

**USING FUNCTIONAL DISTANCE MEASURES
WHEN CALIBRATING JOURNEY-TO-CRIME
DISTANCE DECAY ALGORITHMS**

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TABLE OF CONTENTS

ACKNOWLEDGMENTS	ii
LIST OF TABLES	v
LIST OF FIGURES	vi
ABSTRACT	vii
CHAPTER 1. INTRODUCTION	1
CHAPTER 2. REVIEW OF LITERATURE	11
2.1 Perception of Distance and Space within Behavioral Geography	12
2.2 Concepts in Environmental Criminology	17
2.3 Journey-to-Crime Modeling	23
2.4 Distance Decay Functions	30
2.5 Geographic Profiling	34
2.6 Characteristics of a Serial Offender	48
CHAPTER 3. MATERIALS AND METHODS	52
3.1 Modeling Environment	55
3.2 Test Subjects	58
3.3 Data Sets	60
3.4 The Geographic Profile Procedure	62
3.4.1 Calibration Routine	62
3.4.2 Journey-to-Crime Routine	65
3.5 Determining the Best-Fit Distance Decay Model	67
CHAPTER 4. RESULTS AND DISCUSSION	69
4.1 Frequency Distributions by Metric	69
4.2 Journey-To-Crime Calibration Models	73
4.2.1 Euclidean Distance Decay Model	73
4.2.2 Travel-Path Distance Decay Model	77
4.2.3 Temporal-Path Distance Decay Model	77
4.3 Assumptions	78
4.4 Best Performing Geoprofiles	78
4.5 Geographic Profiles by Euclidean Metric	85
4.5.1 Straight-Line Path Distances	86
4.5.2 Manhattan Distance	86
4.6 Functional Distance Measures	87
4.6.1 Travel-Path Distances	87
4.6.2 Temporal-Path Distances	88
4.7 Further Discussion	89

CHAPTER 5. SUMMARY AND CONCLUSIONS	96
5.1 Conclusions.....	98
5.2 Recommendations.....	101
5.3 Further Topics of Study	103
REFERENCES	107
APPENDIX A TRAVEL DIARY QUESTIONNAIRE	111
APPENDIX B COMMUTER SURVEY	112
VITA.....	114

LIST OF TABLES

Table 4.1 Geographic Profiling Results: Best Performing Geoprofiles	79
Table 4.2 Geographic Profile Results: Direct Path Euclidean Metric	85
Table 4.3 Geographic Profile Results: Manhattan Euclidean Metric	86
Table 4.4 Geographic Profile Results: Travel-Path Functional Distance Metric	87
Table 4.5 Geographic Profile Results: Temporal-Path Functional Distance Metric	88
Table 4.6 Geographic Profiling Results: Cumulative Results by Metric	89
Table 4.7 Commuter Survey Results	92

LIST OF FIGURES

Figure 1.1 Travel Structure Characteristics	7
Figure 1.2 Travel Cost Paradox	9
Figure 2.1 Routine Activity Theory	19
Figure 2.2 Journey-to-Crime Distance Decay Curves	32
Figure 2.3 Negative Exponential Functions	41
Figure 3.1 Mathematical Calibration Algorithms	65
Figure 3.2 Geographic Profiling Metric Calibration Matrix	67
Figure 4.1 Frequency Distributions By Metric	70
Figure 4.2 Calibrated Distance Decay Algorithms for Euclidean Distance Metrics	74
Figure 4.3 Calibrated Distance Decay Algorithms for Travel-Path Functional Distance Metrics	75
Figure 4.4 Calibrated Distance Decay Algorithms for Temporal-Path Functional Distance Metrics	76
Figure 4.5 Geographic Profiling Results: Best Performing Geoprofiles – Test-Sample 1	81
Figure 4.6 Geographic Profiling Results: Best Performing Geoprofiles – Test-Sample 2	82
Figure 4.7 Geographic Profiling Results: Best Performing Geoprofiles – Test-Sample 3	83
Figure 4.8 Geographic Profiling Results: Best Performing Geoprofiles – Test-Sample 4	84
Figure 4.9 Potential Edge Effects When Using Artificial Boundaries	93

ABSTRACT

Spatial analysis has long been a valuable tool used within the criminal investigative process. This is especially true for serial offence 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 an anisotropic landscape. By substituting straight-line Euclidean distances with travel path functional distance measures, the predictive utility and technological prerequisites associated with geographically profiling a localized serial offender was assessed using mathematically calibrated distance decay models. Both the travel-path and temporally optimized functional distance measures were calculated based on the impedance attributes stored within a linearly referenced transportation data layer of East Baton Rouge Parish, Louisiana. Journey-to-crime distance decay algorithms were mathematically calibrated for 'best fit,' based on the distribution of incidents obtained from a calibration sample of thirty-one simulated offenders. Functional distances measured for a series of incident locations attributed to a sample of four simulated serial offenders. Using the calibrated distance decay function measured from the calibration sample, geographic profiles were created for each of the four simulated serial offenders. A probability score was calculated for every point within the study area to indicate the likelihood that it contained the offender's residence. Score surfaces estimating the likely residence of the sample offenders were calculated and compared to the actual, known residences in order to determine predictive value and procedural validity of functional distance metrics. Analyzed results revealed that the functional distance measures can serve as a substitute for traditional Euclidian distances when estimating the likely residence of a localized serial offender.

CHAPTER 1. INTRODUCTION

The criminal investigative process involves a variety of analytical techniques that support the apprehension and successful prosecution of an offender. Typical functions of a criminal investigation include crime scene processing, preservation of physical evidence, witness interviews, and suspect interrogations. Depending on the complexity of the crime, more advanced investigative methodologies may be included. A familiar and often popularly idealized technique is forensic analysis: a multi-disciplined collection of scientific techniques in which investigators attempt to coherently relate various elements of a crime in order to successfully prosecute an offender. Forensics expands upon traditional crime scene techniques to support the scientific exploration of evidence to include the development of a criminal *modus-operandi* (MO), psychological and behavioral profile, ballistics, fiber analysis, DNA analysis, and geographic analysis, to name a few. Of particular interest to this research is the application of geographic analysis for the successful mitigation of serial criminal offences. Specifically, this research will examine a new strategy for modeling serial offender behavior in order to increase the investigative utility and predictive capabilities of a geographically calibrated offender profile.

Analyzing crime events using geography has long been a valuable resource for the criminal investigative process. With records dating back as far as the 1830s (Harries, 1999), sociologists and criminologists have long understood the role geography has played as a fundamental component of crime. By the early 1900's, law enforcement began to realize the advantage of using wall-sized pin-maps that detailed the distribution of crime events. By integrating these maps within their investigations, detectives were able to visualize and explore crime in relation to its surrounding landscape. As technology improved, newer practices and techniques for mapping crime developed. But the spatial analysis of crime would not be fully

leveraged as a research tool until the computer-age; when analytical algorithms could be efficiently and repeatedly computed for large quantities of data. Yet, these techniques were generally limited to theoretical (and in many cases academic) applications, limited to only the largest and wealthiest jurisdictions.

The full potential of geographic analysis was finally realized by the early 1990s, when advances in desktop computing allowed any investigators to not only visualize the occurrence of crimes, but also analyze criminal activity in a variety of contexts in which they occurred. By using geographic information systems (GIS), discrete data points could be stored and analyzed relative to other intelligence assets. The added utility of combining spatial analysis, statistics, and report generation empowered criminal investigators with the ability to identify change, reveal patterns and trends, and model possible methods of mitigation. To this day, law enforcement agencies have come to rely on geographic analysis to quickly analyze and disseminate information in order to provide meaningful and coherent investigation and apprehension strategies.

Because crime is influenced by a number of complex conditions, the ability to map crime will vary according to a criminal's taxonomy. As Harries (1999) pointed out, simple theft is influenced by factors that differ unmistakably from those associated with murder. And just as a distinction should be made between the qualities of a mafia assassination and that of a domestic homicide, so too should like-crimes be investigated differently. Of particular interest to the criminologist is the phenomenon of the serial offender. Serial crime incorporates more complex sets of psychological and ecological circumstances than any other criminal act. It is the serial offender's very nature that presents unique challenges for a criminal investigation. As noted by Rossmo (2000), most crimes are solved by exploring the immediate relationships shared between

offender and victim. However, serial offences often lack an obvious connection. As such specialized investigative strategies beyond traditional methodologies are almost certainly required for offender apprehension. One such strategy is commonly referred to as profiling.

The basic concept of a profile is to identify and develop offender characteristics based on the offence characteristics (Canter & Gregory, 1994). The most commonly referenced criminal profile is the psychological, or behavioral, profile. The objective of the behavioral profile is to generate a consistent set of offender personality traits based on the evidence obtained from a crime scene. However, the ability to successfully apprehend a serial offender on such a profile alone has not been empirically demonstrated (Rossmo, 2000; Grubin *et al.*, 2001). As such, developments within criminology over the past two decades have led to more sophisticated investigative and analytical techniques that have demonstrated relative degrees of success. Not surprisingly, geographic analysis is one such technique. Coined by Louisiana State University Geographer Dr. Milton Newton in the mid-1980s as “geo-forensic” analysis, the concept aims to identify and characterize offender spatial behavior as it relates to the crime site (Newton & Swoope, 1987). Today, this area of research is commonly referred to as geographic profiling.

