continued)

Orlando	0.00	0.69	0.36	0.00	27.12	4.56	0.00	3.77	1.06
Burglary	0.14	0.54	0.33	1.25	9.33	3.21	0.17	3.39	1.27
MVT	0.16	0.47	0.36	1.38	7.95	3.55	0.19	3.71	1.07
Robbery	0.00	0.70	0.36	0.00	27.12	8.12	0.00	3.77	0.77
Gainesville	0.00	0.30	0.12	0.00	25.64	3.62	0.00	10.48	0.72
Burglary	0.00	0.29	0.12	0.00	14.01	2.93	0.00	8.56	0.72
MVT	0.04	0.30	0.13	0.68	8.92	4.06	0.18	10.48	1.19
Robbery	0.00	0.30	0.11	0.00	25.64	4.61	0.00	6.14	0.22

As was discussed in chapter 1, the current study tested the following hypothesis.

H_1: The predictive accuracy of prospective crime hot spot maps that are produced using kernel density estimation will be higher for those that include barriers in the interpolation process than those that do not.

Prior to conducting the analysis, assumptions for the paired sample t-test were examined for each measure of predictive accuracy. The normality assumption was violated because data distributions were skewed and suffered from significant kurtosis. Therefore, Wilcoxon signed-rank tests were used to evaluate the research hypothesis tested in the current study.

The Wilcoxon signed-rank test is a non-parametric statistical test that is an appropriate alternative to the paired-sample t-test. Compared to the parametric test, this non-parametric technique is used to analyze rank-ordered data distributions instead of comparing group means. Results that follow are presented for tests using all aggregated data first, then disaggregated for each jurisdiction; and lastly, by each crime type. By using this approach, the impact of barriers on the predictive accuracy of KDE maps produced with and without barriers to crime can be assessed, while considering the effects of location and crime type.

Aggregated Data

A Wilcoxon signed-rank test was conducted to evaluate whether there were differences in hit rates for KDE crime hot spot maps created with barriers (*Mdn* = .47), compared to those created without them (*Mdn* = .36), for all crimes and locations aggregated. Table 4 presents results of the tests and reveals a statistically significant difference between the predictive accuracy of these maps (W_+ = 17,266, z = 10.17, p < .001), indicating that those created with barriers are more accurate. The magnitude of the difference in predictive accuracy, as measured by the hit rate, was large (r = .71).

Table 4

Wilcoxon Signed-Rank Test Results for Each Predictive Accuracy Measure

	Hit Rate				PAI				RRI			
	W_+	z	p	r	W_+	z	p	r	W_+	z	p	r
All locations	17,266	10.17	<.001	.71	8,230	-2.94	.003	.20	10,235	0.48	.634	n.s.
St. Petersburg	929	-0.54	.586	n.s.	1,661	2.71	.007	.33	1,010	-0.61	.542	n.s.
Burglary	37	-2.91	.004	.61	148	0.30	.761	n.s.	105	-0.70	.485	n.s.
MVT	202	1.95	.052	.40	209	2.16	.031	.45	124	-0.08	.935	n.s.
Robbery	93	0.31	.760	n.s.	215	2.34	.019	.49	124	-0.08	.935	n.s.
Orlando	2,211	7.06	<.001	1.47	419	-4.71	<.001	.58	1,015	-0.58	.563	n.s.
Burglary	253	4.12	<.001	.86	80	-1.76	.078	n.s.	101	-0.83	.408	n.s.
MVT	276	4.20	<.001	.88	81	-1.73	.083	n.s.	108	-0.60	.548	n.s.
Robbery	231	4.02	<.001	.84	10	-3.89	<.001	.81	136	0.31	.758	n.s.
Gainesville	2,078	6.94	<.001	.84	1,004	-1.22	.224	n.s.	1,279	1.11	.268	n.s.
Burglary	251	4.04	<.001	.84	125	-0.40	.693	n.s.	133	0.21	.833	n.s.
MVT	276	4.20	<.001	.88	91	-1.43	.153	n.s.	101	-0.83	.408	n.s.
Robbery	190	3.83	<.001	.80	119	-0.58	.563	n.s.	192	2.13	.033	.45

Significant findings also were observed for the aggregated data between KDE maps when predictive accuracy was measured using the PAI, but the difference was observed in the opposite direction than hypothesized. KDE maps created with barriers (*Mdn* = 2.95) were significantly less accurate at forecasting hot spots, compared to maps created without barriers (*Mdn* = 3.02) (W_+ = 8,230, z = -2.94, p = .003). However, the overall effect observed on the PAI was small (r = .20).

