

**ESSAYS ON THE INTEGRATION OF ANISOTROPIC LANDSCAPES
WITHIN CONTEMPORARY GEOGRAPHIC PROFILING MODELS**

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ABSTRACT

A criminal geographic profile is a tool used by law enforcement professionals for estimating the probable location of a serial offender's anchor point, or domicile. This estimate is constructed according to the distribution of linked crime scenes. While this approach can utilize a number of different modeling techniques, most fail to account for the inherent irregularities of the physical and cultural landscape. Contemporary methodologies have consistently adopted the *a priori* assumption that an offender's crime scenes and anchor point are located across an isotropic surface on which the opportunity to offend is equally distributed around the offender's residence. Simple introspection clearly reveals that this assumption is unrealistic. Landscapes are comprised of heterogeneous collections of physical and cultural features that, by their very nature, bias the location of human activities and the occurrence of phenomena. Accordingly, this research examines four alternative techniques for geographically profiling offender behavior in space using models that are capable of accounting for the intrinsic irregularities present within the surrounding landscapes. The first technique examines the efficacy of functional distance metrics for interpreting an offender's perceptions of travel cost. The second method estimates the serial offender's anchor point by modeling the spatial variability observed for the linked crime scenes using a dynamic standard deviational ellipse. The next method extends the premise of a non-uniform landscape by introducing land cover characteristics within a probability distribution strategy. Finally, a land cover enhanced profiling technique is proposed using an empirical Bayesian formulation. Comparative analyses of the four enhanced techniques validate the premise that landscapes impart a deterministic impact on a serial offender's behavior in space. Consequently, these factors can be incorporated within various analytical frameworks to produce an accurate and precise estimate of an offender's anchor point.

“Environmental criminologists set out to use the geographic imagination in concert with the sociological imagination to describe, understand, and control criminal events.”

- Brantingham and Brantingham (1981, p. 21).

CHAPTER 1: INTRODUCTION

The geographical analysis of crime has been used by law enforcement professionals and researchers since the 1830s (Phillips, 1972). Criminologists have long understood that geography is a fundamental component for understanding, responding to, and mitigating criminal activity. With records dating as far back as the early 1900s, law enforcement agencies across the United States used pin-maps to better understand the nature of crime within their jurisdictions (Harries, 1999). And for decades, the pin-map remained the dominant spatial analytical tool used by law enforcement. This analytical playing field changed in the 1990s as the information age brought forth new techniques for mapping crime; thus transforming the simple analog pin-maps of the past into effective decision-making tools. The combination of geographic information systems (GIS) and statistical analysis allowed investigators to visualize and analyze the occurrence of crime in a variety of social and environmental contexts. In this way, the digital map provided a form of geospatial intelligence that extended the investigatory process (e.g., Getis et al., 2000; Harries, 1999). Furthermore, advanced modeling techniques allowed the criminologists to design custom scenarios which could be used to extract new information that was otherwise hidden to the investigation. In short, crime mapping permits investigators to identify change, reveal patterns and trends, and model possible mitigation strategies in meaningful and coherent ways. In no other application are these capabilities more invaluable than during the investigation of a serial crime.

1.1 Principles of Environmental Criminology

Crime represents the manifestation of a complex relationship between an offender, target, and criminal opportunity (Brantingham & Brantingham, 1981). By examining this relationship in the context of the immediate surroundings, the criminologist is able to identify how the environment influences an offender's legal and illegal activities. This notion represented a departure from traditional criminological research by widening the focus beyond a strictly behavioral context to that of ecological determinism. Such an approach is commonly referred to as *environmental criminology*, a field of study developed in the 1980s that is attributed to Paul and Patricia Brantingham. As a derivative of the Positivist School, environmental criminology explores crime and victimization according to theories and principles that characterize offender perceptions of *target attractiveness* and *criminal opportunity* within a geographical context (Brantingham & Brantingham, 1981; 1984).

Three fundamental concepts dominate research efforts in environmental criminology. The first is known as the *routine activity* theory, which posits that criminal acts are opportunistic events that can occur at any point in time and space (Cohen & Felson, 1979). The approach is conditioned on the willingness of an offender, the presence of a suitable target, and the absence of a capable guardian. This theory emphasizes the importance of opportunity, and how it is perceived by the offender during his/her daily activities. *Rational choice* theory complements the routine activities approach by examining how perception and rational decision making influence the initiation of an illegal act (Cornish & Clarke, 1986). It defines the patterns and processes in which an offender weighs the costs, risks, and rewards associated with perpetrating a crime. Whereas the routine activities approach deals with the perception of opportunities, rational choice deals with the perceptions of consequences. Finally, *crime pattern* theory

provides an operational framework from which investigators are able to characterize an offender' behavior in space according to the tenets of environmental criminology (Brantingham & Brantingham, 1981).

The crime pattern approach represents a synergy of various behavioral patterns and ecological characteristics, which provides a foundation for understanding how the environment impacts criminal phenomenon. In fact, crime pattern theory has proven to be an invaluable resource for the investigation of serial crimes. It is comprised of models that classify an offender's spatial behavior according to the interplay between offender *opportunity and motivation* and offender *mobility and perception* (Brantingham & Brantingham, 1981). Key concepts of crime pattern theory can be summarized into four general paradigms. The first pattern finds that criminals will often *concentrate* their activities within relative proximity to their residence, also known as an *anchor point* (Rengert, 1989) or *haven* (Newton & Swoope, 1987). The implication for this concept is that there is an observable decrease in criminal activity as the distance from the offender's residence increases; commonly referred to as *distance decay* (Brantingham & Brantingham, 1981; Canter, Coffey, Huntley, & Missen, 2000; Capone & Nichols, 1975; 1976; Rhodes & Conly, 1981; Turner, 1969). In many ways, the concept of distance decay can be related to the principle of *least effort*, which posits that behavior is effectively constrained to actions that encounter the least resistance (Zipf, 1949). However, researchers Turner (1969) and Brantingham & Brantingham (1981; 1984) note that the decay is not universal, and that an offender may exhibit a *buffer zone* of inactivity surrounding his/her home. The next pattern theory examines how criminals will typically reside within the same geographic area, a characteristic referred to as *offender clustering*. The initial implication suggests that clustering is an artifact of social determinism. From a geographical context,

clustering suggests that it is a combination of opportunity and convenience factors. The last pattern finds that the distribution of targets/victims is not dispersed evenly across the offender's activity space. That is, the non-uniform spatial distribution of targets is dependent upon the offender's perception of target attractiveness and criminal opportunity. Such dependencies were found to be linked to the surrounding landscapes (Capone & Nichols, 1976; Rengert, Piquero, & Jones, 1999; Rhodes & Conly, 1981). Irregular distributions are further revealed as one examines the offender's *environmental range*: the spatial extents of a criminal's activity area defined by the locations of linked crime scenes (Canter & Larkin, 1993). Overall, these models establish that criminal behavior in space is ultimately the product of opportunity structures and offender perceptions that are inextricably linked to a fixed environment (Brantingham & Brantingham, 1981; Rengert et al., 1999).

1.2 Brief Overview of Geographic Profiling

Clearly, crime represents a number of complex conditions and behaviors that confound its investigation (Brantingham & Brantingham, 1981; Canter et al., 2000; Getis et al., 2000; Harries, 1999). Serial crime, in particular, incorporates more complex sets of psychological and ecological circumstances than any other criminal act (Canter et al., 2000; Kocsis & Palermo, 2008; Rossmo, 2000). Studies have consistently found that an offender's behavior in space will vary according to his/her taxonomy (Capone & Nichols, 1976; LeBeau, 1987a; Holmes & De Burger, 1985) and perceptions of opportunity and target attractiveness (Rhodes & Conly, 1981). As noted by Rossmo (2000), crimes are typically solved by exploring the unique relationships between offender and target. However, serial offenses often lack such obvious associations. Consequently, linked serial crime requires specialized strategies that extend beyond traditional investigative methodologies. One such strategy is commonly referred to as criminal profiling.

As noted by Canter (2004), the basic concept of a criminal profile is to identify and develop a consistent set of traits for an unknown offender based on evidence obtained from the crime scenes. The most commonly referenced criminal profile, especially within popular entertainment, is the psychological or behavioral profile (Kocsis & Palermo, 2008; Snook, Eastwood, Gendreau, Goggin, & Cullen, 2007). However, the ability to successfully and consistently apprehend serial offenders using profiles alone has not been demonstrated empirically (Kocsis & Palermo, 2008; Rossmo, 2000; Snook et al., 2007). As such, developments in criminology have led to more sophisticated investigative and analytical techniques that have demonstrated relative degrees of success (Snook et al., 2007). Of particular value to contemporary criminology is the application of *geoforensic analysis*. Coined by researcher Milton B. Newton Jr. (Newton & Swoope, 1987), geoforensics aims to identify and characterize a serial offender's behavior in space according to the distribution of known linked crime scenes. This field of research is now commonly known as *criminal geographic profiling* (Rossmo, 2000).

Fundamentally, geographic profiling is a decision support tool consisting of various investigative and analytical methodologies, both quantitative and qualitative, from which the criminologist estimates the likely location of a serial offender's anchor point based (Canter & Gregory, 1994; Rossmo, 2000). Geographic profiling complements environmental criminology in that it operationalized many of the concepts and models that characterize a criminal's spatial behavior. Analyzing the distribution of serial crime scenes can reveal specific characteristics about the offender that may lead to his or her apprehension. That is, a spatial relationship exists between the criminal, the environment, the target, and the offender (Brantingham & Brantingham, 1981). Consequently, a serial offender's crime scenes will exhibit characteristics

that follow particular spatial patterns that expose the offender's spatial behavior. These patterns are manifested through nodes, pathways, and edges that define how the offender perceives and operates within his/her environment (i.e., *awareness* and *activity* spaces) (Brantingham & Brantingham, 1981). Similar to the offender's *environmental range* (Canter & Larkin, 1993), the activity space is typically defined as the area immediately surrounding the offender's domicile in which the activity nodes and pathways are perceived intimately. Conversely, the awareness space represents an area beyond the activity space in which the offender's knowledge is not as precise. To exploit these patterns and thus reveal the offender, the investigator can apply appropriately calibrated models for analyzing the crime scene distribution, and (ultimately) identify the location from which the offender initiated the crimes. This location, (commonly referred to as the anchor point or haven), can include the offender's residence, work place, or other significant location that is positioned relative to the offender's activity space.

1.3 Common Profiling Techniques

Despite the theoretical and technological advances of recent years, the process of developing a meaningful and accurate geographic profile has been challenging. As noted by Rossmo (2000), a serial offender's anchor point would be expected to lie at the center of a distribution of crime scenes if it were observed within idealized conditions. But as research demonstrates, serial crimes do not occur within an ideal landscape, and the circumstances that favor such analysis are rarely simplistic. The reality is that crime scenes are often found to be distributed according to complex spatial patterns that are difficult to interpret (Canter & Gregory, 1994; Canter & Larkin, 1993; Harries, 1999; Rossmo, 2000). In fact, research by Canter & Larkin (1993), and later by Kocsis & Irwin (1997) demonstrated that crime scenes are seldom distributed concentrically around an anchor point. Rather, and obviously, criminal behavior is

composed of psychological and environmental characteristics that effectively distort an already complex distribution of crime scenes (Brantingham & Brantingham, 1981; Canter et al., 2000; Capone & Nichols, 1976; Felson & Clarke, 1998; Kocsis & Palermo, 2008). For a geographic profile to provide a meaningful output, specialized geo-analytical and ecological investigative techniques must be combined if these patterns are to be interpreted effectively.

The majority of contemporary geographic profiling techniques employ quantitative methods that emphasize specific geo-analytical modeling strategies (Rich & Shively, 2004). For the purposes of this research, these methods can be organized into two broad categories: *spatial distribution* and *spatial interaction* (Levine, 2007). Spatial distribution strategies include centrographic and circle-based profiling techniques that allow analysts to interpret location, scale, and diffusion of crime scenes. Spatial interaction strategies include distance decay, or gravity models that predict the location of an offender's anchor point according to empirically and theoretically derived travel-demand algorithms (e.g., Journey-to-Crime estimations). Some of these techniques will be discussed briefly in the following text.

1.3.1 Centrography

Centrographic analysis is perhaps the most basic of contemporary geographic profiling technique available to criminologists. This approach employs methods that examine the spatial distribution of discrete events (Ebdon, 1988; Levine, 2007). The most common of these measures includes the geographic mean, median, and center of minimum distance. When applied within geographic profiling models, these measures summarize a distribution of crime scenes as a single location where the sum of differences between the mean and all other locations within the distribution is minimized (Ebdon, 1988). This modeling approach is premised on the assumption that the serial offender will commit crimes within a finite area that is relatively close

to his or her home (e.g., Brantingham & Brantingham, 1981). Centrography has been applied in numerous research applications including a study of serial rapists by LeBeau (1987a), and by British criminologist Stewart Kind (1987a) for the investigation of homicides perpetrated by the “Yorkshire Ripper” during the mid 1970s.

Furthermore, centrographic analysis has been shown to be incredibly cost effective. In a series of studies carried out by Snook et al. (2002; 2004), the researchers were able to demonstrate empirically that centrographic techniques could achieve a level of accuracy comparable (if not better) than those achieved using more sophisticated methodologies. These results were further corroborated in a study coordinated by the National Institute of Justice (Rich & Shively, 2004). While their effectiveness has been demonstrated in research (Paulsen, 2006b), their practical application as an investigative technique remains relatively weak. Centographic profiles are only able to provide a single estimate of the offender's anchor. Consequently, the technique is incapable of providing a robust investigative strategy from which law enforcement agencies can detect and apprehend a serial offender. Such strategies need to model not just the location of crimes, but also account for the patterns observed within the distribution.

1.3.2 Circle Theory

As a spatial distribution strategy, circle-based models are used to characterize the diffusion of some phenomena in space. Circular models extend the capabilities of centrographic techniques by measuring the location and dispersion of crime scenes simultaneously over a finite area. In doing so, criminologists are able to systematically construct a search area defined by the distribution patterns observed from the linked crime scenes.

The first practical implementation of a circle based geographic profile was developed by Milton B. Newton, Jr. (1988). Newton derived *geoforensic analysis* after examining the spatial

characteristics associated with the “Hillside Strangler” homicides of the late 1970s. Newton’s approach was based on the independent hypothesis that an area surrounding the geographic center of a crime distribution may contain the offender’s residence. By sequentially measuring the spatial mean from a series of crime scenes, Newton proposed that the center of the distribution will move toward the offender’s anchor, or haven. With the center of a distribution was defined, Newton introduced a circular search area with a radius defined by the distance between the farthest crime scenes. As each new crime scene was added to the measure, the area of the circle was gradually reduced by dividing the value by N-1 crime scenes, where N is the number of crimes in the series (Newton & Swoope, 1987; Leitner, Kent, Oldfield, & Swoope, 2007). The assumption for this approach established that the accumulation of offenses would effectively shift and shrink the search area to reveal the offender's haven.

In later research, Canter and Larkin (1993) demonstrated the utility of circle based profiling when examining the *environmental range* of serial rapists. The researchers were able to use circles to demonstrate that offenders operate within a distinct offense region defined by a circle’s radius equal to the distance between the farthest crime scenes. Like the approach developed by Newton, the two farthest offenses from each other were used to define the diameter of the circle. When the analysis was completed, it was found that the residence of 87% of their sample was located within the predicted area (Canter & Larkin, 1993). Furthermore, their analysis revealed two distinct patterns to offender mobility: those that offend close to their residence, and those that offend far from their residence. This observation became a means of discriminating offender mobility according to *marauders* and *commuters*, respectively. These classifications would prove to have a profound impact on the development of future geographic profiles.

Yet, the practical value of circle-based techniques is unclear. Numerous studies examining the efficacy of circle theory have been applied for various criminal offenses (Canter & Gregory, 1994; Kocsis & Irwin, 1997; Kocsis et al., 2002; Snook, Taylor, & Bennell, 2004; Paulsen, 2006b). For each study, the usefulness of circle theory is uneven. As Canter and Larkin (1993) demonstrated, the environmental range of an offender is not homogeneous. That is, an offender's specific travel behavior, or mobility pattern, can effectively disrupt the predictability of circle-based profiling techniques. For these situations, crimes committed by commuter offender types define a circle that does not encompass the anchor point. Such scenarios illustrate that linked crime scenes do not necessarily reveal an offender's distinct activity space. The root of its failure lies in the presumption of an isotropic surface in which the likelihood of offending is distributed randomly around the offender's residence. These techniques can be enhanced, however, if the modeling framework were able to calibrate the circle according to the spatial variations observed for solved and unsolved crime scenes. By doing so, the model could effectively account for the anisotropic landscape, and therefore better predict the offender's anchor point.

1.3.3 Distance Decay

Of the analytical methods available to the contemporary criminologist, nearly all geographic profiling software packages include techniques that account for spatial interaction. Studies demonstrate (e.g., Brantingham & Brantingham, 1981; Capone & Nichols, 1995; 1976; Canter & Larkin, 1993; Rossmo, 2000; etc.) that serial crimes are committed in those locations within relative proximity to the offender's anchor. As an offender initiates a crime, there are rational processes in which the cost-benefits of the crime are assessed and used to determine the criminal's course of action. More often than not, the criminal commute is used as a proxy for

this cost. Because the frequency of offenses decreases as the distance from the anchor increases (e.g., Brantingham & Brantingham, 1981), this distance decay characteristic has become a ubiquitous modeling approach. Of the various modeling techniques available, Journey-to-Crime (JTC) probability estimation is perhaps the most frequently employed. The appeal for JTC rests in its ability to generate offender profiles using customizable distance decay algorithms that can accommodate the unique characteristics of the offender's activity space.

Canter et al. (2000) and Rossmo (2000) were among the first researchers to incorporate distance decay functions within a functional geographic profiling software package; though the concept has been recognized since the late 1960s (Brantingham & Brantingham, 1981; Canter et al., 2000; Capone & Nichols, 1975; 1976; Turner, 1969). These findings led to the development of profiling models that are based extensively on the precepts of environmental criminology and classical distance decay models. The most well-known of these implementations include the applications known as Dragnet (see Canter et al., 2000), Rigel™ CGT (see Rossmo, 2000), and the JTC routine provided in CrimeStat® (see Levine, 2009). Each of these software solutions analyze and model serial crime scene distributions using derivatives of empirical calibrated and/or theoretically defined distance decay algorithms. These algorithms assign probability values that indicate the likelihood of identifying an offender's anchor point for the area immediately surrounding the locations of linked crime sites. An estimate for each location within the study area, typically represented as a collection of grid cells, is calculated according to its distance from each crime scene. Collectively, these modeled output values represent a density map, or risk surface, of the offender's anchor point. It is this output on which investigative strategies are derived.

While distance decay models are widely utilized, they are subject to various criticisms. Most significant is the faulty assumption of isotropic surfaces on which the physical and perceived distribution of targets and opportunities are randomly arranged across the criminal's activity space. There are two fundamental implications of this assumption. First, when the decay model is calculated, it is often done so using Euclidean distance metrics. As a consequence of only measuring the “as the crow flies” distance, the decay model fails to account for the offender's perception of temporal and distance based travel costs. Second, because all decay models presume that targets are distributed across a monotonous plane, they therefore assume that criminal opportunity is equally available in all directions and at all distances. If that were the case, then the offender's anchor point would be easily identified within the center of a crime scene distribution. More realistically, the offender's activity space will consist of irregularly distributed physical structures and cultural boundaries that confines criminal opportunities to certain landscapes. The same would be true when searching for the anchor point.

1.4 Impact of Landscape on the Occurrence of Crime

The utility of a geographic profile as an investigative tool is obvious. Nevertheless, research consistently demonstrates that the ability to geographically profile a serial offender's anchor point remains relatively inconsistent. As revealed above, the distribution of crime scenes, targets, and anchor points are inherently distorted by “real-world” factors that can include street layout, traffic congestion, land cover features, psychological bias, and more. Despite this knowledge, geographic profiling and serial offender analysis continues to be applied without explicitly accounting for the irregularities inherent within the surrounding physical and cultural

landscapes (Block & Bernasco, 2009). Accordingly, there is very little literature that sufficiently addresses this issue within an existing analytical framework.

1.5 A New Paradigm

The physical and cultural structures that define an offender's activity space directly influence the offender's perceptions of criminal opportunity and target attractiveness. These influences determine criminal mobility and target distribution (Brantingham & Brantingham, 1981). Contemporary geographic profiling models are generally incapable of accounting for these ecological structures. As revealed earlier, most traditional techniques use methodologies that assume travel and opportunity are isotropic. Models derived from these traditional metrics fail to approximate the actual conditions in which crime patterns occur. The premise for this study posits that the distribution of linked crime scenes should exhibit characteristics that are consistent with the underlying landscape. If these characteristics can be parameterized successfully within a geographic profiling model, it should produce more accurate results than those methodologies that do not. The research presented here will examine the effectiveness of spatial models that are capable of accommodating the criminal activity space within a realistic, irregular landscape.

The practical significance of this research is demonstrated by means of a multi-faceted research approach. Through a series of peer-reviewed journal publications and a soon-to-be published manuscript, the author demonstrates the validity of this thesis by examining and assessing the efficacy of four ecologically enhanced geographic profiling techniques that have been modified to account for anisotropic surfaces: (1) functional distance metrics applied to distance decay algorithm; (2) enhancing spatial distribution and circle theory techniques using a standard deviational ellipse; (3) land cover enhanced JTC estimation; and (4) incorporating land

cover within JTC estimates according to an empirical Bayesian formulation. Accordingly, four individual hypotheses are formulated that test the assumptions and efficacy of this research:

1.5.1 Evaluating the Usefulness of Functional Distance Measures When Calibrating Journey-to-Crime Distance Decay Functions

Capone and Nichols (1976) demonstrate that an offender's behavior in space is directly related to the urban structures that exist within the criminal's activity space. The authors posit that this behavior, when analyzed in context to the spatial characteristics of the criminal commute, can yield insight into the offender's perceptions of opportunity. Similarly, the perception of travel cost is inherently influenced by the offender's interpretation of the environment in which he/she operates. In most cases, the *de facto* metric for modeling travel behavior is Euclidean in nature, which is often contrary to the general perception of travel cost (e.g., optimized for distance and/or time). Therefore, the first essay of this research proposes to challenge contemporary JTC models by introducing two functional distance metrics: *travel path* and *travel time* functional distances. Mathematically calibrated distance decay models based on functional distance metrics were used to generate criminal geographic profiles for a confessed serial killer operating in Baton Rouge, Louisiana. Both the travel path (i.e., shortest road distance) and temporally optimized (i.e., quickest travel time) functional distance measures were calculated based on the impedance attributes stored within a linearly referenced transportation data layer of several parishes in Louisiana. Two separate JTC distance decay functions (i.e., negative exponential and truncated negative exponential) were mathematically calibrated for “best fit,” based on the distances between historic homicide crime scenes and offender anchor points (i.e., the residence). A probability score was calculated for every point within the study area to indicate the likelihood that it contained the offender’s residence. A profiles efficiency was assessed using a hit score value, which quantifies the area that must be searched in order to

locate the offender's residence. Comparisons between the predicted and the actual residence revealed the procedural validity of functional distance metrics, but failed to find them significantly more efficient than existing methodologies when applied to the serial offender within the Baton Rouge study area (Kent, Leitner, & Curtis, 2006).

1.5.2 Efficacy of Standard Deviation Ellipses in the Application of Criminal Geographic Profiling

The second essay uses simple spatial modeling techniques to determine whether it is possible to expose the offender's anchor point while accommodate the impact of the physical and cultural landscapes. The premise for the study is that the distribution of linked crime scenes should exhibit a shape and orientation that is consistent with the underlying landscape. Basic geographic principles of central tendency and spatial diffusion are used to analyze the output of circular and elliptical profile models generated for 30 serial burglaries and 67 serial robberies occurring in Baltimore, Maryland, between 1993 and 1997. Two hypotheses were examined. First, a comparative analysis of the modeled output reveals that the standard deviation ellipse was significantly better able to predict the anchor point of a serial offender than profiles generated from circles. But, the accuracy of the profiles came about at the expense of precision. Next, the position and orientation of each ellipse was examined in relation to the immediate landscape. Findings revealed a weak, but significant, correlation between a profile's orientation and the mean linear orientation of the underlying road network. Together, these findings demonstrated that landscape is a measurable parameter that can improve the accuracy of geographic profiling models (Kent & Leitner, 2008).

1.5.3 Utilizing Land Cover Characteristics to Enhance Journey-to-Crime Estimation Models

The third research topic proposes that JTC probability estimates filtered according to land cover classifications will improve the predictive capabilities of geographic profiles. After establishing that the irregularities inherent in the underlying physical and cultural landscape can be modeled effectively using simple spatial distribution strategies, this study proposed to integrate the landscape according to a probability distance approach. To assess the theory, empirically calibrated JTC probability estimates were constructed for a combined test sample of 70 serial burglaries and robberies (353 offenses) that occurred in Baltimore between 1993 and 1997. Each JTC model was filtered according to land cover classification probability value associated with a dataset of previous offenders (i.e., the calibration sample) that resided within the Baltimore study area. The product of the JTC estimate and the marginal probability of land cover effectively reduced a profile's search area. Filtered and unfiltered geographic profiling models were compared according to three accuracy and two precision measures. Profiles were ranked according to prediction efficiency. Results for four of the five comparisons indicate that filtered models are significantly more accurate and precise than non-filtered profiles for the Baltimore test sample (Kent & Leitner, 2009).

1.5.4 Incorporating Land Cover within Bayesian Journey-to-Crime Estimation Models

The findings provided in the three previous investigations have led to the development of a new methodological approach for generating geographical profiles. The fourth essay incorporates land cover classes within an empirical Bayesian probability framework. Unlike the previous two studies, the goal for this essay is to implicitly account for the offender's perceptions of opportunity and target attractiveness by explicitly accounting for the environment defined by

the criminal's activity space. The efficacy of this approach was measured by comparing the output of seven traditional and land cover enhanced geographic profiles. Profiles were generated for 52 burglary, robbery, and larceny serial offenses from the Baltimore offender dataset. The seven models included the traditional JTC estimate, land cover filtered JTC, center of minimum distance, and various Bayesian formulated JTC estimates. Results were assessed according to the predicted anchor point probability estimate, error distance measured between the predicted and actual anchor point, and hit score that quantifies the anchor point search cost. Overall, land cover enhanced models performed significantly better than non-enhanced techniques for measures of hit score and probability estimation. Results for tests measuring a profile's error distance were mixed, and failed to confirm significance between paired comparisons.

1.6 Organization

As a journal style dissertation, each chapter in this document will explore a landscape enhanced geographic profiling strategy that has been, or will be published in a peer-reviewed scholarly journal. Profiling techniques are introduced and assessed according to their ability to accommodate the physical and cultural landscape, and their ability to predict a serial offender's anchor point accurately and precisely. Each chapter represents a publication or manuscript. Each chapter includes the research question, hypothesis, appropriate assessment techniques, discussions, and conclusions. The concluding chapter will summarize and discuss the findings of this research, focusing on the consequences and implications of the research in context to its applicability to the criminal investigative process. The works cited for each manuscript have been combined and are accessible in the bibliography located at the end of this document. Reprint permissions are included in the dissertation's appendix.

“Criminal mobility is related to urban structure and that the analysis of movement behavior will yield insight into offender decision-making and spatial preferences and contribute significantly to our understanding of the urban system as a crime opportunity structure.”

- Capone and Nichols (1976, p. 200).

CHAPTER 2: EVALUATING THE USEFULNESS OF FUNCTIONAL DISTANCE MEASURES WHEN CALIBRATING JOURNEY-TO-CRIME DISTANCE DECAY FUNCTIONS*

2.1 Introduction

Spatial analysis has long been a valuable tool used within the criminal investigative process. This is especially true for serial offense cases where criminologists apply geographic profiling to model offender mobility and crime distribution patterns in order to estimate a criminal's likely residence. Yet, traditional analytical methodologies have avoided the utilization of functional distance measures when modeling an offender's journey-to-crime within a diverse and varied landscape. By substituting straight-line Euclidean distances with travel-path functional distance measures, the predictive utility and technological costs associated with geographically profiling a localized serial killer was assessed using mathematically calibrated distance decay models.

2.2 Background

The theory and conceptual framework of this research is built upon environmental criminology (Brantingham & Brantingham, 1981). Environmental criminology consists of a number of theoretical concepts, including *routine activity*, *crime pattern*, *rational choice*, and the *buffer zone* postulate that provide an ecological heuristic for understanding the relationship crime

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has with place. These concepts establish a quantitative and qualitative approach for analyzing the operational, behavioral, perceptual, social, legal, cultural, and geographic factors of a crime (Rossmo, 2000).

According to the routine activity theory, the investigator explores the characteristics of a predatory crime by dissecting it into its constituent elements: a willing offender, a suitable target, and an environment that is perceived to be absent of a capable guardian (Felson & Clarke, 1998; Rossmo, 2000). The intersection between the offender and victim activity space implicates a location where the offender is comfortable enough to commit the offense (Canter & Gregory, 1994). As such, routine activity theory supports the concept that the opportunity for crime can manifest itself in the normal activities of everyday life.

While routine activity theory does support observations that criminal opportunity can exist anywhere within the offender's awareness space, an offender does not necessarily choose crime sites randomly. Instead, research finds that criminal activity is spatially dependent upon proximity to the offender's activity nodes, which can include the offender's residence, place of work, and/or favorite recreation spot (Canter & Gregory, 1994). These activity nodes define an offender's awareness space. When examined geographically, the processes that an offender uses for target selection can reveal patterned structures that describe how an offender operates within his/her awareness space, a concept known as crime pattern theory (Brantingham & Brantingham, 1981; 1984; Rossmo, 2000).

The rational choice theory postulates that criminal behavior is an outcome of decisions that are influenced by rational consideration of the efforts, costs, and rewards associated with a crime (Brantingham & Brantingham, 1984). When examining the geographic characteristics of certain types of crime, rational choice theory can describe another environmental criminology

concept: the offender's *buffer zone* (Brantingham & Brantingham, 1984). The buffer zone represents an area surrounding an offender's particular activity node, most notably the residence, from which little to no criminal activity will be observed. This buffer zone is seldom observed for spontaneous and/or crimes of passion. Conversely, research suggests that such a zone will most likely occur for predatory offenses, which can be characterized as pre-meditated (Canter & Larkin, 1993).

2.3 Journey-to-Crime Modeling

As a precursor to geographic profiling, Journey-to-Crime techniques are based on research that shares much of its core analytical functionality with traditional transportation travel demand models (Beimborne, 1995). These techniques were originally founded on macro level sociological research developed from the Chicago School of the 1920s (Ratcliffe, 2001), with particular connection to the Burgess zonal model (Harris & Lewis, 1998). However, the predictive capability of this approach is suspect due to the high-levels of data aggregation and ease of misinterpretation (Gore & Tofiluk, 2002).

This research applies the Journey-to-Crime routine implemented in CrimeStat[®] II to model offender travel characteristics within an urban environment. Some of the more traditional models implemented for journey-to-crime include—but are not limited to—mean center and median center, center of minimum distance, medial circles, mobility triangles, and distance decay functions (Rossmo, 2000). Selecting the most appropriate modeling application depends entirely on the characteristics of the environment in which a crime occurs, usually requiring a trial-and-error approach (Levine, 2002). Understanding the characteristics of the various journey-to-crime models can aid in the decision making process.

The mean and median center, as well as the center of minimum distance use different approaches to measure the center of a distribution of crime sites. The medial circles technique utilizes circle theory to define an area around the occurrences of each offense to identify and develop a list of likely suspects. Each circle's radius is defined by Journey-to-Crime measures of similar crime types. The mobility triangles approach examines the relationship between offender residence, target location, and crime scene in order to solve a crime (Godwin, 2003). Finally, the most effective technique for journey-to-crime analysis is the *distance decay* function.

Distance decay functions are quantitatively rooted in the family of gravity models based on Isaac Newton's fundamental law of attraction. The term, "distance decay," characterizes how the attraction between two bodies decreases as the distance between them increases. When placed in the context of modeling travel behavior, the concept characterizes how individuals typically prefer to produce short commutes rather than long trips for the normal travel activities of their everyday lives (Harries, 1999). Crime, like pedestrian traffic, shopping, telephone conversations, migration, and a host of other behavioral interactions, is subject to the general class of inverse distance variations formulated as gravity laws (Smith, 1976). Transportation planners typically use distance decay functions within their mathematical models to help simulate human travel characteristics (Beimborne, 1995; Levine, 2002). In terms of its usefulness for modeling criminal mobility, distance decay can be used to represent how a criminal offender travels within his or her awareness space. Capone and Nichols (1976) investigate the relationship between urban structure and criminal mobility by describing and explaining the distance biases of robbery offenders in metropolitan Miami. Lu (2003) goes beyond the analysis of a criminal's travel behavior to include journey-after-crime characteristics and finds that journey-after-autotheft involves both distance and direction biases.

As noted by Capone and Nichols (1975), the average distance an offender is willing to travel will vary according to the type of crime, method of offense, time of day, and value of the target (Felson & Clarke, 1998). A number of functions are available that can effectively measure the observable distance decay characteristics of a criminal's Journey-to-Crime. Brantingham and Brantingham (1981) suggested that a buffered normal function could be used to describe a criminal's distance decay following the hypothetical buffer zone. However, Rhodes and Conly (1981) observed that a negative exponential distance decay curve exhibited the best fit when used to characterize the distribution of events relating to serial burglars, robbers, and rapists.

Levine (2002) provides a detailed list of various theoretical and mathematical modeling functions used by transportation researchers that include linear, negative exponential, normal, lognormal, and truncated negative exponential distance decay curves, among others. Each function possesses various characteristics that can be utilized by journey-to-crime models. For example, the normal, lognormal, and truncated negative exponential are functions that characterize how the spatial distribution of criminal activities reaches a peak at a certain distance away from the haven (i.e., the offender's residence) before exhibiting a decay as the distance from the origin increases. This type of function, most notably truncated negative exponential, is often used to describe the presence of the Brantinghams' proposed buffer zone effect (Brantingham & Brantingham, 1981). However, research in spatial interaction modeling points out that parameter estimates used in exponential functions are scale-dependent. In practical terms this means that exponential distance decay functions cannot be transferred from one study area to another, but have to be calibrated anew in order to account for differences between study environments travel distances (Fotheringham & O'Kelly, 1989). Only recently have researchers investigated the effectiveness of the various different distance decay formulae for estimating the

offender's haven (Canter et al., 2000; Levine, 2002; Snook et al., 2004). This research tests the effectiveness of the negative exponential and truncated negative exponential distance decay formulae for estimating the offender's haven.

2.4 Criminal Geographic Profiling

The geographic distribution and associated patterns of linked crime sites are clues left by an offender that describes the geographic behavior associated with a criminal. This approach provides a good example of a contemporary environmental criminology analysis: the process of exploring the relationship between crime, the target, and space/place. More specifically, these clues represent the elements of how an offender perceives his or her immediate awareness space and the distribution of potential targets (Brantingham & Brantingham, 1984). For each successive offense, these clues can be examined and combined, refining the investigator's understanding of the offender's travel behavior. Accordingly, exploring the geographic hunting strategies of an unknown serial offender, defined by the distribution of linked crime sites, can provide valuable resources for the successful apprehension of the perpetrator (Levine, 2002; Rossmo, 2000). When combined with the geo-statistical modeling capabilities of a GIS, these techniques form the basic analytical methodologies associated with modern geographic profiling (Harries, 1999).

Criminal geographic profiling is a decision support tool used by law enforcement to make estimates about the likely location of a serial offender's haven (Godwin, 2003; Rossmo, 2000). Law enforcement can use geographic profiling models to maximize limited resources and create investigative strategies that focus on those locations that possess significant likelihood of being a part of an offender's hunting area (Canter, 2003). Rossmo (2000) notes that Journey-to-Crime estimates, mental map interpretations, Thiessen polygons, and other analytical approaches can

be, and have been, successfully applied for the geographic analysis of crime. In certain circumstances, geographic profiling can also be used as a forensic tool capable of verifying the existence of a serial offender (Newton & Swoope, 1987).

There are many techniques available that can generate geographic profiles. The application of spatial analysis and mapping to develop a geographic profile was first done by Holt in 1979 (Gates & Shah, 1992; Rossmo, 2000), followed by Kind in 1980s (1987a; 1987b), LeBeau (1986; 1987a) and Newton and Swoope (1987). Among the modern and contemporary geographic profiling models are Dragnet (Canter, 2003), Rigel™ Criminal Geographic Targeting (Rossmo, 2000), Predator® (Godwin, 2003) and the CrimeStat® II journey-to-crime routine (Levine, 2002). Dragnet was developed by Canter's Center for Investigative Psychology in Liverpool, UK, and applies the distance decay and buffer zone concepts identified by research in environmental criminology (Canter, 2003; Canter et al., 2000). Criminal Geographic Targeting (CGT) is another approach to the profiling construct, which was developed by Rossmo (2000). CGT follows a process in which geographic models are used to develop probability surfaces indicating the likelihood of an offender living at a particular location. The CGT algorithm utilizes distance decay functions that incorporate the theoretical buffer zone to describe the criminal hunting process expressed by a serial offender as he or she travels between haven and crime scene. Building upon the conceptual framework of Canter's Dragnet, Godwin (2003) developed a geographic profiling application, called Predator®. This geographic profiling application predicts offender residences, presumably, using smallest space analysis (SSA) to represent where an offender resides. According to Godwin (2003) the advantage of Predator® is that it can measure the angular position of a crime, which can significantly support how a

criminologist can direct its investigative strategies. However, very little published information has been identified regarding how Predator[®] implements the models.