Geographic profiling is a decision support tool consisting of various investigative and analytical methodologies, both quantitative and qualitative, in which criminologists estimate the likely location of a serial offender’s residence based on the distribution of linked crime sites (Canter & Gregory, 1994; Rossmo, 2000; Godwin, 2003). The geographic profiling concept extends beyond the traditional spatial classification schemes, such as hotspot and trend analysis, to provide more comprehensive methods for profiling criminal behavior. These techniques include distance to crime research, demographical analysis, environmental psychology, landscape analysis, point pattern analysis, crime site residual analysis, and psychological

criminal profiling. While a geographic profile is usually developed for serial crimes (such as rape, murder, arson, and robbery), certain circumstances exist when such analysis may be able to provide valuable insight for events involving multiple locations, or those events that demonstrate significantly unusual geographic characteristics (Rossmo, 2000). Such applications could be utilized in a variety of offender-defender scenarios that can theoretically include military and anti-terrorism activities.

The ability to estimate the offender's residence is a primary objective for any geographic profiling technique. However, the process of developing a meaningful profile is seldom easily achieved. As noted by Rossmo (2000), a serial offender's residence would simply lie at the center of a distribution of crime sites if given idealized conditions. Yet, serial crimes do not occur within ideal circumstances, and the conditions are rarely simplistic. In reality, crimes scenes are often found to be distributed in complex spatial patterns, making it difficult to map trends. Contributing to the difficulties are the psychological and physical boundaries that, among other impedance factors, conspire to distort an already complex analytical investigation. In order for a geographic profile to provide a meaningful output, specialized geo-analytical and environmental investigative techniques are combined to interpret these patterns. One of the most significant techniques available to a criminologist is the journey-to-crime concept of the distance decay function - a graphical curve used to represent how the number of offenses committed by an offender decreases as the distance from his or her residence increases (Brantingham & Brantingham, 1984; Rossmo, 2000).

Rossmo (2000) is arguably one of the first researchers to incorporate distance decay models for geographically profiling serial offenders. His research led to the development of a profiling model that was based extensively on the concepts of Environmental Criminology and

classical journey-to-crime techniques. Called “Criminal Geographic Targeting” (Rossmo 2000), serial crime sites are analyzed using derivatives of an empirically calibrated collection of distance decay algorithms. In applying the algorithm, locations surrounding linked crime sites are assigned a weight value that indicates the likelihood of being the offender’s residence. Each location’s weight is assigned according to its distance from the crime scenes. These models produce a density map, what Rossmo (2000) refers to as a probability surface which is used to develop and/or enhance investigative strategies. Similar distance decay algorithms are utilized for various implementations of other readily available profiling applications such as CrimeStat II (Levine, 2002a), Dragnet[®] (Canter, 2003), and Rigel[™] CGT (Rossmo, 2003).

While the utility of a geographic profile as an investigative tool is obvious, its ability to accurately estimate a serial offender’s residence remains relatively inconsistent (Snook, 2000; Gore & Tofiluk, 2002). This can primarily be attributed to the complex association of environmental and psychological factors related to crime and associated spatial patterns (Canter, *et al.*, 1983, 1984, 2000; Rossmo, 2000). Traditionally, geographic profiling models measure crime patterns using standard Euclidean distances. However, these measurements are consistently distorted by “real-world” factors such as street layout, traffic congestion, landscape features, psychological bias, and more (Rossmo, 2000). For highly-mobile populations such as those of the United States (US) and Canada, these factors represent significant challenges that make the geographic analysis of crime difficult. The profiling techniques that include distance decay, circle-theory, mean center, center of minimum distance, and other commonly used algorithms assume that travel and opportunity are equally uniform, *i.e.* isotropic (Berry, 1998; Rossmo, 2000; Levine, 2002a). As a result, models derived from traditional Euclidean distance metrics fail to approximate the actual conditions in which crime patterns occur. These

circumstances can best be demonstrated for two distinct travel structure characteristics: travel path and travel cost.

The commuter's travel-path is a representation of an actual route one would take when commuting between an origin and destination. By accommodating for both the structure of the transportation network and subjective bias of the commuter, the commuter's travel-path can provide for a more accurate method of measuring the travel distance values required for geographic profiling models. Yet, most geographic modeling applications rely on traditional Euclidean metrics when measuring the distances between two locations. This can be problematic, as the contemporary urban and suburban landscape consists of a patchwork of non-uniform (anisotropic) network of roads, highways, and interstates. As a consequence, these networks have inherent impedance factors that are influenced by cultural, physical, and psychological characteristics (*e.g.* land use, laws and regulations, rivers, mountains, neighborhoods, *etc.*) that limit travel for certain directions and speeds (Barry, 2000; Rossmo 2000). These factors significantly influence an individual's subjective and objective considerations for travel. As research from Rhodes and Conly (1981) revealed, one of the primary consideration for a commuter is the actual commuter path, or "wheeled distance," of the road network. Furthermore, a study conducted by the Transportation Research Board found that commuters consistently demonstrate a bias against routes that require left-hand turns at busy intersections which have been associated with high rates of collision (Brehmer *et al.*, 2003). Accordingly, the reliance on straight-line Euclidean distance measures, often represented by "crow-flies" distances, fails to account for the actual commuter path between locations *i* and *j* (Figure 1.1A). Distance values obtained for a commuter using Euclidean metrics would be highly suspect and misrepresentative of an actual commute between the two places (Rhodes &

Conly, 1981). To address this limitation, researchers developed an indirect Euclidean distance metric referred to as Manhattan distances (Figure 1.1B). Although an improvement over traditional distance measures, it remains a limited solution. The metric is often unable to provide a realistic representation of the non-uniform transportation structures that characterize many US and foreign cities (Rhodes & Conly, 1981, Levine, 2000a). In fact, research has consistently demonstrated that a primary consideration for movement in space is determined by travel-cost: the expense and effort necessary for one to commute between two or more locations (Brantingham & Brantingham, 1981; Berry, 1998; Rossmo, 2000).

As Rossmo indicated (2000), it is the psychological perception of the distance, not the actual measure that serves as a determining factor for estimating travel cost. The impedances imposed by the physical and cultural landscape dictate a commuter's expectations of travel.

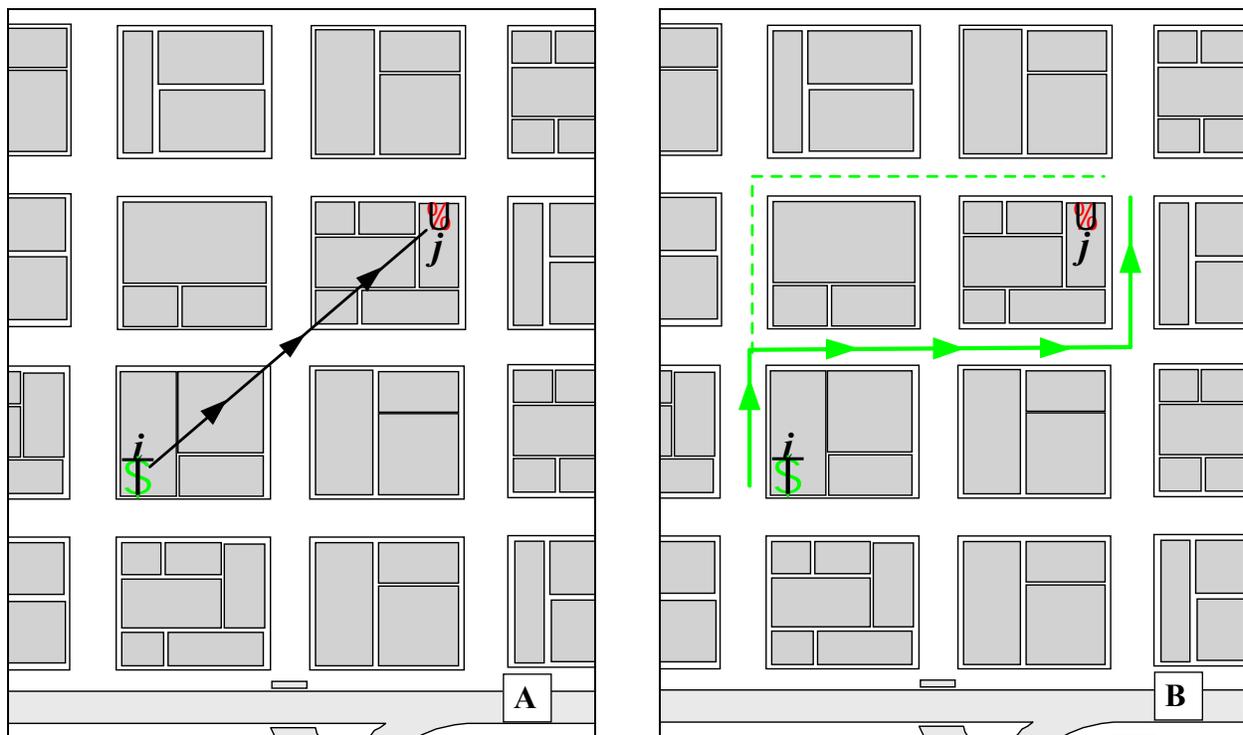


Figure 1.1 Travel Structure Characteristics: (A) straight line, Euclidean distance metric; (B) Manhattan distance metric.