Finally, no significant difference between the predictive accuracy of the hot spot maps created with and without barriers was observed when the RRI was used to gauge forecasting performance for the aggregated data. Hot spot maps that incorporated barriers (*Mdn* = 1.02) produced statistically similar forecasting predictions compared to those that did not (*Mdn* = 0.99), when the RRI was used to measure performance (W_+ = 10,235, z = 0.48, p = .634). Collectively, results based on aggregated data provide mixed support for the hypothesis.

Jurisdiction

Wilcoxon signed-rank tests were also used to evaluate whether there were differences in predictive accuracy metrics for KDE crime hot spot maps created with barriers compared to those created without them in three distinct locations: St. Petersburg, Orlando, and Gainesville. Findings associated with the different jurisdictions were analogous to the results observed for the aggregated data. Specifically, a clear pattern did not emerge when the data were analyzed for each jurisdiction separately.

For example, when predictive accuracy was measured using the PAI in St. Petersburg, the KDE maps created with barriers produced slightly better forecasting predictions compared to maps created without barriers (W_+ = 1,661, z = 2.71, p = .007), indicating that those created with barriers are more accurate. The magnitude of the differences in predictive accuracy was moderate (r = .33). Significant findings in Orlando were also observed when predictive accuracy was measured using the PAI, but in the opposite direction (W_+ = 419, z = -4.71, p < .001), indicating that KDE maps made with barriers were significantly less accurate than maps without barriers. When predictive accuracy was measured using the hit rate in Orlando, the difference in rank-ordered distributions was observed in the hypothesized direction (W_+ = 2211.00, z = 7.06, p < .001). The magnitude of the differences in predictive accuracy was large (r = 1.47). Finally, in Gainesville, significant findings were observed between KDE maps with barriers (*Mdn* = 0.31) compared to maps created without barriers (*Mdn* = 0.12) only when predictive accuracy was measured using the hit rate (W_+ = 2,078, z = 6.94, p < .001). The overall effect size in predictive accuracy, as measured by the hit rate, was large (r = .84). Collectively, findings within each jurisdiction continue to indicate mixed support for the research hypothesis.

Crime Type

Finally, the effect of barriers on the performance of crime hot spot maps was examined for each type of crime, within each of the three jurisdictions studied. As with findings for the aggregated data and the analyses for each jurisdiction, findings were mixed. For example, significant findings were observed in hit rates between burglary KDE maps with barriers and without barriers, when burglary incidents were analyzed in Orlando (W_+ = 253, z = 4.12, p < .001), Gainesville (W_+ = 251, z = 4.04, p < .001), and St. Petersburg (W_+ = 37, z = -2.91, p = .004)—but in the opposite direction. However, when predictive accuracy was measured with the PAI or RRI, including barriers in the analysis of burglary incidents did not affect results significantly, regardless of jurisdiction.

Similar results were observed for KDE maps showing patterns of motor vehicle thefts. Hit rates were significantly better for maps that incorporated barriers for analysis conducted in Orlando (W_+ = 276, z = 4.20, p < .001), Gainesville (W_+ = 276, z = 4.20, p < .001), and in St. Petersburg (W_+ = 202, z = 1.95, p = .052)—this time in the hypothesized direction. Like with burglary patterns, when predictive accuracy was measured using the PAI or RRI, regardless of jurisdiction, significant findings were not observed between KDE maps with barriers and those without, when motor vehicle theft patterns were analyzed.

This pattern was also observed for the analysis of robbery incidents, with a few notable exceptions. For example, in St. Petersburg ($W_+ = 215$, $z = 2.34$, $p = .019$), the PAI was significantly higher for KDE maps that included barriers, compared to those that did not. However, the PAI was significantly lower when barriers were included in the analysis of robbery data in Orlando ($W_+ = 10$, $z = -3.89$, $p < .001$). And in Gainesville, the PAI was not significant for robbery hot spot maps that included barriers in the analysis compared to when they were excluded ($W_+ = 119$, $z = -0.58$, $p = .563$), but the RRI was higher ($W_+ = 192$, $z = 2.13$, $p = .033$). These findings provide additional mixed support for the current study's research hypothesis.