One major limitation of all contemporary geographic profiling applications is that the offender's travel behavior to and from the crime scenes is conventionally measured with a straight-line (Euclidean) distance. This means that current profiling models assume an isotropic surface, where impedance is uniform in every direction. As a consequence, these models do not accommodate the inherent variations exhibited by a particular transportation network, such as path, direction, speed, landscape features, land-use policies, boundaries, congestion, etc. A more realistic way of traveling in downtown areas of larger US cities is along the rectilinear street pattern, a travel behavior that can be measured by the Manhattan distance. This distance metric results in approximately 1.4 times longer trips when compared to the Euclidean metric. The modeling process used to develop a geographic profile for this research is founded on the conceptual application of the CrimeStat[®] II journey-to-crime routine (Levine, 2002). This routine is the “platform” on which the usefulness of applying functional distance measures (shortest travel path and quickest travel time) is evaluated.

2.5 Characteristics of a Serial Offender

Criminal geographic profiling is primarily constructed for serial crimes, which include serial murder, serial rape and sexual assault, serial exposures, serial arson, serial robbery, kidnapping, and other crimes that possess unusual spatial characteristics (Rossmo, 2000). This is because the distribution of multiple, linked crime scenes provide the necessary elements for determining the patterns attributable to a single personality (Canter, 2003; Canter et al., 2000). As such, Rossmo (2000) provides a series of basic conditions that are used to determine the utility of a geographic profile:

- A series of linked crimes must have occurred.
- There must be a minimum of five crime sites within that series.
- The investigation warrants the effort and associated expense needed to produce a profile.

Assessing the suitability for a geographic profile begins when an investigation is reasonably certain that a serial offender is present. In a process commonly referred to as linkage analysis, investigators attempt to connect various crime scene elements to a single offender through the forensic exploration of evidence (Canter et al., 2000; Canter & Larkin, 1993). DNA testing, fiber analysis, and ballistics represent a small fraction of the numerous techniques available to the criminologist. Once linked, the investigation must attribute each individual crime to a series. Most experts agree that a serial offender can be defined as an individual (or a collective group of individuals) who (Hinch & Hepburn, 1998; Holmes & Holmes, 1998):

- Commits an offense on two or more occasions over a period of time, characterized by cooling-off intervals between each event.
- Commits offenses that lack a perceptible relationship with his/her target.
- Chooses targets that lack a perceptible relationship with each other.
- Commits offenses with similar Modus Operandi (MO) and patterns.
- Commits offenses that occur in different geographic locations.
- Commits offenses that appear to possess a psychological component.
- Commits offenses that appear to only have symbolic value.

Arguably, various elements of the list could be added or removed with relative justification.

Newton and Swoope (1987) propose that serial offenders be divided into broad categories: “mobile” (geographically transient) and “static” (geographically stable). Mobile offenders commit crimes over large areas that cross cultural and psychological boundaries. These offenses predominantly occur outside the offender's awareness space and involve complex hunting strategies. A specific characteristic of a mobile offender is that his or her hunting area

lacks a definable anchor point from which the offender operates (Rossmo, 2000). Conversely, static offenders commit crimes within a confined area, usually bounded by psychological barriers and landscape features. Furthermore, static offenders typically operate within their awareness space as they travel between activity nodes. As such, the offender will likely have an anchor point (the haven) from which to operate. These characteristics have been observed and are supported by numerous published findings (Canter & Larkin, 1993; Hickey, 1997; Holmes & Holmes, 1998).

As noted by Rossmo (2000), the primary assumption of a geographic profile is that the offender's haven lies within the distribution of crime sites. Accordingly, mobility characteristics represent a critical element for providing effective geographic profiles. For every crime site that can be attributed to a serial offender, the geographic profile's accuracy increases. Accordingly, both Rossmo (2000) and Newton & Swoope (1987) propose that a minimum of five distinct locations be identified for analysis.

When a localized (static) serial offender (marauder) hunts within his or her activity space, he/she does so within a culturally, psychologically, and geographically homogeneous landscape. As such, that landscape upon which the offender basis his or her movement is contextually the same. Therefore, the ability to model that offender's movement between his or her activity nodes is more easily achieved because there are little variations in the limiting factors that control movement. Conversely, the dispersed (mobile) serial offender (commuter) hunts across various cultural and psychological environments that result in a collection of continuously complex, heterogeneous landscapes. The activity space in which the commuting offender travels is not contextually consistent, and will often lack definable activity nodes. It possesses dissimilar land-use policies, geographic features, cultural constructs, and so on. As a consequence, the ability to

model offender behavior across heterogeneous ecologies is severely handicapped. Any geographic profile created for a non-localized offender will be founded on a diluted collection of crime sites that will most likely lack meaningful patterns due to the variability associated with the mobility of the offender. Consequently, modern and contemporary geographic profiling models yield best results when applied to a geographic stable serial offender, who operates from a definable anchor point (mostly the offender's residence). These models should not be applied to mobile offenders, who commit crimes over large areas and do not possess a definable anchor point. Canter (2003) discusses the complexities and issues involved in geographically profiling a mobile serial offender. It should be noted, though, that even the "homogenous" landscape of the localized serial offender is still a spatially complex environment where all information cannot be processed simultaneously, requiring a degree of hierarchical processing where "like" places are nested together (Fotheringham & O'Kelly, 1989).

2.6 Study Area and Data

The study area used by this research is defined by the maximum spatial extent of crime locations associated with the confessed Baton Rouge serial killer, Sean Vincent Gillis. The 2094.75 mile² study area consists of 4,175 grid cells and covers the following Louisiana parishes (counties) partially or completely: Ascension, East Baton Rouge, East Feliciana, Iberville, Livingston, Point Coupee, St. Helena, St. Martin, West Baton Rouge, and West Feliciana.

The sample data typically utilized for an investigation of this nature incorporates crime data specific to both the study area and the type of serial offense investigated. As Levine (2002) notes, geographic profiling models should be calibrated for the unique parameters that characterize specific criminal offenses for specific jurisdictions. Following these recommendations, two data sets were collected for this research. The first data set was gathered

from police reports made available by the Homicide / Armed Robbery Division, Baton Rouge Police Department (BRPD). It includes a total of 497 homicide cases reported over a 7-year period from 1991 to 1997 (Leitner & Binselam, 1998). Of these, 325 had known offender residence locations, of which 301 were successfully associated with a crime location and geocoded to the road network of the study area. The second data set includes a total of nine crime sites that have been associated with the serial killer. Eight of the nine crime sites are body dumpsites and one is a point of fatal encounter. Gillis' hunting style can be described as that of a typical localized marauder. The locations for all nine crime sites have been reported in detail in the local news media, as was his residence following his apprehension on April 29, 2004. Four of the nine crime sites and the residence of the serial killer are located in Baton Rouge (Figure 2.5). This information reflects the status of the ongoing investigation at the beginning of August 2004, when this manuscript was revised and resubmitted.

ESRI[®] ArcView[™] GIS 3.3 (ESRI, 2002) and the Geographic Data Technology's Dynamap[®] Transportation road network (GDT-Dynamap[®]) were used for both geocoding addresses and network path analysis. Published in 2002, the GDT-Dynamap[®] data provides a full range of addresses which are appropriately segmented for geocoding, as well as including the impedance values (speed limit, direction, and time) necessary for the network path analysis used to calculate functional distances.

2.7 The Criminal Geographic Profile Procedure

The modeling process used to develop a criminal geographic profile is founded on the conceptual application of the CrimeStat[®] II journey-to-crime routine (Levine, 2002). In order to establish a sufficient representation for the travel patterns of like criminals, the calibration group must be large enough to ensure reliable calibration parameters. Accordingly, the 1991–1997

homicide data represent a suitable calibration group from which to empirically derive the most appropriate distance decay models. The crime locations of the serial killer represent the test group. Gillis's first known victim was an 82-year-old woman, who was killed more than ten years ago in March 1994. His last known murder was a 45-year-old woman, found in January 2004. This means there is a sufficient temporal overlap between the calibration and test group. In addition, the major arteries of the road network in and around Baton Rouge have not changed since the beginning of the 1990s.

The entire criminal geographic profiling procedure is composed of two parts: First, a calibration routine identifies an optimal distance decay function based on the travel characteristics exhibited by the calibration group of homicide offenders. The process for calibrating a distance decay function uses the traveled distances measured between each origin and destination stored within the calibration group data set. The origin represents the offender's residence while the destination represents the point of fatal encounter or body dumpsite associated with that offender. The second part integrates the calibrated distance decay functions within journey-to-crime routines in order to estimate the residence of the serial killer. The resulting geographic profile is mapped for the study area and used to illustrate the probability of each cell being the serial killer's residence.

Using the crime locations stored within the test group data set (eight body dumpsites and one point of fatal encounter), the serial killer's residence is estimated based on the mathematically calibrated distance decay function defined for the observed travel patterns of the calibration group (the 301 homicide cases). The calibrated function mathematically assigns a value for each grid cell centroid within the study area. Called a "probability score," the values

are used to indicate the likelihood that any location within the study area is the serial killer's likely residence.

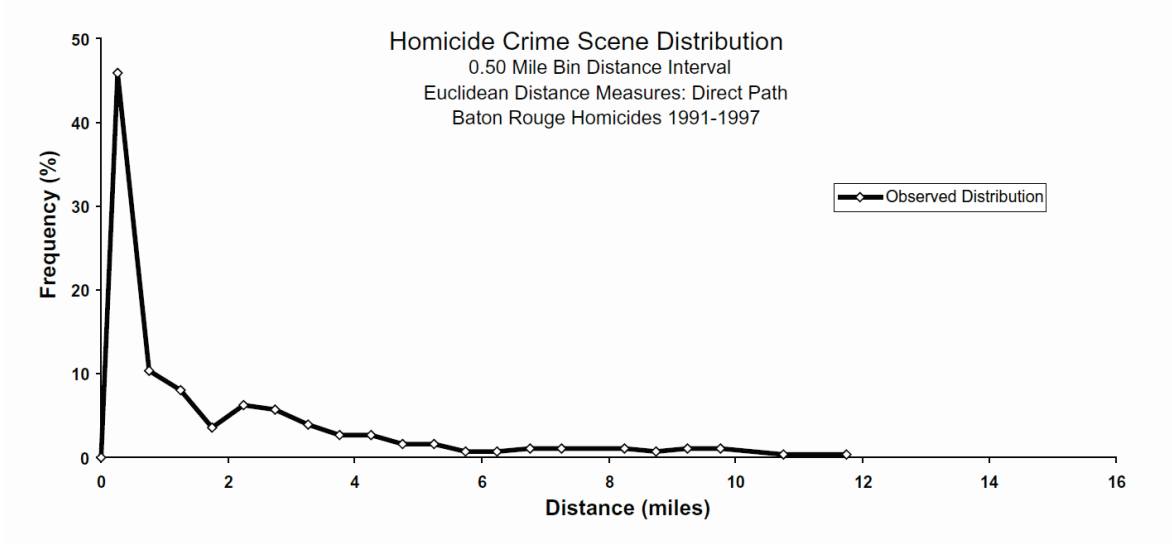
The probability surface estimating the likely serial killer's residence is represented by a density map, termed a geoprofile (Rossmo, 2000). The highest scored grid cell represents the estimated residence (peak likelihood). Because two different modeling functions will be examined, it is necessary to measure each technique's effectiveness based on its ability to prioritize a cost-effective search area from which to identify the individual's residence (Canter et al., 2000). Effectiveness is assessed in two distinct ways: the error-distance and search-cost. Contemporary journey-to-crime models assess error by measuring the distance between the predicted and the actual residence (of the serial killer). The second method estimates accuracy by identifying the proportion of the area that must be searched in order to successfully identify the serial killer's residence.

2.8 Analysis and Results

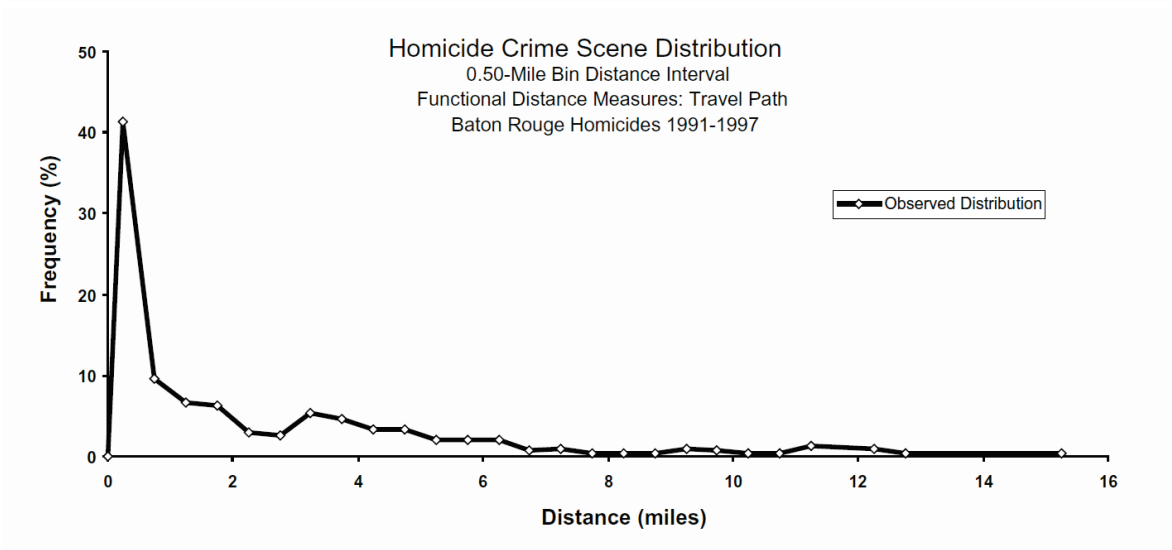
Using direct-path Euclidean, indirect-path Manhattan and two different functional distance measures (shortest travel-path and quickest temporal-path), eight geographic profiles were created using two unique distance decay models. The results of all eight geographic profiles are summarized in Table 2.2 [page 40] and only the best and most accurate geographic profile is mapped (Figure 2.2).

2.8.1 Frequency Distributions of Homicides by Distance Metric

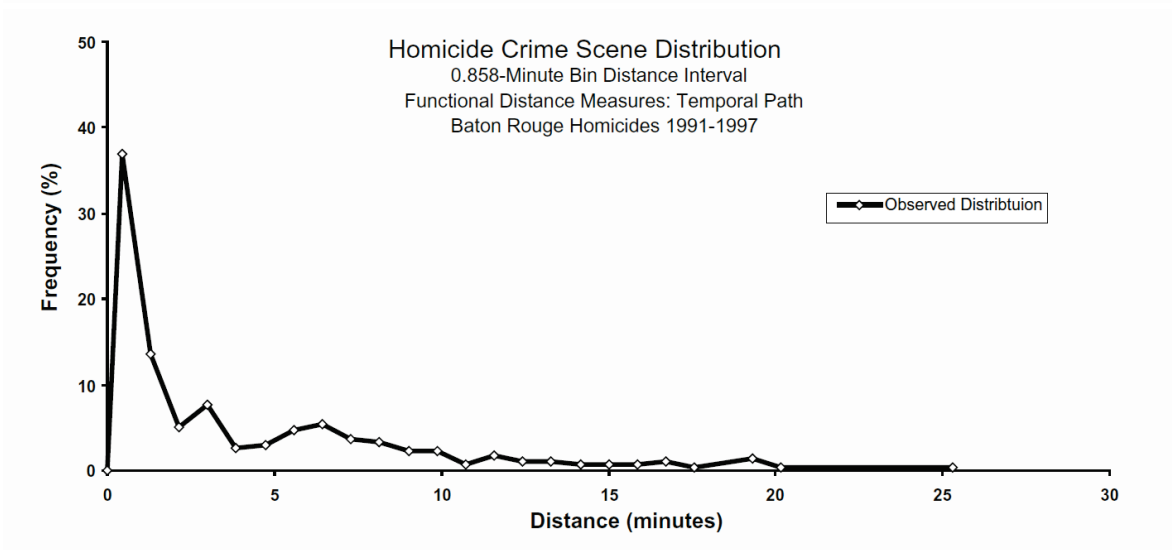
Figure 2.1 illustrates the frequency distributions for each distance measure calculated from the calibration group data set (the 301 homicide cases). The frequency distribution for the indirect-path Manhattan metric is not shown here, as it is a computed metric based on the values measured for the direct-path Euclidean distance. Results show that independent of the distance



A)



B)



C)

Figure 2.1: Frequency distributions of homicides by distance metric: (A) direct-path Euclidean distances, (B) shortest travel-path, and (C) quickest temporal-path.

metric used, the frequency distributions look markedly similar. The significant spike (very high frequency) near the offender's residences corresponds with environmental criminology research results, which indicate that the majority of human activities are performed within close proximity to the home. More than half of all homicides are committed at a location that is within one mile of the offender's residence. In contrast to environmental criminology research, a buffer zone effect is not observed with any of the distance metrics used. As the distances increase, there is a general decrease in activities for each distance metric. The maximum distance an offender is willing to travel to commit a homicide is almost 12 miles straight-line, approximately 15 miles using the shortest path in the road network and just over 25 minutes in travel time using the quickest route.

2.8.2 Journey-to-Crime Calibration Models

Two distance decay functions were selected to model the frequency distributions observed in Figure 2.1. These functions included negative exponential (Equation 2.1) and truncated negative exponential. The latter is a joined function consisting of a linear (Equation 2.2a) and a negative exponential (Equation 2.2b) part. Both functions are implemented in the CrimeStat[®] II journey-to-crime routine (Levine, 2002) and their applicability to geographic profiling has been widely supported in the literature (Section 2.3). The truncated negative exponential function simulates the buffer zone around the offender's haven where little to no criminal activity can be observed (Section 2.2). The negative exponential function does not. The relationship is exposed as:

$$y = Ae^{-Bx} \tag{2.1}$$

where y is the likelihood that an offender will commit a crime at a particular location, x is the distance between that particular location and the offender's haven, A and B are parameters to be estimated, and e is the base of the natural logarithm.

$$y = Cx \text{ for } x > 0 \text{ and } \leq 0.5 \text{ miles (0.858 min)} \quad (2.2a)$$

$$y = De^{-Ex} \text{ for } x > 0.5 \text{ miles (0.858 min)} \quad (2.2b)$$

where y is the likelihood that an offender will commit a crime at a particular location, x is the distance between that particular location and the offender's haven, C , D , and E are parameters to be estimated, and e is the base of the natural logarithm.

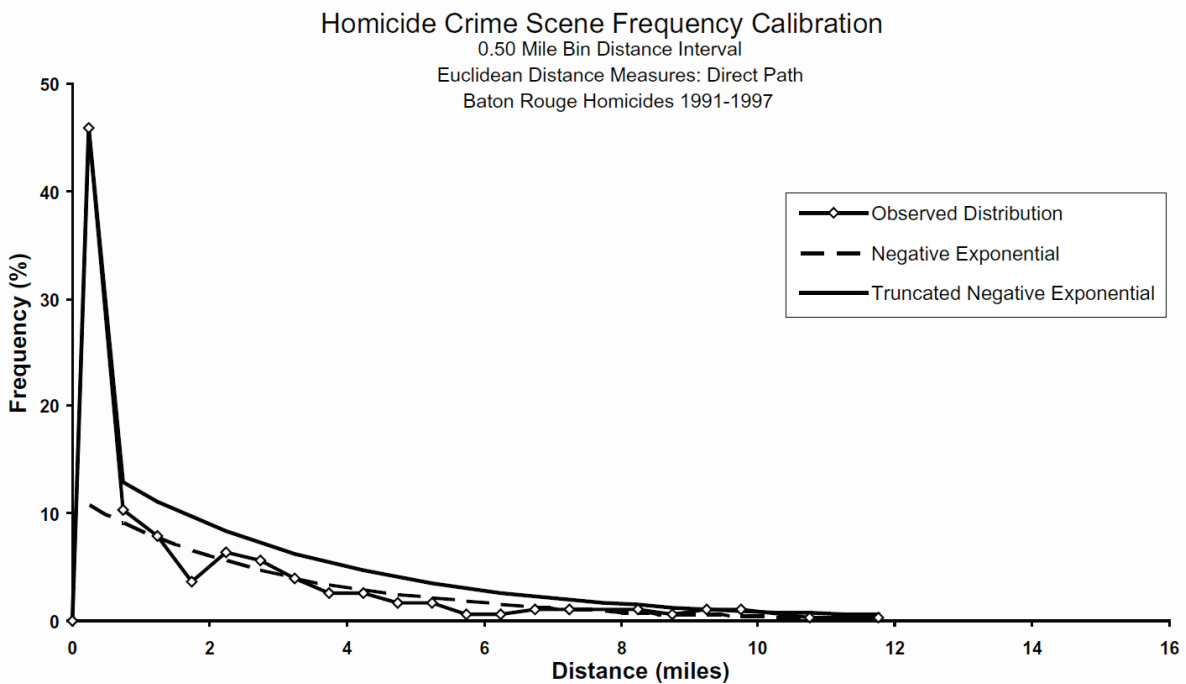


Figure 2.2: Calibrated distance decay functions by direct-path Euclidean metric.

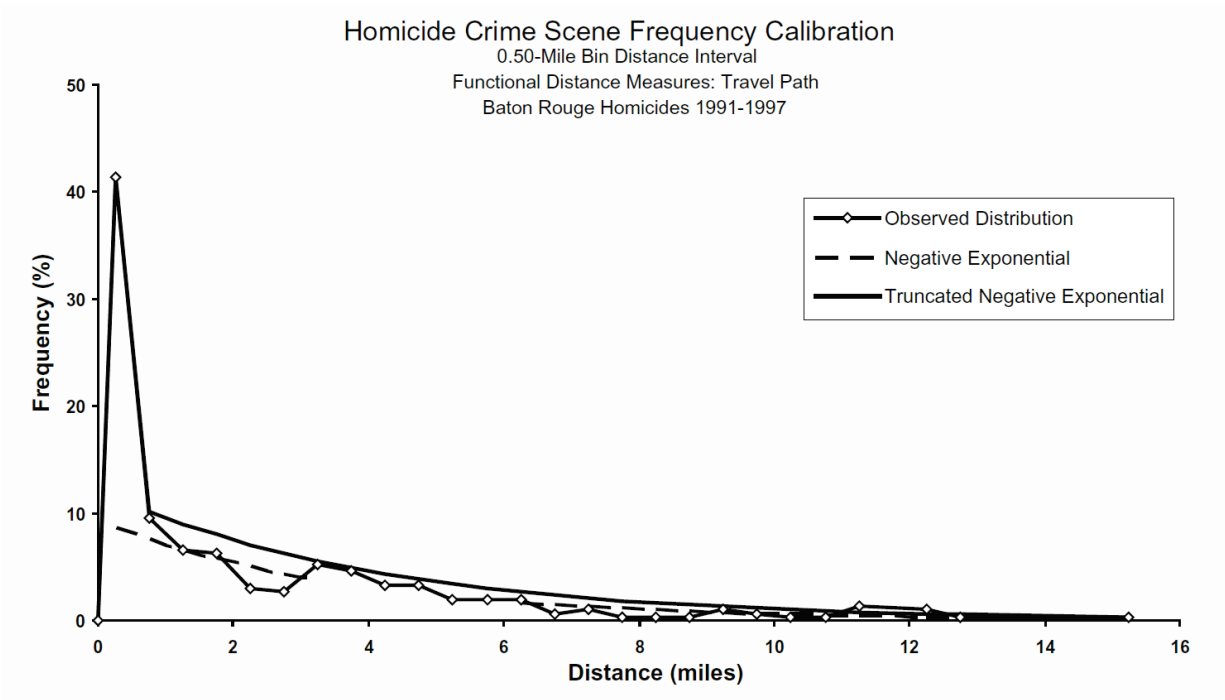


Figure 2.3: Calibrated distance decay functions by travel-path functional distance metric.

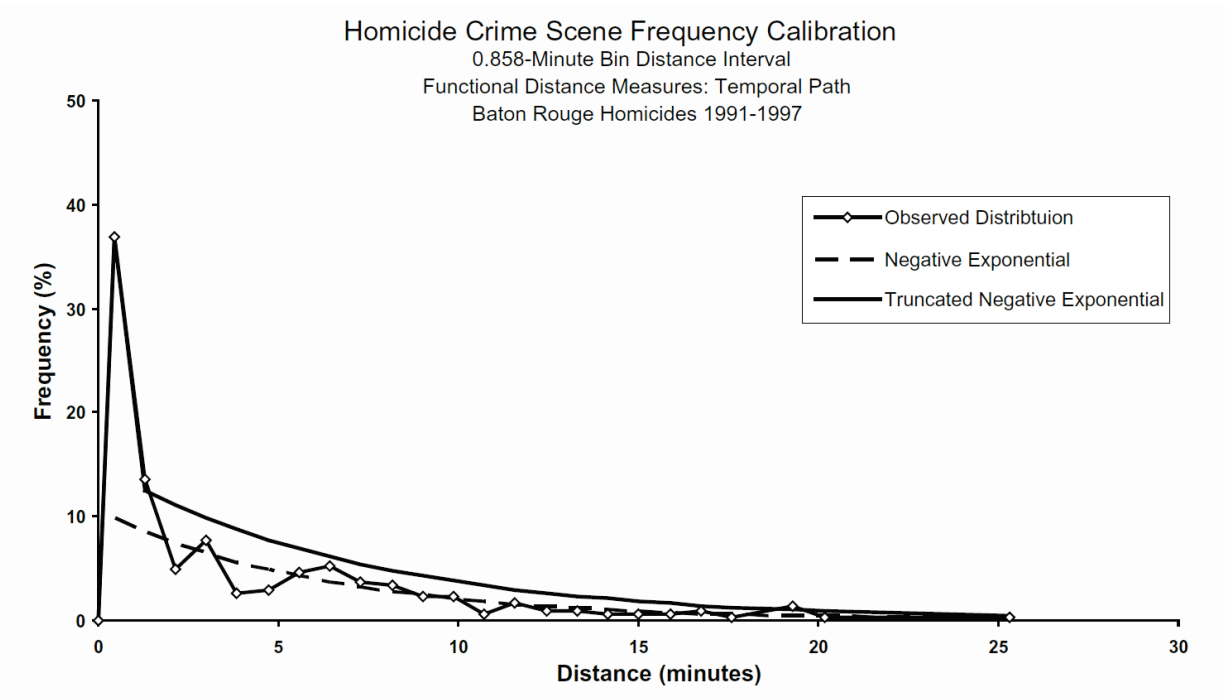


Figure 2.4: Calibrated distance decay functions by temporal-path functional distance metric.

Using SPSS[®] 11.0 for Windows (SPSS, 2001), both functions were individually regressed for each distribution, thus mathematically calibrated to produce a “best fit” model of the provided distributions. Models were organized according to the four distance metrics used for this investigation: direct-path Euclidean, indirect-path Manhattan, shortest travel-path, and shortest temporal-path. The results of all models are visually presented in Figures 2.2 – 2.4. Calibrations were not specifically required for the Manhattan metric as it measures distances as a function of Euclidean distances between two points. As such, the Manhattan metric uses the same calibration decay model as the straight-line Euclidean. Estimated parameters, standard errors, and coefficients of determination (R^2) for all calibrated distance decay functions, with the exception of the Manhattan distance, are summarized in Table 2.1.

The negative exponential model clearly under-estimates the significant spike at the beginning (the first one mile) of the frequency distribution for each distance metric, but provides a relatively good fit for the remainder of the distribution. In contrast, the truncated negative exponential model fits the spike in all distributions very well, but mostly over-estimates the distributions beyond a one-mile distance (Figs. 2.2 – 2.4). The truncated negative exponential model with distances measured as direct-path Euclidean provides the overall best statistical fit ($R^2 = 0.851$). The truncated negative exponential model combined with shortest travel-path distances performs the worst, but still captures 72% of the variations in the original frequency distribution. Independent of the calibration model, Euclidean distances provide the best statistical fit, followed by temporal-path and travel-path distances (Table 2.1).

2.8.3 Best Performing Geographic Profile

All geographic profiles consist of a density surface map measuring 75 columns x 57 rows completely enclosing all crime locations used in this research. Each individual cell covers an

Table 2.1: Parameter Estimates and Coefficient of Determination for Calibrated Distance Decay Models

Distance Metric	Calibration Model	Parameter Estimates (standard errors)					R^2
		<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>	
Direct-Path Euclidean	Negative Exponential	11.628 (2.624)	-0.327 (0.035)	-	-	-	0.819
Direct-Path Euclidean	Truncated Negative Exponential	-	-	183.388	15.975 (2.977)	-0.288 (0.028)	0.851
Travel-Path	Negative Exponential	9.244 (2.419)	-0.271 (0.034)	-	-	-	0.728
Travel-Path	Truncated Negative Exponential	-	-	165.563	12.217 (3.043)	-0.243 (0.032)	0.720
Temporal-Path	Negative Exponential	10.562 (2.297)	-0.163 (0.018)	-	-	-	0.797
Temporal-Path	Truncated Negative Exponential	-	-	85.961	14.905 (3.140)	-0.139 (0.016)	0.785

The parameter notations (A–E) refer to the same parameter notations used in Eqs. 2.1, 2.2a, and 2.2b. No standard error for the parameter of the linear part of the truncated negative exponential model was estimated, but directly calculated from the original frequency distribution of homicides. All R^2 values are highly significant at $p < 0.01$.

area of 0.49 miles² (0.7 x 0.7 miles) and is assigned a probability score indicating the likelihood that it is the residence of the serial killer, Gillis (Figure 2.5). The chosen cell size provides a balance between a large enough study area while ensuring consistent computer performance when estimating geographic profiles.

Assessing the predictive utility of a geographic profile is ultimately measured by an investigator's ability to prioritize an efficient search area from which to identify an individual's residence (Canter et al., 2000). As noted earlier, such a strategy can be developed by evaluating accuracy in two distinct ways: the error-distance and search-cost. Error-distance measures the straight-line distance between the centroid of the grid cell representing the predicted residence (peak likelihood) and the actual residence of the serial killer. Search cost is determined by

calculating each geoprofile's hit score percentage: the ratio of the total number of grid cells with a probability score equal to or higher than the hit score (the probability score assigned to the actual residence), to the total number of grid cells (Rossmo, 2000). A low hit score percentage indicates a more accurate geoprofile. Between the two methods, the hit score percentage is a better measure of a geoprofile's predictive utility because it identifies the amount of effort a criminal investigation would require to successfully identify the offender (i.e., the number of grid cells to search before apprehending the suspect).

Eight geographic profiles combining each distance metric with each distance decay model are shown in Table 2.2. Overall, geoprofiles created with the negative exponential distance decay function predict the residence of the serial killer more accurately. Of all distance metrics, indirect-path Manhattan distances performed slightly better than direct-path Euclidean. In contrast, geographic profiles created from the two functional distance metrics estimate the residence of the serial killer rather poorly. This is good news, because geographic profiles based on functional distance metrics, and especially shortest travel-path are time-consuming, computationally intensive, and costly to create. In contrast, geoprofiles created from Euclidean and Manhattan distance metrics are readily available in existing software packages.

The straight-line distance between the predicted and the actual residence (error distance) measured a very low distance of 0.49 miles for all eight geoprofiles. Of those, three geoprofiles are able to identify the actual residence of the serial killer with an averaged hit score of 0.05%, approximately 0.98 miles², of the 2,094.75 miles² study area. Relative to the size of this large study area, this is an extremely low hit score and a very small area to be searched (Table 2.2).

Figure 2.5 illustrates a density map for one of the three best performing geoprofiles, combining the Euclidean distance metric with the negative exponential distance decay function.

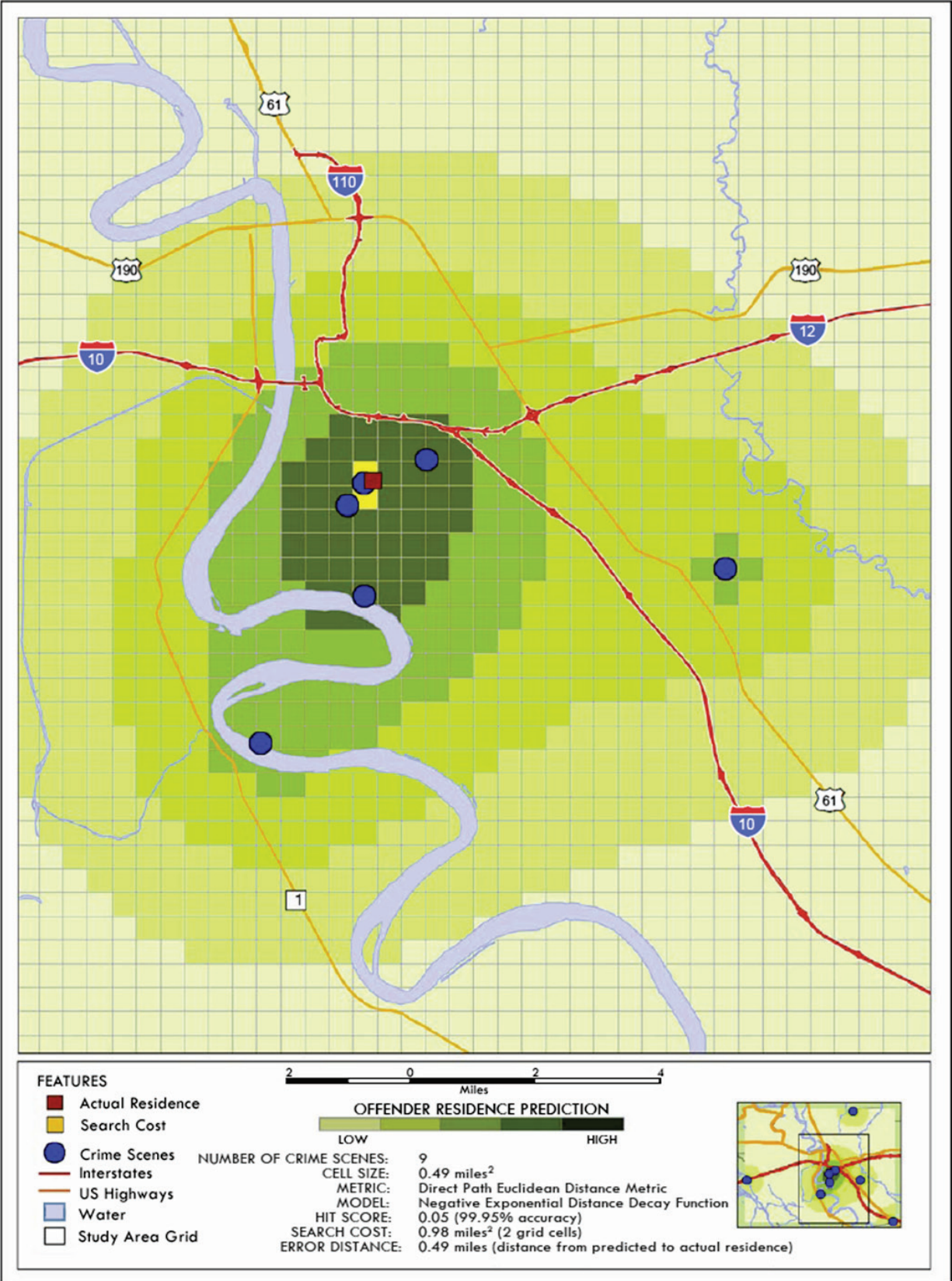


Figure 2.5: Best performing geographic profile overall.

Table 2.2: Geographic Profile Model Results

Distance Metric	Calibration Model	Hit Score (%)	Accuracy (%)	Grid Cell Count	Search Cost (miles²)	Error Distance (miles)
Direct-Path Euclidean	Negative Exponential	0.05	99.95	2	0.98	0.49
Direct-Path Euclidean	Truncated Negative Exponential	0.07	99.93	3	1.47	0.49
Indirect-path (Manhattan)	Negative Exponential	0.05	99.95	2	0.98	0.49
Indirect-path (Manhattan)	Truncated Negative Exponential	0.05	99.95	2	0.98	0.49
Travel-Path	Negative Exponential	0.19	99.81	8	9.32	0.49
Travel-Path	Truncated Negative Exponential	0.22	99.78	9	3.92	0.49
Temporal-Path	Negative Exponential	0.24	99.76	10	4.9	0.49
Temporal-Path	Truncated Negative Exponential	0.26	99.74	11	5.39	0.49

The main map shows a portion of the study area with six of the nine crime sites. The inset map in the lower right corner shows the entire study area including all nine crime sites. The actual residence of the serial killer clearly falls within the two grid cells with the highest probability scores. These two cells cover a mostly residential neighborhood in the southern part of the city of Baton Rouge with single-family houses, apartment complexes, retail stores, and some gas stations.

2.9 Discussion of Results

The geographic profiles created in this research predicted the actual residence of a Baton Rouge serial killer extremely accurately. The error distance for all geoprofiles was within 0.49 miles of the actual residence and the three best profiles estimated an averaged hit score of 0.05%,

defining a search area of 0.98 miles². These results strongly support the notion that geographic profiles should be created and used as often as possible when a criminal investigation involves a serial offender. The results also indicate that a geographic profile cannot identify the exact location of the residence of the serial offender. However, from a practical point of view, law enforcement can focus their limited resources and investigative strategies to the search area identified by a geographic profile.