Accordingly, commuters will operate within a behavioral space in which they know how best to travel (Felson and Clarke, 1998). The same can be said of a serial offender, who will no more or less likely be expected to choose a convoluted path between two locations than a law-abiding citizen (Brantingham & Brantingham, 1981; Newton & Swoope, 1987). An offender will optimize his/her travel with the same approach as an individual leaving her home for the grocery store: to travel in the most economical manner possible within the limits of the surrounding landscape and prevailing opportunity (Zipf, 1950). Yet, most efforts to measure travel-time costs have typically relied upon centographic techniques that demonstrate variations of the least-effort principle. Again, the assumption of an isotropic surface fails to represent the actual environment in which these locations exist (Berry, 1998; Rossmo, 2000).

Consider this travel cost paradox illustrated in Figure 1.2: A commuter must travel from location i (origin) to location j (destination). The two available paths, a surface street (Figure 1.2A) or a high-speed “beltway” (Figure 1.2B), will equally result in accomplishing the task. As the figure illustrates, when selecting the route that uses the highway (Figure 1.2B), the commuter is able to travel from origin to destination in much less time when compared to traveling on the surface street (Figure 1.2A). The distance traveled using the highway may be longer than the distance on the surface street, but the travel time is measurably less. This example demonstrates how temporal distances can be used to identify an optimal travel path by accommodating a commuter’s subjective notion of cost. As such, the perceived distance the offender is willing to travel can become a function the time it takes to commute to a destination, not the Euclidean distance measured between them.

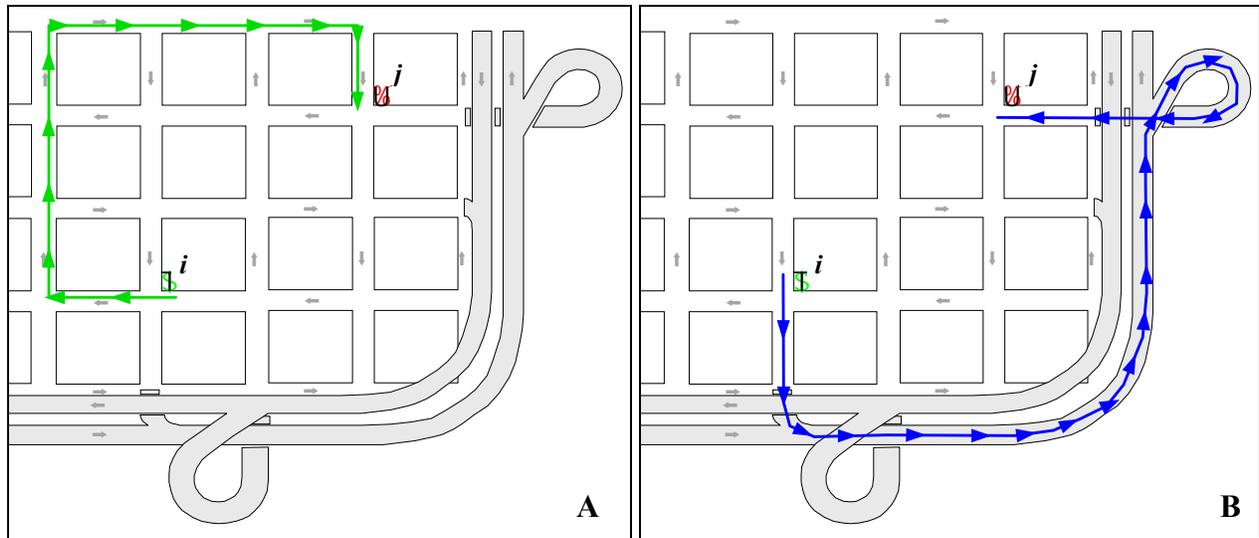


Figure 1.2 Travel Cost Paradox: (A) surface street commute; (B) beltway commute.

The empirical question therefore arises: to what extent can functional distance measures improve the predictive utility of a geographic profile? Godwin and Canter (1997) note the significant contribution time and distance provide an investigation when successfully solving serial homicide cases. And as research by Stea (1969), Brantingham & Brantingham (1981, 1984), Rossmo (2000), and Canter *et al.*, (1993, 1994) demonstrate, the objective and subjective characteristics of an offender’s commute represents a critical set of components necessary for the meaningful development of an offender profile. Because functional distance measures can be used to accommodate both the objective (physical distinctiveness) and subjective (psychological biases) characteristics of an offender’s commute, it may provide a valuable advantage over the straight-line Euclidean measures when estimating an offender’s likely residence.

Given the obvious theoretical value of the functional distance metric for geographic profiling applications, it is curious as to why so few researchers have explored its potential. A possible explanation may be provided by examining the economic and technological prerequisites necessary for obtaining functional distance values. As the most significant resource

for calculating functional distances, linearly referenced transportation data layers that contain the necessary impedance attributes are typically priced beyond the budgetary constraints for many cash-strapped law enforcement agencies. Furthermore, the advanced technological prerequisites needed to process many of the network-path calculations have only recently been achieved using relatively inexpensive workstation-class personal computers (PC). As such, agencies that may have had the resources to invest in the costly data may not have the realistic technological capabilities to process the data, until now.

This research will examine and assess, as a proof of concept, the predictive utility and technological cost of functional distance metrics when estimating the likely residence of a localized serial offender. By substituting straight-line Euclidean distance values with both travel-path and temporally optimized (temporal-path) distance measures, this research theorizes that it is possible to develop an accurate model of an individual's travel behavior within a realistic, anisotropic landscape. Travel-path functional distance measures are calculated based on the impedance attributes stored within a routable transportation data layer of East Baton Rouge Parish, Louisiana. The functional distances measured for a series of simulated serial offences will be modeled using a distance decay function empirically derived from a sample of like-simulated offenders. Probability surfaces estimating the likely residence of four simulated serial offenders will be calculated and evaluated against the offender's known residence in order to determine predictive utility and procedural validity of functional distance metrics.

CHAPTER 2. REVIEW OF LITERATURE

The occurrence of crime is the inherent outcome of a unique set of complex circumstances that can be characterized as both behavioral and environmental in nature. While there are a number of intricate factors at play, an important dimension of any criminal investigation is the analysis of place. As noted by Felson & Clarke (1998), crime occurs at a spatial and temporal intersection between both the offender and victim. The ability to understand the geographic implications an offender's spatial behavior leading up to the commission of a crime is considered to be just as important for solving a case as the physical evidence remaining at a crime scene. Implementing the necessary techniques for identifying and exploring the geographic patterns possessed by a serial offence is the result of established research in ecological criminology.

Perhaps one of the first successful uses of geographic analysis for the apprehension of a serial offender was applied by forensic scientist Stewart Kind (1987). Kind analyzed the homicide locations of twenty victims of the "Yorkshire Ripper" in northern England between the late 1970s and early 1980s. By estimating the center of minimum distance of each crime scene, weighted by time of day for each incident, Kind was able to accurately identify the community within which the offender resided at the time of the homicides. The techniques associated with this type of centographic analysis had been utilized by numerous serial criminal investigations: Police in Georgia used geographic analysis when investigating the "Atlanta Child Murders" in the early 1980s; LeBeau (1987) recognized that geo-statistical analysis could be utilized as an investigative strategy for serial rape cases in California; and Newton and Swoope (1987) demonstrated how the spatial mean between crime scenes of the "Hillside Strangler" could be used to develop an empirically derived investigative search strategy. While much of this work,

and other similar investigations, relied on intuitive investigative processes, the conceptual framework for these techniques had only recently been established by contemporary Environmental Criminology. Brantingham & Brantingham (1981) theorized that geographic modeling techniques can be used to describe the spatial behavior of a criminal offender by simply examining the spatial distribution of linked crime scenes. As a result of their work, the Brantingham's derived the 'geometry of crime' concept: a modeling technique used to identify the criminal's target selection, or hunting strategy, which examines the relationship between the distribution of offenders and targets within the context to the prevailing environment.

An important characteristic for the geographic analysis of crime is the understanding that crime does not occur in random or unpredictable locations. Rather, criminal offences occur in observable structures that are influenced by the landscape in which they occur, and the psychological factors that dictate the offender's movement. It is this maxim that makes geographic profiling a powerful investigative tool. As noted by Newton and Swoope (1987), landscapes work. That is, objects flow through landscapes in rational and predictable ways. As such, any occupant of the land must adhere to the pattern that dictates their movement throughout its space. Identifying an offender's spatial pattern(s), and likely residence, can positively impact the investigative process by focusing limited resources in critical areas. Consequently, the ability to construct a meaningful geographic profile is dependent upon an investigator's understanding of the geographic and ecological principles discussed in the following text.