In summary, results suggest that the impact of barriers on KDE crime hot spot maps can be meaningful; however, it may depend on the type of crime being analyzed, the location of the analysis, and the type of metrics used to measure performance. The final chapter will discuss these findings in greater detail, including recommendations for future research, and limitations of the current study.

CHAPTER 5

DISCUSSION AND CONCLUSIONS

Previous KDE studies have examined the effects of KDE hot spot maps across different study areas and types of crimes. They have also examined how different parameter settings involved with created KDE hot spot maps can influence crime forecasting. However, to date, no known study has examined whether including barriers (e.g., waterways, parks, and commercial properties) into spatial interpolation methods can improve the predictive accuracy of prospective crime hot spot maps. Using data gathered from three Florida law enforcement agencies (i.e., St. Petersburg, Orlando, and Gainesville), the current study hypothesized that the predictive accuracy of prospective crime hot spot maps produced using KDE would be higher for those that include barriers in the interpolation process, compared to those that do not.

Prior studies have shown that hot spot mapping techniques can differ in the results they generate depending on conditions and set parameters (e.g., cell size and bandwidth). These conditions determine the technique's ability to accurately predict future crime events based on past crime events (Chainey et al., 2008; Hart & Zandergen, 2014). Informed by this research, the current study began by aggregating data and analyzing KDE hot spot maps utilizing hit rates, PAIs and RRIs—common and valuable comparative measures applied in predictive policing research—to investigate the extent and quality of hotspot maps' performance when analyzing distinct locations and crime types.

Collectively, findings in the current study were mixed. First, it was observed when analyzing all locations and crime types, hot spot maps that contain barriers produce slightly more accurate results than KDE maps without barriers. This was limited to when performance was measured by the PAI or hit rate. Unexpectedly, effects of barriers were seen in the opposite direction for KDE maps created with barriers, meaning they were slightly less precise at forecasting than maps created without barriers. Additionally, it was observed that across all locations and crime types, there was no significant difference between the predictive accuracy of the KDE maps when RRI measured performance. These findings suggest that the predictive accuracy of KDE maps with barriers were neither consistently more nor less precise for the aggregated data. This pattern of mixed results continued when the data were disaggregated to jurisdictions and to specific crime types.

Despite the lack of consistent findings regarding the impact of barriers on crime hot spot maps produced from KDE, the current results have important implications for researchers and practitioners alike. For example, results showed that the predictive accuracy of KDE maps created with barriers rather than without barriers had the most impact on performance when forecasts were assessed by hit rates. This suggests that the importance of barriers in the analysis of crime patterns may be more or less meaningful, based on how forecasting accuracy is measured. These conclusions are supported by the fact that many of the significant results for the PAI were in the opposite direction and that only one significant finding was associated with the RRI. Overall, these results suggest that barriers can affect predictive accuracy of prospective crime hot spot maps, but how they affect them may depend on how performance is measured.

Furthermore, based on the results, the current study found that the environment can impact crime patterns. By analyzing historic crime locations to forecast future patterns, in context of where physical barriers to crime are located in the environment, the current research provided new insight into the impact that environmental factors can have on the places where crime occurs. In other words, the research shows that structural barriers in the physical environment can have some impact on routine patterns of everyday life, which can in turn affect the spatial distribution of crime. By incorporating barriers to crime into the KDE process, one can better understand the unique influence that the built environment has on potential offenders. These findings support the theoretical frameworks of environmental criminology, particularly, routine activities theory.

Finally, the observed results have important implications for practitioners, revealing that including barriers in the KDE process can assist agencies to better understand how certain natural restrictions in places or along pathways in their own jurisdictions can influence individuals' movement patterns and subsequent crime patterns for certain types of incidents. This knowledge, which could be refined to specific jurisdictions and specific crime types, would allow agencies to target their resources in the appropriate areas more strategically. Again, given the variation in findings of the current study, these strategies would have to carefully consider the type of crime, performance measures, and specific environmental factors that could be considered physical barriers to crime within their own jurisdiction. Current findings also provide guidance for future crime mapping and crime pattern analysis research.