In this research two different distance decay functions and four different distance metrics were evaluated for their usefulness to geographic profiling. The results reveal that the negative exponential function performs slightly better than the truncated negative exponential function. This might be explained by the lack of a buffer zone of little to no criminal activities around the offender's residences in the calibration data set. The selection of an appropriate distance decay function to model the spatial distribution of crime scenes from the calibration data is an important step in the creation of a geographic profile. Another important step is how the travel of the serial offender to and from the crime scene is measured. The results in this research clearly suggest that the best and most accurate geoprofiles are created when distances are measured as direct-path Euclidean or indirect-path Manhattan. When distances are measured using the shortest or the quickest route through a street network, the size of the search area becomes four to five times larger, when compared to distances measured with Euclidean or Manhattan metrics. All modern and contemporary geographic profiling models measure travel distances as straight-line (and some with Manhattan distances, as well) and the results in this research find it unnecessary to add functional distance measures into existing models. These findings support research by Canter (2003), which suggests that the actual travel path does not define the offender's awareness space. Rather, the offender's behavior is predicated on the individual's

mental map - the selective perception of physical features within the actual landscape. As such, the offender perceives the path between two points as a straight line.

Why shortest travel-path and quickest temporal-path performed so poorly is not clear. The results may be unique to the specific crime data and study area used or may reveal a general pattern in geographic profiling. To answer this question, the same research should be repeated with similar crime data in different study areas. There are many more research questions related to geographic profiling that are worthwhile to be pursued further. One example would be the development of a geographic profiling model for mobile serial offenders (Canter & Larkin, 1993). A second example would be to find out if the travel behavior of non-criminals differs significantly from the travel behavior of criminals (Kent, 2003). If there is no difference, then non-criminal travel behavior could be used to calibrate distance decay functions in geographic profiling models. Non-criminal travel behavior could be easily obtained from travel-diary and commuter surveys. A third example relates to the spatial choice decision making and the concept of competing destinations (Curtis, 1998; Curtis & Fotheringham, 1995; Fotheringham, 1986a; 1986b; 1988; Fotheringham & Curtis, 1999; Fotheringham & Trew, 1993) and how this concept could be implemented and evaluated for its usefulness in geographic profiling models.

Spatial choices are not made involving all potential geographic locations due to the overwhelming number of spatial alternatives; rather these locations are stored as hierarchical clusters with similarly defined elements (Fotheringham, 1981). The structure of this hierarchy will vary according to the amount of available spatial information, with individuals originating in more densely-packed environments having more evolved spatial surfaces (Gould, 1975), which in turn can result in a more strongly defined hierarchical decision tree containing larger clusters.

It is reasonable to believe that the serial killer is likely to process location according to accessibility and a range of attributes, and that due to the number of these spatial options a form of hierarchical processing is employed. If this is so, then it is important to include this hierarchical processing of choice in the model formulation as it has been shown that distance decay based models, in other words aspatial choice models, can be misspecified, producing spurious associations regarding the impediments of distance (Fotheringham, 1986c).

“Landscapes ‘work,’ that is, things flow rationally through them. The streams flow in accordance with laws. Routes connect such as to form a hierarchically organized network. Any occupant of the landscape moves in terms of this network; and the pattern that his movements create focuses on the places that are most important to him, usually home or work.”

-Milton B. Newton, Jr. (1988, p. 9)

CHAPTER 3: EFFICACY OF STANDARD DEVIATIONAL ELLIPSES IN THE APPLICATION OF CRIMINAL GEOGRAPHIC PROFILING*

3.1 Introduction

The primary objective of a criminal geographic profile is to analyze the distribution and pattern of linked crime scenes in order to estimate the likely residence of a serial offender. However, developing a meaningful profile is seldom achieved easily. Crime scenes are typically distributed in seemingly random patterns, making it difficult to identify trends and characteristics that implicate a single perpetrator (Brantingham & Brantingham, 1981; Canter & Larkin, 1993; Canter & Gregory, 1994; Rossmo, 2000). Yet, research consistently demonstrates that crime scenes are not located randomly (Brantingham & Brantingham, 1981; Canter & Gregory, 1994; Rossmo, 2000; Rengert et al., 1999; Kocsis & Irwin, 1997; Kocsis et al., 2002; Harries, 2006). Rather, they occur at the confluence of offender, target, and opportunity (Brantingham & Brantingham, 1981; Cohen & Felson, 1979). As a result, these locations represent a partial record of the offender’s spatial preferences that are, to some extent, determined by the immediate landscape, or *target backcloth* (Brantingham & Brantingham, 1981; Rossmo, 2000; Capone & Nichols, 1976). And whilst many contemporary techniques recognize the importance of the landscape, very few models are able to accommodate its effect (Snook, Canter, & Bennell, 2002;

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Snook et al., 2004; Canter, 2005). Therefore, this study proposes that geographic profiling models that are capable of parameterizing the effects of the landscape will more accurately predict the location of a serial offender's residence.

3.2 Principles of Environmental Criminology

Much of the theoretical bases for geographic profiling can be traced back to fundamental tenets of environmental criminology, including: *Least Effort Principle* (Cornish & Clarke, 1986; Zipf, 1949), *offender activity space* (Brantingham & Brantingham, 1981), *routine activity* theory (Cohen & Felson, 1979), *crime pattern* theory (Brantingham & Brantingham, 1981), *rational choice* theory (Cornish & Clarke, 1986), *distance decay* (Capone & Nichols, 1976), *environmental range* (Canter & Larkin, 1993), and *buffer zone* effect (Brantingham & Brantingham, 1981). In general, these theories can be summarized into three basic concepts. First, most crimes occur relatively near the offender's residence. Second, the frequency of crime decreases as the distance from the offender's home increases. Finally, different crimes will exhibit different spatial patterns.

As a whole, these concepts establish a qualitative framework for examining the complex relationship between the offender, the crime, the victim, and the environment. But as Brantingham & Brantingham (1981) cautioned, it is impractical to examine this relationship outside the context of *place*. Accordingly, nearly all contemporary profiling methodologies apply quantitative models that utilize, at their core, fundamental geographical principles. Two of the most prominent principles are *centrography* and *spatial diffusion* (Canter & Larkin, 1993; Rossmo, 2000; Snook et al., 2004; Snook, et al., 2005; LeBeau, 1987a; Rich & Shively, 2004; Paulsen, 2006b). A summary of these techniques and their application to geographic profiling are provided in Table 3.1.

Table 3.1: Predominant Spatial Measure used in Criminal Geographic Profiling

Measure	Model	Strategy	Model Input	Model Output
Central Tendency	Spatial Mean, Median, and Center of Minimum Distance	Spatial Distribution Strategy	Points	Point
Spatial Dispersion	Circular Search Area Elliptical Search Area	Spatial Distribution Strategy	Points	Points and Polygons
Spatial Diffusion	Distance Decay Algorithms	Probability Distance Strategy	Points	Probability Surfaces

3.3 Applications of Centrography

Centrographic techniques characterize phenomena by providing a single measure of central tendency (i.e., an average location) (LeBeau, 1987a). This approach constitutes a spatial distribution strategy (Levine, 2007). When applied to geographic profiles, these measures summarize a distribution of crime scenes to a single location where the sum of differences between the mean and all other points within the distribution is minimized (Ebdon, 1988). The strategy is premised on the assumption that the serial offender will commit crimes within a finite area that is relatively close to their home. This area defines the offender’s activity space (Brantingham & Brantingham, 1981). Thus, by defining the center of a crime’s distribution, one effectively reveals some portion of the offender’s activity space.

The most common measures of central tendency include the geographic mean, median, and center of minimum distance. But analyzing distributions using this approach can be limited, as they are only capable of characterizing complex processes with a single descriptive measure (Rossmo, 2000; Levine, 2007). As such, centrographic analysis is often augmented by measures of dispersion, including *circles*, *ellipses*, and *convex hulls*. One such example has been documented in the application of the *circle hypothesis*, which demonstrates that a circle large

enough to encompass the two farthest crimes of a distribution will most likely encompass the serial offender's residence (Canter & Larkin, 1993). Another example includes Newton's geoforensic analysis, which iteratively analyzes the sequence of crime scenes in order to define the likely activity space of a serial offender based on the dispersion of the crimes around a central point (Newton, 1988). The combination of central tendency and spatial dispersion has proven to be simple but effective profiling strategies (Snook et al., 2002; Snook, et al., 2005; Paulsen, 2006b; Levine, 2007; Leitner, et al., 2007). Because of their relative simplicity and intuitive workflow, these techniques have provided valuable insight for criminal investigations. However, centographic techniques are often susceptible to outliers that potentially distort their effectiveness. And on their own, these simple measures are seldom able to reflect the inherent complexities of either the landscape or an offender's perception of place (Canter & Hodge, 2000).

3.4 Applications of Spatial Diffusion

Geographical profiling will also utilize models that apply concepts typically utilized in spatial interaction models. The most common approach is to profile a distribution of crime scenes using empirically calibrated *distance decay* algorithms. These center-of-gravity techniques constitute *probability distance* strategies which measure the likelihood of finding an offender's residence in the areas immediately surrounding linked crime scenes (Levine, 2007). The strength of this approach lies in its ability to model the condition in which the frequency of crime decreases as the distance from the offender's residence increases (Capone & Nichols, 1976). Not surprisingly, distance decay models have found popular support in nearly all geographic profiling applications (Rich & Shively, 2004). The most well-known of these applications include Dagnet (Canter, et al., 2000), Rigel™ CGT (Rossmo, 2000), and the

Journey-to-Crime routine provided in CrimeStat[®] III (Levine, 2007). But in spite of their popularity, distance decay methodologies have been criticized for their reliance on homogeneous spatial structures that can distort nuanced, but significant, characteristics associated with the criminal commute (Rengert et al., 1999; van Koppen & De Keijser, 1997). And like centrophagic techniques, these techniques presume an ideal framework in which the patterns of crime scenes are normally distributed.

3.5 Landscape's Impact on the Occurrence of Crime

With few exceptions (Capone & Nichols, 1976; Kent et al., 2006; LeBeau, 1987a; Rengert et al., 1999), the majority of contemporary geographic profiling techniques have failed to account for the landscape's impact on the occurrence of crime. Instead, contemporary methods consistently adopt an *a priori* assumption that both crime scenes and the offender residence are located on an isotropic surface where the opportunity to offend is uniformly distributed around the offender's residence. But as established by Brantingham and Brantingham (1981), and later by Rengert et al. (1999), the location of a crime involves complex factors that make it unlikely to occur randomly. In a study on the environmental range of serial rapists, Canter & Larkin (1993), and later Kocsis et al. (2002) empirically demonstrated that the location of a serial offender's residence is not generally positioned within the center of a distribution. Rather, the relationship between the crime scenes and the offender's residence suggest an irregularly distributed activity space that is, in some measure, influenced by the landscape and offender perceptions (Brantingham & Brantingham, 1981; Canter & Hodge, 2000). In effect, these findings validate the premise that crime scenes and offender residences are actually located on anisotropic surfaces. And just as a crime's location is a partial record of the offender's spatial preferences, so too is it a reflection of the irregularities consistent within

the underlying physical and cultural landscapes. Such irregularities are typically characterized according to three geographic analysis measures: *location*, *dispersion*, and *orientation* (Yuill, 1971).

Newton's (1988) circle-based geoforensic analysis technique is a practical method for measuring these characteristics. First, the model output predicts a location of an offender's residence (what Newton called the '*haven*') according to the geographic center of the crime distribution. Second, a circle with a diameter defined according to the number and spatial extent of known crime scenes is generated. This output represents a search area in which the offender's residence is expected. Finally, the technique iteratively refines the output as each new crime scene is added to the model, thus accounting for changes to the distribution's location and size over time. However, there are limits to the technique's ability to model a serial distribution. Because the technique utilizes a circle-based strategy by default, the circular output presumes an isotropic surface. As such, it is ill-suited to measure variations in the shape and orientation of the distribution in relation to the anisotropic landscape.

As an alternative to the circle, the standard deviational ellipse model is better able to account for irregularities in the landscape. Like the circle, the ellipse is capable of identifying the center of a distribution (i.e., location), as well as its spatial extents (i.e., dispersion). But unlike the circle, an ellipse measures the shape and orientation of the distribution by summarizing the maximum and minimum variance along the x- and y- axes (Ebdon, 1988). As a result, the ellipse is able to account for a non-uniform arrangement of events (Lefever, 1926; Levine, 2007). These differences are illustrated in Figure 3.1, which depicts circular and elliptical profiles generated for a theoretical distribution of crime events. With both profiles positioned over the geographic center of a distribution, the elliptical model is better able to match

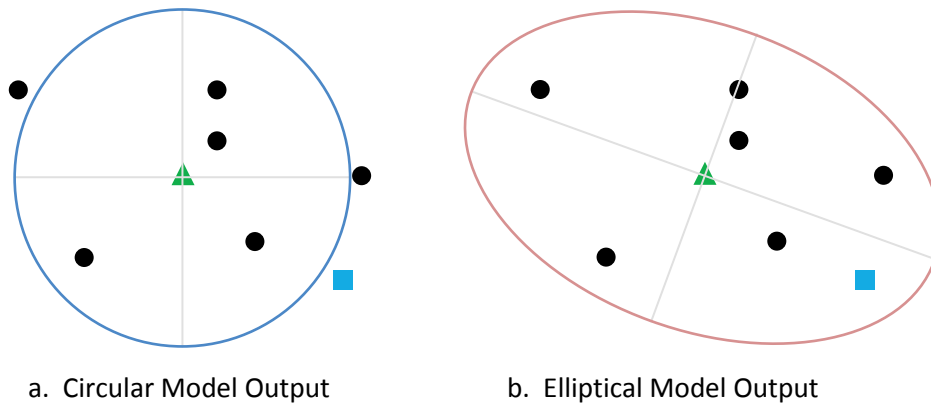


Figure 3.1: Example of circular (a) and elliptical (b) model output generated by Newton’s geoforensic analysis. Each model is positioned over the geographic center (triangle) of a theoretical distribution of crimes. The offender’s residence (square) is captured by the elliptical model, but not the circle.

both the orientation and variation in the dispersion. While overly simplistic, the graphic in Figure 3.1 effectively demonstrates that an ellipse is better able to account for the irregular distribution of events than the circular model.

3.6 Hypothesis

This research proposes that the spatial relationship between the locations of an offender’s residence and linked crime sites will exhibit spatial patterns and characteristics that are consistent with the underlying landscape. Accordingly, a geographic profiling model that is capable of measuring the *location*, *dispersion*, and *orientation* of crime scenes should predict the residential location of a serial offender more accurately than circle models that only emphasize the location and width of the action space. Furthermore, because the landscape has a deterministic effect on the distribution of serial crime, the orientation of elliptical profiles should correlate with the orientation of landscape features that are coincident with the spatial extents of the crime scenes. These measures can be achieved using a standard deviational ellipse model

similar to that proposed by Lefever (1926), and later modified by Yuill (1971), Ebdon (1988), and Levine (2007). As such, the hypotheses for this research can be summarized accordingly:

1. Geoforensic profiling models using the standard deviational ellipse will produce more accurate profiles than those created using circles.
2. The orientation of an elliptical profile will correlate with the orientation of the corresponding physical landscape.

In order to test these hypotheses, Newton's geoforensic analysis was used to calculate both circular and elliptical profiles for 30 burglary and 67 robbery serial offenses occurring in Baltimore, Maryland, between 1993 and 1997. The output from both profile models were assessed according to their profile accuracy, proximity to the offender's residence, and size of the search area. Next, the angular direction of each ellipse was calculated and compared to the linear directional mean of the underlying road network in order to determine if the orientation of the ellipses matches the orientation of the coincident physical landscape.

These hypotheses are established on a number of assumptions. First, each crime series consists of offenses that have been perpetrated by a single individual. Second, a profile's effectiveness assumes that the offenders initiate and conclude all criminal activities from a fixed location (i.e., their residence). The third assumption posits that an offender's spatial behavior can be organized according to one of two offense characteristics: offend inside a defined activity space (i.e., marauder model), or outside a defined activity space (i.e., commuter model) (Canter & Larkin, 1993). The fourth assumption posits that pattern and distribution of the crime types (i.e., burglary and robbery) do not differ significantly, and thus their profile results can be compared equally. Finally, in order to support the hypothesis that the orientation of the crime

scenes correlates with the underlying landscape, it is assumed that both crime sites and offender's residence are positioned in locations accessible by existing transportation networks.

3.7 Methodology and Data

3.7.1 Evaluation Criteria

Contemporary literature details a number of different evaluation methodologies that can gauge profile accuracy (Canter et al., 2000; Canter Canter & Gregory, 1994; & Larkin, 1993; Rossmo, 2000; Snook et al., 2005; Paulsen, 2006b). However, there is currently no one standard for measuring performance (Rich & Shively, 2004). As a consequence, many of these measures have been at the center of contention within existing literature (Canter, 2005; Rossmo, 2005a; Snook, Taylor, & Bennell, 2004). In a report issued to the National Institute of Justice (NIJ), authors Rich and Shively (2004) detailed a collection of geographic profiling evaluation criteria recommended by an expert-panel of criminologists and researchers. Based on their applicability to this study, three of the performance measures listed in the NIJ report were chosen to compare the efficacy of circular and elliptical model output:

- **Profile accuracy:** Binary value (true/false) that indicates whether or not the offender's residence was located within the predicted search area.
- **Profile error distance:** The Euclidean distance measured from the actual residence to the nearest point on the profile's final predicted search area (i.e., top profile).
- **Profile search area score:** The ratio of the predicted profile search area to the required profile search area (i.e., search cost).

3.7.2 Data

The data used in this analysis were selected from a database of 267 solved serial crimes that occurred in Baltimore County, MD, between 1994 and 1997. The sample chosen for this

research consisted of 30 burglary ($n=164$) and 67 robbery ($n=370$) crime series. An average of 5.51 (min=4, max=12, SD=2.07) crimes per series was identified for all 97 offenders. Table 3.2 provides additional statistics regarding the sample data. In order to accommodate a fair and comparative evaluation, the data selected for this analysis followed the recommendations provided in the 2004 NIJ geographic profiling report (Rich & Shively, 2004):

- Crime series should be comprised of at least 3 offenses.
- Data should include both marauder and commuter offender types.
- Crime series should include a variety of offender traits (i.e., sex, age, race, *etc.*).
- Data should resemble information actually available to law enforcement agencies.

Additionally, those crime series exhibiting a residential location that was spatially coincident with 50% or more of the crime scenes were removed from the sample. The occurrence of multiple, coincident events resulted in mathematical singularities that made it difficult to analyze a model's output.

3.7.3 Assumptions

In order to meet the assumptions and evaluation criteria adopted by this research, each crime series was categorized according to its corresponding offender model. This process was carried out in two steps. First, the offender model was determined according to parameters defined by Canter & Larkin (1993). Because the sample data consists of more robberies (67) than burglaries (30), the spatial patterns (i.e., measured distances between points) observed for burglary and robbery crime types were assessed statistically to determine if their distributions could be analyzed together or separately.

Research indicates that spatial patterns observed within a crime series will exhibit distinct characteristics which can be organized according to offender type (Canter & Larkin, 1993;

Table 3.2: Crime Series Descriptions - Totals

Crime Type & Offender Model	Number of Crimes	Number of Series	Average Crimes per Series	Average Distance Between Crimes	Average Max. Distance Between Crimes	Average Max. Distance From Residence	Average Criminal Offense Area
Burglary	164	30	5.47 (SD=2.13)	7.056 km (SD=11.047)	10.246 km (SD=9.634)	11.365 km (SD=12.993)	27.723 km ² (SD=45.285)
Robbery	370	67	5.52 (SD=2.06)	7.522 km (SD=6.162)	10.198 km (SD=7.852)	10.893 km (SD=7.429)	30.789 km ² (SD=52.544)
Commuters	229	45	5.09 (SD=1.53)	9.213 km (SD=10.442)	7.782 km (SD=7.547)	12.415 km (SD=11.767)	19.459 km ² (SD=34.633)
Marauders	305	52	5.87 (SD=2.40)	5.791 km (SD=4.360)	12.317 km (SD=8.584)	9.847 km (SD=6.699)	38.825 km ² (SD=59.418)
Totals	534	97	5.51 (SD=2.07)	7.378 km (SD=7.938)	10.213 km (SD=8.392)	11.039 km (SD=9.433)	29.841 km ² (SD=50.196)

Kocsis & Irwin, 1997; Kocsis et al., 2002; Meaney, 2004). These types are traditionally categorized as either commuter or marauder offender models. These categories were coined by Canter & Larkin (1993) to describe competing spatial characteristics observed for serial rapists. By definition, the marauder model describes an offender who typically commits crimes within a defined range from a home base of operations (i.e., offends inside a defined activity space). Conversely, the commuter model is characterized as an offender who travels away from a home base to commit crimes in another area (i.e., offends outside a defined activity space). Traditionally, the method for distinguishing an offender's spatial preference is accomplished according to the "Circle Hypothesis" procedure detailed by Canter & Larkin (1993). For the purposes of this research, their approach was mathematically automated by calculating the ratio of the maximum distance between crime scenes and offender residence to the maximum distance between the two farthest crime scenes (Canter & Larkin, 1993):

$$\textit{Offender Model} = \frac{d_{cr}}{d_{cc}} \quad (3.1)$$

where d_{cr} is the distance from the farthest crime to the offender's residence, and d_{cc} is the maximum distance between crimes. The offender was categorized as a marauder if the ratio was less than 1.0, or a commuter if the ratio was equal or greater than 1.0.

Next, the spatial patterns of serial burglary and robbery were analyzed in order to assess the relationships between crime type (i.e., burglary and robbery). Because the distributions were right-skewed, the Mann-Whitney U -test, a non-parametric equivalent to Student's two independent sample t -test, was used to determine if burglary and robbery serial crimes could be analyzed equally. In support for the fourth assumption of this research, the Mann-Whitney U -

test failed to demonstrate a difference between the burglary and robbery distributions [$U=863$, $Z=-1.668$, $p = 0.095$ (2-tailed)], concluding that average distance between these crime types is not significantly different. As such, burglary and robbery distributions were combined and analyzed according to the offender model.

3.7.4 Profiling Models

Geoforensic analysis is arguably one of the first geographical profiling techniques operationalized for use in a serial crime investigation (Leitner, et al., 2007). Developed in the late 1980s by Milton B. Newton, Jr., the model calculates both the location and dispersion of linked crime scenes committed by a localized (i.e., marauding) serial offender (Newton, 1988). The approach was developed on the premise that an area surrounding the geographic center of a crime distribution (i.e., the offender's activity space) may contain a marauding offender's residence, or *haven*. Furthermore, Newton proposed that the predicted location of the offender's haven will move closer to the actual haven after each successive crime event (Leitner, et al., 2007; Newton, 1988; Newton & Swoope, 1987). To provide a search parameter for this effect, the algorithm generates a circular search area with a radius defined by the extent of the two farthest crime scenes in the sequence. As each new crime scene is added, the size of the search area is reduced (equation 3.3).

Accordingly, Newton's geoforensic analysis is implemented in three steps (Newton, 1988):

1. A quadrilateral study area is defined by the distance between the farthest east-west and north-south extents of the known, linked crime sites.
2. Coordinates for the geographic center of the crime distribution is calculated iteratively in sequential order. Each spatial mean represents the predicted location of the haven for the number of crimes observed in the given sequence:

$$\bar{X} = \sum_{i=1}^n \frac{x_i}{n} \text{ and } \bar{Y} = \sum_{i=1}^n \frac{y_i}{n} \quad (3.2)$$

where n is the number of incidents for the i th crime, and the spatial mean (\bar{X}, \bar{Y}) is calculated for all x_i and y_i values in the sequence.

3. A circular search area of varying size, centered on the predicted haven, is calculated using the radius, R , defined by:

$$R = \sqrt{\frac{rx \cdot ry}{\pi}} \quad (3.3)$$

where rx is the range along the x-axis and ry is the range along the y-axis; and n is the number of incidents in the sequence.

After the second offense, a map is created to illustrate an area in which a serial offender's residence is likely located. This search area is centered over the calculated geographic center of the offender's likely activity space. As each new crime scene is added to the routine, the geographic center is recalculated, and the search area is adjusted (i.e., repositioned and resized). Accordingly, each crime series will have multiple search areas that are successively refined as each crime scene is processed. The final search area is typically referred to as the *top profile*.

Geoforensic profiles based on the standard deviational ellipse can be generated in a similar fashion. An elliptical search area of varying size centered over a distribution's geographic center is sequentially determined according to the variance calculated along major and minor axes. The ellipse's major and minor axes are determined by measuring the distribution's standard deviations along the x- and y-axis such that they are orthogonal to each other (Ebdon, 1988; Levine, 2007; Yuill, 1971).

The standard deviational ellipse model for Newton's geoforensic analysis is generated in four steps (Ebdon, 1988; Levine, 2007):

1. Transpose the coordinate system by moving the origin of the ellipse to the geographic center of the distribution:

$$\acute{x} = (x - \bar{x}) \quad \text{and} \quad \acute{y} = (y - \bar{y}) \quad (3.4)$$

where the mean, \bar{x} and \bar{y} , is subtracted from each of the original x and y coordinates to give the transposed coordinates denoted by \acute{x} and \acute{y} .

2. Determine the angle of rotation along the x - and y - axis so that the sum of squared differences is minimized:

$$\theta = ARCTAN \left\{ \frac{(\sum \acute{x}^2 - \sum \acute{y}^2) + \sqrt{(\sum \acute{x}^2 - \sum \acute{y}^2)^2 + 4(\sum \acute{x} \acute{y})^2}}{2(\sum \acute{x} \acute{y})} \right\} \quad (3.5)$$

where θ is the angle of rotation observed in the distribution, and \acute{x} and \acute{y} are the transposed x and y coordinates.

3. Calculate the standard deviations along the transposed axes (Ebdon, 1988; Levine, 2007):

$$S_x = \sqrt{2 \cdot \frac{\text{Cos}^2 \theta \sum \acute{x}^2 - 2(\text{Sin} \theta \text{Cos} \theta \sum \acute{x} \acute{y}) + \text{Sin}^2 \theta \sum \acute{y}^2}{n - 2}} \quad (3.6)$$

$$S_y = \sqrt{2 \cdot \frac{\text{Sin}^2 \theta \sum \acute{x}^2 + 2(\text{Sin} \theta \text{Cos} \theta \sum \acute{x} \acute{y}) + \text{Cos}^2 \theta \sum \acute{y}^2}{n - 2}} \quad (3.7)$$

where S_x and S_y are the standard deviations parallel to the x - and y - axis of the ellipse, θ is the angle of rotation, \acute{x} and \acute{y} are the transposed x and y coordinates, and n is the number points in the given sequence.

Levine (2007) notes that the standard deviations on both axes should be estimated using two (2) degrees of freedom in order to produce an unbiased estimator of the two parameters (\bar{x} and \bar{y}). Additionally, Levine (2007) proposes that the variance should be multiplied by 2 in order to compensate for the under-estimations in X and Y (see equations 3.6 and 3.7). These notes are explained more fully in the CrimeStat[®] III documentation (Levine, 2007).

4. Finally, the elliptical search area is reduced in accordance with Newton's hypothesis:

$$\hat{S}_x = \frac{S_x}{n-1} \text{ and } \hat{S}_y = \frac{S_y}{n-1} \quad (3.8)$$

where \hat{S}_x and \hat{S}_y represent the final standard deviations on the major and minor axes, respectively, and where n is the number of incidents in the sequence. Finally, the area of an ellipse is measured as $\hat{S}_x \hat{S}_y \pi$.

Similar to the output generated using circular models, elliptical profiles will contain multiple (n-2) search areas defining the space in which the serial offender's residence is predicted.

Both the circular and elliptical models were developed separately as Python geoprocessing scripts used in ESRI[®] ArcGIS[™] 9.2 environment, and imported as custom tools within the ArcGIS[™] Desktop toolbox (ESRI, 2006). The dialog box for the circle-based Geoforensic algorithm prompts the user for three values: (1) input feature class (points), (2) output search area (polygon), and (3) optional output for the profile's geographic centers (points). The elliptical Geoforensic algorithm provides a dialog box that prompts the user for the following three fields: (1) input feature class (points), (2) output search area (polygon), and (3) drop-down menu for selecting the optional standard deviations.

3.7.5 Evaluation Procedure

The comparative evaluation of the circular and elliptical profiles was executed in three stages. First, crime scenes and offender residences were organized according to offender model (i.e., commuter and marauder) and mapped using ESRI's ArcGIS™ geographic information systems (GIS) software. All measurements were calculated in meters according to the Universal Transverse Mercator (UTM) coordinate system, Zone 18 North, 1983 North American Datum (NAD83). Next, Newton's geoforensic analysis tool was applied to each crime series in order to generate profiles using circular and elliptical models. Finally, profile effectiveness was calculated according to the measured differences between the profile output and the offender's actual residence. Because these differences were not normally distributed, results were tested for significance using the Wilcoxon signed-rank *Z*-test; a non-parametric alternative to the Student's paired *t*-test.

The relationship between the orientations of the elliptical profile and the corresponding landscape was calculated using the *Linear Directional Mean* tool found in the ArcGIS™ software package. The tool calculated the mean direction of all road features that were coincident with the area defined by the spatial extents of a crime series. The directional angle was measured clockwise from 0° north. Angles greater than 180° were normalized by subtracting 180 from the observed value, resulting in a simple orientation. Finally, the correlation between the orientation of elliptical profiles and orientation of the corresponding road network was calculated using Pearson's product-moment correlation routine.

3.8 Results and Discussion

3.8.1 Geoforensic Analysis Results

Summarized profiled results for each of the test criteria are presented in Table 3.3. There is an important distinction to be made between geoforensic analysis and other circle-based techniques in that the generated profiles are iteratively refined over the sequence of analyzed crime scenes. That is, the size and location of the search area varies according to the spatial extent and number of the crimes analyzed. As such, Newton's method generates three distinct output characteristics (Newton, 1988; Leitner et al., 2007): first, the predicted residence will move closer to the actual residence; second, the search area will vary (e.g., shrink) with the inclusion of each additional crime scene; and finally, the actual residence will fall within the predicted search area (i.e., profile accuracy).

The results obtained for this research closely matched those detailed by Leitner et al. (2007). That is, the assumed movements and varying size of the profiled search area were observed for both circular and elliptical models. And consistent with their previous findings (Leitner et al., 2007), the third assumption regarding profile accuracy was marginally successful for circular search areas. However, profile accuracy increased substantially for elliptical models. In fact, elliptical models exhibited a quantifiable improvement over circular outputs for each of the three evaluation criteria: profile accuracy, error distance, and search area score (Table 3.3).

Profile accuracy: A profile was considered accurate when the location of the offender's actual residence was topologically coincident with a profile's predicted search area.

As detailed in Table 3.3, circular geoforensic profiles were accurate for 3 of 97 (3.09%) crime series. Not surprisingly, these three successes were captured for marauding offenders, whose patterns of criminal activity occur within a distinct area surrounding a fixed base of

Table 3.3: Geoforensic Profiling Summary Results

Profile Model	Commuter Profile Accuracy	Marauder Profile Accuracy	Mean Commuter Profile Error Distance	Mean Marauder Profile Error Distance	Mean Commuter Search Area Score	Mean Marauder Search Area Score
Circle	0 (0.00%)	3 (3.09%)	7.773 km (SD=9.401)	2.854 km (SD=3.180)	0.055	0.222
Ellipse 1 SD	1 (1.03%)	2 (2.06%)	7.341 km (SD=9.544)	2.399 km (SD=2.717)	0.131	0.229
Ellipse 2 SD	7 (7.23%)	16 (16.49%)	6.229 km (SD=8.792)	1.522 km (SD=2.322)	0.278	0.522
Ellipse 3 SD	10 (10.31%)	27 (23.84%)	5.354 km (SD=8.011)	1.075 km (SD=1.929)	0.397	0.681

operation (Canter & Larkin, 1993). Elliptical models at 1 standard deviation (SD) performed equally well, accurately predicting one commuter and two marauders. As the number of standard deviations increased, so too did the performance. Overall, elliptical profiles were more accurate than circles when constructed with 2 SD and 3 SD, accurately profiling 23 (23.7%) and 37 (38.1%) residences, respectively.

The performance observed for elliptical models is noteworthy. In their study of serial crimes occurring in London, UK, Leitner et al. (2007) were able to predict 19.3% (n=57) of serial offender residences in any of the multiple search areas derived by Newton's method. Of those predictions, only one model (1.75%) predicted the offender's residence in the final search area. With a maximum of 37 residences predicted accurately, the elliptical model shows a clear improvement in the technique's ability to predict an offender's haven. Moreover, approximately one-third of the successful elliptical profiles were commuter offenders. A likely explanation for this observation is that both the elongation and orientation of the elliptical models match the shape and direction of the commuter's crime scene patterns more accurately.

Profile error distance: Profile error distances were measured according to the Euclidean distance from the offender's residence to the nearest edge of a profile's final predicted search area (i.e., top profile). Shorter distances indicate better results.

The combined measures for commuter and marauder offender models revealed that error distances were generally shorter for elliptical profiles than for the circular profiles (Table 3.3). And as expected, marauding offenders demonstrated shortest profile error distances across all profiles. Ellipses constructed using 1 SD exhibited modest improvement over circular profiles. However, the shorter error distances were more significant for profiles constructed using 2 and 3

SD (Table 3.4). This is primarily attributed to the fact that the increased number of standard deviations made the ellipses larger than the default (1 SD) elliptical model.

Table 3.4: Profile Error Distance - Wilcoxon Signed-Ranks Test Statistics

	Circle and Ellipse (1 SD)	Circle and Ellipse (2 SD)	Circle and Ellipse (3 SD)
Combined Results: <i>Z</i>	-3.950	-7.559	-8.124
Asymp. Sig. (2-tailed)	0.000	0.000	0.000
Commuter Results: <i>Z</i>	-3.414	-5.841	-5.841
Asymp. Sig. (2-tailed)	0.001	0.000	0.000
Marauder Results: <i>Z</i>	-2.287	-4.859	-5.645
Asymp. Sig. (2-tailed)	0.022	0.000	0.000

Profile search area score: The profile search area score indicates how much of the required search area was predicted by the model. The score was measured as the ratio of the predicted search area (i.e., modeled output) to the required search area (i.e., theoretical search area needed to encompass the offender’s residence). To calculate the required search area, the top profile output was scaled until its outer-edge intersected the offender’s residence. The resulting ratio provided a relative measure of search cost where higher scores values indicate more accurate profile output.

Elliptical models once again outperformed the circle model (see Table 3.3). However, the difference between the circular and elliptical profile generated at 1 SD was not found to be significantly different according to the Wilcoxon signed rank test [$Z = -1.813, p < 0.07$ (2-tailed)] (Table 3.5). The reason becomes clear when examined according to offender model: At 1 SD, circular and elliptical marauding profiles results are nearly identical [$Z = -0.230, p = 0.822$ (2-tailed)]. Conversely, elliptical profiles constructed using 2 SD and 3 SD were significantly different from circles [2SD: $Z = -7.442, p < 0.00$ (2-tailed); 3SD: $Z = -8.117, p < 0.00$ (2-tailed)].

Table 3.5: Profile Search Area Score - Wilcoxon Signed-Ranks Test Statistics

	Circle and Ellipse (1 SD)	Circle and Ellipse (2 SD)	Circle and Ellipse (3 SD)
Combined Results: <i>Z</i>	-1.813	-7.442	-8.117
Asymp. Sig. (2-tailed)	0.07	0.000	0.000
Commuter Results: <i>Z</i>	-2.69	-5.488	-5.712
Asymp. Sig. (2-tailed)	0.007	0.000	0.000
Marauder Results: <i>Z</i>	-0.230	-5.342	-5.874
Asymp. Sig. (2-tailed)	0.822	0.000	0.000

The success of elliptical models can be attributed to the large search areas defined by the 2- and 3- standard deviations. While these search areas are considerably larger than the circular and 1 SD ellipse, they are successful at locating offender residences for both commuter and marauder offender types.

3.8.2 Directional Correlation

According to the criminal's *environmental range* hypothesis (Canter & Larkin, 1993), the spatial pattern observed for marauding serial offender can be expressed as a linear relationship between the maximum distances between crimes, and the distance between the offender's residence and the farthest crime. The researcher's posit that this relationship, represented by the regression coefficient, serves as a comprehensive indicator of the location of the offender's residence within a distribution (Canter & Larkin, 1993). Accordingly, a coefficient value of 0.5 indicates that the residence is located within the center of the distribution; alternatively, a value greater than 0.5 and less than 1.0 indicates eccentricity within the distribution.