2.1 Perception of Distance and Space within Behavioral Geography

An individual's perception of distance is unique. How one perceives distance is influenced by numerous factors, both objective and subjective, that ultimately act to bias ones

movement within space. As such, the ability to model human travel behavior represents a significant challenge when investigating serial crime. Researchers often approach the analytical exploration of human travel behavior using models derived from the application of Location Theory. This concept consists of various methodologies that explore the relationship between the perceived and actual landscape characteristics in order to identify the optimal location for any distribution of activities or populations (Newton & Swoope, 1987; Levine, 2002). Traditionally, Location Theory has been a critical component of the supply and demand models utilized by shipping companies (e.g. UPS[™], DHL, US Postal Service[®], FedEx[®], *etc.*). These models, founded by concepts in Economic Geography, look to maximize the placement of distribution facilities in order to minimize travel costs. The significance of these applications for the criminologist is enormous. As demonstrated by Kind (1987), when applied in reverse, it is possible to estimate a central location from which travel distance is minimized. This application is a frequently used technique founded on Least Effort Principle. Sometimes referred to as the nearness principle (Rossmo, 2000), the theory states that given a distribution of equally desirable locations, the closest destination is the one most frequently chosen (see also Zipf, 1950). This condition, however, can only be demonstrated on an isotropic surface, where opportunity for success is equally distributed for any given direction. As demonstrated earlier, however, the geographic landscape is never isotropic.

The environment in which any commute is produced will have inherent impedances that are dictated by factors which ultimately limit travel for certain directions, distances, and speeds. As such, movement between locations will be easier in some directions than in others. Consequently, the straight-line distances measured between two locations may not correspond to the closest possible destination in terms of the actual travel path (Rhodes and Conley, 1981).

This represents a non-trivial paradox for any criminal investigation where the distance measurement is a critical element for analysis. Both Canter (1994, 2000) and Rossmo (2000) proposed the use of an alternate distance measure known as the Manhattan metric. The Manhattan distance metric (Equation 2.1) is an orthogonal distance algorithm used to enumerate travel costs for commutes between origin and destination on a uniformly arranged, grid-based road network often identified within urban environments. The Manhattan metric is defined as:

$$d_{xy} = |x_i - x_j| + |y_i - y_j| \quad (2.1)$$

where the Manhattan distance, d , is equal to the straight-line distance between two locations measured along the x-axis, plus the straight-line distance between two locations measured along the y-axis. While an improved method for calculating distances, the exclusive use of the Manhattan metric may be problematic. As noted by Levine (2002a), Manhattan distances are often speculative measures that can lead to overestimated travel path distances when applied to locations where street networks are irregularly arranged.

Consideration for the wheel distance (Rhodes & Conley, 1981), or the actual travel path, is not the only factor associated with an individual's perceived notion for a successful travel production. All commuters express some measurable bias for specific routes (Brehmer *et al.*, 2003). To accommodate this bias, Stea (1969) identified five influential factors associated with the perception of travel distance:

- Attractiveness of both origin and destination;
- The impedance between the origin and destination;
- Familiarity of the route;
- The distance between origin and destination;
- The condition of the route.

As a method for quantitatively measuring these elements, the analyst can utilize temporal functional distance metrics. As indicated by Rossmo (2000), the perception of distances as a function of time is often more important than the actual distance itself (see also Brantingham & Brantingham, 1981; and Berry, 1998). Thus, by optimizing the actual travel path using the temporal distance value, criminologists should theoretically be able to accommodate for elements of the commuter's subjective notion of optimized distance. However, the analyst must be able to identify an actual commutable path between an origin and destination. As such, if the least effort principle is to provide a meaningful approximation of an offender's spatial behavior, it must incorporate both the objective (physical) and subjective (cognitive) factors identified above. The concept of a criminal's "mental map" supports this conclusion.

A mental map is an individual's cognitive image of familiar locations that are formed through the every-day interaction one has with his or her surroundings (Brantingham & Brantingham, 1984). As noted by Canter (1994), the mental map represents an individual's subjective awareness of the features and spatial relationships that exist within his or her environment. Rather than it being an exact picture, the mental map is a generalized concept of the landscape stored within the person's memory – hierarchically categorized for various scales. As such, it is based entirely on the individual's objective awareness and subjective perceptions and attitude towards a place (Brantingham & Brantingham, 1984). The mental map postulate represents a significant concept for criminologists because it allows an investigator to explore the relationship a crime's location has within the context of an offender's awareness of target and awareness of location.

As demonstrated, the processes associated with the commission of a crime can reveal a wealth of information for an investigation. The fact that a crime occurs at a particular location

indicates that the offender has some degree of knowledge of that location. That knowledge is based in part on the offender's mental map. The information available within a mental map is characterized in two ways: actual knowledge of a place, and intellectual awareness of a place (Brantingham & Brantingham, 1981). For example, an individual's intimate understanding of home, the immediate neighborhood, and the route to the grocery store represents the environment in which the majority of his or her activities are carried out. It is a place that is implicitly understood. However, the individual that has never left his or her home-town can be aware of the general characteristics of another town without knowing how to travel within it. It is a foreign place that is understood in the abstract. These two conditions represent the ecological concepts of the Activity Space and Awareness Space, respectively (Brantingham & Brantingham, 1981, 1984). In order to extract information from these spatial characteristic, the criminologist must know how to interpret the subtle spatial relationships that exist between an offender's activity space and the crime scenes.

Research demonstrates that most criminals spend the bulk of their daily lives in pursuit of non-criminal activities (Canter *et al.*, 1994). As such, their actions are inexorably tied to the confines of normal societal behavior. For example, a person is presumably expected to work, eat, sleep, and recreate. The locations encompassing these acts are defined as activity nodes. The implication is that the offender's activity and awareness space is defined by the distribution and subsequent travel between activity nodes. As such, it is likely that the offender will initiate a criminal act within the limits of his or her awareness space (Brantingham & Brantingham, 1981). This characteristic was empirically demonstrated by the Brantingham's (1981) from a study of crime in Washington D.C. where it was found that the further an offender was from his or her residence the less likely he or she would commit an offence.

By identifying the various elements that constitute the mental map, the criminologist can implement variations on the least effort principle to identify specific characteristics of the criminal's spatial behavior. As indicated by Rossmo (2000), individuals perceive their shared surroundings in similar ways. As such, each person's mental map will possess similar features based on shared experiences. Landmarks, roads, malls, rivers and mountains, and other distinctive landscape characteristics and activity centers represent commonly perceived features of the environment. As such, these elements can be used to identify unique spatial behavior characteristics expressed by both offender and victim. The body of research that examines criminal behavior within a geographical construct is commonly referred to as Environmental Criminology.

2.2 Concepts in Environmental Criminology

Environmental Criminology consists of a number of theoretical concepts that provide a heuristic for understanding and predicting criminal offences. Theories such as Routine Activity, Rational Choice, Crime Pattern, and the Buffer Zone postulate each represent the broad approach Environmental Criminology provides for analyzing the operational, behavioral, perceptual, social, legal, cultural, and geographic factors of a crime (Rossmo, 2000). Contemporary Environmental Criminology represents a paradigm shift away from traditional analytical techniques that examined offender characteristics, and toward the exploration of the ecological circumstances associated with a crime's occurrence. As a result, Environmental Criminology provided the construct on which new techniques could be used to explore the unique characteristics of an offence. By studying the relationship crime shares with place, the criminologist can identify how the immediate environment shapes the legal and illegal activities of both victim and offender. As such, the ecological criminologist can explore patterns, test

concepts, and formulate investigative processes in the context of a crime's immediate landscape. These concepts embody a research approach which Newton and Swoope (1987) referred to as the "Sociology of Crime." Prior to this ecological construct, investigative techniques focused exclusively on quantitative analytical methodologies that explored aggregated patterns and trends within an objective space. By incorporating the qualitative assets of the immediate environment, the criminologist can identify subjective characteristics that may reveal an offender's unique perception of his or her surroundings (Canter & Gregory, 1994).

The value of identifying a criminal's spatial behavior can only be measured by the ability of a criminologist to extract some meaning from it. If the patterns inferred from a series of criminal acts do in fact describe the spatial behavior of a serial offender, how can they be used to mitigate further offences? In exploring the elementary characteristics of a crime, Felson and Clarke (1998) demonstrated that there must be a juxtaposition of three key elements to support the commission of a crime:

- A willing offender;
- A suitable target;
- A location that is perceived to be absent of a capable guardian.

Known as Routine Activity theory, the concept permitted an investigator to explore the characteristics of predatory crime by dissecting it into its constituent elements (Figure 2.1). Most Routine Activity theory analysis begins by assuming the presence of a willing offender. As such, more effort can be focused on examining the relationship that exists between the victim and crime scene(s).

The concept of a target, while integral for the occurrence of a crime, is not entirely a significant spatial element in terms of geographic analysis. This is because potential targets can be distributed across numerous locations, referred to by Rossmo (2000) as the 'target backcloth.'