Limitations and Future Research

Despite the new knowledge about the effect of barriers to crime on the predictive accuracy of hot spot forecast that was produced from the current study, there are certain methodological limitations that should be acknowledged. First, the current study was limited to only three Florida jurisdictions; therefore, it is not representative of all agencies. In other words, it is unclear whether similar findings would be observed in other locations. Expanding the scope of the current study can help to establish whether findings observed in the current study are more generalizable.

Second, data analyzed in the current study were limited to the effect of three general types of physical barriers commonly found in many jurisdictions. Thus, future research should consider the influence that other physical barriers to crime could have on crime forecasts. For example, vacant lots and golf courses are physical barriers to residential burglaries and may have a different impact on crime patterns than those observed in the current study. Therefore, future research should expand the scope of the current study in terms of the types of barriers that can influence crime patterns and subsequent crime forecasts.

Finally, the current study only considered predictive accuracy and the reliability of crime forecasts, when the influence of physical barriers to crime on prospective hot spot mapping was examined. Other performance measures were not considered, but have been used to assess hot spot predictions, including measures of patrollability like the area-to-perimeter ratio, clumpiness index, and dynamic variability index. Future research should therefore consider whether these alternative measures of forecasting performance are impacted when physical barriers to crime are used in KDE. Through additional research, our knowledge about where crime clusters could be improved, which could help law enforcement agencies develop for effective and efficient crime-fighting strategies and academics refine their theoretical perspectives in the field of environmental criminology.

Conclusions

In conclusion, the current study shows that the predictive accuracy of prospective crime hot spot maps created with KDE and that consider physical barriers to crime in the interpolation process can produce crime forecasts that are more predictively accurate than maps that do not take barriers to crime into account. Findings were mixed, however, showing results that were generally dependent on crime type and jurisdiction considered. Although the current research advances existing knowledge of predictive hot spot crime mapping and yielded results that can contribute to the further practical and academic understanding of crime pattern analysis, more work in this area is needed.

REFERENCES

Armitage, R. (2007). Sustainability versus safety: Confusion, conflict and contradiction in designing out crime. In: G. Farrell, K. J. Bowers, S. D. Johnson & M. Townsley (Eds.), *Imagination for Crime Prevention: Essays in Honour of Ken Pease*. Monsey, NY: Criminal Justice Press.

Andresen, M. A. (2017). A spatial analysis of crime in Vancouver, British Columbia: A synthesis of social disorganization and routine activity theory. *The Canadian Geographer, 50*(4), 487–502.

Beauregard, E., Proulx, J., Rossmo, K., Leclerc, B., & Allaire, J. (2007). Script analysis of the hunting process of serial sex offenders. *Criminal Justice and Behavior, 34*(8), 1069–1084.

Bottoms, A. E., & Wiles, P. (1997). Environmental Criminology. In M. Maguire, R. Moran, & R. Reiner (Eds.), The Oxford handbook of Criminology (pp. 620-656). Oxford: Clarendon Press.

Braga, A., Papachristos, A., & Hureau, D. (2012). Hot spots policing effects on crime. *Campbell Systematic Reviews*, *8*(1), 1–96. https://doi.org/10.4073/csr.2012.8

Braga, A. A., Andresen, M. A., & Lawton, B. (2017). The law of crime concentration at places: Editors' introduction. *Journal of Quantitative Criminology, 33*, 421–426.

Brantingham, P. J., & Brantingham, P. L. (1975). The spatial patterning of burglary. *The Howard Journal of Criminal Justice*, *14*(2), 11–23. https://doi.org/10.1111/j.1468-2311.1975.tb00297.x

Brantingham, P. J. and P. L. Brantingham (1978) A theoretical model of crime site selection, in M. Krohn and R.L. Akers (eds.) *Crime, Law and Sanction.* Beverly Hills, CA: Sage Publications, 105–118.

Brantingham, P. J., & Brantingham, P. L. (1981). Introduction: the dimensions of crime, in P. J. Brantingham and P. L. Brantingham (eds.). *Environmental Criminology*. Prospect Heights IL, Waveland Press.

Brantingham, P. J., & Brantingham, P. L. (1984). *Patterns in crime*. New York: Macmillan.