The scatter plot in Figure 3.2 depicts this relationship for the marauding crime series used in this study. Accordingly, the regression coefficient was calculated as 0.745, which is supported by a strong coefficient of determination (R^2) of 0.912 [$F(1, 50) = 520.4, p = 0.000$]. As the

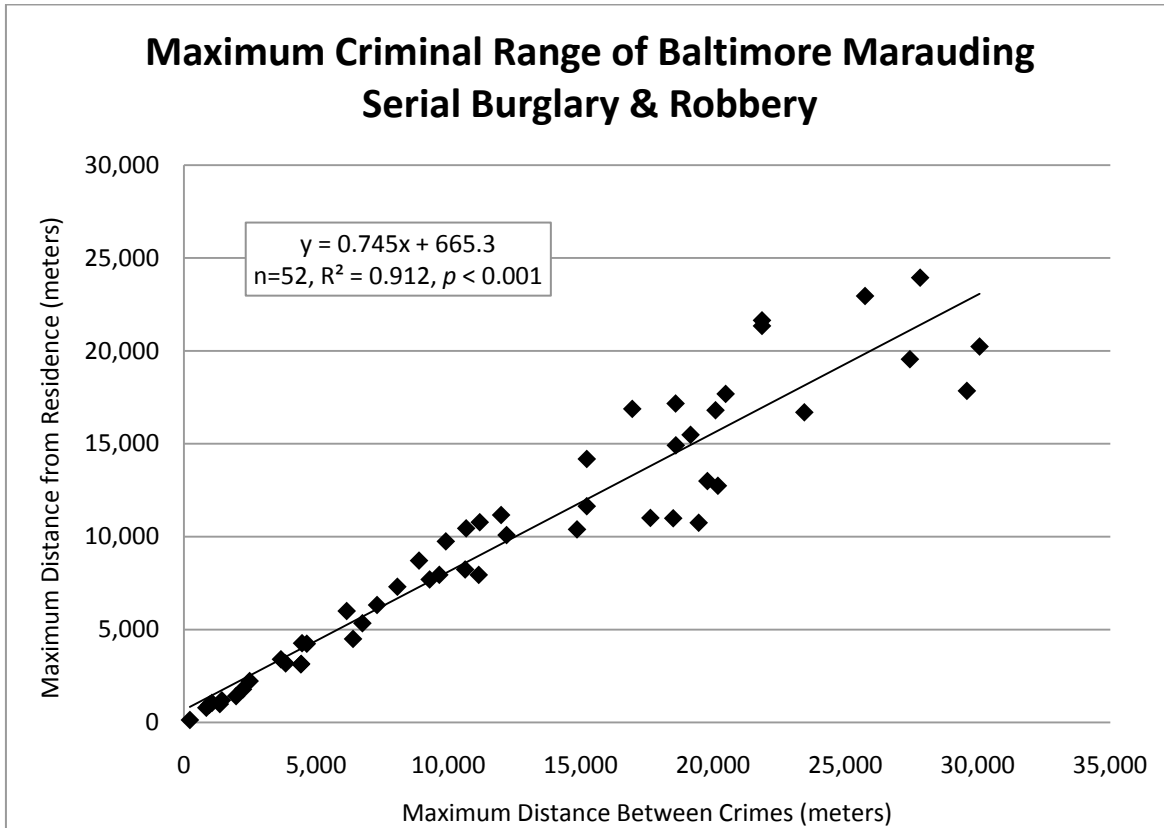


Figure 3.2: Maximum Criminal Range: the relationship between the maximum distance between offenses and the maximum distance between crimes and the marauding offender's residence.

coefficient value reveals, there is reason to conclude that, on average, a marauding offender's residence is unlikely to be located near the center of a distribution (Canter & Larkin, 1993; Kocsis, et al., 2002).

Of course, an eccentric finding is not unexpected as it demonstrates that a marauding offender commits crimes within an anisotropic activity space where opportunity to offend is not equally distributed. This effect can be measured by comparing the angle of rotation of each ellipse to the angle of rotation of the directional mean of the underlying road features that are coincident with the spatial extents of the crime scenes. The findings reveal a moderate but significant correlation ($r = 0.511, p < 0.001$) between the two angles, which differed on average

by 31.77° (min = 0.00° ; max = 125.25° ; SD = 29.07). When examined according to offender model, the relationship between ellipse and road network exhibited a slightly weaker correlation ($r = 0.489$, $p < 0.001$) for the commuter offender type. Conversely, the marauder offender exhibited a slightly stronger relationship ($r = 0.525$, $p < 0.000$). Whilst not very large, these moderate correlations support the premise that the general orientation of the crime scenes is partially related to the orientation of the underlying landscape. In other words, the existing transportation network governs the offender's Journey-to-Crime behavior.

3.9 Conclusion

The primary objective for this research was to parameterize the effects of an irregular landscape in the application of geographic profiling. Newton's geoforensic analysis demonstrated how a simple and intuitive geographic profiling technique could be utilized for the investigation of a serial crime. The application systematically analyzed a distribution of crime scenes in order to predict the geographic center and estimate the areal extents of a serial offender's activity space. However, the circular search areas defined by this profiling technique, as with other circle-based methodologies, assume an isotropic surface whereby any location within the profile's extents has an equal opportunity at being the offender's residence. Yet, research demonstrates that serial crime events are distributed as phenomena which are influenced, in part, by the physical and cultural landscape (Brantingham & Brantingham, 1981; Capone & Nichols, 1976; Canter et al., 2000; Harries, 2006; Kocsis et al., 2002; LeBeau, 1987a; Rengert et al., 1999; Rossmo, 2000). In effect, the spatial patterns observed in the distribution are actually a reflection of the irregularities consistent within the underlying landscape. As such, they exhibit spatial characteristics that can be analyzed geographically according to their location, dispersion, and orientation.

In order to address this premise, this study proposed that geographic profiling models capable of parameterizing the effect of the landscape will predict the location of a serial offender's residence more accurately. Circular and elliptical models were used to generate profiles for 97 serial offenses that occurred in Baltimore, during the late 1990s. Each profile was assessed according to profile accuracy, error distance, and search cost in order to identify which model predicted the serial offender's residence more effectively. To further demonstrate the validity of this approach, this study proposed that the orientation of the underlying road network would correlate to the elliptical profile's angle of rotation, thus revealing the mechanics behind the anisotropic distribution of incidents. The strength of this relationship was determined by comparing the angle of rotation of each elliptical profile to the linear directional mean of the road features coincidentally located within each of the crime's study area.

Before the analysis could proceed, four assumptions regarding offender characteristics needed to be satisfied. The first two assumptions were validated by filtering the dataset for those offenders that had his/her residence located within the study area, and that all criminal activity initiated and concluded from this fixed location. These two assumptions were used to classify offenders as either a commuter or marauder, the third assumption. Next, the non-parametric Mann-Whitney *U*-test was used to confirm the assumption that each serial event could be analyzed comprehensively and according to offense style (i.e., commuter or marauder), regardless of type (i.e., burglary or robbery). The final assumption established that both crime sites and the offender's journey-to-crime are governed by the existing transportation network, which was confirmed by examining the orientations of crime events along the Baltimore road network.

As the findings revealed, geoforensic analysis models based on the standard deviational ellipse will generally perform better than circular models. It does so because the standard deviational ellipse is summarizing the minimum and maximum variance within the distribution (i.e., variance measured along a rotated x- and y-axes). Furthermore, because the model is based on the standard deviations measured along the distribution's x- and y-axes, it is possible to modify the size of the ellipse according to the empirical rule of statistics. In effect, this functionality allows the standard deviational ellipse to perform like a two-dimensional confidence interval; as the interval increases, so too does the size of the ellipse and the likelihood of capturing the offender's residence (see Table 3.3).

In addition to demonstrating the efficacy of elliptical profile models, this study also confirmed the second hypothesis that the orientation of elliptical profiles should correlate with the orientation of the underlying landscape. As the findings revealed, a moderate but significant correlation was observed when comparing the ellipse's angle or rotation with the directional mean of the underlying road network. While a few extreme values were measured, the results further validate the premise that the landscape impacts the location of crime scenes. Further research should be applied to identify the extent to which the road network, and other factors, demonstrates a deterministic effect on the direction and dispersion of crime scenes.

The standard deviational ellipse model works because crime does not occur randomly in space. Rather, the fundamental tenants of environmental criminology propose that crime represents a remarkably complex framework of social, economic, and environmental factors that are characterized by physical and social conditions. In this context, place not only represents that discrete location in which a crime occurs; it has a deterministic impact on the other dimensions of crime (i.e., offender, target, and law) (Brantingham & Brantingham, 1981). That

is, place serves as the independent variable in which offender, target, and law are dependent. By parameterizing the effects of an anisotropic landscape, the theoretical constructs of environmental criminology are applied more meaningfully to the profiling process. In this way, Canter and Larkin's (1993) observation of eccentrically located offender residences represent both psychological and environmental factors.

However, the techniques presented here are not beyond reproach. An initial challenge for this study was to generate profiles from a sample that consisted disproportionately of more robberies (67) than burglaries (30). In order to eliminate the possibility of differing spatial characteristics, it was necessary to determine whether the observed distributions for the two crime types could be analyzed comprehensively, as if they originated from the same population. While tests suggested that this was appropriate for the sample, future research would benefit from a larger sample with even number of crime types and offender characteristics. Furthermore, this assessment was limited to one major metropolitan area. Future evaluations should assess these hypotheses in different geographic locations, especially those that consist of urban, rural, and/or a combination of both land use characteristics.

Additional criticisms can be applied to the modeling techniques employed. First, research by Snook, et al. (2005), Paulsen (2006b), and Levine (2007) demonstrate that the center of minimum distance (CMD) is often a better measure of a distribution's central tendency. CMD calculates the location where the travel distance to each event is the smallest. Further research should examine geoforensic analysis models that calculate the CMD and similar measures, such as median center. Furthermore, future studies should consider comparing the performance of standard deviational ellipses against circles of similar areas. In doing so, one can more accurately judge the effectiveness of the elliptical model. Finally, larger ellipses result in

prohibitive search costs. And while these search areas may not be as large as those derived from the circle hypothesis (Canter & Larkin, 1993), such search areas remain quite daunting for those investigations operating with limited budgets and man-power.

An unexpected finding from this study suggests that Newton's geoforensic analysis technique may offer a new strategy for apprehending an active serial offender. As one of the assumptions set forth by Newton, the central location of the profile's search areas was successively refined as each new crime was added to the model. Because of its operational nature, the standard deviational ellipse was able to reveal the positional and dispersal trends of the crime events as they were modeled sequentially. For example, if an offender's spatial behavior caused the number of crimes to cluster in a fixed geographic space, then the elliptical output consistently revealed a stable geographic location characterized by generally symmetrical major and minor axes (i.e., more spherical than elliptical). Conversely, if the offender's spatial preferences caused the crimes to move outward in specific directions, the resulting elliptical profiles began to mimic the outward movement, characterized by a generally un-equal major and minor axes (i.e., more elliptical than spherical). As indicated in Table 3.2, the size of the commuter's offense area is notably smaller than the area defined by marauders. While seemingly counterintuitive, this is likely the result of elongated convex hulls defined by offenses that occur along the transportation network. And like the results noted by LeBeau (1987a) and later by Kocsis et al. (2002), commuter style offenders generally exhibit narrow dispersion patterns with orientations that correlate with the transportation corridors. With further research, this roving profile effect may be exploited for use in predicting future serial crime events.

“...individuals do not operate on an isotropic plane, and thus, they search for social, environmental, and physiological constraints that confound the isotropic plane at the individual level.”

- Rengert et al. (1999, p. 440)

CHAPTER 4: UTILIZING LAND COVER CHARACTERISTICS TO ENHANCE JOURNEY-TO-CRIME ESTIMATION MODELS*

4.1 Introduction

Criminal geographic profiling is an investigative technique that utilizes information collected from solved serial crimes to estimate the likely residence of an unknown serial offender. This approach is frequently employed within law enforcement communities as a decision support tool from which offender apprehension strategies can be derived. The methodological premise for geographic profiling is based on research demonstrating how the geographic arrangement of crime scenes can reveal unique details about a serial offender's spatial preferences and underlying opportunity structures (Brantingham & Brantingham, 1981; Capone & Nichols, 1976; Rhodes & Conly, 1981; Rossmo, 2000). Geographic profiling relies on the fundamental assumption that offenders commit crimes within a finite space surrounding an anchor point (i.e., residence). This area is commonly referred to as the offender's activity space, which is partially defined by activity nodes and network paths an offender utilizes for legal and illegal activities (Brantingham & Brantingham, 1981). In order to successfully locate the residence, or anchor point, the geographic profile must provide a reasonable characterization of the offender's behavior within the activity space.

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Most geographic profiling methodologies utilize quantitative techniques founded on spatial distribution and spatial interaction models (Levine, 2007; Rossmo, 2000). Spatial distribution techniques characterize criminal activity according to the geographic arrangement of crime scenes. Spatial interaction models are typically used to describe an offender's geographic behavior according to mobility characteristics (Canter & Larkin, 1993; Canter et al., 2000; Capone & Nichols, 1975; 1976; Rengert, 1989; Rossmo, 2000). And while these techniques are proven resources for characterizing an offender's behavior in space, they are generally unable to account for the impact of the surrounding environment. Despite consistent acknowledgement of the importance that the physical and cultural landscape has on the occurrence of crime (e.g., Brantingham & Brantingham, 1981; Canter et al., 2000; Capone & Nichols, 1975; 1976; Kocsis & Irwin, 1997; Levine, 2007; Ratcliffe, 2001; Rengert, 1981; Rhodes & Conly, 1981; Rossmo, 2000; Snook et al., 2004), very few studies have integrated environmental structures within an operational framework (Kent et al., 2006; Kent & Leitner, 2008; Levine & Block, 2009; Rengert, 1981; Rhodes & Conly, 1981). Accordingly, this study proposes to augment existing geographic profiling techniques by incorporating land cover characteristics within spatial interaction models. To validate the efficacy of this approach, traditional and land cover-enhanced geographic profiles are compared to assess accuracy and precision.

4.1.1 Land Cover and Crime

The theoretical basis for geographic profiling is rooted within environmental criminology, a derivative of the Positivist School, which proposed that crime occurs at the confluence of offender, target, and law (Brantingham & Brantingham, 1981). Within this context, a criminal's geographical offense pattern becomes a function of the distribution of potential targets, the offender's perceptions of target attractiveness and criminal opportunity, and

the inherent spatial biases inherently defined by the offender's activity space (Brantingham & Brantingham, 1981; Canter et al., 2000; Rhodes & Conly, 1981; Rossmo, 2000). The Brantinghams (1981) synthesized these relationships into a comprehensive series of crime pattern models which illustrated how environmental structures (e.g., cultural and physical landscapes) influence criminal opportunity and impacts an offender's decision making. Crime pattern theory has a number of implications for profiling a serial offender's spatial behavior (Brantingham & Brantingham, 1981; Felson & Clarke, 1998; Rhodes & Conly, 1981). First, the models reveal how criminals typically express spatial biases that result in higher concentrations of crime within the offender's immediate activity space. Next, an offender's criminal commute exhibits a general decrease in crime frequency as the distance from the residence increases (i.e., distance decay) (Capone & Nichols, 1975). However, the distance an offender is willing to travel (i.e., cost) is directly related to the type of crime and magnitude of the perceived reward (i.e., gain). Third, certain portions of the urban landscape will exhibit disproportionately higher concentrations of offenders than others (i.e., offender clustering). And finally, the distribution of potential targets varies according to target attractiveness and the offender's perceptions of opportunity (Rhodes & Conly, 1981). Overall, these models depict how an offender's criminal behavior in space is ultimately the product of rational decision making in which the evaluation of an objective opportunity structure is inextricably linked to a fixed environment (Brantingham & Brantingham, 1981; Rengert, 1981).

4.1.2 Journey-to-Crime Estimation

As referenced earlier, spatial distribution and spatial interaction models constitute the predominant methodological approaches for contemporary geographic profiling. Spatial distribution techniques typically characterize criminal phenomena according to univariate

measures of central tendency and/or dispersion. Previous studies established that a successful geographic profile is premised on the assumptions that (a) an offender's anchor point is located in relative proximity to the crime scenes, and (b) the crime scenes partially define the criminal's activity space (e.g., Canter & Larkin, 1993; Levine, 2000; Rossmo, 2000). Thus, by defining the center of a distribution of linked crime scenes, one effectively reveals some portion of that offender's activity space associated with the anchor point (e.g., Leitner et al., 2007). Measures of central tendency commonly include the geographic mean, median, and center of minimum distance. While simplistic, these techniques have proven to be remarkably effective as a fast and intuitive profiling approach (Levine, 2000; Snook et al., 2002; 2004; 2005; Paulsen, 2006b; Taylor, Bennell, & Snook, 2009). But, analyzing distributions with this technique can be limited. Critics argue that single descriptive measures are sensitive to outliers, and are seldom able to provide a systematic strategy for locating an offender's residence (Levine, 2005; Rossmo, 2005; Snook, Zito, Bennell, & Taylor, 2005). Despite these concerns, centographic techniques are frequently used by researchers as a benchmark when comparing output from multiple profiling techniques (e.g., Paulsen, 2006a; Levine, 2007; Levine & Block, 2009).

Geographic profiles also employ principles of spatial interaction that attempt to characterize an offender's geographic behavior according to probability distance functions (Levine, 2007). Similar to analysis that measure a phenomena's "center of gravity," this approach is typically utilized to describe the movement of ideas, material, and resources across space. In fact, spatial interaction models have long been an effective measure for interpreting an offender's spatial behavior (e.g., Capone & Nichols, 1975; Lottier, 1938; Turner, 1969). As environmental criminology research demonstrated, a principal characteristic of crime pattern theory is the distance decay effect: the condition in which the frequency of criminal activity

decreases as the distance from the offender's residence increases (Brantingham & Brantingham, 1981). Not surprisingly, many contemporary profiling techniques adopted distance decay as the primary method for representing an offender's behavior in space.

JTC estimation techniques are perhaps the most established and widely utilized approach for analyzing offender mobility (Brantingham & Brantingham, 1981; Capone & Nichols, 1976; Lottier, 1938; Rhodes & Conly, 1981; Rich & Shively, 2004; Turner, 1969). Though several methods exist, JTC routines typically model a criminal's spatial offense patterns either by fitting a mathematical trend function through a calibration sample of solved crimes (e.g., Canter et al., 2000), or by using an interpolation kernel to fit a non-linear function through individual crime scenes (e.g., Levine, 2007). Once a decay model has been selected, the equation is applied to the distribution of linked crime scenes, and used to estimate the likelihood of identifying the unknown offender's anchor point within the study area.

While JTC estimation techniques provide an effective means for modeling spatial behavior, distance decay methodologies have been criticized for their reliance on aggregated trip distributions that distort nuanced, but significant, variations of individual criminal commutes (van Koppen & de Keijser, 1997; Rengert et al., 1999; Snook et al., 2005; Smith et al., 2009). Indeed, Levine (2005; 2007) notes that individual travel behavior varies by offender. As a consequence, cost assumptions derived from aggregated decay models can lead to false estimates. Furthermore, the traditional utilization of decay models assumes that both the opportunity to offend and distribution of attractions are uniformly distributed across the environment (Canter et al., 2000; Rossmo, 2000). Research demonstrates (e.g., Capone & Nichols, 1976; Kent & Leitner, 2008; Kocsis et al., 2002; Rengert et al., 1999) that decay functions alone are incapable of accommodating the asymmetrical impedances inherent within

the built environment. Consequently, empirically calibrated algorithms often exhibit estimation errors within the modeled framework. Canter and Hammond (2006) found that the choice of decay model may have little influence on the efficacy of profiling results. Consequently, numerous studies on the effectiveness of ‘simple’ spatial methods have consistently demonstrated that centrographic measures are effective strategies (Levine, 2000; 2005; Paulsen, 2006b; Snook et al., 2004; 2005; Taylor et al., 2009). In all, geographic profiling research has confirmed what Brantingham & Brantingham illustrated decades earlier (1981): The factors that influence offender’s spatial behavior are not random elements. Rather, the relationship between crime scenes and the offender’s residence suggest an asymmetrical activity space that is, by some measure, influenced by offender’s perceptions and of the physical and cultural landscape (Brantingham & Brantingham, 1981; Capone & Nichols, 1976; Rengert et al., 1999; Rhodes & Conly, 1981; Rossmo, 2000).

4.1.3 Research Proposal

To summarize, the structures that define an offender’s perceptions of criminal opportunity and target attractiveness exist within a geographic context in which criminal mobility and target distribution shape the offender’s activity space (Brantingham & Brantingham, 1981; Capone & Nichols, 1976; Canter & Gregory, 1994; Rhodes & Conly, 1981; Rossmo, 2000). Contemporary geographic profiling techniques model these relationships according to spatial distribution and probability distance strategies. However, such methods are often incapable of characterizing the complex relationship between crime scenes, offender perceptions, and the surrounding environment. The implication for geographic profiling is that an offender’s anchor point must therefore exist within an asymmetrical landscape differentiated by physical and cultural constructs. Accordingly, the location of an anchor point is constrained to

those physical and cultural landscapes that are relevant to the offender's activity space. If land cover classifications are used as a proxy for those constructs, it may be possible to refine existing profiling techniques to generate improved profile estimates. To that end, this research proposes that a geographic profiling model capable of parameterizing both probability distance functions and land cover characteristics will better estimate a serial offender's anchor point than traditional techniques alone. To test this hypothesis, traditional and land cover-enhanced JTC estimates are used to generate geographic profiles for a random sample of solved serial crimes that occurred in Baltimore, Maryland, between 1993 and 1997. Land cover characteristics collected for the Baltimore study area will be used to filter JTC estimates. Results derived from each technique will be compared for accuracy and precision.

The hypothesis presented in this study is conditioned on a number of assumptions. First, each crime series consists of offenses perpetrated by a single individual. Next, the offender is assumed to have initiated and concluded all criminal activities from a single, fixed location (i.e., their residence) within their activity space. Third, the offender's activity space and residence must exist within the study area. Furthermore, the land cover classifications used in this study reflect the actual environmental structures that influenced an offender's spatial behavior and target opportunity structures (i.e., target backcloth). And finally, land cover data used for this research approximates the actual land cover characteristics observed for the study area.

4.2 Data and Methodology

This study proposes to enhance existing JTC techniques by introducing land cover characteristics as a filtering mechanism to constrain estimations to those land cover types most likely inhabited by the serial offender. To that end, the methodology employed for this investigation is organized into three distinct parts. First, the crime and land cover datasets

utilized for this analysis are described. This is followed by a brief overview of five JTC techniques used in this study. Finally, the methods for assessing each of the JTC techniques are presented.

4.2.1 Data Used

Crime dataset: The crime data used for this study were comprised of 732 solved serial burglary and robbery offenses that occurred in Baltimore, Maryland, between 1993 and 1997 (Table 4.1). The dataset included only those records where the coordinates for each crime scene were paired with coordinates for the offender's known residence, presumed to be the anchor point for all criminal activities. The dataset included 162 criminal series (burglary = 61, robbery = 101), averaging 4.52 crimes per series (burglary = 4.26, robbery = 4.67). Burglary and robbery offenses were combined to create a comprehensive dataset from which adequately sized test and calibration samples would be drawn. Figure 4.1 illustrates the average JTC distance for the combined dataset, which is characterized by a mean distance of 7.21 km (SD=7.93) and a median distance measured at 5.11 km.

The dataset was assessed to ensure that it met the criteria published in a 2004 National Institute of Justice (NIJ) guidelines for evaluating geographic profiling techniques (Rich & Shively, 2004). First, the dataset included crime series that consisted of three or more offenses. While less than the five-crime minimum proposed by Rossmo (2000; 2005b), the three case minimum was adopted due to the limited number of records available in the dataset. Furthermore, the data were not segregated according to a particular mobility characteristic [e.g., commuter or marauder mobility types (Canter & Larkin, 1993)]. While studies have recognized a performance distinction between the profiles generated for marauders and commuters (Paulsen, 2007; Rossmo, 2000; Santtila, Laukkanen, & Zappala, 2007), this study did not examine the

Table 4.1: Serial Crime Dataset - Baltimore, MD, 1993-1997

Crime Type	Number of Series	Number of Offenses	Series Statistics	Distances			
				Min	Max	Mean	Median
Burglaries	61	260	Min:3, Max:12 Mean: 4.26 (SD=1.89) Median: 3	0.00 m	56.28 km	6.63 km (SD=10.59)	1.71 km
Robberies	101	472	Min:3, Max:14 Mean: 4.67 (SD= 2.04) Median: 4	165.6 m	36.95 km	7.52 km (SD= 5.94)	6.48 km
Combined	162	732	Min:3, Max:14 Mean: 4.52 (SD=2.00) Median: 4	0.00 m	56.28 km	7.21 km (SD=7.93)	5.11 km

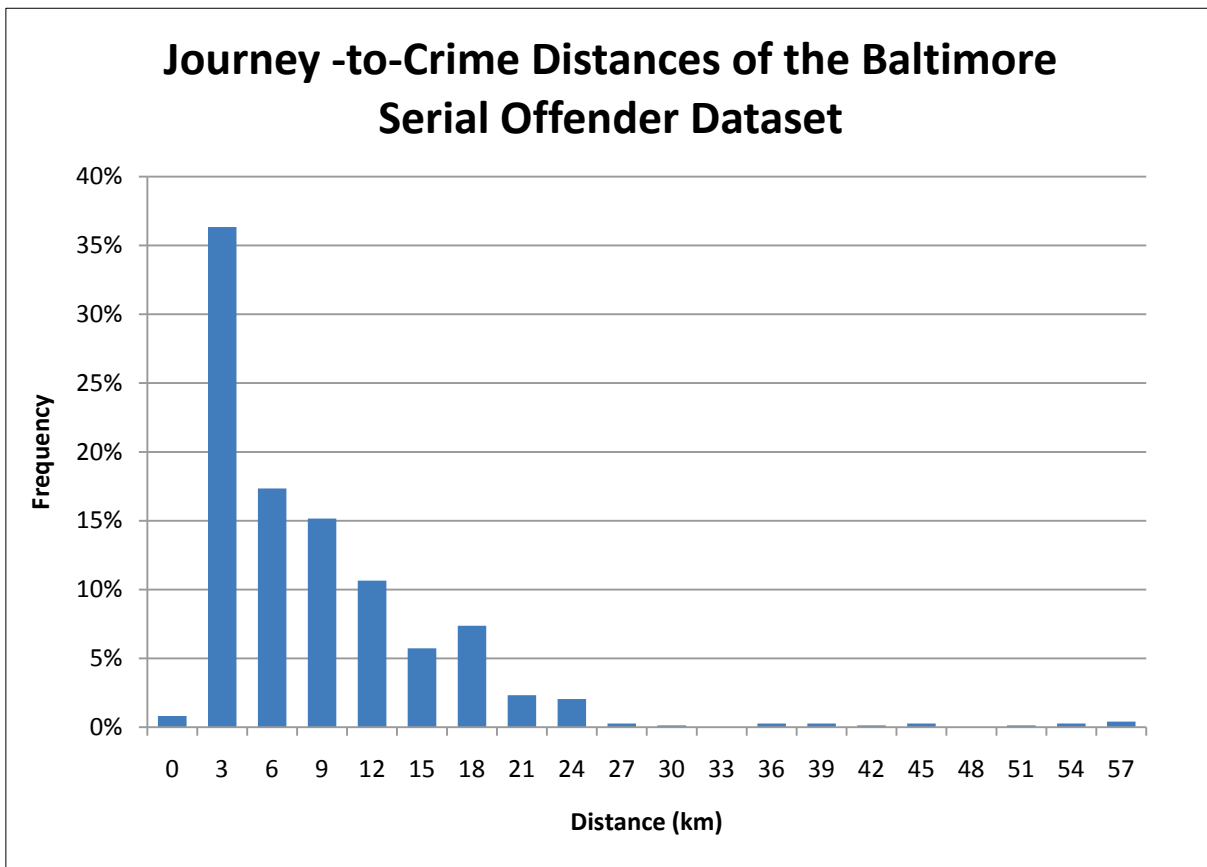


Figure 4.1: Journey-to-Crime distribution of Baltimore, MD, serial offenders.

impact of these offense patterns on the profiled output. Finally, the dataset was divided into two groups: A calibration sample and a profile sample. As depicted in Table 4.2, the calibration sample consisted of 92 randomly selected crime series with a median count of four crimes per offender (min=3, max =11, n=379), an average travel distance of 8.47 km (SD=8.76) per trip, and median distance of 6.47 km. The profile sample (i.e., testing sample) included 70 crime series with a median travel distance of 3.55 km, an average distance of 5.85 km (SD=6.67), and a median count of five crimes per series (min=3, max=14, n=353).

Table 4.2: Serial Crime Profile & Calibration Sample Datasets-Baltimore, MD, 1993-1997

Sample Set	Number of Series	Number of Offenses	Series Statistics	Distances			
				Min	Max	Mean	Median
Profile	70	353	Min:3, Max:14 Mean: 5.04 (SD=2.29) Median: 5	0.00m	43.05 km	5.85 km (SD=6.67)	3.55 km
Calibration	92	379	Min:3, Max:11 Mean: 4.12 (SD=1.64) Median: 4	0.00 m	56.28 km	8.47 km (SD=8.76)	6.74 km
Combined	162	732	Min:3, Max:14 Mean: 4.52 (SD=2.00) Median: 4	0.00 m	56.28 km	7.21 km (SD=7.93)	5.11 km

Land cover dataset: Land cover data for the Baltimore study area were extracted from the 1996 Land Cover Analysis dataset distributed by the U.S. National Oceanic and Atmospheric Administration (NOAA) for the Coastal Change Analysis Program (C-CAP). The source dataset included twenty-three land cover classifications derived from 30-meter resolution Landsat Thematic Mapper and Landsat Enhanced Thematic Mapper satellite imagery (NOAA, 1996). Each classification was represented by a unique integer value. In order to increase the

operational efficiency of profile generation, the land cover data were aggregated from 30 meter to 480 meter cell sizes. Cells were assigned the statistical mode of the land cover integer value calculated from the 256 (16x16) contiguous 30 meter cells. Following the aggregation process, the data set was reduced from twenty-three to eighteen land cover classifications (see Figure 4.2). The resulting coverage, which comprised 12,932 grid cells, was trimmed to fit the geographic extents of the Baltimore, MD, study area. Figure 4.3 illustrates the proportion of land cover that comprises the aggregated coverage.

4.2.2 Geographic Profile Techniques

Five modeling techniques were chosen to compare the effectiveness of land cover-enhanced geographic profiles:

- Journey-to-Crime Estimation, *JTC*
- Bayesian JTC Product, *Bayesian-JTC*
- Filtered Journey-to-Crime Estimation, *Filtered-JTC*
- Filtered Bayesian JTC Product, *Filtered-Bayesian-JTC*
- Center of Minimum Distance, *CMD*

Journey-to-Crime Estimation, *JTC*: This profiling technique produces a probability surface representing the likelihood of locating an offender's anchor point within the study area. Values are calculated according to an empirically calibrated probability distance function (i.e., decay curve) derived from the calibration sample of 92 solved cases (see Table 4.2). A JTC frequency distribution consisting of 480-meter distance intervals (i.e., bins) is constructed for all incidents in the sample. While effects of various distance decay algorithms have been studied (e.g., Canter & Hammond, 2006; Levine, 2007), this investigation selected the exponential (negative) algorithm due to its robust utilization by transportation modelers and other JTC

Baltimore, Maryland, Study Area

1996 NOAA C-CAP Land Cover Data Set
480m Resolution

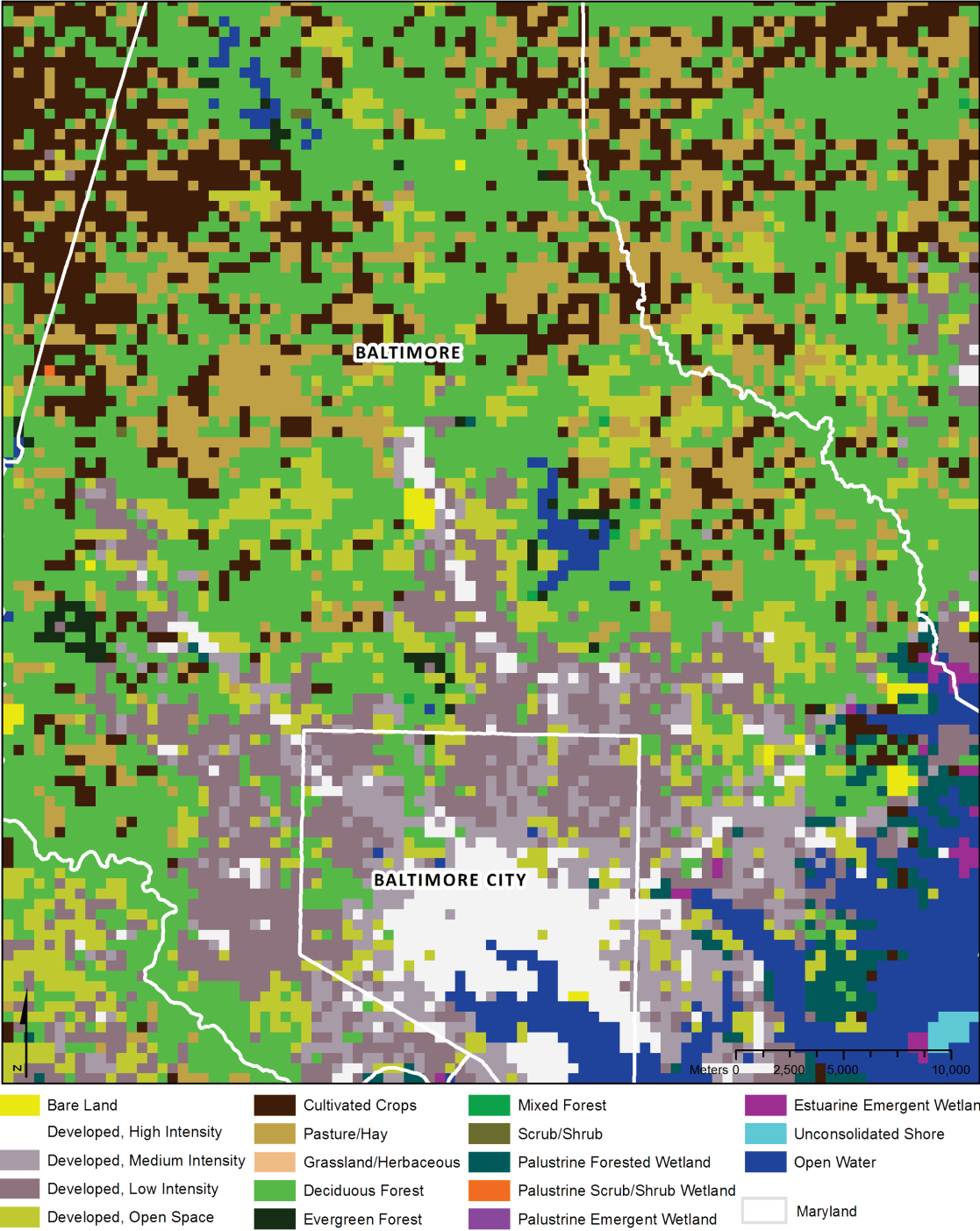


Figure 4.2: Aggregated land cover map of Baltimore, MD, study area.

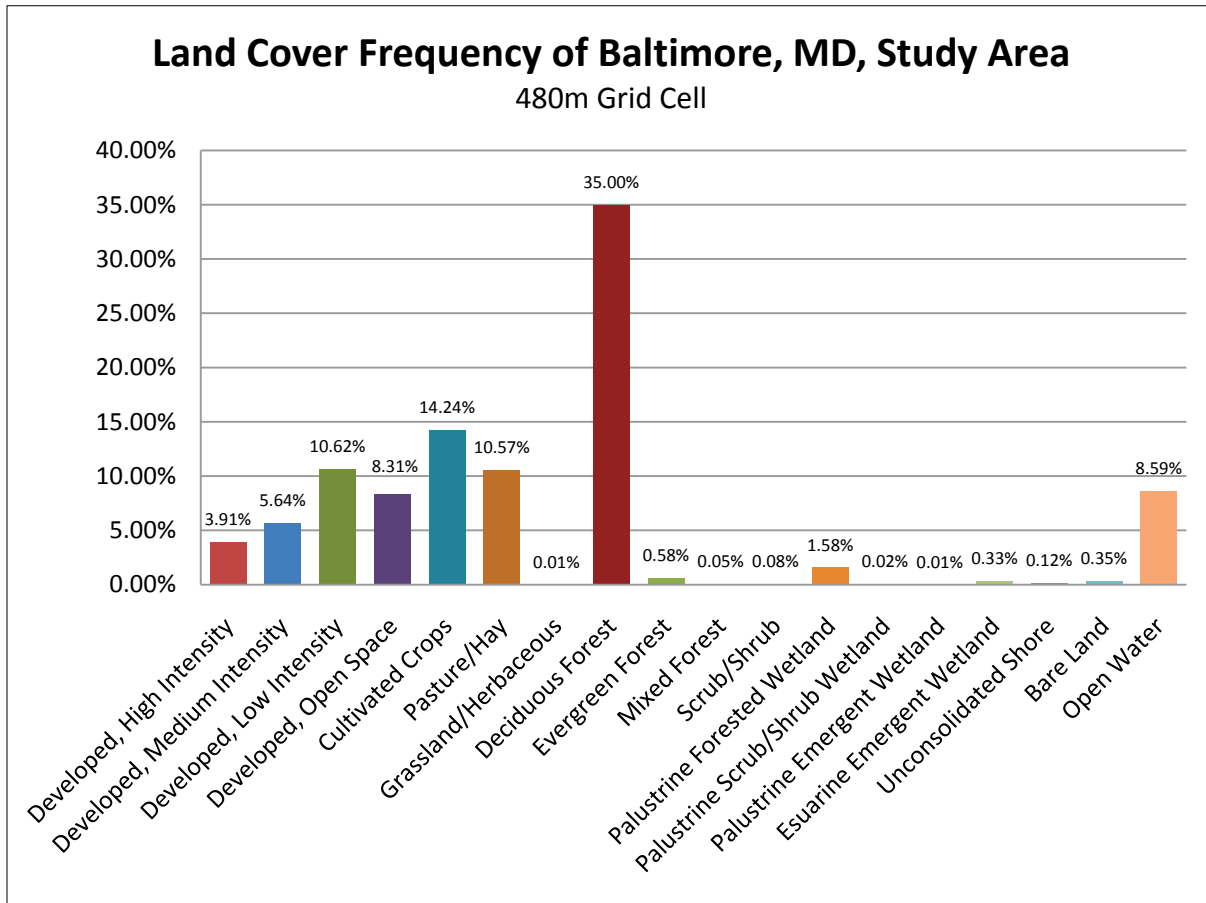


Figure 4.3: Distribution of aggregated land cover classes in the Baltimore, MD, study area.

modeling applications [e.g., Canter et al., 2000; Federal Highway Administration (FHWA), 1977; and Levine, 2005; 2007]. Accordingly, a negative exponential curve was regressed and fit onto the JTC frequency distribution (Figure 4.4). While the coefficient of determination was low, it proved to be a significant fit: $R^2 = 0.506$ ($F = 119.69$, $p < 0.000$).