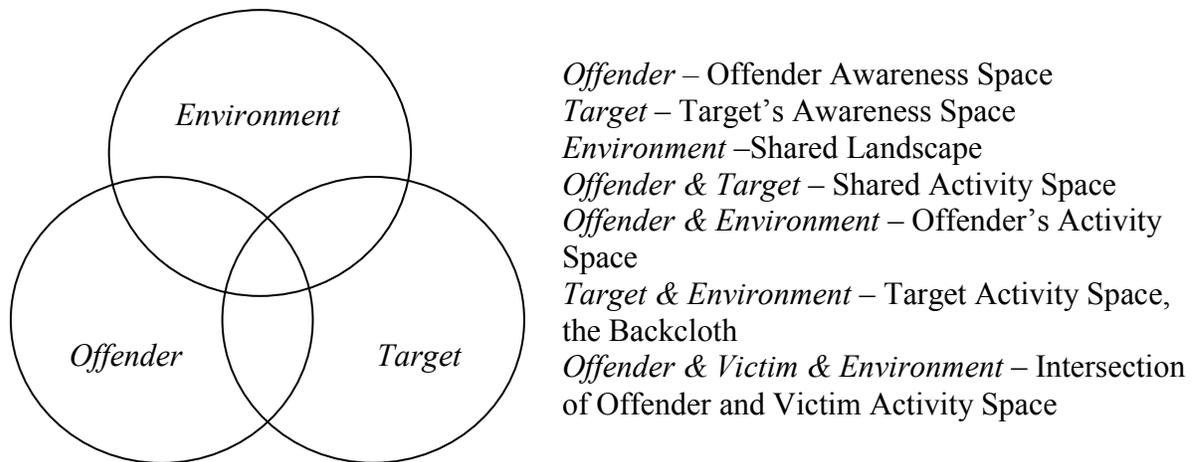


Figure 2.1 Routine Activity Theory (Rossmo, 2000)

However, it is the absence of a capable guardian which represents the non-random, geographic circumstances from which crime occurs. As such, the location of the offence represents the shared environment where the criminal’s awareness space intersects the target backcloth (Brantingham & Brantingham, 1981, 1984). Spatially, this intersection implicates a location where the offender is comfortable enough to commit the offence (Canter & Gregory, 1994). As such, Routine Activity theory supports the concept that crime opportunity 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. Although any given target may be selected by chance, the process of selection is spatially structured whether the offender realizes it or not (Rossmo, 2000). As presented earlier, the landscape in which objects and events exist is ultimately dictated by numerous objective and subjective conditions. When explored geographically, the processes used for target selection will actually reveal patterned structures that describe the offender’s objective space, a concept known as Crime Pattern theory.

Another concept of Environmental Criminology is the Rational Choice theory. As demonstrated in Routine Activity theory, target selection occurs wherever the awareness space of an offender overlaps the awareness space of a suitable target (Brantingham & Brantingham, 1981). Therefore, one can infer that the inherent environmental structure of an offender's established activity space will ultimately control where a crime occurs. That is, target selection becomes a dynamic process dictated by the spatial interactions and conditions between offender and target spaces. Accordingly, the occurrence of a crime represents a location within the offender's awareness space. However, it must be noted that potential targets are not considered an abstract entity within the offender's awareness space. Instead, research suggests that the perceived relationship between target and the environment must be assessed by an offender and deemed an acceptable opportunity before a crime can occur (Brantingham & Brantingham, 1984; Canter *et al.*, 1993, 1994; Rossmo, 2000). This process represents the theory of *Rational Choice*; which postulates that criminal behavior is an outcome of decisions that are influenced by rational consideration of the efforts, rewards, and costs associated with the crime (Brantingham & Brantingham, 1984). As such, Rational Choice suggests that the criminal's decision to commit a crime will be assessed based on the perceived benefit and opportunity for success. This also suggests that a criminal can learn from past experiences in order to develop new strategies and improve his or her decision making skills (Canter *et al.*, 2000).

Canter and Gregory (1994) extended the concepts of Crime Pattern and Rational Choice by applying the theories to analyze the spatial characteristics exhibited by forty-five serial rapists in the United Kingdom (UK). Their observations revealed a hierarchical approach to target selection whereby crime scene locations exposed the offender's target selection preferences, or hunting area. Their research found that the occurrence of rape could be differentiated as either

inside or outside the offender's activity space. A majority of crime scenes (86%) were found to occur inside the offender's activity space. These offences were often characterized as premeditated attacks typically committed by offenders with previous criminal history. Canter classified this type of localized offender as a "marauder." Conversely, a minority of offences (14%) were found to occur outside the offender's activity space. These offences were characterized as opportunistic, and often the result of little to no planning. Canter defined this type of mobile rapist as a "commuter."

Canter and Gregory's findings confirmed a predominant characteristic identified by the Brantingham's (1981) which suggested that the majority of criminal acts are spatially dependent upon proximity to the offender's activity nodes. As the offender moves further away from his or her activity nodes, the occurrence of criminal activity decreases. Concordant findings were obtained by Rhodes and Conly (1981) whose research observed reluctance by criminals to travel far from their residence. Furthermore, LeBeau (1987) notes that property crime commutes tend to be further than personal crime travel. All told, the empirical evidence supports the concept that criminal behavior is influenced by least effort principle. In fact, Canter and Godwin (1997) observed that US serial offenders often disposed of their victim's bodies closer to their activity nodes as the series of offences progressed. Because the commission of crime is tied to its proximity to an offender's activity nodes, Canter and Gregory (1994) proposed that target selection characteristics could be used to define an area whereby an offender perceives a balance between maximum opportunity and minimum risk. Canter would refer to this area as the criminal's safety zone.

The Brantingham's (1984) identified the region as the offender's Buffer Zone; an area surrounding a particular activity node, most notably the residence, from which little to no

criminal activity will be observed. Newton and Swoope (1987) proposed this characteristic as the “coal-sack effect” whereby the offender, either intentionally or otherwise, avoids committing an offence in particular areas surrounding his or her residence. Presumably, such an area would represent an elevated level of risk associated with operating too close to the home. Notably, the Buffer Zone is seldom observed for spontaneous and/or passion crimes (LeBeau, 1987). Conversely, research suggests that such a zone will most likely occur for predatory offences which can be characterized as pre-meditated (Canter & Larkin, 1993). A specific consideration for the existence of the buffer zone is that it may not always be applied around the offender’s residence. Referred to by Newton and Swoope (1987) as the criminal’s “haven,” this particular activity node could represent any single or shared (i.e. home and work) location in the criminal’s routine activity space. The idea of a safety zone, however, can be misleading in that some criminal activity may exist if the offender perceives conditions and circumstances to be favorable for the commission of a crime (Rossmo, 2000). This rationale was supported by Canter and Godwin (1997) for US serial offender body dump sites. Other examples can include peeping, stalking, and other illegal surveillance activities.

Support for the existence of buffer zone-like features can be observed quantitatively. Rossmo (2000) suggests that there may be a positive linear relationship between the number of potential targets and the distance an offender is willing to travel from the haven. Accordingly, when combining the linear increase in opportunity with the decrease in travel desire, a criminologist should be able to observe a buffered distance decay function (Rossmo, 2000). This application was revealed by Canter and Larkin (1993). Using regression equations, the researchers were able to approximate a one-kilometer buffer zone around the havens of UK serial rapists. Rossmo (2000) notes that such zones also existed for similar studies of US and UK

serial killers (see also Canter and Godwin, 1997); and Levine (2002b) cites similar characteristics for various offences in the US. Such a linear increase, however, assumes an equally available distribution of opportunities and targets. As noted by Gore *et al.*, (2001, 2002), making assumptions about such a homogeneous distribution can be problematic, potentially distorting the models effectiveness when estimating offender travel behavior. However, anisotropic environments can be accommodated within available modeling applications by incorporating the various qualitative constructs thus far presented. An offender's hunting ground, target selection, spatial travel preferences, and buffer zone can be estimated using available geographic modeling applications. As proposed by this thesis, these elements can be modeled by calculating the measurable travel characteristics expressed by the distribution of a serial offender's known, linked crime scenes. To accomplish this task, criminologists utilize one of the most significant modeling applications available: journey-to-crime.

2.3 Journey-to-Crime Modeling

Prior to the availability of geographic profiling applications, criminologists exploring the geo-spatial relationships of serial offences typically relied on the proven analytical algorithms associated with journey-to-crime modeling. For years, the journey-to-crime approach has been used to estimate the likely point of origin of a serial offender based on the properties associated with the distribution of crime incidents (Levine, 2002a). As a modeling technique, journey-to-crime is established on research that shares much of its core analytical functionality with traditional travel demand models developed for transportation planners (Biemborn, 1995). It uses the measured distances between known crime sites and an offender's known residence in order to identify travel behavior. These measures are statistically aggregated and typically plotted to illustrate the percentage of crime for a given distance unit. These techniques have traditionally

been implemented by analysts to provide an empirical foundation for quantifying the travel characteristics of a given community's criminal population. Many contemporary criminologists utilize some variation of journey-to-crime model results in order to obtain or verify specific criminal spatial characteristics. These characteristics provide a basis for developing new analytical processes and mitigation techniques. In terms of its descriptive statistical capabilities, journey-to-crime models are dependent upon numerous conditions, including the scale of observation. As noted by Ratcliff (2001), traditional journey-to-crime techniques were founded from sociological research developed from the Chicago School of the 1920s. Using the Burgess zonal model, journey-to-crime characteristics were analyzed at a macro level (Harris & Lewis, 1998). However, the predictive capability of this technique is notably suspect due to the high-levels of data aggregation and ease of misinterpretation (Gore *et al.*, 2002). Contemporary methods, however, utilize a micro level, intra-urban approach to modeling offender travel characteristics (Gore *et al.*, 2001, 2002). At this scale, residence-to-offence (origin to destination) travel characteristics reveal the inherent spatial patterns associated with an offender's travel behavior within an ecological construct (Brantingham & Brantingham, 1981, 1984; Biemborn, 1995, Anselin *et al.*, 2000). Some of the more commonly utilized algorithms implemented for journey-to-crime include: mean and median distance measures, medial circles, mobility triangles, and distance decay algorithms, to name a few (Rossmo, 2000). Each approach is associated with its own unique qualities. Selecting the most appropriate modeling application will depend entirely on the characteristics of the environment in which a crime occurs; usually requiring a trial-and-error approach (Levine, 2002a). Understanding the characteristics of the various journey-to-crime models can aid in the decision making process. As such, brief overviews of these techniques are provided below.