Brantingham, P. L., & Brantingham, P. J. (1993). Nodes, paths and edges: Considerations on the complexity of crime and the physical environment. *Journal of Environmental Psychology*, *13*(1), 3–28. https://doi.org/10.1016/s0272-4944(05)80212-9

Brantingham, P. (1994). The influence of street networks on the patterning of property offenses: *Semantic scholar*. https://www.semanticscholar.org

Brantingham, P., & Brantingham, P. (1995). Criminality of place: crime generators and crime attractors. *European Journal on Criminal Policy and Research*, *3*(3), 5–26. https://doi.org/10.1007/bf02242925

Brantingham, P. J., Brantingham, P. L. (1998). Environmental criminology: from theory to urban planning practice. *Studies on Crime and Crime Prevention*

Brantingham, P. J., & Brantingham, P. L. (2013). Environmental criminology and crime analysis. https://doi.org/10.4324/9780203118214

Brantingham, P. J., Brantingham, P. L., & Andresen, M. A. (2016). The geometry of crime and crime pattern theory.

Caccato, V. & Uittenbogaard, A. C. (2013). Space-time dynamics of crime in transport nodes. *Annals of the Association of American Geographers*, *1*(104), 131–150.

Caplan, J.M., Kennedy, L.W., & Miller, J. (2011). Risk terrain modeling: Brokering criminological theory and GIS methods for crime forecasting. *Justice Quarterly*, *28*(2), 360–381.

Caplan, J.M., Kennedy, L.W., & Baughman, J. (2012). Kansas City's violent crime initiative: A place-based evaluation of location-specific intervention activities during a fixed time period, *Crime Mapping: A Journal of Research and Practice*, *4*(2), 9–37.

Caplan, J.M. & Kennedy, L.W. (2016). *Risk Terrain Modeling: Crime Prediction and Risk Reduction*. Los Angeles, CA: University of California Press.

Chainey, S. (2005). Methods and techniques for understanding crime hot spots. In John E. Eck, Spencer Chainey, James G. Cameron, Michael Leitner, and Ronald E. Wilson (Eds.), *Mapping crime: Understanding hot spots*, (Pp. 15–33). Washington, DC: USGPO.

Chainey, S., & Ratcliffe, J. (2005). GIS and Crime Mapping https://doi.org/10.1002/9781118685181

Chainey, S., Tompson, L., & Uhlig, S. (2008). The utility of hotspot mapping for predicting spatial patterns of crime. *Security Journal, 21*(1), 4–28.

Chainey, S. (2013). Examining the influence of cell size and bandwidth size on kernel density estimation crime hotspot maps for predicting spatial patterns of crime. *Bulletin of the Geographical Society of Liege, 60*, 7–19.

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

Clarke, R., & Cornish, D. (1985). Modeling offenders' decisions: A Framework for research and policy. *Crime and Justice, 6*, 147–185. http://www.jstor.org/stable/1147498

Clarke, R. (1995). Situational crime prevention. *Crime and Justice, 19*, 91–150. http://www.jstor.org/stable/1147596

Cornish, D. B., & Clarke, R. V. (1987). Understanding crime displacement: An application of rational choice theory. *Criminology*, *25*(4), 933–948. https://doi.org/10.1111/j.1745-9125.1987.tb00826.x

Cornish, D. B. (1994) "The procedural analysis of offending and its relevance for situational prevention." In: Clarke R (ed) *Crime Prevention Studies, 3, 151–196*

Cornish, D. B., & Clarke, R. V. (2003). *Opportunities, precipitators and Criminal decisions: A reply to Wortley's critique of Situational crime prevention*. Criminal Justice Press.

Cornish D. B., Clarke R. V. (2008) The rational choice perspective. In: Wortley R, Mazerolle L (eds) *Environmental criminology and crime analyses.* Willian, Cullompton

Cozens, P.M., Saville, G. and Hillier, D. (2005). Crime Prevention Through Environmental Design (CPTED): A Review and Modern Bibliography

Eck, J., Chainey, S., Cameron, J., & Wilson, R. (2005). *Mapping crime: Understanding hotspots*. UCL Discovery - UCL Discovery. https://discovery.ucl.ac.uk/id/eprint/11291.

Eck, J., & Weisburd, D. L. (2015) *Crime places in crime theory*. SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2629856.

ESRI (2019). *ArcGIS Desktop: Release 10.71*. Redlands, CA: Environmental Systems Research Institute.