Next, a 480 meter study grid consisting of 12,932 cells was placed over the Maryland study area. The grid was designed to match the coverage and resolution of the aggregated land cover dataset. For each crime in a given series, the Euclidean distance was measured between a cell's centroid and crime scene. Next, the exponential decay model was applied to each cell-to-crime distance, and summed over the series to produce a density estimate (Equation 4.1).

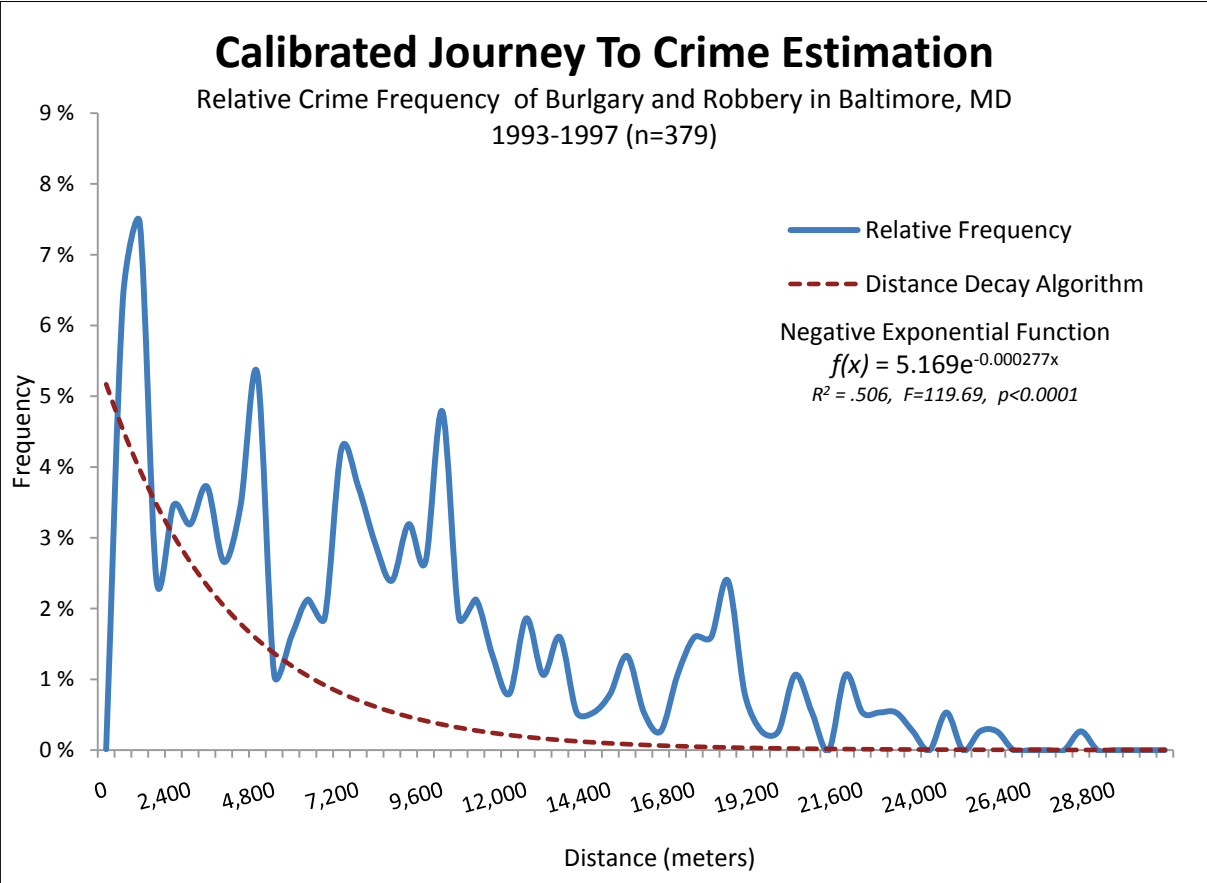


Figure 4.4: Calibrated Journey-to-Crime distance decay model for Baltimore serial offenders.

Finally, a cell’s modeled output was converted into a probability by scaling the estimates such that the sum of all cell values equaled 1. Once normalized, the cell’s output represents the discrete probability of identifying an offender’s anchor point according to the distance decay model (Levine, 2007):

$$P(\text{JTC}) = \sum_{i=1}^n f(d_{x_i y}) = 1 \tag{4.1}$$

where d_{xy} is the distance measured between each crime scene, x_i ($i = 1, 2, 3, \dots, n$), and each grid cell, y , which is applied to the corresponding decay function, $f(d)$.

Bayesian JTC Product, *Bayesian-JTC*: Version 3.1 of the CrimeStat[®] software package introduced the Empirical Bayes Journey-to-Crime model for predicting the anchor point of a serial offender (Levine, 2007). This Bayesian formulation follows an intuitive process in which the prior JTC estimate of the unknown serial offender is updated using a likelihood function. The likelihood represents the conditional probability of anchor points for known offenders that committed crimes the same grid cells as the unknown offender [see the CrimeStat[®] 3.1 documentation for more details (Levine, 2007)]. When the likelihood is combined with the empirically derived prior JTC probability, it produces what the CrimeStat[®] manual refers to as the *Empirical Bayesian JTC Product* (Levine, 2007). As noted (Levine, 2007), the Bayesian formulation will often represent this conditional probability in a proportional form of the posterior probability (Bolstad, 1997), taking the form:

$$P(JTC|O) \propto P(O|JTC) \cdot P(JTC) \quad (4.2)$$

where the posterior, $P(JTC|O)$, represents the relative weight of a JTC estimate after the conditional likelihood, $P(O|JTC)$, has been observed.

For this study, the conditional likelihood estimate was estimated by first identifying those grid cells where the incident locations from the profile and calibration sample were coincident. Of the 70 cases in the profile sample, 53 had an incident that was spatially coincident with the calibration sample. For each coincident pair, the anchor points from the calibration sample were summed and interpolated onto the study grid as a probability surface using a normal kernel density estimate. Each of the resulting density surfaces were combined and scaled such that the sum of all cell values equaled 1. Finally, the product of the conditional and the prior JTC

probability values were calculated for each cell and scaled to produce the proportional Bayesian-JTC probability surface.

Filtered Journey-to-Crime Estimation, *Filtered-JTC*: This study asserts that the location of an offender's residence is spatially dependent upon the physical and cultural landscape. Thus, an offender's anchor point should be constrained to certain environmental characteristics that are common among other offenders. Using land cover classifications as a proxy for these characteristics, traditional JTC models can be modified to effectively filter out those locations that are unlikely to contain an offender's anchor point. To illustrate this effect, Figure 4.5 depicts the output of a theoretical geographic profile using a simplified study area comprised of three grid cells. Each grid cell has been assigned a JTC probability estimate, $P(JTC_n)$. Additionally, each grid cell has a corresponding probability for land cover, $P(LC_n)$, which represents the marginal probability of observing a particular land cover class that is spatially coincident with the anchor point of previous (i.e., solved) serial offenders. Based solely on the JTC estimation, cell A₃ was assigned the highest prior probability of containing the anchor point [$P(JTC) = 0.40$]. However, cell A₃ had also been assigned the lowest marginal land cover probability for an offender's residence [$P(LC)=0.15$], indicating that few offenders reside in that land cover class. When the product of the two marginal probabilities was calculated, the JTC estimation for cell A₃ was updated to reflect the influence of the land cover probabilities, revising the profile estimate from 0.40 to 0.33. Simultaneously, the profile estimated for cell A₂ (the cell containing the offender's anchor point) increased from 0.35 to 0.39. In short, the marginal land cover probability was able to filter the prior JTC probability, resulting in a more precise estimate of the offender's anchor point.

$P(JTC_1)=0.25$ A_1 $P(LC_1)=0.20$	(Location of Anchor Point) $P(JTC_2)=0.35$ A_2 $P(LC_2)=0.20$	$P(JTC_3) =0.40$ A_3 $P(LC_3)=0.15$
--	--	---

Grid Cell	Prior Probability $P(JTC)$	Marginal Land Cover Probability $P(LC)$	Product $P(LC) \cdot P(JTC)$	Filtered-JTC $P(\text{Filtered-JTC})$
A ₁	0.25	0.20	$0.25 \times 0.20 = 0.05$	$0.05/0.18 = 0.28$
A ₂	0.35	0.20	$0.35 \times 0.20 = 0.07$	$0.07/0.18 = 0.39$
A ₃	0.40	0.15	$0.40 \times 0.15 = 0.06$	$0.06/0.18 = 0.33$
Totals:			$\Sigma = 0.18$	$\Sigma = 1.00$

Figure 4.5: A simplified geographic profile illustrating how land cover probability values can update Journey to Crime estimations. Marginal land cover probabilities update the JTC estimate to correctly identify cell A₂ as the offender's anchor point.

To incorporate land cover probabilities within the JTC framework, the observed frequency of a given land cover category was calculated for those grid cells that were spatially coincident with offender anchor points maintained within the calibration sample. These values represent the *marginal probability* of identifying an offender's residence according to a particular land cover type. The product of the marginal and JTC probabilities was calculated and scaled for each grid cell to produce the proportional Filtered-JTC estimate:

$$P(\text{Filtered-JTC}) \propto P(JTC) \cdot P(LC) \tag{4.3}$$

where $P(LC)$ is the marginal probability of land cover, and $P(JTC)$ is the prior JTC estimation for a grid cell.

As illustrated in Figure 4.6, only four of the eighteen aggregated land cover types corresponded to the residences in the calibration sample. These few categories include all developed land cover classes in which impervious surfaces comprise a significant portion of the

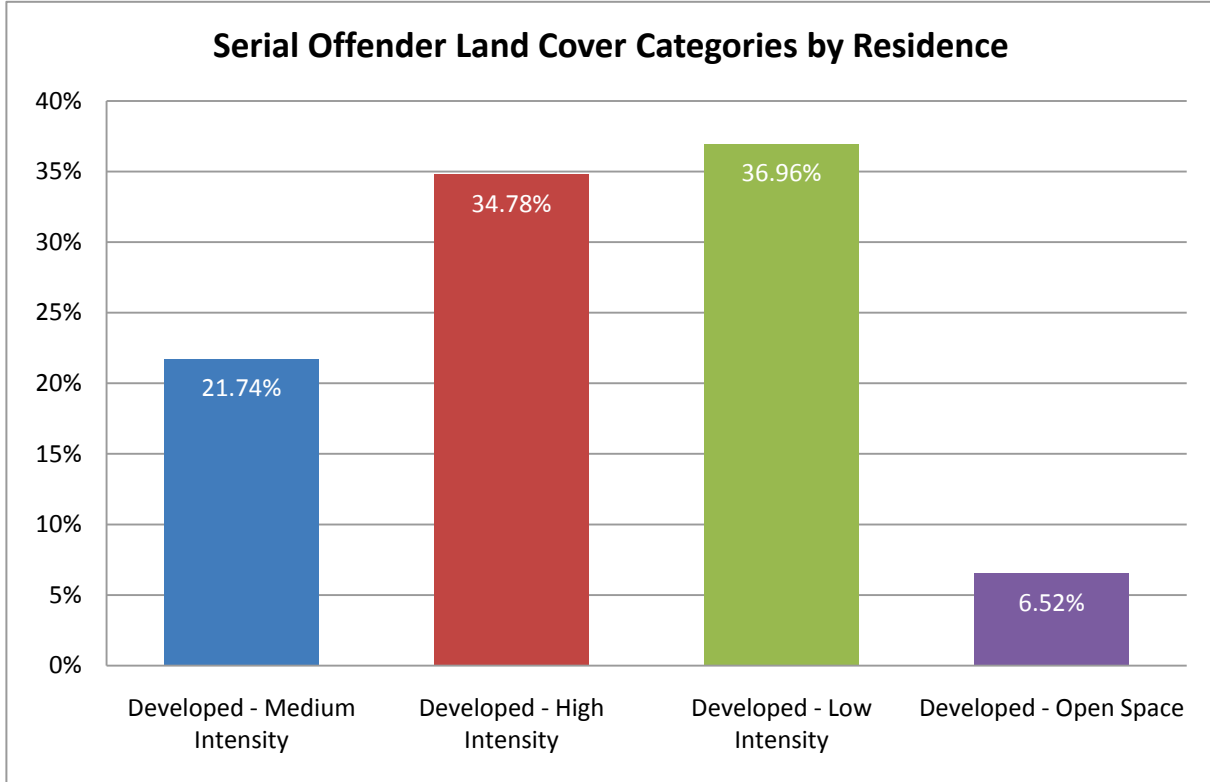


Figure 4.6: Frequency of land cover type for serial burglars and robbers from the Baltimore calibration sample.

total cover (NOAA, 1996). The most frequently observed categories are the low and high-intensity land use classes, which correspond to a mix of residential and commercial structures, transportation routes, and various outbuildings (NOAA, 1996). The remaining developed land cover types are represented by medium intensity and open spaces, which correspond to a mixture of both impervious and exposed surfaces. Note that these probabilities are based on the assumptions that (a) an offender's residence corresponds to a land cover type consistent with those observed in the study area, and (b) the land cover type assigned to a grid cell approximates the actual characteristics for anchor points within that grid cell.

Filtered Bayesian JTC Product, *Filtered-Bayesian-JTC*: A noteworthy advantage of the Bayesian formulation is that it follows an intuitive process similar to that of a criminal investigation: As new evidence is observed, prior knowledge is updated to reflect a revised degree of belief in the criminal suspect(s). Accordingly, it is reasonable to introduce the marginal probability of land cover as another independent variable within the *Bayesian-JTC* estimate:

$$P(\text{Filtered-JTC}|\text{O}) \propto P(\text{O}|\text{JTC}) \cdot P(\text{JTC}) \cdot P(\text{LC}) \quad (4.4)$$

where $P(\text{Filtered-JTC}|\text{O})$ is proportional to the product of the conditional Bayesian JTC likelihood, $P(\text{O}|\text{JTC})$, the prior JTC estimate, $P(\text{JTC})$, and the marginal probability of land cover, $P(\text{LC})$. The procedure for assigning Filtered-Bayesian-JTC estimates onto the study grid follows the same steps detailed for the earlier estimates. Similarly, the final grid values were mathematically scaled such that the sum of all cell values equaled 1.

Center of Minimum Distance, *CMD*: Spatial distributions strategies are often used by researchers as a baseline for comparing output from different geographic profile techniques (e.g., Levine, 2000; Paulsen, 2006b). Accordingly, the center of minimum distance (CMD) has become a seemingly ubiquitous technique for profiling an offender's anchor point relative to distribution of crime scenes. The CMD is iteratively defined as a point within the study area where the sum of the distance to all other crime locations is smallest (Levine, 2007):

$$CMD = \sum_{i=1}^n d_{min}(x_i, CMD_{\bar{x}}) \quad (4.5)$$

where x_i represents a crime at location i , $CMD_{\bar{x}}$ represents the current center of minimum distance within the distribution, and the function d_{min} represents the minimum distance between

the crime scene x and the $CMD_{\bar{x}}$. Because CMD estimations are represented as a single point, the technique provides a good indicator for the spatial accuracy of a geographic profile (though, it is vulnerable to outliers). However, it is not compatible with many evaluation criteria that gauge a profile's efficacy using probability measures (e.g., traditional or the Bayesian JTC estimates). Furthermore, some studies caution that the interpretation of precision for CMD profile should be limited to symmetrical output (Rossmo, 2005b). As such, comparisons to the CMD output must accommodate these limitations.

4.2.3 Evaluation Criteria

The profiling methods proposed for this investigation (e.g., JTC, Bayesian-JTC, Filtered-JTC, Filtered-Bayesian-JTC, and CMD) were assessed using evaluation criteria that measure both accuracy and precision (Levine & Block, 2009; Paulsen, 2006b). Though controversial (Levine, 2005; Rossmo, 2005a), this study elected to evaluate the profiling output according to methods detailed in a report issued by the National Institute of Justice (Rich & Shively, 2004). The methods used, and their descriptions are provided:

- **Profiled probability value:** The probability value assigned to the grid cell where the offender's anchor point is predicted. The higher the probability, the more accurate the model.
- **Error distance:** A diagnostic accuracy estimate that measures the Euclidean distance between the offender's true anchor point and the cell with the highest probability estimate. Shorter distances indicate a more accurate model.
- **Search cost/hit score:** The proportion of the study area that must be searched in order to identify the cell containing the offender's residence. This method accommodates the search cost value published by Canter et al. (2000), and the hit score defined by Rossmo (2000). It is essentially a percentage of cells that must be searched before finding the offender's residence. Smaller percentages reveal a higher model precision.

The first technique, the profile probability value, indicates the strength of the profile's ability to model the offender's spatial mobility characteristic. Accordingly, this measure is applicable to the four JTC-based profiling routines. As a point estimate, the CMD strategy does not produce a probability value, thus it was not evaluated with this method. The second evaluation procedure examines the Euclidean distances measured between the grid cell with the highest profile value and the offender's anchor point (i.e., error distance). The final measure, search cost/hit score, provides insight into the variability associated with predicting an offender's anchor point. The value is calculated by first sorting grid cell values in descending order, and then counting the number of cells that must be searched before encountering the offender's anchor point (Canter et al., 2000; Rossmo, 2000). Because the CMD measure is a point estimate, it is incapable of independently generating a search cost. However, a comparable estimate can be derived by counting the number of grid cells that fall inside a circle defined by a radius equal to the error distance.

Because each method compares different treatments on the same profiled sample, two non-parametric tests are proposed to validate the diagnostic results. First, the Friedman test is used to determine if the output generated by each of the profiling techniques is different, thus supporting their individual comparisons (SPSS, 2004). Next, the individual differences between techniques are assessed using the Wilcoxon signed ranks test for related samples.

4.3 Results

This section presents the output generated from the geographic profiling models and their subsequent evaluation measures. The overall performance of each model is summarized in Table 4.3. Additionally, the matrix provided in Table 4.4 details how well the individual routines performed relative to the traditional JTC estimation. The number of times an estimate was

observed to be more accurate or precise is indicated by *positive ranks*. Conversely, *negative ranks* indicate the number of worse performing estimations. Because the Bayesian-JTC routine could only generate estimates for 53 of the 70 crime series in the profile sample, the comparisons presented below will be limited to those results.

4.3.1 Profiled Probability Value

This diagnostic gauges profiling efficacy along a finite-continuum. Higher probability values indicate a greater likelihood that the offender's residence can be located within a grid cell. Because the study area consisted of a total of 12,932 grid cells, probability estimates were small (Table 3). Of the four profiling techniques, the Filtered-Bayesian-JTC produced the highest mean and median probability values of all 53 profiles (0.003484 and 0.002523 respectively). In fact, the average Filtered-Bayesian-JTC probability value was almost triple that of the average JTC estimate. The Filtered-JTC estimate measured the second highest average and median probability. Finally, the Bayesian-JTC and standalone JTC estimates rounded out the performance results. The Friedman test indicates significant differences between the four profiling results, thus supporting these findings.

When the estimations were compared individually, the Bayesian-JTC technique produced 40 profiles that had a probability value greater than those produced using the standard JTC method (see Figure 4.4). However, the Filtered-JTC technique performed better: generating 50 of 53 profiles (94.34%) that had probability values higher than the traditional JTC technique. Similarly, though not as high, the Filtered-Bayesian-JTC method produced 46 estimates that were more accurate than the JTC output. This finding also demonstrates that the filtered approach was able to improve upon the Bayesian-JTC estimate for six crime series. The

Table 4.3: Profile Comparisons - Accuracy & Precision Measures.

Profiling Strategy	Profile Probability Values ^a larger is better		Error Distances ^b shorter is better		Search Cost / Hit Score ^c smaller is better	
	Mean	Median	Mean	Median	Mean	Median
Journey to Crime Estimate (JTC)	0.001211 (SD=0.000913)	0.001012 %25 th = 0.00041 %75 th = 0.00205	4.671 km (SD =4.562)	3.398 km %25 th = 0.441 %75 th = 7.679	0.041053 (SD=0.070428)	0.010284 %25 th = 0.00023 %75 th = 0.04961
Bayesian JTC Product (Bayesian-JTC)	0.001787 (SD =0.001437)	0.001352 %25 th = 0.00072 %75 th = 0.00248	4.891 km (SD =5.210)	3.347 km %25 th = 1.108 %75 th = 7.242	0.041707 (SD =0.095084)	0.011599 %25 th = 0.00197 %75 th = 0.03542
Land Cover Filtered JTC (Filtered-JTC)	0.002647 (SD =0.002226)	0.002188 %25 th = 0.00084 %75 th = 0.00404	4.617 km (SD =4.515)	3.541 km %25 th = 0.497 %75 th = 7.962	0.026679 (SD =0.040507)	0.006418 %25 th = 0.00035 %75 th = 0.02842
Land Cover Filtered Bayesian JTC Product (Filtered-Bayesian-JTC)	0.003484 (SD = 0.003573)	0.002523 %25 th = 0.00101 %75 th = 0.00561	4.843 km (SD=4.980)	3.429 km %25 th = 1.153 %75 th = 7.236	0.025992 (SD = 0.047411)	0.007423 %25 th = 0.00143 %75 th = 0.02536
Center of Minimum Distance (CMD)	--	--	4.408 km (SD =4.132)	3.912 km %25 th = 0.689 %75 th = 6.736	0.039374 (SD=0.063002)	0.015698 %25 th = 0.00101 %75 th = 0.04605

Friedman Test for group differences between profile values

^a N = 53; $\chi^2 = 72.357$; $df = 3$; $p \leq 0.000$ (Asymp. Sig.)

^b N = 53; $\chi^2 = 0.735$; $df = 4$; $p \leq 0.947$ (Asymp. Sig.)

^c N = 53; $\chi^2 = 46.5$; $df = 4$; $p \leq 0.000$ (Asymp. Sig.)

Table 4.4: Profile Evaluation Results for 53 Profiled Crime Series

Evaluation Method	Bayesian JTC Product (Bayesian-JTC)	Land Cover Filtered-JTC (Filtered-JTC)	Land Cover Filtered Bayesian JTC Product (Filtered-Bayesian-JTC)	Center of Minimum Distance (CMD)	Rank
Profile Probability Value¹	13	3	7		Negative
	40	50	46	--	Positive
	0	0	0		Tie
Error Distance²	19	13	20	27	Negative
	16	13	22	25	Positive
	18	27	11	1	Tie
Search Cost / Hit Score³	21	7	16	35	Negative
	25	35	31	14	Positive
	7	11	6	4	Tie

¹ Wilcoxon Signed Ranks for pairwise differences of profile values

JTC < B-JTC: $Z = -4.245, p \leq 0.000$ (2-tailed)

JTC < F-JTC: $Z = -6.069, p \leq 0.000$ (2-tailed)

JTC < F-B-JTC: $Z = -5.719, p \leq 0.000$ (2-tailed)

² Wilcoxon Signed Ranks for pairwise differences of profile values

JTC > B-JTC: $Z = -0.524, p \leq 0.600$ (2-tailed)

JTC = F-JTC: $Z = -0.470, p \leq 0.638$ (2-tailed)

JTC < F-B-JTC: $Z = -0.619, p \leq 0.536$ (2-tailed)

JTC > CMD: $Z = -0.373, p \leq 0.709$ (2-tailed)

³ Wilcoxon Signed Ranks for pairwise differences of profile values

JTC < B-JTC: $Z = -0.737, p \leq 0.461$ (2-tailed)

JTC < F-JTC: $Z = -4.233, p \leq 0.000$ (2-tailed)

JTC < F-B-JTC: $Z = -3.080, p \leq 0.002$ (2-tailed)

JTC < CMD: $Z = -1.611, p \leq 0.107$ (2-tailed)

Wilcoxon signed ranks test found the pair-wise comparisons between each of these results significant.

4.3.2 Error Distance

This evaluation technique measures the Euclidean distance (kilometers) between the predicted residence and the offender's actual residence (e.g., Levine, 2000; 2007; Snook *et al.*, 2002; Rich & Shively, 2004; Paulsen, 2006b). Accordingly, shorter distances are better. As presented in Table 4.3, the CMD estimate produced the shortest average error distances of all five techniques (4.408 km), whereas the Bayesian-JTC produced the shortest median distance (3.35 km). Interestingly, the average error distance of the two Bayesian formulations did not perform as well as either the traditional JTC or the Filtered-JTC averages. The relatively large variances observed for this diagnostic technique makes it difficult to identify any subtle differences between routines. Consequently, the Friedman chi-square analysis failed to identify significant differences for the error distance.

Despite producing the shortest average error distance, the CMD technique was only equal or better than the JTC method for 26 of 53 cases (49.06%). This was followed by the Filtered-Bayesian-JTC, which produced 33 equal or better estimates (62.26%). The next best results came from the Bayesian-JTC estimates (34), and finally the Filtered-JTC technique which peaked with 40 (75.5%) estimates that were equal or better than those of the JTC routines. However, the Filtered-JTC model produced far more ties (27) than positive ranks (13). In fact, the Filtered-JTC method had the fewest positive ranks of the other methods. Conversely, the CMD technique produced the greatest number of positive ranks (25) and the fewest ties, (1). While these results are noteworthy, statistical significance remained elusive according to the Wilcoxon tests.

4.3.3 Search Cost/Hit Score

Arguably the best measure for evaluating a profile; the search cost/hit score represents the proportion of the study area that must be searched in order to locate the offender's anchor point. Because it is an indicator of cost, profiles that produce smaller proportions signify higher precision. Overall, profiles that incorporated land cover within the JTC framework required, on average, fewer grid cells to identify offender anchor points when compared to other methods (see Table 4.3). Accordingly, the smallest average search cost was produced by the Filtered-Bayesian-JTC routine (~0.026), and the smallest median result produced by the Filtered-JTC routine (~0.064). Results from the Friedman tests support these findings, confirming significant differences among output values and within these individual techniques. Once again, the filtered approach improved the output derived by the Bayesian routines. Not surprisingly, the average hit score produced by the CMD routine (~0.0394) performed better than those of the traditional and Bayesian-JTC techniques. However, the large amount of variability in the CMD output made it difficult to recreate this performance for the median value (~0.0157).

As illustrated in Table 4, pair-wise comparisons between the Bayesian-JTC and standard JTC strategies show a large improvement between hit score results (60.4%). However, the Wilcoxon tests failed to identify significance for this result. Comparatively, the Filtered-JTC profiles exhibit a significant gain, producing 46 (86.8%) precise estimates when compared to JTC estimates. Again, land cover filters were able to improve upon the Bayesian estimations, increasing the number of positive ranks to 31, while dropping the ties from 7 to 6. Finally, the CMD routine produced 18 estimates that were more accurate than the JTC technique. Yet, these results were not significant.

4.4 Discussion

The results presented above confirm that that land cover characteristics can be used to enhance existing JTC estimation routines. By combining the marginal probability of land cover with a distance probability function, the likelihood of identifying an offender's anchor point was effectively constrained to those land cover types inhabited by previous offenders. This filtering methodology was able to refine and improve the JTC estimates for both the traditional and Bayesian-enhanced methodologies (see Tables 4.3 and 4.4). For instance, the cumulative output of the Filtered-JTC routine equaled or outperformed the standard JTC results for all three evaluation measures: probability value (+50), error distance (+40), and Search cost/hit score (+46). Similarly, cumulative results generated for the Filtered-Bayesian-JTC routine demonstrated an improvement of the Bayesian-JTC estimates for two out of three evaluation methods: probability value (+6), error distance (-1), and search cost/hit score (+5). Indeed, the land cover-enhanced methods produced the smallest average and smallest median search cost/hit score of all profiles (Table 4.3). The effects of the filtering approach are best observed when comparing JTC surface maps. For example, Figure 4.7 illustrates the probability (risk) surface of a traditional JTC estimate produced for a particular serial robbery offense. The ubiquitous configuration of concentric probability rings surrounding the crime scenes illustrates the classic effects of a distance decay function. The probability of identifying the offender's anchor point is 0.00045, with a hit score of 5.0115%. In contrast, Figure 4.8 illustrates the effectiveness of the land cover-enhanced Bayesian strategy. Here, the probability of the offender's anchor point is 0.00193, with a hit score of 0.495%. While both techniques predicted the same grid cell, the search cost is significantly reduced, more than ten times.

Baltimore, Maryland, Study Area

Geographic Profile: Burglary Series (BR041)
480m Grid Cell

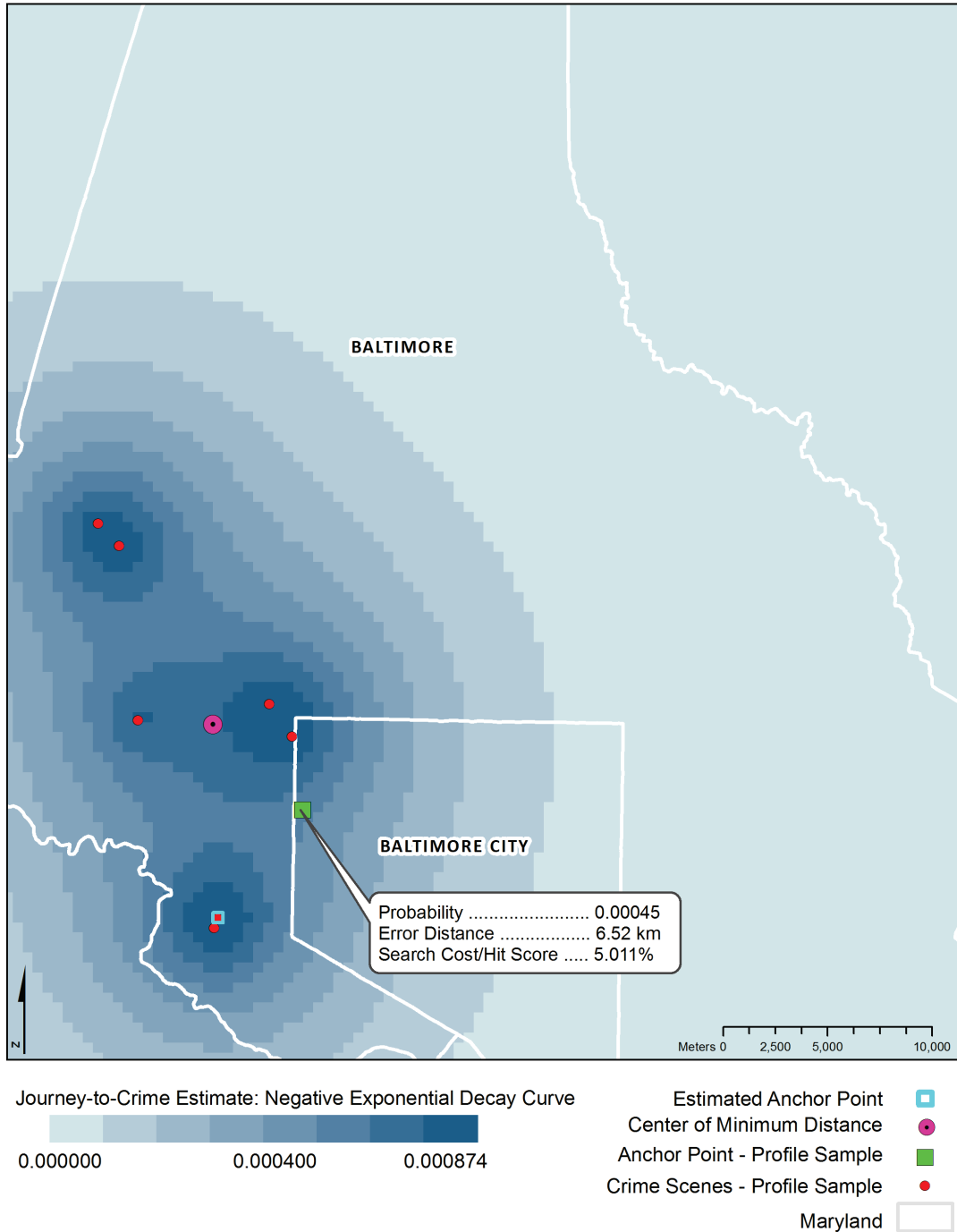


Figure 4.7: Journey-to-Crime probability map.

Baltimore, Maryland, Study Area

Geographic Profile: Burglary Series (BR041)
480m Grid Cell

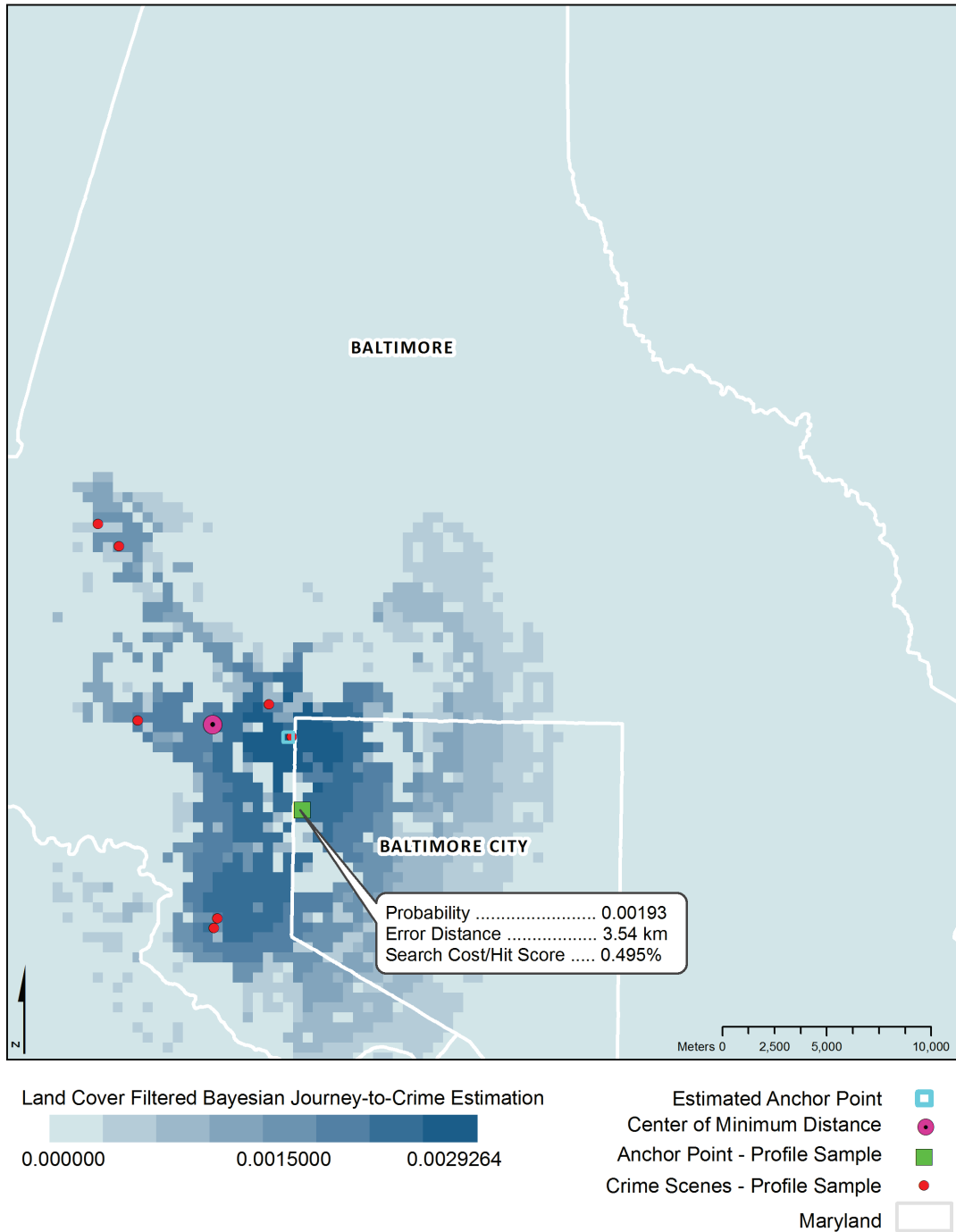


Figure 4.8: Filtered Bayesian Journey-to-Crime estimate probability map.

Still further, the land cover-enhanced approach more effectively accounts for the Baltimore landscape: locations that were otherwise unsuitable as a potential residence were effectively devalued or excluded from the analysis. Accordingly, both physical and cultural structures become prominent elements within the modeled output. And by virtue of their land cover classifications; these locations were assigned values that reflect the marginal probability of containing the offender's residence. Thus, non-residential land cover categories are devalued while residentially-favorable categories are amplified. This approach, however, may distort profile estimates when the assumptions about an anchor point cannot be met (i.e., if the offender's anchor point is not his/her residence).

Despite the obvious enhancements to a profile's efficiency, these findings were not consistent over all estimation techniques. Table 4.3 reveals that the mean and median error distances estimates were notably shorter (i.e., better) for the CMD and Bayesian-JTC techniques when compared to the other routines. The Filtered-JTC produced 27 tied estimates, more than any other technique. The CMD also had the fewest number of ties. These findings match those produced by Levine (2000) and Paulsen (2006b), and further support the efforts by Snook et al. (2002; 2004; 2005) and Taylor et al. (2009) for the application of alternate heuristics for profiling offender anchor points. But as is evident in the tables, the CMD method exhibits considerable variance, which likely explains the lack of significance in the outcomes. Similar inconsistency is observed for the search cost/hit score evaluation: the Filtered-JTC produced lower hit scores for 35 of the 53 cases. However, this number drops to 31 for the Filtered-Bayesian-JTC estimates. The likely source for the inconsistent outcomes relates to an overestimation of anchor points introduced by the Bayesian likelihood function.