The mean and median analytical techniques are founded on the centographic models discussed earlier. These models essentially identify the optimal location for a given distribution of events where the travel distance is minimized for all locations. It must be noted, however, that the mean and median techniques often result in a limited interpretation of travel behavior. This is due to their susceptibility to spatial outliers and assumption of isotropic surfaces. Furthermore, these techniques often aggregate offenders into single groups, thus assimilating their unique spatial characteristics; resulting in average travel distances for an entire population at the expense of an individual distinctiveness. The second technique, Medial Circles, utilizes circle theory to define an area around the occurrences of each offence in order to identify and develop a list of likely suspects. Each circle's radius is defined by journey-to-crime measures of like-crime types. While accommodating for uniqueness of the different crime types, it often fails to account for suspects that may offend and or reside outside the circles' radii. The third approach, Mobility Triangles, examines the relationship between offender residence, target location, and crime scene in order to solve crime. While this approach demonstrates value for modeling offender-target spatial behavior, it over-emphasizes the importance of the target's location, which may or may not be a factor for offender mobility. This is easily demonstrated by the characteristics of auto theft and narcotics cases, both of which demonstrate dynamic behavioral characteristics whereby target selection and criminal opportunity are not easily predicted and often spontaneous. The fourth, and most effective technique for journey-to-crime analysis, is the distance decay algorithm.

Distance decay algorithms, like many geographic analytical measures, are quantitatively rooted in center of gravity functions based on Isaac Newton's fundamental law of attraction (Equation 2.2). As cited by Levine (2002a), traditional Newtonian gravity models calculate the

attraction, F , between two bodies, M_1 and M_2 , separated by a distance, D . The equation appears below:

$$F = g \frac{M_1 M_2}{D^2} \quad (2.2)$$

where g , represents the gravitational constant. The term, ‘distance decay’ characterizes how the attraction between two bodies decreases as the distance between them increases. The concept characterizes how individuals typically prefer to produce short commutes rather than long trips for the normal travel activities of their every day lives (Harries, 1999). This qualitative concept demonstrates how journey-to-crime is also associated with Least-Effort Principle. Transportation planners typically use distance decay functions within their mathematical models that simulate human travel characteristics (Biemborn, 1995; Levine 2002a). 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. As cited earlier (see Section 2.2), contemporary literature has observed a prominent distance decay effect whereby criminal activity decreases as the distance from the offender’s residence increases. Brantingham & Brantingham (1981) cite research from the 1950s which observed that 40% of Houston homicides occurred within one block of the offender’s residence; and 74% of the total occurred within 2 miles. Capone and Nichols, (1976) found that personal robberies generally occurred close to the offender’s residence, while property theft occurred further away. This differentiation between personal and property offences was also observed by LeBeau (1987), who found that most personal crime offenders, serial rapists, perpetrated offences within approximately two miles of their haven, where as property crime offenders traveled further away. Similar results were obtained by Canter and Larkin (1993) who found that the amount of distance decay was more pronounced for

sexual assaults than for other offences. These findings were further supported by a Federal Bureau of Investigation (FBI) report (Warren *et al.*, 1995) which indicated that the first attack in a serial homicide was most likely to occur closest to the offender's home. Based on these and other empirical studies noted earlier, it is generally accepted that journey-to-crime behavior can be described by these basic characteristics (Rossmo, 2000):

1. Crime occurs in relatively close proximity to an offender's haven, often within one mile of the offender's residence (McIver, 1981, Rossmo 2000).
2. Criminal offences follow some type of distance decay pattern, where the number of crimes decreases as the distance from the offender's residence increases (Brantingham & Brantingham, 1984).
3. Property crime distances are often observed to be longer than personal/violent crime distances (Capone and Nichols, 1976).
4. Personal offences typically demonstrate a buffer zone effect where little to no activity is observed surrounding the offender's haven (Brantingham & Brantingham, 1984; LeBeau, 1987; Newton & Swoope, 1987; Canter & Larkin, 1993).

As noted by Capone and Nichols (1976), the average distance an offender is willing to travel will vary according to the crime type, method of offence, time of day, and value of the target (see also Felson and Clarke, 1998).

The theoretical construct from which these journey-to-crime characteristics were derived are found within the context of Environmental Criminology discussed earlier. Accordingly, these characteristics are best understood as they relate to the combination of Least-Effort Principle and Rational Choice theory. Just as an individual will likely their optimize travel long to purchase a gallon of milk, an offender will likely optimize the commit an offence. However, journey-to-crime modeling is bound by certain assumptions and limitations. First, the distance a criminal is willing to travel is conditioned upon the perceived notions of success and benefit to one's self, and the awareness of other opportunities. As demonstrated by Rational Choice

theory, an offender's journey-to-crime will ultimately be based on availability of a suitable target, opportunity for success, and perceived level of risk (Brantingham & Brantingham, 1981, Felson and Clarke, 1998). And while, these patterns will reveal observable geographic structures whereby the offender confines his or her activities to known areas, they cannot preclude the possibility that an offender's journey-to-crime will increase, or decrease, over time.

Variability associated with the distance a criminal is willing to travel represents another observable condition for journey-to-crime. As suggested by Canter and Larkin (1993), as an offender's criminal career matures, the offender's activity and awareness spaces increase. Thus, the offender's willingness to travel further away from his haven(s) intensifies. In circumstances such as these, marauding characteristics that may have been assigned to a static offender must be reconsidered in favor of those of a commuter. However, this concept could also be applied in reverse. Canter proposed that as the serial offender becomes more confident in his or her abilities, the target selection pattern may become less specific, and thus moves closer to the haven. This bold (or lazy) behavior, associated with criminal maturity, could correlate with Canter's (1993) observation of increased violent behavior as offences moved closer to the haven. In their research of 54 US serial killers, Canter & Godwin (1997) observed that as the series of offences progressed, the location of body dump sites moved closer to the offender's residences. This finding supports the Environmental Criminology concept that criminal acts increasingly become a part of the offender's daily life. Numerous circumstances can provide reasonable explanations for the change in target selection pattern. However the condition from which journey-to-crime measures a distance the offender will travel is ultimately defined by the offender's subjective interpretation of his or her activity space.

This third condition proposes that the journey-to-crime distance is a perceived notion that is not likely measured by the offender. As demonstrated earlier (Figure 1.2), when taking the interstate to commit a crime as opposed to a congested surface street, the actual distance traveled may be further than the distance the offender perceived. In this sense, the time traveled between destinations using the interstate was characterized by less impedance, fewer starts, stops, and turns that would normally be associated with a surface route. Consequently, distance can be perceived differently by different offenders, dependent upon route selection. As such, journey-to-crime models should be calibrated for homogeneous populations which will more often perceive like-conditions within similar contexts. Accordingly, a serial rapist is less likely to perceive distances, and likewise target opportunity, in the same manner as a serial burglar. However, this cannot preclude that either criminal type could change their method of operation.

A final condition for journey-to-crime is related to the taxonomy of the serial offender examined. Discussed in greater detail later, journey-to-crime models assume that the serial offender operates from a static activity node. However, certain circumstances exist in which the offender may not operate from a static haven. Noted by Rossmo (2000), convicted criminals tend to be less residentially stable than non-criminals, and psychotics have been observed to be particularly nomadic. Canter and Larkin (1993) found that while most sexual offenders were marauders, a significant number were identified as commuters. As noted by Newton (1987), the ability to develop a meaningful geographic estimate of a serial offender's haven is dependent upon the mobility characteristic of the offender. Because most serial offences go undiscovered (or lack the necessary association to a crime series) by an investigation, a collection of linked crime sites can be difficult to achieve. Consequently, a too-small sample of criminal features can reduce the overall effectiveness and investigative reliability of the analysis. Furthermore, the

operational characteristic of a mobile activity node can further hinder the investigative capabilities of geographic analysis, as demonstrated by both the ‘D.C. Serial Snipers’ and ‘South Louisiana Serial Killer’ cases during 2002 and 2003.