Federal Bureau of Investigation (FBI). (2004). *Uniform crime reporting handbook: UCR*. Retrieved from www.fbi.gov/ucr/ucr.htm.

Felson, M. (2013). *Routine activity Approach: Taylor & Francis Group*. Taylor & Francis. https://www.taylorfrancis.com/chapters/edit/10.4324/9780203118214-12/routine-activity-approach-marcus-felson.

Gottfredson, D. C., McNeil, R. J., & Gottfredson, G. D. (1991). Social area influences on delinquency: a multilevel analysis, *Journal of Research in Crime and Delinquency, 28*(2), 197–226.

Groff, E. R., & LaVigne, N. G. (2001). Mapping an opportunity surface of residential burglary. *Journal of Research in Crime and Delinquency, 38*(3), 257–278.

Guertte, R. (2009). *Tool guides: Analyzing Crime displacement And Diffusion: ASU Center for Problem-Oriented Policing*. Tool Guides https://popcenter.asu.edu/content/tool-guides-analyzing-crime-displacement-and-diffusion

Hart, T. C., & Zandbergen, P. A. (2013). Reference data and geocoding quality. *Policing: An International Journal of Police Strategies & Management*, *36*(2), 263–294. https://doi.org/10.1108/13639511311329705

Hart, T. C., & Zandbergen, P. A. (2014). Kernel density estimation and hotspot mapping: Examining the influence of interpolation method, grid cell size, and bandwidth on crime forecasting. Policing: *An International Journal of Police Strategies & Management, 37*(2), 305–323.

Hart, T. C. (2020). Hot spots of crime: Methods and predictive analytics. In Kim M. Lersch and Jay Chakraborty (Eds.), *Geographies of Behavioral Health, Crime, and Disorder: The Intersection of Social Problems and Place* (pp. 87–103). Abingdon, UK: Routledge.

Hillier, B. (2004). Can streets be made safe? *Urban Design International, 9*, 31–45.

Hindelang, M. J., Gottfredson, M. R., & Garofalo, J. (1978), *Victims of Personal Crime: An Empirical Foundation for a Theory of Personal Victimization* (Cambridge, Mass.: Ballinger).

Jeffery, C. R. (1971) *Crime Prevention Through Environmental Design.* Beverly Hills, CA: Sage Publications

Jeffery, C. R. (1977) *Crime Prevention Through Environmental Design, Second Edition.* Beverly Hills, CA: Sage Publications

Johnson, S. D. (2017). Crime mapping and spatial analysis. In Richard Wortley & Michael Townsley (Eds.), *Environmental criminology and crime analysis* (2nd ed.) (pp. 199–223). Abingdon, UK: Routledge.

Jones, R. W. & Pridemore, W. A. (2019). Towards an integrated multilevel theory of crime at place: Routine activities, social disorganization, and the law of crime concentration. *Journal of Quantitative Criminology, 35*, 543–572.

Leclerc, B. (2014). Script analysis for crime controllers: Extending the reach of situational crime prevention. In Stefano Caneppele and Francesco Calderoni (Eds.), *Organized crime, corruption, and crime prevention: Essays in honor of Ernesto U. Savona* (pp. 13–20). Springer, New York, NY.

Lemieux, A. M., & Felson, M. (2012). Risk of violent crime victimization during major daily activities. *Violence and Victims, 27*(5), 635–655.

Levine, N. (2008). The "hottest" part of a hotspot: Comments on "the utility of hotspot mapping for predicting spatial patterns of Crime." *Security Journal*, *21*(4), 295–302. https://doi.org/10.1057/sj.2008.5

McGuire, P. G., & Williamson, D. (1999). Mapping tools for management and accountability. In *Paper presented to the Third International Crime Mapping Research Center Conference, Orlando, Florida, December 11–14*.

Meier, R. & Miethe, T. D. (1993). Understanding theories of criminal victimization. *Crime and Justice, 17*, 459–499.

Moffatt, R. E. (1983). Crime prevention through environmental design: A management perspective. *Canadian Journal of Criminology, 25*(1), 19–31.

Newman, O. (1972) *Defensible Space: Crime Prevention Through Urban Design.* New York, NY: Macmillian

Osborne, J. R. & Capellan, J. A. (2017). Examining active shooter events through the rational choice perspective and crime script analysis. *Security Journal, 30*, 880–902.