Recall that the Bayesian-JTC formulation uses the conditional probability of anchor points for known offenders as a means of updating the prior JTC probability. In order to derive that likelihood function, at least one crime scene from both the calibration and test samples must fall inside a coincident grid cell. To ensure that this occurs, either the grid cells and/or calibration sample must be sufficiently large. The consequence of either, or both, is non-trivial. When the study grid becomes too large, the precision of the estimate decreases. Likewise, when the calibration sample is increased, so too is the possibility of introducing anchor point outliers. The implications for this scenario increase with the introduction of heterogeneous offense types. Research has established that different crime types will exhibit different spatial patterns (e.g., Rhodes & Conly, 1981; LeBeau, 1987; Canter & Larkin, 1993; Rossmo, 2000; and Snook, 2004). And referencing Table 4.1, the median and average distances traveled for burglary and robbery cases are noticeably different, though not significant. As such, combining the travel characteristics of these two offense types could have biased the conditional probability of locating an anchor point away from its actual location.

Model bias is not limited to the conditional probability function. A plausible source of bias relates to both the marginal probability of land cover and the JTC distance decay model. As illustrated in Figure 4.6, the majority of the offenders within the calibration dataset have anchor points located within developed land cover zones (e.g., high, medium, and low - intensity). Not surprisingly, developed land cover zones were also the most frequently observed category for crime scenes in the Baltimore study area (mode = developed-low intensity). Because the shape of the distance decay curve emphasized the grid cells immediately surrounding the crime scenes (Figure 4.2), and because the majority of cells surrounding crime sites were classified as developed land cover zones, the highest profile probability estimates were calculated for these

developed zones. As a consequence, the product of the JTC estimation and the marginal land cover probability is behaving as a pseudo maximum likelihood estimator (similar to the Bayesian likelihood function). For that reason, the product of the independently estimated marginal land cover and JTC probabilities results in a profile that over-emphasizes developed land cover zones at the exclusion of all others. In short, when the estimator is correct, it works well; when it is wrong, it works poorly.

Concerning the JTC decay models, the implications of over-fitting a probability distance function was recently examined within the context of a model's goodness of fit (Canter & Hammond, 2006). As Brantingham & Brantingham (1981) postulated, the distance decay effect is a ubiquitous characteristic for nearly all serial crime cases. While it is important to optimize a model's fit for the JTC distribution, the choice and significance of that regression algorithm may ultimately be arbitrary constructs that distract from the offender's unique spatial behavior (Canter & Hammond, 2006; Smith, Bond, & Townsley, 2009). In a study published by Smith et al. (2009), the authors caution that the distance decay pattern observed for aggregate JTC distributions cannot be considered statistically independent, thus may result in biased estimations (Taylor, Bennell, & Snook, 2009). Such concerns are not new (e.g., van Koppen & de Keijser, 1997; Rengert et al., 1999). Journey-to-crime distributions are, by their very nature, idiosyncratic to the offender. Thus, the unique characteristics of an offender's spatial behavior are lost when the data are aggregated. For that reason, the resulting decay functions may only be applicable for inferring criminal mobility characteristics from the calibration sample (Smith et al., 2009). So, while aggregate models may over-emphasize (if not misinterpret) the mobility characteristics of the unknown serial offender, the distance decay model remains the only

systematic mechanism for calculating the maximum likelihood of an offender's journey to crime (Levine, 2005; O'Leary, 2009).

4.5 Conclusions

The primary objective for this research was to determine the efficacy of incorporating land cover characteristics within a geographic profiles framework. To that end, this study proposed that an offender's anchor point is spatially constrained to certain land cover characteristics that are common to other offenders. The premise for this assertion is based on research that has demonstrated how the location of linked serial crime scenes will exhibit spatial patterns and distribution characteristics that are influenced by structures within physical and cultural landscapes (Brantingham & Brantingham, 1981). Accordingly, a geographic profiling model capable of parameterizing the deterministic impact of these underlying structures should predict the residential location of a serial offender more accurately. This study proposed to measure this efficacy of this approach by comparing five profiling models generated using traditional and land cover-enhanced techniques. Geographic profile estimates were created for 53 serial crimes occurring in Baltimore County, MD, over a four year period. The first profiling technique estimated an offender's JTC using an empirically calibrated, exponential distance decay model. Next, a Bayesian-JTC estimate was calculated using methods published by Levine (2007). The third profile technique, Filtered-JTC, was constructed according to the marginal probability of identifying an offender's anchor point within a particular land cover type. Fourth, the Bayesian-JTC technique was updated using the marginal land cover probability estimate as a filtering mechanism. Finally, the simple and ubiquitous CMD technique completed the collection of profiling strategies. A comparative analysis was performed on each profiling strategy.

The first of the three accuracy assessments compared the different profile probability values of the estimates. The data revealed that the two land cover-enhanced methods (Filtered-JTC and Filtered-Bayesian) had the highest significant probability averages of all profile measures. The introduction of the marginal probability of land cover effectively constrained the profiled output to those land cover types that most likely supported offender anchor points. While the filtering technique cannot be used to prioritize criminal suspects, it can eliminate areas such as woodlands, water bodies, and other unlikely areas from investigatory consideration. The next measure, the average profiled error distance, was not able to demonstrate a significant improvement. However, the CMD strategy out-performed the probability distance strategies. This was not a surprise, as the CMD represents the physical location of the maximum likelihood estimate of the offender's anchor point (Levine, 2005; O'Leary, 2009). Finally, the search cost/hit score was employed to assess a profile's precision. For the sample used in this study, the results further support the use of land cover characteristics within a modeling framework. Both the Filtered-JTC and Filtered-Bayesian-JTC methods showed improvement over the non-filtered JTC and CMD methods. The marginal probability of land cover was able to further enhance the performance of the Bayesian-JTC method.

While this study has demonstrated the efficacy of land cover-enhanced geographic profiles, there are some aspects that deserve further research. Specifically, attention must be paid toward the method of assigning land cover probabilities. All offenders in the calibration sample resided in the developed land cover zones. As the dominant category, profiles generated for offenders living in this zone performed better than profiles generated for offenders living in other zones. That is, land cover-enhanced profiles favored a particular land cover type. The implication for this finding is that there is a dependent relationship between the JTC probability

function and land cover. While these probabilities are independent (i.e., the land cover is the marginal probability defined by offender anchor points; and the JTC is a probability distance function defined by crime scenes), both the marginal land cover and JTC probabilities follow distributions which are inherently geographically dependent. Accordingly, future studies should examine the impact this may have on the efficacy of land cover-enhanced estimates.

Additional studies should investigate profiling strategies that operate at finer resolutions, thus permitting improved search strategies and suspect prioritization. Similarly, the Bayesian likelihood function used in this study could be refined. The Bayesian-JTC conditional probability (i.e., likelihood) estimate depends on the spatial coincidence of crimes from the calibration and test sample. To ensure that this would happen, the grid cells used in this investigation were increased in size from 30m to 480m resolutions. Additionally, the calibration sample included mixed offense types (i.e., burglary and robbery), which may have adversely altered the modeled output. Once the scale issues have been addressed, it may be feasible to incorporate higher-resolution land use information within the filtering framework. For instance, this study chose the NOAA C-CAP data due to its age and accessibility. Alternatively, some law enforcement jurisdictions may have access to higher resolutions of data, including parcel-scale land use data.

Finally, future studies should attempt to incorporate the probability of land cover within a true Bayesian framework. Indeed, the authors of this study have begun to investigate methods by which land cover likelihood estimates can be derived according to the distribution of anchor points from a calibration sample. And, while such a method remains susceptible to the caveats identified above, the successful implementation of this approach could further enhance the capabilities of law enforcement to mitigate serial crime.

"Crime is a dependent phenomenon modified by urban form and general patterns of perception or cognition."

- Brantingham & Brantingham (1981, p. 48)

CHAPTER 5: INCORPORATING LAND COVER WITHIN BAYESIAN JOURNEY-TO-CRIME ESTIMATION MODELS

5.1 Introduction

The unknown serial offender initiates criminal activity from an anchor point, or points, located within an anisotropic plane. That is, the relationship between offender, target, and criminal opportunity does not exist as random events distributed across space (Brantingham & Brantingham, 1981; Capone & Nichols, 1975; 1976). Rather, these dimensions of crime are governed by physical and cultural structures that are unique to the environment in which they occur (Brantingham & Brantingham, 1981). Yet, contemporary techniques for modeling a criminal's spatial behavior will typically adopt the *a priori* assumption that opportunity and target access reside on an isotropic surface surrounding the offender's anchor point. Because these techniques are incapable of accounting for inherently asymmetrical landscapes, modeled output becomes susceptible to errors that can result in the over and under-estimation of the offender's actual point of origin (Kent & Leitner, 2009; Rengert et al., 1999). By focusing on those factors that reflect the restrictions imposed by the environment, it may be possible to identify the criminal anchor point and apprehend the offender more consistently.

Previous research by Kent & Leitner (2009) demonstrated that the social and environmental constraints influencing the criminal activity space (i.e., the finite area defined by the event nodes and paths utilized by the offender) can be parameterized using land cover

characteristics. When applied as a filtering mechanism, the marginal land cover probability associated with the residences of known serial offenders proved to be an effective approach for generating accurate and precise predictions of the unknown criminal's anchor point. But, to what extent could land cover enhance the predictive accuracy of a geographic profile if it were directly integrated within contemporary modeling techniques? This research will examine this question, and expand on previous findings to assess the efficacy of incorporating land cover probabilities within a discrete Bayesian framework. To test this hypothesis, traditional and land cover-enhanced models will be used to create geographic profiles for a random sample of solved serial crimes that occurred in Baltimore, Maryland. Results derived from each profile will be compared and assessed for accuracy and precision. This study will conclude with a discussion of findings and recommendations for continued research.

5.1.1 The Ecology of Crime

The utility of a geographic profile is realized through its ability to formulate inferences and reveal characteristics about an offender's spatial behavior (Brantingham & Brantingham, 1981; Rossmo, 2000). This approach originates from concepts derived from environmental criminology. Four theories that best characterize the ecological relationships between criminal behavior and place are *routine activity* theory (e.g., Cohen & Felson, 1979; Felson & Clarke, 1998), *rational choice* theory (e.g., Cornish & Clarke, 1986), *crime pattern* theory (e.g., Brantingham & Brantingham, 1981), and *environmental range* (e.g., Canter & Larkin, 1993). Comprehensively, these concepts establish that an offender's behavior in space is the product of rational decision making from which the perception of criminal opportunity and target attractiveness is constrained by the physical and cultural environment located in relative

proximity around an offender's residence (Brantingham & Brantingham, 1981; Canter & Larkin, 1993; Cohen & Felson, 1979; Rengert et al., 1999; Rhodes & Conly, 1981).

5.1.2 Contemporary Geographic Profiling Models

As demonstrated in numerous studies (e.g., Brantingham & Brantingham, 1981; Canter & Larkin, 1993; Capone & Nichols, 1975; 1976; LeBeau, 1987b; Leitner et al., 2007; Kocsis & Irwin, 1997), an offender's geographic behavior will exhibit deliberate biases that coincide with the tenets of environmental criminology. Consequently, these patterns of spatial behavior can be modeled with varying degrees of success. Nearly all contemporary criminal investigations apply some method for geographically profiling an offender's behavior in space. Most of these techniques apply quantitative models that are based on fundamental geographical principles. Spatial distribution and spatial interaction models dominate contemporary geographic profiling methods. The spatial distribution approach includes measures of central tendency (e.g., geographic mean, median, and center of minimum distance) and diffusion (e.g., areal circle, standard deviational ellipse, and convex hull). These simple techniques have demonstrated notable effectiveness as fast and intuitive investigative tools (Levine, 2005; Paulsen, 2006a; 2006b; Snook et al, 2004; 2005; Leitner et al.,2007). Furthermore, centrographic methods are often found within contemporary research as diagnostic routines that provide benchmarks for assessing the performance of multiple profile models (e.g., Paulsen, 2006a; Levine, 2009; Levine & Block, 2009). However, single descriptive measures such as these are susceptible to outliers. As a consequence, these techniques are often criticized for their inability to provide an efficient search strategy for locating an offender's anchor point (Levine, 2005; Rossmo, 2005; Snook et al., 2005; Taylor et al., 2009).

The second approach typically involves sophisticated spatial interaction models to assess the criminal commute. Specifically, these models characterize the observed *distance decay* effect in context to the costs and benefits of committing a criminal offense (Brantingham & Brantingham, 1981; Capone & Nichols, 1975; 1976; Lottier, 1938; Turner, 1969). Perhaps the most common approach for modeling distance decay is the Journey-to-Crime (JTC) estimation. JTC estimations consist of density surfaces calculated using the travel patterns observed for solved serial crimes. The techniques for this approach are well documented and will not be discussed here (see Levine, 2007 and Rossmo, 2000). Despite the popularity, JTC estimation models are often criticized for theoretical and empirical limitations (van Koppen & de Keijser, 1997; Rengert et al., 1999; Snook et al., 2005; Smith et al., 2009). To overcome these caveats, many researchers have pursued, with notable success, alternative heuristics for profiling offender behavior in space (e.g., Paulsen, 2006b; Snook et al., 2002; 2004; 2005; Taylor et al., 2009). However, these techniques continue to omit the factors associated with criminal opportunity and target attractiveness. Another approach, based on Bayesian probability theory, appears well-suited to account for the fundamental tenets of environmental criminology.

5.1.3 The Empirical Bayesian Paradigm

Bayesian probability represents an intuitive process for quantifying the degree of belief in a hypothesis before and after evidence has been observed. In many respects, the Bayesian approach follows the same process as the scientific method: when new evidence has been observed, our prior state of knowledge is updated to reflect a revised measure of confidence in the hypothesis. As evidence is accumulated, the hypothesis adjusts according to how likely that new evidence would be observed under all conditions. Thus, Bayesian theory quantifies the degree to which new evidence alters the confidence in one's hypothesis (Bolstad, 1997).

A Bayesian formulation for modeling an offender's spatial behavior was first operationalized for the CrimeStat[®] III software package (Levine, 2007). Since then, numerous studies have utilized the Bayesian approach for modeling criminal behavior in space and predicting future crimes (e.g., Block & Bernasco, 2009; Levine & Block, 2009; O'Leary, 2009). The methodological advantage of the Bayesian formulation is that it is capable of incorporating the principles of environmental criminology as conditional factors associated with the distance decay models used in JTC estimates. It does so by relating the crimes committed by an unknown offender with the crimes committed by a calibration sample of known offenders (i.e., solved cases). Levine (2007) applied this approach by combining two new Bayesian derived probability estimates with traditional JTC estimates. The first value represents the conditional probability of locating an offender's anchor given the location of anchor points from solved cases. The second estimate is known as the marginal probability of anchor points, which represents the probability assigned to the locations of all anchor points observed for solved criminal cases. When combined with the JTC estimate (i.e., the empirical prior probability of an anchor point), these values produce a refined prediction of the unknown offender's residence. By combining the elements from solved cases with those of the unsolved, criminal opportunity and target attractiveness become implicit factors that are manifest through (a) the likelihood of an anchor point derived from for known offenders that committed crimes the same location as the unknown offender, and (b) the marginal probability of all known anchor points located in the study area.

The ability to account for offender perception and mobility characteristics notwithstanding, the Bayesian framework is incapable of excluding those locations (e.g., rivers, lakes, parks, forests, bridges, malls, etc.) that are *a priori* unlikely to contain an anchor point. As

a consequence, the inherent environmental structures distributed across the study area are only implicitly accounted for when using the Bayesian JTC model. Furthermore, the product of the JTC prior and conditional likelihood functions is vulnerable to over- and under- estimation errors that can mislead an investigation. For instance, the conditional probability estimate can only emphasize, at the exclusion of all others, those locations immediately surrounding the anchor points of previous offenders. This is especially problematic if the unknown offender initiated crimes from locations that are not consistent with those observed for solved cases. To overcome such limitations, environmental characteristics of the offender's activity space should be incorporated within this modeling framework. Doing so would ensure that the JTC estimates are constrained to those places that are most likely to contain the offender's anchor point.

5.1.4 Incorporating Land Cover

Kent & Leitner (2009) demonstrated that land cover characteristics can be used as a proxy for the physical and cultural features that constrain the offender's activity space. The authors compared the performance of traditional and Bayesian JTC models with land cover enhanced models. Their results revealed significant, but sometimes mixed, performance gains when predicting and locating the offender's anchor point (see Kent & Leitner, 2009 for details). Despite the mixed outcomes, their findings effectively validated the premise that a deterministic relationship exists between land cover characteristics and location of an offender's anchor points. Indeed, the product of the two marginal probabilities, the JTC and the land cover, improved a model's ability to estimate the offender's anchor point. However, these estimates also suffered from biases similar to those cautioned in the preceding discussion on the Bayesian JTC paradigm.

For instance, Kent & Leitner (2009) found that the land cover filtered JTC estimates performed best for those anchor points that were located in the dominant land cover categories. That is, the product of the two marginal probabilities was improved whenever those values represented the maximum likelihood estimate for their respective parameters. While the performance of the filtered approach showed improvement in accuracy and precision, this approach becomes vulnerable to a “rotten apple” effect. That is, if land cover parameter estimates were wrong or otherwise failed to adequately represent the value for the true anchor point, then the resulting product would bias the estimate of the true location of the anchor point. And just as before, this scenario becomes problematic for those unknown offenders who initiate crimes from land cover types that are inconsistent with those observed in the calibration sample. To compensate for this effect, the product of the JTC and marginal land cover must be reformulated as a joint probability between the conditional land cover likelihood and the prior anchor point estimate. In other words, it must take on the Bayesian formulation.

5.2 Research Proposal

This research proposes that a geographic profiling model that can formally parameterize both spatial interaction and landscape characteristics will produce more accurate estimates of the serial offender's anchor point than existing techniques. To test this hypothesis, traditional and land cover enhanced geographic profiling models will be generated for a random sample of solved serial burglary, larceny, and robbery offenses that occurred in Baltimore, Maryland, between 1993 and 1997. Profiles will be used to estimate the location of an offender's known residence. Spatial interaction models will be calculated according to distance decay algorithms, derived from a calibration sample, and applied within traditional JTC estimation routines. Landscape characteristics used for this research will be approximated by land cover

classifications collected for the Baltimore study area. Land cover will be integrated within a JTC modeling framework according to an empirical Bayesian formulation similar to that issued by Levine (2007). The efficacy of this approach will be assessed by comparing the accuracy and precision of the estimates produced by each technique.

This hypothesis is conditioned on three assumptions. First, each crime series consists of offenses perpetrated by a single individual. Second, the offender is assumed to have initiated and concluded all criminal activities from a fixed anchor point (i.e., the residence) located within the study area. Third, the land cover classifications used in this study reflect the actual physical and cultural structures that influenced the offender's spatial behavior (e.g., perceptions of opportunity and target attractiveness) and the distribution of available targets (i.e., target backcloth).

5.3 Data and Methodology

The methodology employed for this study is organized into three sections. The first part describes the crime and land cover datasets utilized in this investigation. Next, descriptions of the seven geographic profiling models are provided. The final section presents the tests used to assess the modeled estimates.

5.3.1 Data Used

Crime dataset: The crime data used for this study were comprised of 781 solved serial burglary, larceny, and robbery offenses that occurred in Baltimore, MD, between 1993 and 1997. The 781 crimes comprised 167 crime series (burglary=47, larceny=43, robbery=77), averaging 4.68 crimes per series (burglary=4.40, larceny=4.32, robbery=5.04). Figure 5.1 illustrates the journey to crime frequency distribution for the entire Baltimore dataset. The average criminal commute measured 6.79 km (SD=6.88 km) with a median value of 4.94 km. The shortest

measured distance was 0.00 km and the longest measured 52.76 km. The Baltimore dataset was split into two randomly assigned groups. The *profile sample* consisted of 263 offenses associated with 52 series. The number of crimes per series averaged of 5.06 (SD=2.22) with a median of 4 (Table 5.1). The *calibration sample* was comprised of 518 offenses for 115 crime series. Each case had an average of 4.50 (SD=1.90) and median of 4 crimes per series (Table 5.2). A larger calibration sample was chosen to ensure modeling efficiency.

Land cover dataset: As in their earlier study, Kent and Leitner (2009) used land cover data obtained from the 1996 Coastal Change and Analysis Program (C-CAP) dataset developed

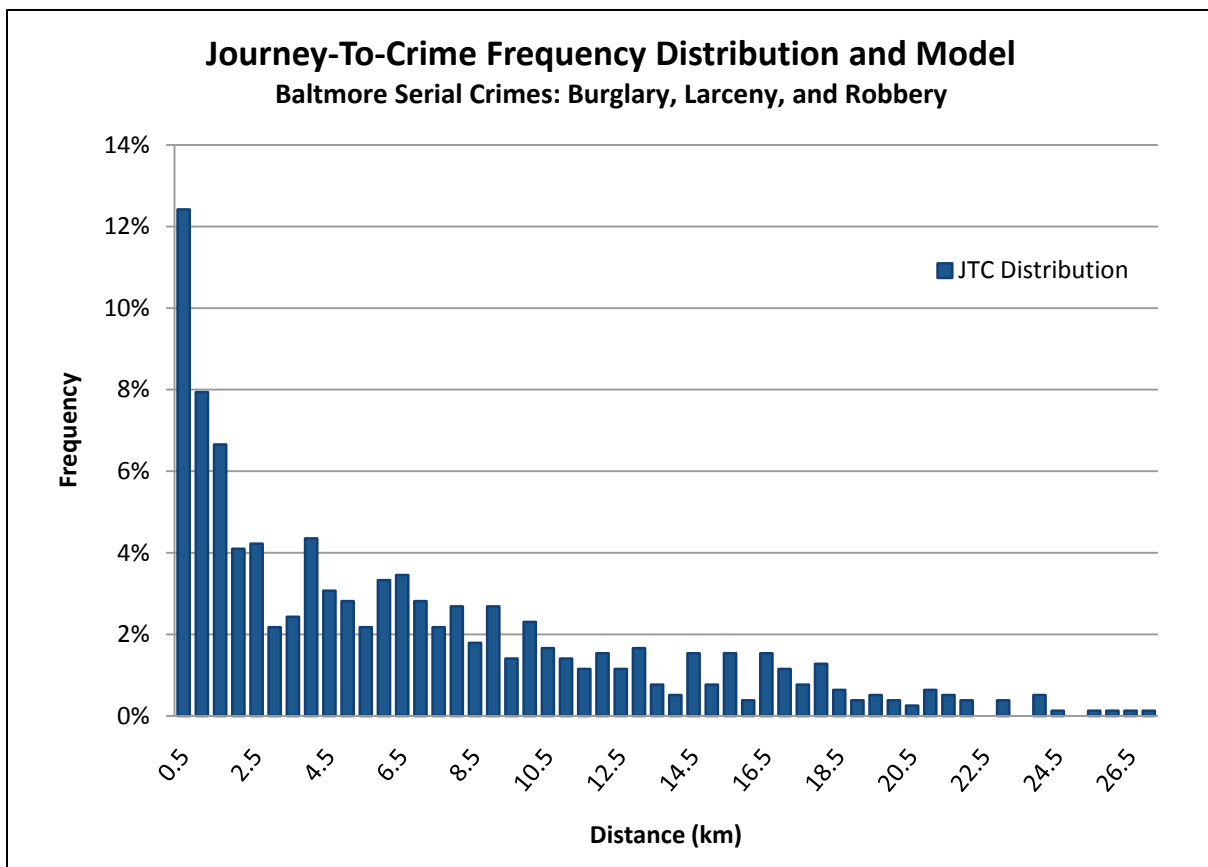


Figure 5.1: Journey-to-Crime frequency distribution of the serial crime dataset for Baltimore, MD.

Table 5.1: Profile Sample of Baltimore, MD, Serial Crimes

	Count	Offenses				Journey-to-Crime (km)				
		sum	mean	stdev	median	mean	stdev	min	median	max
Burglary:	11	60	5.45	2.98	4	5.01	6.65	0.00	1.43	22.95
Larceny:	14	60	4.29	1.20	4	7.687	7.00	0.00	5.44	26.60
Robbery:	27	143	5.30	2.25	4	7.732	5.202	0.33	6.71	23.56
Totals:	52	263	5.06	2.22	4	7.101	6.08	0.00	5.47	26.60

Table 5.2: Calibration Sample of Baltimore, MD, Serial Crimes

	Count	Offenses				Journey-to-Crime (km)				
		sum	mean	stdev	median	mean	stdev	min	median	max
Burglary:	36	147	4.08	1.56	4	5.99	9.36	0.00	1.61	52.76
Larceny:	29	126	4.34	1.72	4	7.472	7.36	0.00	5.87	38.23
Robbery:	50	245	4.90	2.17	4	6.613	5.539	0.00	5.64	23.94
Totals:	115	518	4.50	1.90	4	6.646	7.25	0.00	4.53	52.76

by the U.S. National Oceanic and Atmospheric Administration (NOAA). The source data consisted of twenty-three land cover classifications derived from 30-meter resolution Landsat Thematic Mapper and Enhanced Thematic Mapper satellite imagery (NOAA, 1996). Performance requirements necessitated aggregation of the land cover data from 30 meter to 480 meter cell sizes. Each cell was assigned the statistical mode of the land cover classification calculated from the 256 (16x16) contiguous 30 meter cells. As a consequence of the aggregation process, the number of usable land cover classes shrunk to eighteen (Figure 5.2). The resulting coverage contained 12,932 grid cells. The coverage fit the geographic extents of the Baltimore study area, measuring approximately 2,956 km². The chart provided in Figure 5.3 illustrates the proportion of land cover classes available within the aggregated dataset.

5.3.2 Geographic Profiling Models

Seven models were chosen to compare the effectiveness of land cover-enhanced geographic profiles. Techniques consisted of traditional and landscape enhanced spatial interaction models. A centrographic technique was also utilized for diagnostic comparisons.

The models are presented below:

- JTC Estimation
- Bayesian JTC Product
- Bayesian JTC Posterior
- Filtered JTC Estimation
- Land Cover Bayesian Product
- Land Cover Bayesian Posterior
- Center of Minimum Distance

Baltimore, Maryland, Study Area

1996 NOAA C-CAP Land Cover Dataset

480m resolution

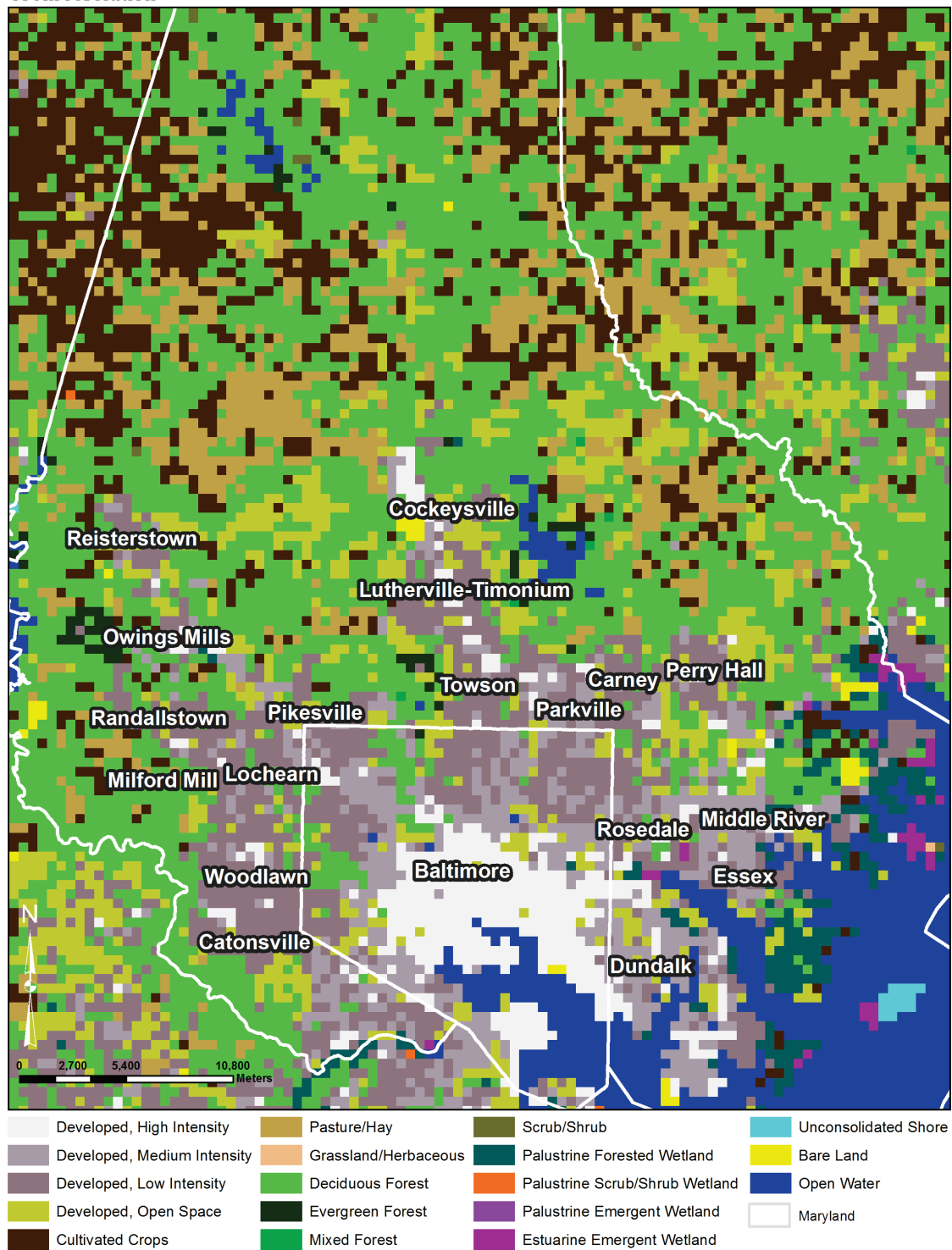


Figure 5.2: Land cover dataset for the Baltimore, MD, study area.

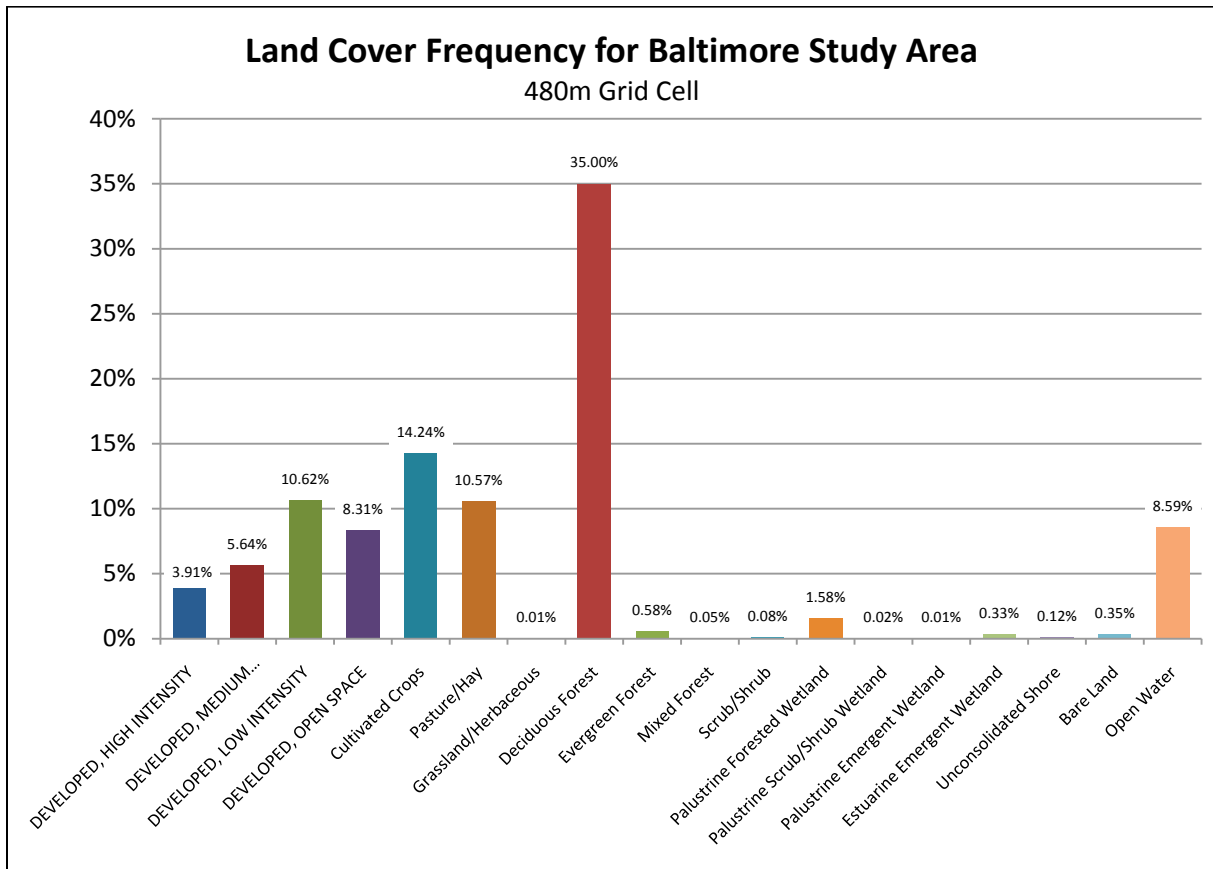


Figure 5.3: Distribution of aggregated land cover classes in the Baltimore, MD, study area.

Journey-to-Crime Estimation: The JTC profiling technique estimates the probability of locating an offender's anchor point by applying an empirically calibrated distance decay function to the distribution of linked crime scenes. The decay function is used to assign likelihood values to a density surface representing the criminal study area. There are two methods for calculating the decay algorithm. The first method fits a mathematical trend function through a sample distribution of solved serial crimes (i.e., the calibration sample). More often than not, this equation belongs to an exponential family of functions (Canter et al., 2000, Rossmo 2000). However, alternate techniques have been used (e.g., Canter & Hammond, 2006 and Levine, 2007). The second approach uses an interpolation kernel routine to regress a non-linear function directly through the calibration distribution (Levine, 2007). Once a distance decay function has

been determined, it is applied to the distribution of crimes committed by the unknown offender. The result is a discrete probability surface that represents the likelihood of locating an offender's anchor point within the study area.

The calibration sample used to derive the distance decay curve contained 120 solved serial cases (see Table 5.2). A JTC frequency distribution consisting of 500-meter distance intervals (i.e., bins) was constructed for all incidents in the sample. An exponential function, chosen due to its simplicity and popularity within the geographic profiling literature (e.g., Canter et al., 2000; Canter & Hammond, 2006; Levine, 2005; 2007), was regressed, and fit onto the frequency distribution (Figure 5.4). Although the coefficient of determination was weak, $R^2 = 0.4306$, the equation proved to be a significant fit ($F = 96.81, p < 0.000$).

With the decay function defined, the JTC estimate proceeded in four general steps. First, a 480 meter regularly spaced grid consisting of 12,932 cells was placed over the study area. Second, the Euclidean distance between a cell's centroid and crime scene was measured for each crime in a given series. Next, the exponential distance decay function defined by the calibration sample (see Figure 5.4) was applied to each cell-to-crime distance, and summed over the series to produce a density estimate (Equation 5.1). Finally, a cell's modeled output was converted into a probability value by scaling the estimates such that the sum of all cell values equaled 1.0. The resulting surface represents the probability of identifying an offender's anchor point according to the distance decay model (see Levine, 2009):

$$P(\text{JTC}) = \sum_{i=1}^n f(d_{x_i z}) \quad (5.1)$$

where d is the Euclidean distance measured between each crime scene x_i and grid cell z , and the function, f , represents the negative exponential decay along the distances.

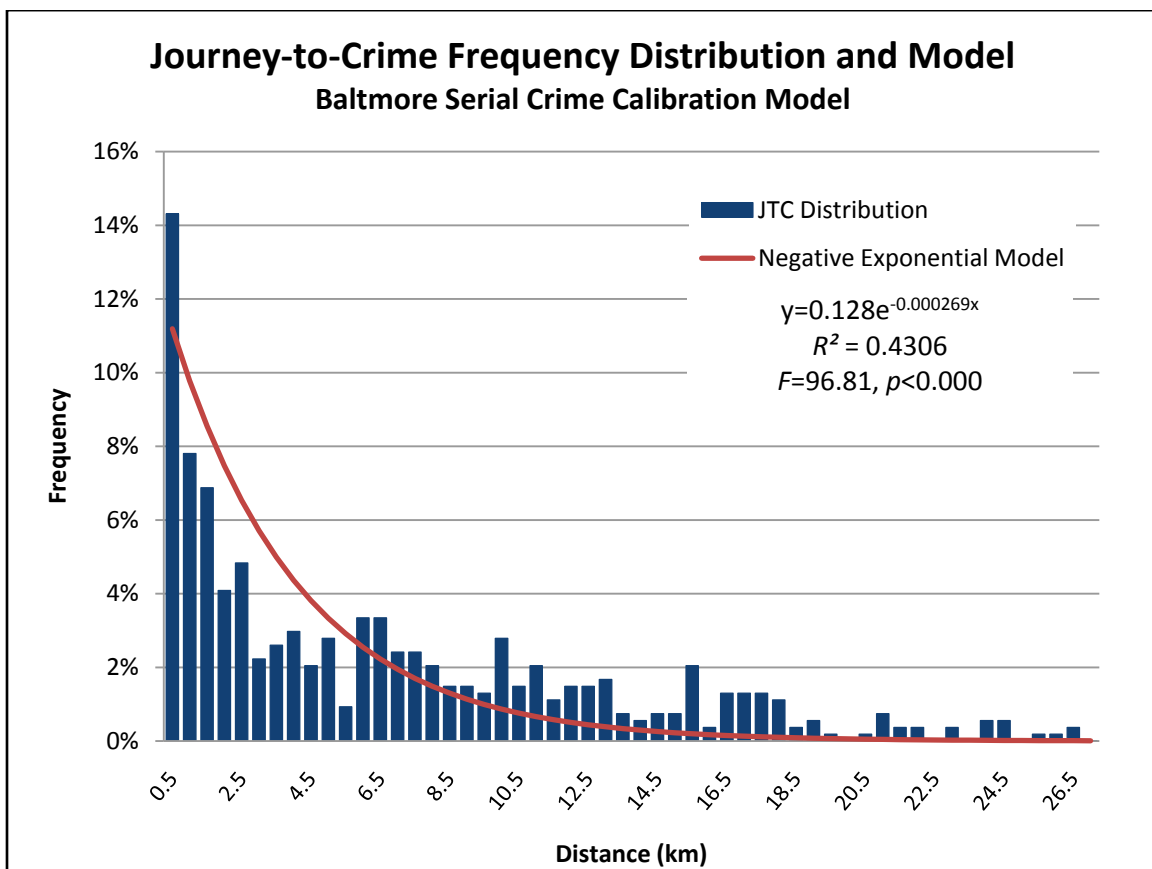


Figure 5.4: Journey-to-Crime frequency distribution and model of the Baltimore, MD, calibration sample.