2.4 Distance Decay Functions

In an effort to understand the underlying significance of distance decay effect for criminal activity, various theoretical models have been suggested based on existing migration algorithms and intervening opportunity theory; which are founded on the ecological context of Sir Isaac Newton’s gravity function (Levine, 2002a). Rengert (1981) developed a mathematical equation that defined journey-to-crime based on a modified general opportunities model (Gore *et al.*, 2002; Levine 2002a):

$$P_{ij} = K \cdot E_i \cdot V_j \cdot f(d_{ij}) \quad (2.3)$$

where the probability, P , that an offender from zone i , committed a crime in location j is related to the product of the enumerated number of trips produced (emissiveness) from the origin, E_i , and the number of potential targets (attractiveness) at the destination, V_j , for travel cost, $f(d_{ij})$ (Levine, 2002a). Basically, this model theorized that the probability an offender would commit a crime at a given location is entirely dependent on both the production cost, what Rengert called emissiveness, and the attractiveness for that destination. Rengert’s cost value is an undefined functional distance metric that is, presumedly, a straight-line Euclidean measure of the distance between origin and destination. While not empirically defined, the hypothetical results of his model were compared against observed burglaries in Philadelphia, PA in order to measure its effectiveness. As noted by Gore *et al.* (2002), the theoretical value of Rengert’s model is that it can be used to predict crime patterns for locations that have empirically quantified the observable travel production and zone attractiveness; essential components used within travel demand

models. Conceptually, the model presents a sound foundation for modeling offender hunting behavior by quantifying the production from the origin, attractiveness of the destination, and cost of the commute. By allocating offender trip behavior according to origin, destination, distance, mode, and path, this formulation stands out in its ability to account for the available opportunity a particular destination has over another potential destination. In doing so, it addresses the elements of routine activity theory and intervening opportunities, making the model more complete. To operationalize the formula, as Levine (2002a) states, consideration must be made for the method of travel.

Because gravity formulas have traditionally been utilized by journey-to-crime models, Levine (2000a) cautions that, as the distance between locations decreases, the gravity equation's denominator will approach infinity thus making it suspect for crimes that are dispersed over short distances (see Equation 2.1). Fortunately, a number of alternative functions are available that can effectively measure the observable distance decay characteristics of a criminal's journey-to-crime. Brantingham and Brantingham (1981) suggested a buffered normal function could be used to describe a criminal's distance decay following the hypothetical Buffer Zone. However, Rhodes and Conley (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 (2000a) 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 (Figure 2.2). Each function possesses various characteristics that can be utilized by journey-to-crime models. For example, the *Normal*, *Lognormal*, and *Truncated Negative Exponential* are algorithms that characterize how the spatial distribution of criminal

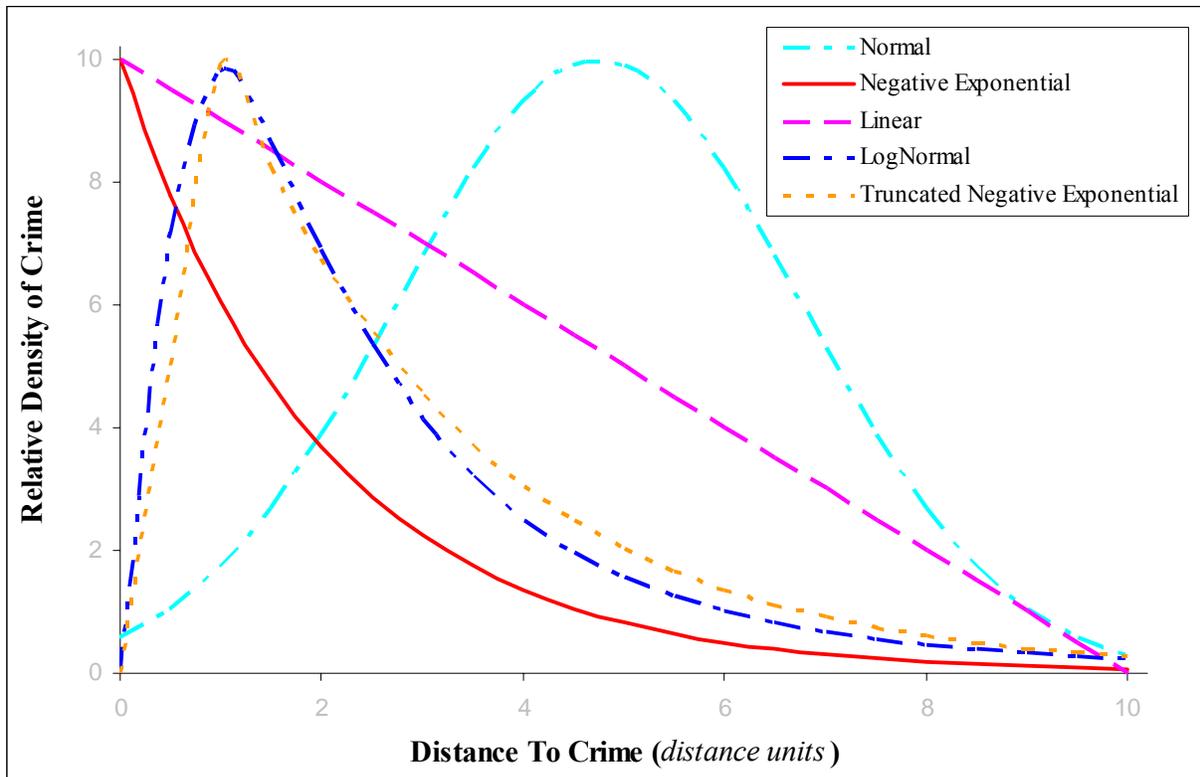


Figure 2.2 Journey-to-Crime Distance Decay Curves (Levine, 2002a)

activities reaches a peak a certain distance away from the haven before exhibiting a decay as the distance from the origin increases. This type of function, most notably the Truncated Negative Exponential, is often used to describe the presence of the Brantingham’s proposed buffer zone effect.

Only recently have researchers investigated the effectiveness of the various different distance decay formulae for estimating the offender’s haven (Canter *et al.*, 2000). While Levine (2002a) provided a comparative evaluation of the different models utilized within the CrimeStat[®] software, the results failed to overwhelmingly endorse any particular algorithm. Citing the additional research by Taylor, Snook, and Bennell (2002), Levine (2002a) acknowledged that no significant difference was observed in measuring the effectiveness of either the negative exponential or truncated-negative exponential functions for estimating offender residency. In

some instances, research has suggested that distance decay may actually work in reverse. According to Godwin's (1996) findings, the further American serial killers traveled from their haven, the greater the frequency of murder. While these findings appear to be unique, it does place credence on the suggestion that the current models are overly simplistic (Levine, 2002b). A consistent criticism for distance decay is that they fail to directly accommodate for intervening opportunities. As Levine (2002b) notes, the attractiveness exhibited by a destination should be enumerated in order to provide a more realistic model of human behavior. Furthermore, most mathematical distance decay functions assume isotropic landscapes, a characteristic that has been demonstrated as being impractical. As such, empirically describing a criminal's journey-to-crime provides for a more adequate method of modeling offender behavior. As it will be demonstrated later in this thesis, the distance decay observed for most crime trips are irregular, and are more appropriately modeled using calibrated distance functions. In fact, most modeling techniques used today incorporate some variation of a calibrated negative exponential function due to its mathematical stability as distance measures approach zero, and its observed fit for given distributions of criminal journey-to-crime.

As it has been demonstrated continuously throughout this research, the process of modeling human spatial behavior involves quantifying various, complex subjective and objective characteristics that are shared between the offender, target, and environment. As such, the interaction between the various elements involved in the commission of a crime requires a combination of sophisticated algorithms which incorporate special processes capable of integrating various concepts of Environmental Criminology within models used by journey-to-crime. Given the difficulties associated with modeling serial target selection, a more comprehensive theory of journey-to-crime should incorporate some enumeration of the

subjective biases attributable to an offender (Brantingham & Brantingham, 1981; Rengert, 1981, see also Levine, 2002a). By most estimates, geographic profiling applications can better model these elements.

2.5 Geographic Profiling

As established earlier, the distribution and associated patterns of linked crime sites are clues left by an offender that describe the geographic behavior associated with a criminal. Such analysis represents a primary application of contemporary Environmental Criminology: the process of exploring the relationship crime shares with target and place in the context of the immediate landscape. Accordingly, these clues represent the elements of how an offender's perceives his or her immediate awareness space and the distribution of potential targets (Brantingham & Brantingham, 1984). For each successive offence, these clues can be examined and combined, refining the investigators understanding of the offender's travel behavior. As noted by Cantor and Gregory (1994), understanding the unique characteristics of where an offender has been will ultimately lead to the discovery of where the offender will be. 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 (Rossmo, 2000; Levine 2002a). 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).

Geographic profiling is a decision support tool used by law enforcement to make estimates about the likely location of a serial offender's haven (Rossmo, 2000; Godwin, 2003). By providing an empirical foundation for identifying offender characteristics, geographic profiling is capable of producing intelligence resources not before thought possible. In many

ways, it extends beyond the theoretical constructs of Environmental Criminology to support the actual criminal investigation by augmenting existing strategies and creating new opportunities for offender apprehension. 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 *et al.*, 2000). In certain circumstances, geographic profiling can also be used as a forensic tool capable of verifying the existence of a serial offender. As noted by Newton & Swoope (1987), the regional patterns of "normal" criminal offences can be used to identify anomalous patterns of a serial offence. Canter (2000) supports this as well, noting that linkage techniques augmented by geographic analysis can reveal the existence of unique offender signatures or distinctive MO's that innately describe serial offences.