Ratcliffe, J. H. (2004). The hotspot matrix: A framework for the spatio-temporal targeting of crime reduction. *Police Practice and Research: An International Journal, 5*(1), 5–23.

Rosenblatt, M. (1956). Remarks on some nonparametric estimates of a density function. *The Annals of Mathematical Statistics, 27*(3), 832–837.

Rossmo, D. K. (2000). *Geographic profiling*. Boca Raton, FL: CRC Press.

Rossmo, D. K., Lu, Y., & Fang, T. (2012). Spatial-temporal crime paths. In M. A. Andresen & J. B. Kinney (eds.), Patterns, prevention, and geometry of crime (pp. 16–42). London, England: Routledge.

Rossmo, D. K., & Rombouts, S. (2016). Geographic profiling. In R. Wortley & M. Townsley (eds.), *Environmental criminology and crime analysis* (2nd ed.) (pp. 162–179). Abingdon, Oxfordshire: Routledge.

Sampson, R. J. (1985). Neighborhood and crime: The structural determinants of personal victimization. *Journal of Research in Crime and Delinquency*, *22*(1), 7–40. https://doi.org/10.1177/0022427885022001002

Sampson, R. J. & Groves, W. B. (1989) Community structure and crime: Testing social-disorganization theory. *American Journal of Sociology*

Sampson, R. J., Raudenbush, S.W. & Earls, F. (1997) *Neighborhoods and Violent Crime: A Multilevel Study of Collective Efficacy*. Science, 277, 918–924. http://dx.doi.org/10.1126/science.277.5328.918

Shaw, C. R. & McKay, H. D. (1942). *Juvenile Delinquency and Urban Areas: A Study of Rates of Delinquency in Relations to Differential Characteristics of Local Communities in American Cities.* Chicago, IL: University of Chicago Press

Sherman, L. W., Gottfredson, D., Mackenzie, D., & Eck, J. (1997). Preventing crime: What works, what doesn't, what's promising (NCJ# 165366). National Institute of Justice: USGPO: Washington, DC.

Sherman, L. W., Gartin, P. R., & Buerger, M. (1989). Hot spots of predatory crime: Routine activities and the criminology of place. *Criminology, 27*(1), 27–56.

Silverman, B. W. (1986). *Density estimation for statistics and data analysis*. London, England: Chapman.

Smith W. R., Frazee, S. G., & Davison, E. L. (2000). Furthering the integration of routine activity and social disorganization theories: Small units of analysis and the study of street robbery as a diffusion process. *Criminology, 38*(2), 489–523.

Snook, B., Zito, M., Bennell, C., & Taylor, P. J. (2005). On the complexity and accuracy of geographic profiling strategies. *Journal of Quantitative Criminology, 21*(1), 1–26.

Van Patten, I. T., McKeldin-Coner, J., & Cox, D. (2009). A microspatial analysis of robbery: Prospective hot spotting in a small city. *Crime Mapping: A Journal of Research and Practice, 1*(1), 7–32.

Weisburd, D., Hinkle, J. C., Famega, C., & Ready, J. (2012). *Legitimacy, Fear and Collective Efficacy in Crime Hot Spots.* Washington, DC: National Institute of Justice.

Weisburd, D. (2015). The law of crime concentration and the criminology of place. *Criminology, 53*(2), 133–157.

Williamson, D., McLafferty, S., McGuire, P., Goldsmith, V. & Mollenkopf, J. (1999) A Better Method to Smooth Crime Incidence Data, ArcUser Magazine, January - March, 1999, 1–5.

Williamson, D., McLafferty, S., McGuire, P., Ross, T., Mollenkopf, J., Goldsmith, V. and Quinn, S. (2001), "Tools in the spatial analysis of crime", in Hirschfield, A. and Bowers, K. (Eds), *Mapping and Analysis Crime Data: Lessons From Research and Practice,* Taylor & Francis, London, pp. 187–202.

Wortley, R., & Townsley, M. (2016). Environmental criminology and crime analysis: Situating the theory, analytic approach and application. In R. Wortley & M. Townsley, M. (eds). Environmental Criminology and Crime Analysis (2nd ed). London: Routledge.