Bayesian JTC Estimates: Bayesian probability relates the product of the *prior* and *conditional* probabilities of two events, A and B (Bolstad, 1997; Koch, 2007). The *prior probability* denotes the unconditional probability of some unknown phenomena before additional information has been obtained. That is, the probability of some event, A, is independent of any other condition. This information may be determined *a priori*, or can be derived empirically from a sample dataset. The *conditional probability* corresponds to the *likelihood* of some event, B, given a statement about the unknown phenomena, A. When normalized for all possible conditions, the product of this statement represents the *posterior probability* of A given B (Equation 5.2), and is combined according to Bayes' theorem:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \quad (5.2)$$

where $P(A|B)$ is the *posterior probability* of A given the observed event B. $P(B|A)$ is the *conditional probability* that B occurs given that A is true, which is also known as the *likelihood*. The *prior probability* is represented by $P(A)$, and $P(B)$ is the *marginal probability* of B under all circumstances, and serves as a normalizing factor.

The Empirical Bayesian JTC model for predicting the anchor point of a serial offender was first introduced in CrimeStat[®] version 3.1 (Levine, 2007). This formulation updates the empirically calculated JTC estimate of the unknown serial offender, the prior, using a likelihood function derived from solved serial crimes. The likelihood, $P(O|JTC)$, is the conditional probability of origin anchor points, O, given the anchor point for known offenders that committed crimes in the same locations as the unknown offender. The CrimeStat[®] manual refers to this as the *Conditional JTC estimate* [see the CrimeStat[®] v.3.1 manual for details (Levine, 2007)]. Two Bayesian probability estimates are generated according to this approach. The first is the product of the likelihood and prior, what is referred to as the Bayesian JTC Product (Equation 5.3). The Bayesian JTC Product represents the proportion of the posterior probability, taking the form:

$$P(JTC|O) \propto P(O|JTC)P(JTC) \quad (5.3)$$

where the posterior, $P(JTC|O)$, represents the relative weight of a JTC estimate that has been updated according to the conditional likelihood of previous offender anchor points, $P(O|JTC)$. The second probability estimate (Equation 5.4) is the full Bayesian JTC Posterior probability:

$$P(JTC|O) = \frac{P(O|JTC)P(JTC)}{P(O)} \quad (5.4)$$

where $P(O|JTC)$ is the likelihood estimate given the anchor point locations for known offenders that share spatially coincident crime scenes as the unknown offender, $P(JTC)$ is the empirically calibrated JTC estimate, and $P(O)$ is the marginal probability of all previously solved anchor points within the study area. Both the Bayesian JTC Product and Posterior probabilities were used to estimate offender anchor points in this study.

Following the methodological approach established by CrimeStat[®] III, the conditional probability, $P(O|JTC)$, was estimated by first identifying those grid cells where the crime scene locations from the profile and calibration sample were coincident. For each coincidence, the anchor points from the calibration sample were summed and interpolated onto the study grid as a probability surface using a kernel function. An adaptive normal kernel was chosen for this study, but other functions can be used. Probability surfaces were combined and scaled such that the sum of all cell values equaled 1.0. Finally, the product of the conditional and the prior JTC probability values were calculated for each cell and scaled; producing both the Bayesian JTC Product and numerator for the Bayesian JTC Posterior probability estimates.

Filtered JTC Estimate: Kent and Leitner (2009) demonstrated that land cover classes can enhance a JTC estimate when used as a proxy for the physical and cultural landscape. Specifically, the marginal probability of land cover was used to filter those locations that were *a posteriori* unlikely to contain an offender's anchor point. The frequency of a given land cover category was calculated for all grid cells that were spatially coincident with anchor points of the calibration sample. Of the eighteen land cover categories, only four classes could be associated

with the residences within the calibration sample. These values represent the marginal probability of identifying an offender’s residence according to a particular land cover type.

The Filtered JTC Estimate (Equation 5.5) represents the product of the marginal and JTC probabilities:

$$P(\text{Filtered} - \text{JTC}) = P(\text{JTC})P(\text{LC}) \quad (5.5)$$

where the *Filtered JTC Estimate*, $P(\text{Filtered-JTC})$, is equal to the product of marginal probability of land cover, $P(\text{LC})$, and the prior JTC estimation for a grid cell, $P(\text{JTC})$. The estimate is then scaled for each grid cell such that the sum is equal to 1.

Land Cover Bayesian JTC Estimates: This study proposes a new formulation of the Empirical Bayesian approach. It is intended to conditionally update an empirically derived prior probability, the JTC estimation, given the observance of a particular land cover type. As established earlier, the premise for this approach asserts that the location of an offender’s anchor point is spatially dependent on the surrounding physical and cultural environment. Thus, an offender’s residence must be confined to certain land cover characteristics inherent within the study area. Accordingly, the posterior probability of a JTC estimate can be conditionally related to the probability of observing a given land cover type (Equation 5.6), and takes on the form:

$$P(Z|\text{LC}) = \frac{P(\text{LC}|Z)P(\text{JTC})}{\sum_{i=1}^n P(\text{LC}|Z_i)P(Z_i)} \quad (5.6)$$

where each term of the Bayesian equation has a conventional name within the context of a geographic profile:

- $P(Z|LC)$ is the *posterior probability* of the offender's anchor point estimate, Z , given a particular land cover type, LC .
- $P(LC|Z)$ is the conditional probability of land cover given an offender's anchor point. This value represents the *likelihood* of the conditional estimate, and is interpreted to be the probability that a particular land cover class would be observed in the presence of the offender's actual residence.
- $P(JTC)$ represents the empirically estimated JTC prior probability of an offender's anchor point. It is *prior* in the sense that it was assessed independently from the observance of land cover.
- The denominator is the *marginal probability* of land cover for each grid cell in the study area, and is derived using the anchor points maintained in the calibration sample. As such, the denominator acts as a normalizing constant to the Bayesian function, which is $\sum_{i=1}^n P(LC|JTC_i)P(JTC_i)$. This marginal value may also be represented as $P(LC)$.

Two land cover enhanced Bayesian estimations are calculated. The first estimate is the enhanced *Bayesian JTC Product* (Equation 5.7), which represents the product of the conditional and prior probability (i.e., the numerator in Equation 5.6). This estimate is calculated independently of the marginal distribution (i.e., the denominator). The product takes on the form:

$$P(Z|LC) \propto P(LC|Z)P(JTC) \tag{5.7}$$

where the Land Cover Bayesian Product, $P(Z|LC)$, is proportional to the joint probability of the likelihood, $P(LC|Z)$, and the empirical prior, $P(JTC)$, probability values. This formulation provides the relative weights of a JTC estimate updated using land cover values observed for

previous offenders. The second estimate is the full Land Cover Bayesian Posterior, which is equivalent to the Land Cover Bayesian Product divided by the marginal probability of all land cover types used by the calibration sample offenders. The formula matches the form presented in Equation 5.6.

To calculate both the Land Cover Bayesian Product and Posterior, the conditional probability of land cover given the anchor point of known offenders had to be estimated. The routine first identified those grid cells in which crime scenes for the unknown offender were spatially coincided with crime scenes of the calibration sample. For each coincident pair, the anchor points from the calibration sample were selected. Next, the land cover classes for each of the selected calibration anchor points were summed and interpolated onto the study grid as a probability surface using a kernel function. The kernel was from the exponential (negative) family, though other functions can be applied. Anchor point probability surfaces were combined and scaled such that the sum of all cell values equaled 1.0. The rationale for using a negative exponential function is similar to the formulation detailed in the CrimeStat[®] manual. First, the kernel ensures that the area immediately surrounding the coincident anchor points will adequately represent the actual land cover. Such an approach was necessary given that the land cover data was aggregated from 30 meter to 480 meter grid cells. Second, the rapid decay and skew of the exponential kernel guaranteed that the land cover corresponding to the anchor points are not overly exclusive or inclusive. Only four land cover classes were associated with the calibration sample. As such, the model was at risk of excluding potential grid cells for locations that exhibited highly variable land cover types (e.g., suburban, recreational, and urban forested landscapes).

Center of Minimum Distance (CMD): Spatial distributions strategies are often utilized in geographic profiling studies as a diagnostic routine for comparing the efficacy of various models and profiling techniques (e.g., Levine, 2005; Paulsen, 2006a; Snook et al., 2005). Because of its simplicity and intuitive implementation, the center of minimum distance (CMD) has become a popular measure for predicting the anchor point location relative to the distribution of crime scenes (Equation 5.8). The CMD is iteratively defined as a point within the study area where the sum of the distance to all other crime locations is smallest (Levine, 2007):

$$CMD = \sum_{i=1}^n d_{min}(x_i, CMD_{\bar{x}}) \quad (5.8)$$

where the function d_{min} represents the minimum distance between the crime scene, x , at location i , and the current center of minimum distance, $CMD_{\bar{x}}$ for the distribution. In contrast to the six JTC routines described above, the CMD estimate represents a single point to indicate the predicted anchor point. Accordingly, this routine is vulnerable to outliers, which can distort the results. Furthermore, the CMD is often incompatible with investigative techniques that require search strategies for apprehending an offender.

5.3.3 Evaluation Techniques

The seven profiling models evaluated for this study were compared using techniques that measure accuracy and precision (Levine & Block, 2009; Paulsen, 2006b). The statistical significance for the groupwise and pairwise comparisons of each model was calculated using two non-parametric tests for dependent samples. The following text details the evaluation techniques and statistical tests used to assess these models.

A review of the contemporary literature reveals that there are many evaluation techniques for assessing the efficacy of a criminal geographic profiling model (e.g., Canter et al., 2000; Levine, 2009, Paulsen, 2006a, Rich & Shively, 2004; Rossmo, 2000). Though some of these measures are controversial (see Levine, 2005; Rossmo, 2005), three of the most common measures were chosen for this study:

- **Profile probability value:** The probability value assigned to the grid cell in which the true anchor point (i.e., offender residence) is located. Higher probability values indicate higher accuracy. Because the CMD technique does not produce a probability estimate, this evaluation technique was only applicable to the other six profiling models.
- **Error distance:** Measures accuracy according to the Euclidean distance between the predicted and the true the anchor point. Shorter distances indicate a more accurate model. This evaluation technique was applied to all seven profiling models.
- **Search cost:** Calculates the proportion of the study area that must be searched in order to identify the offender's residence (Canter et al., 2000; Levine, 2009; Rossmo, 2000). The profile probability values assigned to each grid cell are sorted in descending order. Starting with the highest value, search cost is equal to the number of grid cells that must be searched before identifying the offender's residence. Accordingly, fewer cells indicate higher precision. Because the CMD model returns a point estimate, it is incapable of generating a search cost without modification. A comparable estimate was derived by counting the number of grid cells that fall inside a circle defined by a radius equal to the error distance. Such a measure is only an enumeration, and cannot be interpreted as a density surface.

The evaluation methods presented above compare different treatments on the same profiled sample. Accordingly, two non-parametric tests are proposed to validate the results. First, the Friedman test was applied to the entire group and used to determine if the modeled output was different across each measure. The second test compared the pairwise differences between each model using the Wilcoxon signed ranks test for related samples. Comparisons between modeled output should not be interpreted universally, regardless of the number of tests performed. That is, the acceptance or rejection of the null hypothesis for each comparison is of more interest when examined individually, not collectively. Accordingly, the Bonferroni adjustment, often applied for multiple comparisons, was deemed inappropriate for this study (Rothman, 1990; Feise, 2002).

5.4 Results

This section examines the results generated for the seven geographic profiling models and their subsequent evaluation. Table 5.3 summarizes the overall performance of each model, and organizes the results by evaluation criteria. Individual comparisons for each evaluation technique are provided in Tables 5.4, 5.5, and 5.6. These tables detail how often a model performed as well or better than other techniques.

5.4.1 Profile Probability Value

The profile probability value denotes the predicted probability value assigned to the grid cell containing the offender's actual residence. Because the CMD routine does not produce a probability estimate, it was excluded from this evaluation. Large probability estimates indicate a greater likelihood of the grid cell possessing the anchor point. Grid cell probability values were small because the study area consisted of 12,932 cells. As indicated in Table 5.3, the Filtered JTC Estimate produced the highest mean (0.002259) and median (0.001561) probability

estimates of all 52 profiles. Model estimates were ranked and compared using the Friedman test. Higher ranks equates to better model performance. The Filtered JTC Estimate had the highest mean and median ranks of all the estimates calculated for the profile sample. The Bayesian JTC Product was assigned the second highest average probability, while the Land Cover Bayesian *Product* had the second highest median value. With the exception of the traditional *JTC Estimate*, all models were found to have relatively large variances. The Friedman chi-square statistics for the modeled output indicates significant differences between the six estimates.

Results from the pairwise comparisons between all modeled output are provided in Table 5.4. This matrix enumerates the number of times a particular model had a lower, equal, or higher probability estimate when compared to the other models. A model's *success*, *failure*, and *tie* correspond with the Wilcoxon Singed Ranks output of positive, negative, and tied ranked comparisons. Success and failure relate to the sign of a rank, which is assessed according to the arithmetic difference between estimates. Higher ranks equate to better performance. Lastly, a tie occurred whenever two models estimated the same probability value for an offender's residence. The pairwise significance for each test is provided. Similar to the results observed from the Friedman test, the Filtered JTC Estimate was the most accurate for 180 of the 260 comparisons (69.2%). The poorest comparative performance was observed for the JTC Estimate, which had a success rate of 75 of 260 (28.8%). Overall, the three land cover enhanced techniques were ranked in the top four most successful estimates, along with the Bayesian JTC Product estimate. In some instances, significance between modeled output was elusive. For example, the Filtered JTC and Bayesian JTC Product estimates produced the same number of profiles (26 each), resulting in no significant difference in performance. Similarly, the Land

Table 5.3: Geographic Profile Model Evaluation Results

Model	Profile Probability Value Larger is better			Error Distance (meters) Smaller is better			Search Cost / Hit Score Smaller is better		
	Mean (sd)	Median	Freidman Rank ^a	Mean (sd)	Median	Freidman Rank ^b	Mean (sd)	Median	Freidman Rank ^c
JTC Estimate	0.000914 (0.00072)	0.000645	2.44	6,137.25 (5,086.48)	5,275.94	3.80	708.06 (1,177.9)	301.00	4.13
Filtered JTC Estimate	0.002259 (0.00275)	0.001561	4.46	6,101.85 (5,103.89)	5,556.52	3.82	597.25 (1,354.4)	149.50	3.03
Bayesian JTC Product	0.002249 (0.00284)	0.000849	3.86	6,957.30 (6,093.01)	6,076.35	3.66	1,215.56 (2,173.4)	350.50	3.84
Bayesian JTC Posterior	0.001352 (0.00171)	0.000530	2.65	7,144.67 (5,971.78)	6,278.36	4.38	1,323.17 (2,141.2)	490.00	5.11
Land Cover Bayesian Product	0.001918 (0.00203)	0.001202	4.11	6,673.18 (5,783.85)	5,058.01	4.39	451.19 (753.1)	188.00	3.28
Land Cover Bayesian Posterior	0.001524 (0.00171)	0.000968	3.48	6,243.71 (5,408.78)	4,836.40	4.01	537.33 (808.3)	229.00	3.60
Center of Minimum Distance	-	-	-	6,104.70 (5,048.72)	5,543.07	3.94	867.54 (1,252.8)	472.00	5.03

Friedman Test Statistics, N=52

- a) $\chi^2=48.573$, $df=5$, $p\leq 0.000$ (Asymp. Sig.)
- b) $\chi^2 = 5.626$, $df=6$, $p\leq 0.466$ (Asymp. Sig.)
- c) $\chi^2=44.518$, $df=6$, $p\leq 0.000$ (Asymp. Sig.)

Friedman Mean Ranks:

- a) Filtered JTC > Land Cover Bayesian Product > Bayesian JTC Product > Land Cover Bayesian Posterior > Bayesian JTC Posterior > JTC Estimate
- b) Bayesian JTC Product < JTC Estimate < Filtered JTC Estimate < CMD < Land Cover Bayesian Posterior < Bayesian JTC Posterior < Land Cover Bayesian Posterior
- c) Filtered JTC Estimate < Land Cover Bayesian Product < Land Cover Bayesian Posterior < Bayesian JTC Product < JTC Estimate < CMD < Bayesian JTC Posterior

Table 5.4: Wilcoxon Signed Ranks Test for Pairwise Comparisons of Model Probability

		JTC Estimate	Filtered JTC Estimate	Bayesian JTC Product	Bayesian JTC Posterior	Land Cover Bayesian Product	Land Cover Bayesian Posterior	Sum (n=260)
JTC Estimate	Success		7	22	25	11	10	75
	Failure	--	45	30	27	41	42	185
	Tie		0	0	0	0	0	0
	P-Value		0.000	0.000	0.001	0.055	0.000	
Filtered JTC Estimate	Success	45		26	39	32	38	180
	Failure	7	--	26	13	20	14	80
	Tie	0		0	0	0	0	0
	P-Value	0.000		0.953	0.003	0.061	0.000	
Bayesian JTC Product	Success	30	26		36	24	28	144
	Failure	22	26	--	8	27	24	107
	Tie	0	0		8	1	0	9
	P-Value	0.001	0.953		0.000	0.459	0.061	
Bayesian JTC Posterior	Success	27	13	8		14	20	82
	Failure	25	39	36	--	38	32	170
	Tie	0	0	8		0	0	8
	P-Value	0.055	0.003	0.000		0.006	0.236	
Land Cover Bayesian Product	Success	41	20	27	38		35	161
	Failure	11	32	24	14	--	17	98
	Tie	0	0	1	0		0	1
	P-Value	0.000	0.061	0.459	0.006		0.000	
Land Cover Bayesian Posterior	Success	42	14	24	32	35		147
	Failure	10	38	28	20	17	--	113
	Tie	0	0	0	0	0		0
	P-Value	0.000	0.000	0.061	0.236	0.000		

Table 5.5: Wilcoxon Signed Ranks Test for Pairwise Comparisons of Modeled Error Distance

		JTC Estimate	Filtered JTC Estimate	Bayesian JTC Product	Bayesian JTC Posterior	Land Cover Bayesian Product	Land Cover Bayesian Posterior	CMD	Sum (n=312)
JTC Estimate	Success		19	18	25	28	25	31	146
	Failure		21	23	18	21	21	21	125
	Tie	--	12	11	9	3	6	0	41
	P-Value		0.925	0.591	0.108	0.227	0.731	0.089	
Filtered JTC Estimate	Success	21		22	27	28	25	29	152
	Failure	19		27	23	21	20	23	133
	Tie	12	--	3	2	3	7	0	27
	P-Value	0.925		0.622	0.126	0.313	0.433	0.591	
Bayesian JTC Product	Success	23	27		26	26	28	29	159
	Failure	18	22		17	22	22	23	124
	Tie	11	3	--	9	4	2	0	29
	P-Value	0.591	0.622		0.391	0.854	0.703	0.597	
Bayesian JTC Posterior	Success	18	23	17		23	22	22	125
	Failure	25	27	26		28	28	30	164
	Tie	9	2	9	--	1	2	0	23
	P-Value	0.108	0.126	0.397		0.303	0.138	0.099	
Land Cover Bayesian Product	Success	21	21	22	28		14	19	125
	Failure	28	28	26	23		28	33	166
	Tie	3	3	4	1	--	10	0	21
	P-Value	0.227	0.313	0.854	0.303		0.242	0.111	
Land Cover Bayesian Posterior	Success	21	20	22	28	28		23	142
	Failure	25	25	28	22	14		29	143
	Tie	6	7	2	2	10	--	0	27
	P-Value	0.731	0.433	0.703	0.138	0.242		0.402	
CMD	Success	21	23	23	30	33	29		159
	Failure	31	29	29	22	19	23		153
	Tie	0	0	0	0	0	0	--	0
	P-Value	0.089	0.591	0.597	0.099	0.111	0.402		

Table 5.6: Wilcoxon Signed Ranks Test for Pairwise Comparisons of Modeled Search Cost

		JTC Estimate	Filtered JTC Estimate	Bayesian JTC Product	Bayesian JTC Posterior	Land Cover Bayesian Product	Land Cover Bayesian Posterior	CMD	Sum (n=312)
JTC Estimate	Success		14	25	32	18	20	36	145
	Failure		36	24	20	34	30	14	158
	Tie	--	2	3	0	0	2	2	9
	P-Value		0.001	0.474	0.033	0.002	0.020	0.004	
Filtered JTC Estimate	Success	36		28	38	29	31	42	204
	Failure	14		23	14	23	20	9	103
	Tie	2	--	1	0	0	1	1	5
	P-Value	0.001		0.124	0.000	0.407	0.043	0.000	
Bayesian JTC Product	Success	24	23		38	22	21	30	158
	Failure	25	28		8	30	29	21	141
	Tie	3	1	--	6	0	2	1	13
	P-Value	0.474	0.124		0.000	0.061	0.111	0.899	
Bayesian JTC Posterior	Success	20	14	8		15	14	24	95
	Failure	32	38	38		37	37	28	210
	Tie	0	0	6	--	0	1	0	7
	P-Value	0.000	0.000	0.000		0.000	0.000	0.196	
Land Cover Bayesian Product	Success	34	23	30	37		32	37	193
	Failure	18	29	22	15		19	15	118
	Tie	0	0	0	0	--	1	0	1
	P-Value	0.002	0.407	0.061	0.000		0.008	0.000	
Land Cover Bayesian Posterior	Success	30	20	29	37	19		38	173
	Failure	20	31	21	14	32		13	131
	Tie	2	1	2	1	1	--	1	8
	P-Value	0.020	0.043	0.111	0.001	0.008		0.000	
CMD	Success	14	9	21	28	15	13		100
	Failure	36	42	30	24	37	38		207
	Tie	2	1	1	0	0	1	--	5
	P-Value	0.004	0.000	0.899	0.196	0.000	0.000		

Cover Bayesian Product estimates were not significantly different from the Filtered JTC or the Bayesian JTC Product. Finally, the output from the Land Cover Bayesian Posterior was not significantly different than the output from either the Bayesian JTC Product or Posterior.

5.4.2 Error Distance

The profiled Error Distance represents the Euclidean distance measured between the predicted and true location of an offender's residence. Small error distances equate to more accurate profiles. As indicated in Table 5.3, the Filtered JTC Estimate produced the smallest average error distance of all techniques, while the Land Cover Bayesian Posterior produced the smallest median distance (6.10 km and 4.84 km, respectfully). The CMD and JTC Estimate also had low mean error distances, while the median distance for the Land Cover Bayesian Product was the second shortest in this sample. For this evaluation technique, the Friedman test compares and ranks the error distances measured for each model. Recalling that shorter distances measures are better, ranks are assigned in ascending order (i.e., lower values are better). The lowest mean rank difference of 3.66 was assigned to the Bayesian JTC Product model. Despite being highly variable, the error distances for this model were frequently more accurate than other techniques. Conversely, the lowest performing model was the Land Cover Bayesian JTC Product (rank = 4.39), which indicates that this technique, on average, produced error distances that were frequently inaccurate when compared to the other estimates. The rank order from shortest to longest is available in the bottom margin of Table 5.3. Significant differences between the Friedman ranks proved inconclusive according to the chi-square test. Indeed, the variances observed between these measures were large, making it difficult to interpret these results.

The pairwise comparisons in Table 5.5 represents number of times a particular model produced the shortest (success), farthest (failure), or equal (tie) error distance when compared to all other estimates. As revealed in the matrix, the Bayesian JTC Product and JTC Estimation models produced more estimates with error distances equal to or shorter than those produced by the other techniques, 188 (60.26%) and 187 (59.94%), respectively. The Filtered JTC Estimate was third best, producing shorter error distances for 179 of 312 (57.37%) estimates. And like the results from the Friedman ranks, the two worst performing models included the Bayesian JTC Posterior (148 of 312) and Land Cover Bayesian Product (146 of 312). The Wilcoxon Z-tests were unable to confirm significance for any of the pairwise comparisons.

5.4.3 Search Cost

A profile's Search Cost quantifies the proportion of the study area that must be searched in order to locate the offender's anchor point. Accordingly, profile estimates that require fewer grid cells signify higher precision. Table 5.3 illustrates that land cover enhanced models performed better than the other techniques. Estimates generated from the Land Cover Bayesian JTC Product models required the smallest average search cost, 451.19 grid cells (median = 188), while the Filtered JTC Estimate models required the fewest median of grid cell count, 149.5 (mean=597.25). The Land Cover Bayesian JTC Posterior followed, with an average and median search cost of 537.33 and 229 grid cells, respectively. Results from the Friedman test, which ranks success in ascending order, found the Filtered JTC Estimate to be the best performing model, followed by the Land Cover Bayesian JTC Product and Posterior, Bayesian JTC Product, JTC Estimate, CMD, and Bayesian JTC Posterior (see Table 5.3). Despite having a relatively short median error distance, the CMD routine produced the second-worst performing estimates,

ranked sixth (mean rank = 5.03) of the seven models. In all, the Friedman chi-squared test confirmed significant differences between the modeled outputs, validating these findings.

As with the previous two evaluation measures, the Wilcoxon signed ranks test provides pairwise comparisons between modeled output. Like the error distance measure, successful models are ranked from smallest to largest. Table 5.6 depicts the results of these tests. The top three performing models incorporate land cover within its framework: Filtered JTC Estimate, Land Cover Bayesian Product, and Land Cover Bayesian Posterior (66.9%, 62.2%, and 58%, respectively). Indeed, each of these three techniques showed significant performance gains over the traditional JTC Estimates and Bayesian JTC Posterior. The highest performing model was assigned to the Filtered JTC Estimate, which had a pairwise ranking of 209 equal or better outcomes. In terms of the lowest performance, the Bayesian JTC Posterior was consistently surpassed by the other seven models, having produced only 102 (32.7%) estimates that were equal or better than the other techniques. This model was slightly outperformed by the CMD estimate, which had 105 successful estimates (33.7%). However, the Wilcoxon Z-test was unable to assign significance for various combinations of modeled comparisons (see Table 5.6 for details).

5.5 Discussion

The efficacy of incorporating land cover within Bayesian a formulated JTC estimation model has been confirmed. Land cover characteristics associated with the anchor points of known serial offenders residing in the Baltimore, MD, were successfully parameterized as marginal and conditional probability values. When applied in accordance with Bayesian theory, these estimates were combined to update the prior knowledge of an offender's anchor point (i.e., the empirically calibrated JTC estimate) using information about the conditional land cover

characteristics of known offender activity spaces. As more information about this conditional relationship accumulated, the anchor point estimation changed according to how probable that land cover was observed under all conditions. Based on these findings, this new approach to modeling a criminal's spatial behavior has improved the probability estimates and lowered the search costs associated with predicting the location an offender's anchor point.

The output generated by the four traditional and three land cover enhanced models were assessed for accuracy and precision. Model performances were measured according to three evaluation criteria: profile probability, error distance, and search cost. Overall, the Friedman chi-square test found statistically significant results for two of the three evaluation techniques used in this study: profile probability and search costs. The first evaluation routine, the profile probability estimate, assessed the strength of a model's ability to predict the anchor point. Of the six models that were compared, the three land cover enhanced techniques ranked in the top four best performing techniques (see Table 5.3). The Filtered JTC estimate ranked first among the comparisons, followed closely by Bayesian JTC Product, and then the two Land Cover Bayesian techniques. As depicted in the pairwise comparisons of Table 5.4, the land cover Filtered JTC Estimate produced the best probability estimate more frequently than all other models (180 or 69.2%). The two Land Cover Bayesian estimates followed, producing 162 (62.3%), and 147 (56.5%) better performing estimates. Figure 5.5 illustrates the success rate for pairwise model comparisons, depicting the values provided in Table 5.4.

The second evaluation criteria, error distance, assessed a model's performance according to the Euclidean distances measured between the offender's known residence and the grid cell with the highest likelihood value. Although statistically inconclusive, the Bayesian JTC Product ranked highest for overall performance, while the Filtered JTC and Land Cover Bayesian

Posterior techniques produced the best mean and median estimates (see Table 5.3). The land cover filtered technique was ranked third, while the remaining two land cover estimates ranked very low according to the Friedman test for groupwise rankings. When compared individually, the Bayesian JTC Product was more efficient at a 60.3% success rate, which was followed closely by the JTC Probability estimate at a 59.9% (see Figure 5.6). Again, the individual comparisons proved statistically inconclusive. Perhaps it is no coincidence that the error distance assessment is often criticized as being incapable of accurately assessing the inherently non-linear mechanics of a geographic profile (Rossmo, 2005a). This criticism is somewhat justified as a criminal investigation has no *a priori* knowledge of the distance an anchor point is from the predicted location. However, the error distance does provide a diagnostic measure for assessing a model's accuracy (Levine, 2005; Paulsen, 2006a; 2006b; Rich & Shively, 2004). One such technique is to use a profile's error distance to calibrate a model's study grid. That is, this measure can be used to customize the resolution (i.e., cell size), shape, and position of a model's study grid for a given activity space. Consider the scenario in which the true anchor point of a calibration dataset has been assigned a low probability value. As a consequence, the search costs were very large, thus requiring the search of numerous grid cells before identifying the true anchor. If, however, the error distance between the true and predicted anchor point was short, the researcher may conclude that the poor probability estimation and search costs were associated with a poorly calibrated study grid. Such was observed for approximately ten of models evaluated in this study. While this finding is only anecdotal, future research should consider the contribution of this routine for calibrating a model's study grid.

The last procedure used to assess modeled output was the search cost evaluation. This technique is arguably the best indicator for assessing a model's precision because it establishes a

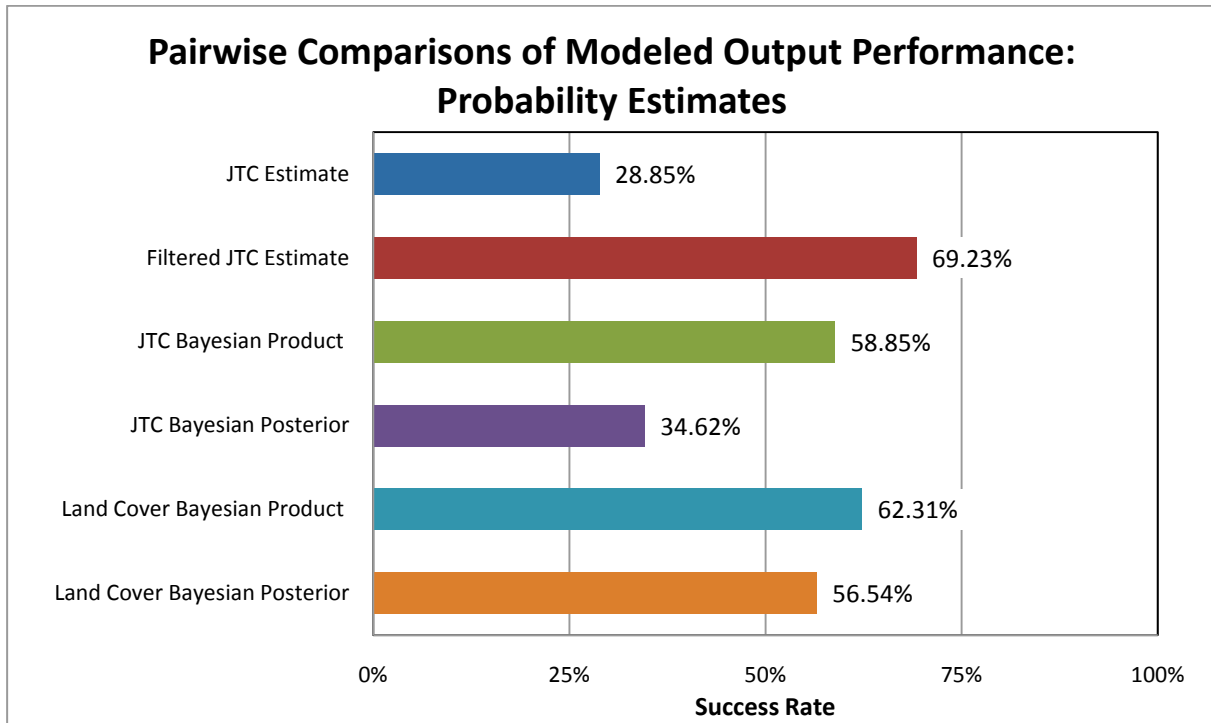


Figure 5.5: Pairwise model performance for profile probability estimation values.

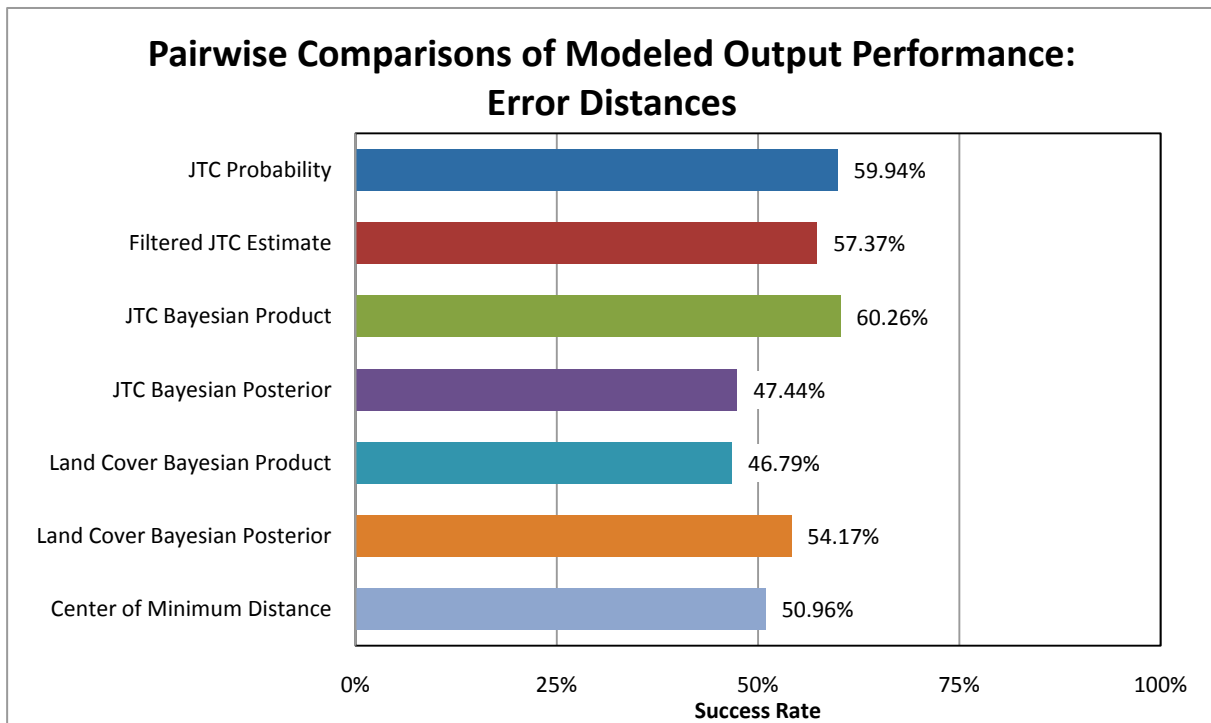


Figure 5.6: Pairwise model performance for error distances.

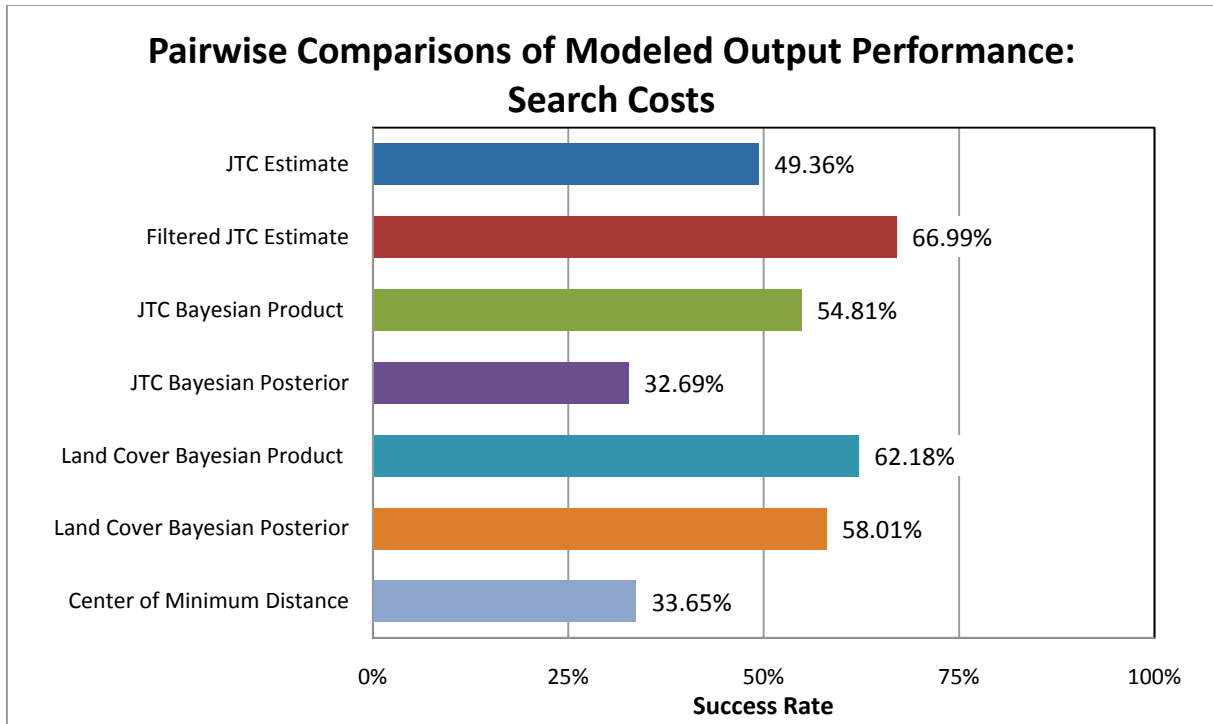


Figure 5.7: Pairwise model performance for search costs.

priority-based strategy for locating the anchor point (Canter et al., 2000; Levine, 2007; Rossmo, 2000). According to the Friedman test, all three land cover techniques ranked at the top in the groupwise comparison (see Table 5.3). In fact, all three models produced estimates that had the lowest average and lowest median search costs of the techniques evaluated. Pairwise comparisons produced similar results, though differences between some of the models were not found to be significant (see Table 5.6). As illustrated in Figure 5.7, the land cover Filtered JTC model had a pairwise success rate of 66.9% (209), followed by the Land Cover Bayesian Product and Posterior at 62.2% (194) and 58.0% (181), respectively.

While the land cover enhanced Bayesian approach provides an effective improvement over contemporary models, the success of this technique is tempered by the better performing Filtered JTC Estimate. So it begs the question: what makes the Filtered JTC Estimate different

from the Land Cover Bayesian approach? The difference lies in how the models are constructed. Recall that the Filtered JTC model is the product of the JTC Estimate and the marginal probability of land cover observed for all offenders within the calibration sample (see Equation 5.5). In essence, the JTC distribution represents a maximum likelihood estimate of the unknown offender's anchor point (Levine, 2005). Similarly, the distribution for the marginal land cover can be interpreted as the most likely land cover types for the same anchor. Whenever the modes of these two frequency distributions spatially intersect, one effectively generates an increasingly more precise maximum likelihood of the unknown anchor point. Due in part to the resolution of this study, this product frequently resulted in more accurate and precise anchor point estimates than any other model. Consequently, this approach exposes the fact that these optimal distributions are geographically dependent. Thus, the leveraging of this implicit bias improved performance, which was observed in more than twenty models. However, this approach comes with a *caveat*. As stated earlier, this bias is susceptible to a “rotten apple” effect that can negatively impact a profile's efficiency. Specifically, if the JTC or the marginal land cover estimates do not represent an optimized estimation, the resulting model will produce a dramatically inaccurate estimate.

This scenario is best illustrated by comparing Figures 5.8 and 5.9, in which the probability surfaces for the anchor point of a serial larceny is presented using traditional, and filtered JTC estimation techniques. Figure 5.8 depicts the surface generated for the traditional JTC estimate. The JTC Estimation produces a search cost of 879 grid cells. But as illustrated in Figure 5.9, the search cost for the Filtered JTC estimate was 4,611 grid cells. In this case, the JTC Estimate for the true anchor point was high, but it was very low for the land cover Filtered JTC estimate. The product of these two values resulted in an increased search cost. To

compensate for this effect, a Bayesian formulation similar to that used by CrimeStat[®] was chosen. As noted for Equation 5.7, the conditional probability of land cover for the anchor point parameter was calculated using an exponential kernel function. This approach represents a functionally pragmatic method for optimizing the conditional land cover probability for the area surrounding a known offender's anchor point. Accordingly, Figures 5.10 and 5.11 illustrate the Bayesian product (Equation 5.7) and posterior (Equation 5.6) probabilities for the same criminal. For the Bayesian product, the effect of a poorly assigned land cover estimate remains evident. Nevertheless, a search cost of 719 is lower than 4,611, thus producing a six-times smaller search cost. However, when normalized for all possible anchor point scenarios, the Bayesian posterior produced an enhanced estimate of 506 grid cells. In short, by reformulating the joint probability of the JTC prior and land cover likelihood according to Bayes' estimation, this new model was able to uniquely compensate for errors that can over and under estimate an offender's anchor point. Simply put, the probability of land cover for a given anchor point became an optimized likelihood distribution derived from an exponential kernel function. When combined, the product of the likelihood and the prior resulted in an estimate that was more tolerant to the “rotten apple” effect. Thus, it produced a more reliable estimate of the anchor point. So while the overall performance was not as strong (see Tables 5.3- 5.6), the Bayesian formulation represents a more suitable technique for accommodating the intrinsic geographical biases that define the unknown offender's activity space.

Still, problems remain. Many of the concerns initially identified in the previous study remain unaddressed. For instance, a recent study has expressed caution on the over reliance on calibrated distance decay functions when modeling a criminal's overriding spatial behavior (Smith et al., 2009). The issue is that that of ecological fallacy: warning that the aggregated

Baltimore, Maryland, Study Area
 Journey-to-Crime Estimation
 Larceny Serial Crime

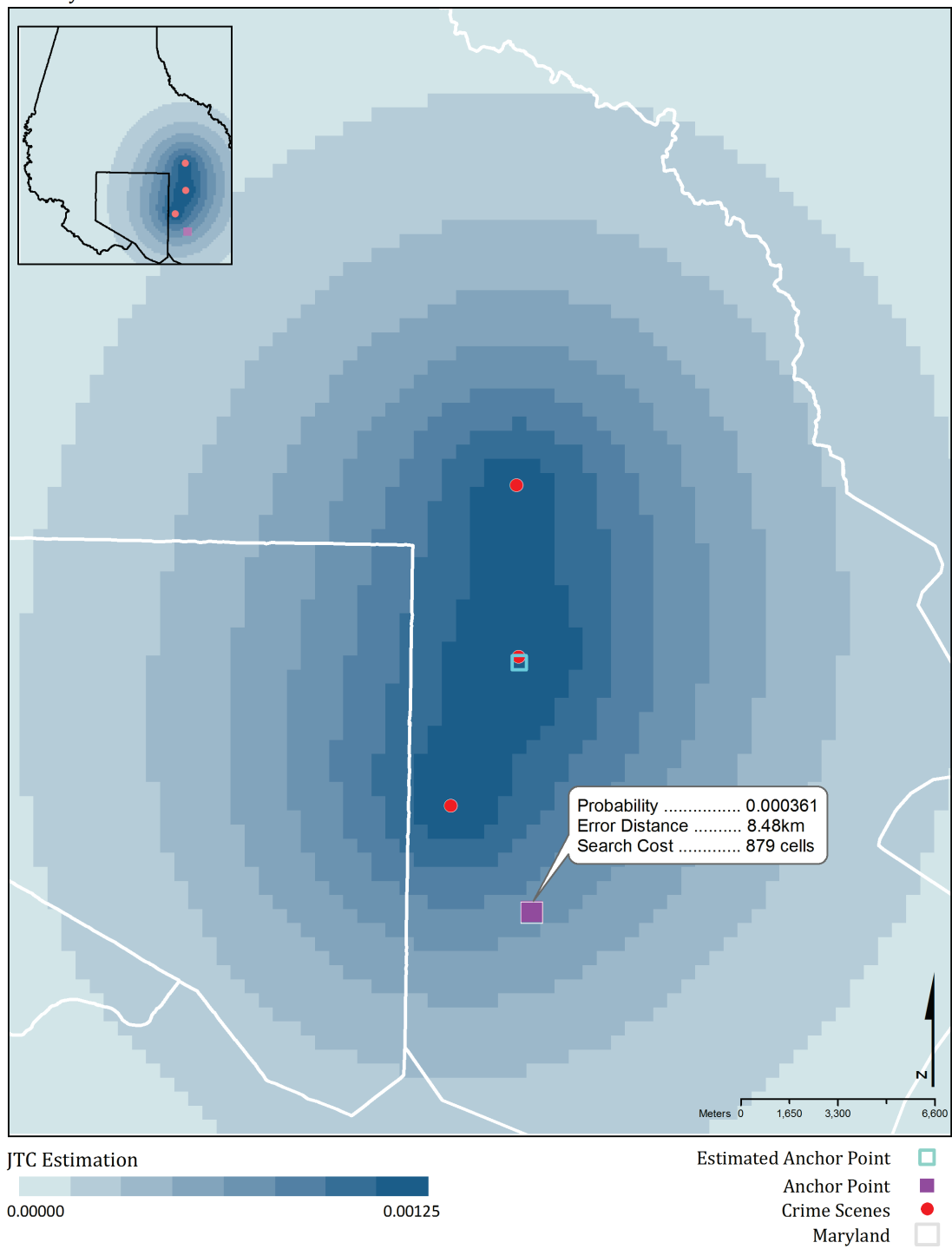


Figure 5.8: Geographic profile generated using the JTC estimation model.

Baltimore, Maryland, Study Area
Filtered Journey-to-Crime Estimation
Larceny Serial Crime

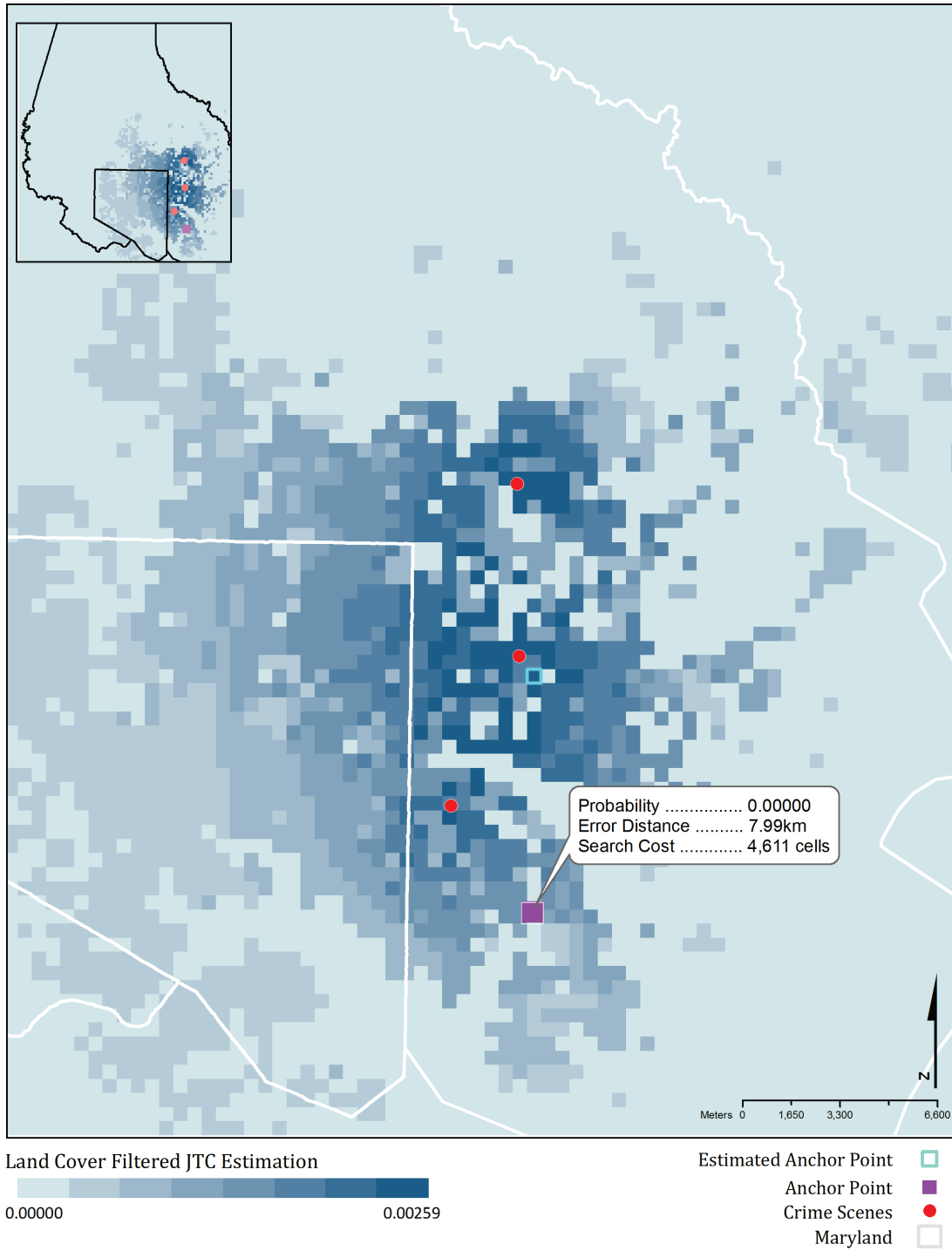


Figure 5.9: Geographic profile generated using the Filtered JTC estimation model.

Baltimore, Maryland, Study Area
 Land Cover Enhanced Bayesian Product Estimation
 Larceny Serial Crime

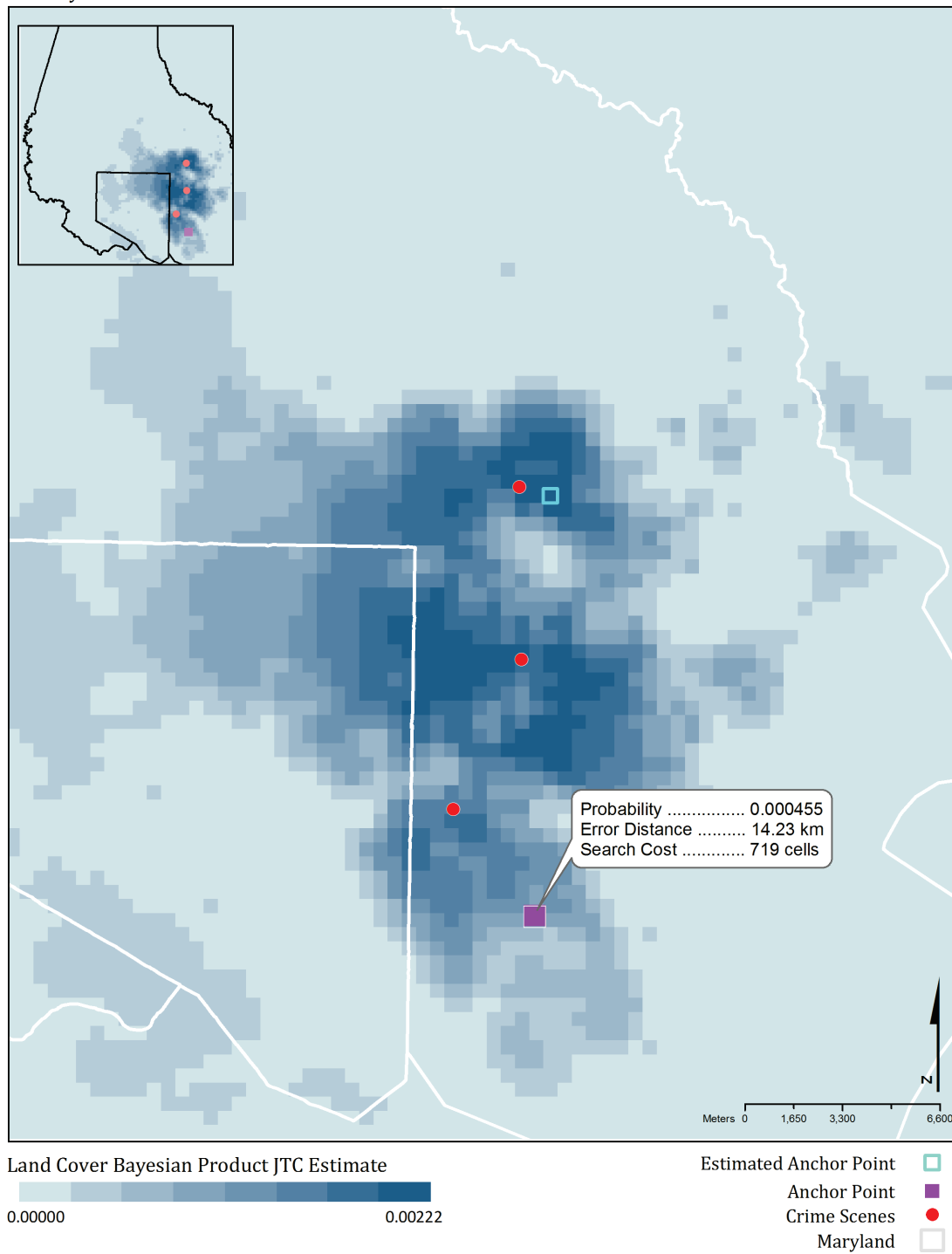


Figure 5.10: Geographic profile generated using the Land Cover Bayesian Product model.

Baltimore, Maryland, Study Area
 Land Cover Enhanced Bayesian Posterior Estimation
 Larceny Serial Crime

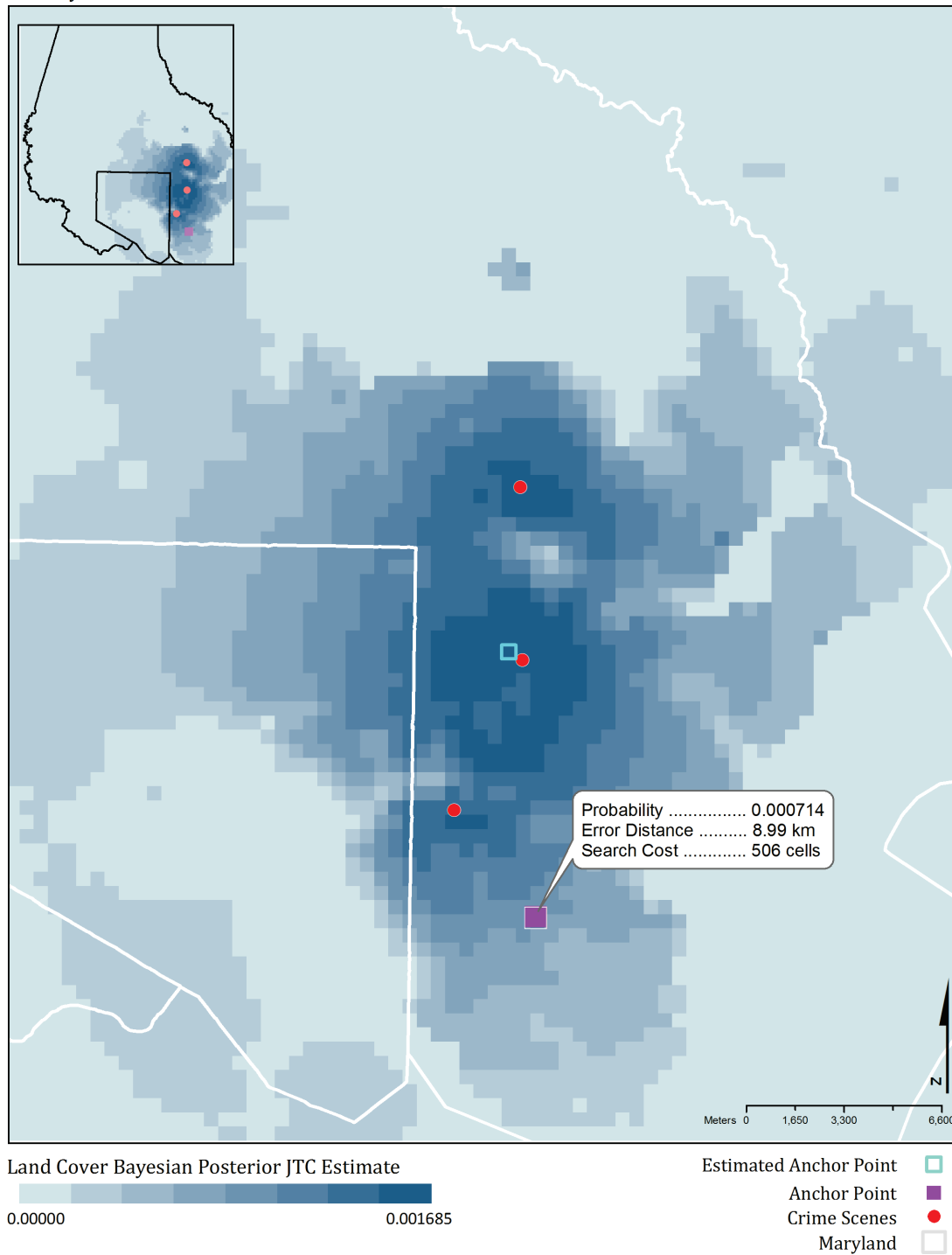


Figure 5.11: Geographic profile generated using the Land Cover Bayesian Posterior model.

decay pattern cannot be considered statistically independent, and thus are not suitable for inferring behavior characteristics on any crime series other than the calibration sample. An approach for addressing this issue would be to disaggregate the JTC characteristics of the calibration sample, and identify a common set of commuting trends based on the individual crime series. While compelling, the implementation of a tactic such as this would require an extensive re-working of existing software subroutines. Another unaddressed issue relates to the spatial resolution of the Baltimore study grid. In order to accommodate both computational and operational limitations, the study grid size was enlarged to 480m squared. The large cell size made the model estimations proceed faster than cells maintained at smaller sizes. The larger areas also made it easier to identify coincident profile and calibration crime scenes. Coincident events are an essential operational element of the current Bayesian formulation, without which conditional probability values would almost certainly be non-existent. The CrimeStat[®] manual proposes the use of a separate and coarser grid that can accommodate the coincident events. This grid would then be spatially interpolated onto the more refined study grid for analysis. However, conditional probability estimates derived from large grids will reduce profile precision. A finer resolution grid can narrow the focus, thus enhance the estimate. Additionally, a tight grid would permit the integration of other landscape proxy data, including municipal land use data (e.g., residential, commercial, light industrial, etc.). Such a grid would have to balance precision while ensuring that the known and unknown crime scenes find coincident pairing. This balance could be aided with the inclusion of additional crime scenes. As detailed in the 2004 NIJ report on geographic profiling (Rich & Shively, 2004), the prediction efficiency of profiling models is best when more crime scenes are included in the analysis. Many of the series used within this study were comprised of as few as three crimes. As Leitner & Kent (2009) revealed,

modeling performance can only benefit from larger calibration samples and the inclusion of multi-offence crime series. Ideally, each one of these issues should be accommodated in future research.

5.6 Conclusion

This study set out to measure the efficacy of incorporating land cover within a Bayesian formulated JTC estimation model. It represents an extension of previous research in which Kent and Leitner (2009) examined the efficacy of filtering a JTC estimate using the marginal probability of land cover. The authors demonstrated that the likelihood of identifying an offender's anchor point was constrained to the particular land cover characteristics inherent to the offender's activity space. By incorporating these land cover probabilities within a Bayesian framework, this study confirmed that landscape characteristics can be used to exploit the relationship between an offender's anchor point and his/her perceptions of criminal opportunity and target attractiveness. Particular emphasis was placed on the formal inclusion of land cover within a profiling model, not just the product of two independent marginal probabilities. Accordingly, the Bayesian JTC model originally derived for CrimeStat[®] was modified to incorporate the marginal and conditional probability of land cover.

The rationale for this approach was established on biases identified in the previous study, in which the Filtered JTC Estimate suffered from an implicit geographic dependency that made it susceptible to estimation errors. Two Bayesian formulations were chosen to compensate for this effect. The first represents the Bayesian product, which is based on prior estimate of an offender's anchor point and the conditional probability for observing land cover for anchor points of previous offenders who committed crimes in similar locations. The conditional land cover probability estimate was calculated using a negative exponential kernel, primarily because of its

abilities to account for land cover variability inherent with the size of the study grid. The exponential kernel was also chosen due to the rapid decrease in intensity as the function decays. Together, they provided a relative estimate of the offender's anchor point according to the likelihood of land cover. The second formulation was the full Bayesian posterior probability estimate. This is a normalized estimate of the Bayesian Product that has been divided by the marginal probability of all land cover classes associated with previous offender anchor points. In effect, these two estimations represent a pragmatic solution to overcoming the over- and under-estimation biases inherent to the model. However, this paradigm comes at the expense of precision and accuracy that is otherwise observed for the filtered approach. Future studies, using larger calibration and profile samples, must be initiated in order to develop a set of expectations for modeled performance. Clearly, the inclusion of auxiliary datasets that are inherent to the criminal activity space will enhance a profile's output. Future research, capable of addressing the issues presented here, can result in the development of more refined methodologies that will ensure its beneficial contribution to law enforcement.

“There is a need for constant improvement and innovation in methods of analysis, no matter what questions are being asked or what levels of resolution are being studied.”

- Brantingham & Brantingham (1998, p. 265)

CHAPTER 6: CONCLUSION

This research has successfully demonstrated how contemporary geographic profiling models can be modified to account for the anisotropic characteristics of the underlying physical and cultural landscape. Four enhanced profiling techniques were studied: modeling the criminal commute using *functional distance measures* (Kent et al., 2006); accounting for landscape variability observed in the spatial distribution of crime scenes using *standard deviational ellipses* (Kent & Leitner, 2008); *filtering JTC estimates* using land cover characteristics (Kent & Leitner, 2009); and incorporating *land cover within empirical Bayesian JTC estimation* models. Each approach was able to relatively improve the efficacy of a geographic profiling model when predicting the location of a serial offender's residence. Such techniques can be invaluable resources for the investigation and successful apprehension of a serial offender.

The basis for this research was founded on the theories and principles established in environmental criminology, which posit that crime is the result of the juxtaposition of an offender, target, opportunity, and place. These “dimensions of crime” constitute an investigatory framework from which a criminal's psychological and geographical behavior in space can be modeled (Brantingham & Brantingham, 1984). However, such techniques rarely produce accurate estimates of the offender's anchor point. Instead, traditional models are generally limited to exposing an abstraction of the offender's true activity and awareness spaces. As noted by Rengert (1989), the landscape is composed of anisotropic distributions of social, environmental, and psychological structures that effectively confound the traditional approach of

characterizing the prevailing precepts that govern human behavior in space. Only by accounting for these constructs can a model effectively represent an offender's spatial patterns (Brantingham & Brantingham, 1981; 1984; Felson & Clarke, 1998; Rengert et al., 1999).

6.1 Functional Distance Measures

Those methodological strategies that can effectively accommodate both the characteristics of the landscape as well as the principles of environmental criminology are best suited for constructing offender profiles. By taking into account the offender's perceptions of cost, criminal commute models that optimized travel path metrics (e.g. Manhattan distances) produced a more accurate estimate of a serial killer's residence. This approach, presented in Chapter 2, was inspired by research published by Capone and Nichols (1976) and Rhodes and Conly (1981), who demonstrated that the physical characteristics of the offender's activity space (e.g., streets, parks, buildings, etc.) influence the perceptions of criminal opportunity and success. The advantage of this technique was that it was able to explicitly account for the impact of the road network on which the offender traveled. Accordingly, this method served as a proxy for criminal opportunity structures as it relates to the resolve of an offender to commit a crime given the cost of the commute. However, this modeling approach is based on an *a priori* assumption that the offender perceived criminal opportunities relative to the road network. However, the model was unable to account for the psychological motivations of the offender beyond the cost of the commute. Nor was it able to account for the offender's perception of target attractiveness. Furthermore, the approach was incapable of discriminating the various land use characteristics inherent within the study area. Consequently, even the most unlikely locations within the criminal's activity space (e.g., river, industrial land use areas, agricultural lands, etc.) were assigned a probability estimate for the offender's anchor point. Lastly, the

approach proved to be programmatically and operationally prohibitive when compared to existing methods that utilize the Manhattan (e.g., grid based) travel distance metrics. And as the study revealed, the Manhattan metric provided a better estimate of the offender's true residence.

Questions remain, however. For instance, how well might the Manhattan metric perform for serial offences that occur within rural environments, where the uniform and grid-shaped road networks common in urban settings are not the dominate characteristic? Furthermore, how does one distinguish an activity space or awareness space within a rural setting? Still further, how does one differentiate the offender typologies of commuter and marauder for serial crimes that occur within an environment that exhibits large distances between activity nodes? Clearly, the ecological contexts in which crimes occur are important factors that influence the efficacy of a geographic profile. However, the practical implications for these scenarios have yet to be addressed adequately.

6.2 Standard Deviation Ellipses

The impact of the physical and cultural landscape was addressed in Chapter 3, which used simple spatial distribution models to accommodate the variations observed for the distribution of linked crime scenes. The premise for this approach asserts that crime scenes are not distributed randomly around an offender's anchor point; therefore making it unlikely that the offender's residence would be identified within the center of that distribution. Instead, the distribution of crime is partially determined by the physical and cultural environment, and the offender's perceptions thereof. Utilizing basic geographic principles of central tendency and spatial diffusion, the essay presented in Chapter 3 measured the efficacy of an elliptical search area applied within a geographic profiling technique originally proposed by Newton and Swoope (1987), known as *geoforensic analysis*. Geographic profiles were generated for 97 serial

offenses that occurred in Baltimore County, Maryland. Comparative analysis revealed that profiles based on the standard deviational ellipse model, which accounted for the non-uniform distribution of linked crime scenes, produced significantly better estimates of the offender's anchor point (or haven) than circle-based models, which presume a uniform distribution of linked targets. Furthermore, the relationship between the orientation of the elliptical profiles and the mean linear orientation of the underlying landscape (as measured by the road network), revealed a weak, but significant, correlation. These findings demonstrated how the physical characteristics of the landscape impact phenomena within a criminal's activity space.

Despite the ability to accommodate the anisotropic plane, the accuracy exhibited by this technique was achieved at the expense of precision. Specifically, the investigatory costs associated with the large elliptical search areas were fundamentally prohibitive. Indeed, scale is an important factor for the practical significance of any spatial analytical technique. Accordingly, the impact of scale on a geographic profile must be examined in future research. Moreover, this modeling approach failed to account for the offender's perceptions of criminal opportunity and target attractiveness. As the study in Chapter 2 demonstrated, the offender's perception of the landscape is an important factor on the commission of crime. The extent to which this factor can be integrated within a geographic profile would be examined in Chapter 4.

6.3 Land Cover Filtered JTC Estimations

Having established that the landscape does exhibit a deterministic influence on the nature of criminal behavior, the essay presented in Chapter 4 explored a new technique for incorporating the characteristics of the physical and cultural landscapes within a geographic profiling framework. Comprised of two parts, the first approach utilized the JTC distance decay modeling technique to account for the offender's perception of cost. Next, the JTC approach was

enhanced using land cover characteristics, which served as a proxy for the underlying physical and cultural structures that influence the offender's behavior in space. Traditional and land cover enhanced geographic profiles, generated for 35 serial burglaries and 35 serial robberies, were compared using tests that measured a profile's accuracy and precision. Results found that offender anchor point estimates derived using the land cover filtering strategies were, on average, significantly more accurate than traditional techniques. Furthermore, the land cover enhancements produced smaller search costs, reflecting the technique's improved precision. While the results for the third evaluation procedure, error distances, were statistically inconclusive, the center of minimum distance and empirical Bayesian JTC modeling approaches exhibited the shortest error measurements of all of the models studied.

Despite the impressive results, concerns remain. For example, the technique's approach for aggregating the land cover dataset could be refined. Many land cover sub-classes were preserved after the dataset was aggregated to 480m cells. These sub-classes may have unintentionally biased the final land cover assignments for the aggregated cell values. If land cover sub-classes were merged into their respective master categories (e.g., aggregate each sub-classes into “forest,” “agricultural,” “developed,” and “wetland” master classes), the estimate of the true anchor point might improve. Still further, the land cover filtering technique revealed how the landscape introduces an implicit bias within the model's framework. The implication of this bias supports the premise that landscapes, both physical and cultural, exhibit a dependent relationship with the crime scenes. As such, this dependency is inherently geographic in nature. This bias also reveals potential flaws, including a paradox scenario in which the product of the marginal land cover and JTC probability values can result in a poorly predicted anchor point estimate that significantly distorts the modeled output (see Figure 5.9). Specifically, the land

cover estimate for the true anchor point could be miss-classified, and thus assigned a probability value that is not representative of its true land cover classification. Strategies for addressing these issues would be explored in the final essay.

6.4 Land Cover Enhanced Bayesian JTC Estimates

The research presented in Chapter 5 expanded on the previous essays to construct more accurate and precise anchor point estimations using a modeling strategy that combined land cover characteristics directly within a Bayesian framework. The Bayesian JTC approach originally derived for CrimeStat[®] III was modified to incorporate the marginal and conditional probability of land cover observed from previous offenders. Like the study presented in Chapter 4, traditional and land cover-enhanced models were used to generate geographic profiles for 52 serial crimes observed in Baltimore, MD. Overall, the study demonstrated that land cover enhanced models performed significantly better than non-enhanced techniques when measuring a profile's search cost and probability estimation. And just as in the earlier study, results comparing a profile's error distances were inconclusive due to a lack of statistical significance between the compared output. Nevertheless, land cover enhanced Bayesian techniques improved the likelihood of identifying an anchor point by effectively constraining the estimate to those locations attributable to the activity spaces of known offenders. This approach differed from the previous study in that the emphasis was placed on the formal inclusion of land cover within a Bayesian JTC model, not just the product of two probabilities. This Bayesian approach ensured that offender perceptions would be implicitly accounted for, while explicitly accommodating the physical and cultural landscapes (Kent & Leitner, 2008; 2009).

Furthermore, the approach effectively restrained the “rotten apple” effect revealed in the previous study, by adjusting the method for calculating the product of the JTC and land cover

probability estimates. That is, the conditional probability of land cover based on solved cases was calculated using a kernel density routine. As a result, the probability estimates for the environment immediately surrounding these historic anchor points were incorporated within the model, thus reducing the vulnerabilities associated with aggregation errors, which had been observed for the land cover filtering technique. However, this *fix* for ecological fallacy remains vulnerable to decreased precision and accuracy (see Tables 5.3 - 5.6). Moreover, the land cover assignment for an offender's anchor point was found to be susceptible to biases similar to those associated from the modifiable areal unit problem (MAUP). The implications for this are threefold. First, the scale and position of the study grid can negatively impact the predictive ability of the model. For instance, a grid positioned a few meters in any direction surrounding a water body can have a significant impact on the land cover classification assigned to a grid cell. The consequence for this scenario is to reject the true anchor point that had been erroneously assigned the wrong land cover class. Second, too many land cover classes were preserved prior to the cell aggregation, potentially distorting profiled output. Aggregated values most likely overwhelmed smaller, but significant, land cover classifications for the study area. The practical consequence for such errors could result in the misappropriation of resources by the criminal investigators. Finally, the precision associated with the modeling technique is compromised by the scale of the grid. The catchment area (i.e., grid cell), used to determine coincident offense, was too large. As stated earlier, the Bayesian JTC routine constructs a likelihood estimate of an anchor point using historic crime data that were spatially coincident with the unknown offender. In order to ensure spatial coincidence, the grid cell must be large. An alternative method for assessing spatial coincidence needs to be developed such that it can operate at a finer resolution (e.g., municipal land use codes).

6.5 Closing

In all, the efficacy of incorporating land cover characteristics within a variety of geographic profiling models has been demonstrated. These findings further reveal that the inclusion of auxiliary data can enhance the predictive capabilities of locating an offender's anchor point. Such methodologies are reasonably accessible, reproducible, and defensible by researchers and analysts within law enforcement communities. Ideally, a combination of each of the presented methodologies can be achieved using a Bayesian formulation. Indeed, Bayesian theory represents an exciting new approach for profiling criminal behavior in space. Techniques such as these promise to enhance the traditional spatial distribution and spatial interaction models of the past with concepts traditionally associated with decision theory and optimal search theory. One particular example includes the work by O'Leary (2009), who used Bayesian methods to explicitly formulate connections between offender behavior and the surrounding environment. An additional example includes the work by Mohler & Short (2009), who used Bayesian theory and kinetic models of criminal behavior to account for anisotropic landscapes associated with serial offenses. Combining the quantitative benefits of Bayesian theory with the theoretical precepts of environmental criminology has very practical implications. That is, the adoption of newer and more efficient analytical methodologies will ensure that geographic profiling techniques will be able to accommodate a broad range of modeling possibilities that are only limited to the imagination of the investigator.

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Kent, J., Leitner, M., & Curtis, A. (2006). Evaluating the usefulness of functional distance measures when calibrating journey-to-crime distance decay functions. *Computers, Environment, and Urban System*, 30, 181-200.

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VITA

Joshua Kent has served the Louisiana geospatial community in various capacities for nearly two decades. His first foray into mapping occurred early in his career, spending nearly three years on a contract to digitally preserve historic maps and land titles for the state. Josh spent another three years as a Geographic Information Systems (GIS) analyst for the Louisiana Office of State Lands. Next, he served ten years as the Technical Services Manager for the Louisiana Geographic Information Center. Recently, Mr. Kent accepted the position as the GIS Manager for the Center for GeoInformatics at Louisiana State University. To date, Josh has collaborated on over half-a-dozen crime mapping studies, and has authored and co-authored multiple research articles on the subject. In his capacity as the technical services lead, Josh has functioned as a principle investigator (PI) and co-PI on multiple Web-mapping grants totaling nearly \$100,000. Josh's current research interests include the spatial analysis of dynamic phenomena, implementation of geostatistical process in Web based applications, visualization techniques for spatial data, and enterprise GIS/T systems design strategies.