Like journey-to-crime models, geographic profiling works on the assumption that a relationship exists between crime locations and the activity nodes within the offender's awareness space (Rossmo, 2000). As such, that relationship can be modeled on some form of distance decay function. This represents the conceptual framework for a geographic profile, a process that incorporates behavioral analysis and mobility studies (Levine, 2002a). The various techniques applied can be categorized into two distinct methodologies, both qualitative and quantitative, that build upon the theoretical construct of Environmental Criminology and the descriptive statistically techniques of journey-to-crime modeling. Qualitative methodologies incorporate analyses that examine the sociology of criminal activities (Brantingham & Brantingham, 1984; Newton & Swoope, 1987). This approach combines the various theories of Environmental Criminology by providing a process from which inferences can be made about an offender's behavior, the target, and the elements of an attack based on the distribution

characteristics of the various crime sites (Newton & Swoope, 1987; Canter *et al.*, 2000; Godwin, 2003). The ecological analysis developed from these methodologies creates a picture of how the offender understands his or her activity space in context to his or her cognitive map (Brantingham & Brantingham, 1984). Quantitative methodologies build upon the basic qualitative typologies above, to provide mathematical models that focus on the statistical relationships of a spatial distribution of crime events. Accordingly, these techniques provide an empirical foundation and scientific basis for developing an offender profile (Canter *et al.*, 2000). As cited earlier, the approach uses the journey-to-crime mathematical models to examine the characteristics associated with human travel behavior (Beimborm, 1995). As such, the predominant quantitative model used by geographic profiling applications is the distance decay algorithm discussed earlier.

As the primary objective for creating a geographic profile, the ability to effectively estimate the likely residence, or haven, of the serial offender requires the integration of a complex set of ecological parameters and analytical models that can accommodate for various subjective and objective conditions. Of course, there are many techniques available that can generate geographic profiles. 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. Quite possibly the first application of geographic analysis for the detection and apprehension of a serial offender was developed by Louisiana State University Geography professor, Milton Newton. Geoforensic Analysis, as it was referred to, was developed in order to provide an empirical foundation for making estimates about the haven of a “localized” (marauding) offender based on the characteristics of linked crime sites (Newton & Swoope, 1987). Using geographic centers to model the distribution of

linked crime sites, Newton and Swoope created a geographic profiling technique which utilized a search radius that decreased with each new crime site. The model was created in four steps

(Newton & Swoope, 1987):

1. A quadrilateral study area is defined by the distance measured between the latitudinal and longitudinal most extents of the known, linked crime sites. Practically, the area represents hundreds of square kilometers of which any location within the area might be the offender's haven.
2. The geographic mean for each location is plotted on a map in successive order to represent the approximation of the haven

$$\bar{X} = \sum_{i=1}^N \frac{x_i}{N} \quad \text{and} \quad \bar{Y} = \sum_{i=1}^N \frac{y_i}{N} \quad (2.4)$$

where the \bar{X} represents the mean of all of the crime sites x-coordinates, and \bar{Y} represents the mean of all crime sites y-coordinates for each crime scene according to its sequence, i in the total population of crime locations, N .

3. A search radius of decreasing size, centered on the predicted haven, is based on the assumption that the predicted \bar{X} and \bar{Y} ought to move closer to the haven with each successive offence. The search radius, R , is measured by

$$R = \frac{\sqrt{A_{xy} / \pi}}{N-1} \quad (2.5)$$

where the square-root for the product of the study area, A_{xy} , represented by the distance measured between the furthest extents of the x and y coordinates, divided by π . In order to reduce the size of the search radius after each successive offence, the radius value is divided by the total number of crime sites, $N-1$.

4. Finally, after the fourth or fifth offence, a map is created to illustrate the predicted locations of a serial offender's residence based on the geographic mean calculated using the sequential distribution of each crime scene. Surrounding each successive location is a iteratively refined search area, a circle described by the algorithms calculating search radius.

Newton points out that the geo-forensic analysis of the dispersing localized serial offender requires a minimum collection of data characteristics; the location of each event (within 100 meters), the chronological order of each event, and the professional support of the criminal

investigative process to ensure proper linkage between cases (Newton & Swoope, 1987). An element not directly calculated within the equation is the area surrounding the predicted offender haven that lacks various clues and/or elements of a crime, the so-called “Coal-Sack Effect.” Like the proposed buffer zone, it is observed as an absence of offences observed on the resulting map. Furthermore, Newton references another significant pattern whereby the primary streets and network arterials that lead into the Coal-Sack Effect intersect near the estimated haven. Newton and Swoope (1987) note that the analyst conceptually facing outward from the estimated haven can connect the routes with those believed to be used for by the offender.

Clearly, Newton and Swoope’s geo-forensic process demonstrates an intuitive process whereby the criminologist can explore the ecological factors that dictates how an offender can travel within his or her environment. In fact, this author was able to develop a computer program, a script, of the geo-forensic model. Because of the intuitive approach and simplistic implementation, the algorithm can be utilized for any jurisdiction. Furthermore, it provides a systematic approach for identifying the likely haven of the serial offender by iteratively examining the role of each successive crime site. However, there are a number of problems with the process. Most importantly, the search radius assumes an isotropic surface whereby any location within the radius has an equal opportunity for being the offender’s residence. While Newton does acknowledge the significant impact the prevailing landscape has on the commission of a criminal act, there is no attempt to accommodate for such an anisotropic surface when estimating residency. Because the algorithm uses simplistic descriptive statistics, it is susceptible to spatial outliers and edge effects. Considering the circumstances discussed earlier, the criminal who offends at various distances near and far from their activity space can ultimately distort the search radius values, resulting in search areas that become increasingly

larger after each iteration. As such, the search parameter, which in itself can be considered a form of distance decay, is not empirically defined, and is, thus, pragmatic in conception. Finally, the algorithm does not provide a measure to address attraction that any particular location may have for the offender. As Routine Activity theory purports, criminal opportunity can exist for intervening locations. The search area defined by the algorithm only infers opportunity based on the distribution of incidents. Despite the shortcomings, the model is a useful tool for investigations looking to identify new, or support existing strategies for mitigating serial crime.

Canter and Gregory (1984) expanded on the modeling framework created by Newton and Swoope, and the concepts established by Environmental Criminology to demonstrate how a simple geographic model can be used to indicate the residence of a serial rapist. Referred to as the Circle Hypothesis, the researchers were able to accurately identify the residence of rapists by using the distance between the two furthest crime scenes as the diameter for a series of circles placed around first offence crime sites. An average search area of 19 km² was predicted by the model, which demonstrated its ability to assign priorities to preexisting suspect lists and utility as a geographic modeling technique. However, the researchers admit that this technique was not precise enough to predict the likely residence of an offender (Canter & Gregory, 1984). The model was unable to account for those locations that fall outside the circle. As a result, the technique assumed that the only potential offenders are localized marauders, and as such exclude those potential locations outside the circle where a commuter offender may be present (Canter *et al.*, 2000). Despite the initial limitations, Canter and fellow researchers were able to develop an advanced application that became known as Dragnet[®].

The Dragnet[®] geographic profiling application, developed by Canter's Centre for Investigative Psychology in Liverpool, UK, addressed the limitations associated with Circle

Hypothesis to include the distance decay and buffer zone concepts identified by research in Environmental Criminology. In doing so, Canter *et al.* (2000) proposed that each location around a crime site could be assigned a weighting value, its B-value, indicating the likelihood of it being the offender's residence. Taking the research developed by Rhodes and Conley (1981), Canter *et al.*, (2000) proposed the use of a family of negatively exponential decay functions:

$$Y = \alpha e^{-\beta x} \quad \beta=1/10, 1/9, 1/8 \dots 1, 2, 3 \dots 10 \quad (N=19) \quad (2.6)$$

where Y is the likelihood of an offender living at a particular location, α is an arbitrarily constant used to calibrate the values, x is the distance of that location from the offence site, β is the exponential coefficient, and N is the number of β values used to estimate the sensitivity of the model. This new strategy provided a method for assigning an investigative search strategy using an easily applied five-step process (Canter *et al.*, 2000; see also Levine, 2002a):

1. A study area is defined by a rectangle 20% larger than the farthest extents of the known linked crime sites. A matrix of 13,300 grid cells is imposed over the study area.
2. A distance decay coefficient is selected, β , for the distance term, x , to determine the likelihood that any location within the study areas is the estimated home base of the serial offender. The model uses a family of negative exponential decay equations (see Equation 2.5) where the function number increased from 1 ($\beta=10$) to 19 ($\beta=1/10$) in order to represent a broad selection of various distance decay curves that may be observed within a sample (Figure 2.3).
3. The measured distances for each cell to incident pair, x , is divided by a normalization parameter that adjusts all distances to a comparable range. Because no two offenders will hunt for targets in the same way, two normalization parameters are used to adjust for different perceived activity areas: (a) Mean inter-point distance (MID), used to give equal weight to all distances (isotropic); and (b) the QRange, an index used to account for orientation and variability within landscapes (anisotropic).
4. For each grid cell, the measured distance to the incidents is applied to the negative exponential function. A coefficient, α , is assigned to calibrate the function between 0.0 and 1.0 (to rank success), and model the effects of a buffer zone. The normalized likelihoods are summed for each incident to provide a prioritized search strategy.

5. Finally, a search cost index is defined by enumerating the proportion of the study area that needed to be searched in order to find the offender. For example, if 30% of the defined area had to be searched before identifying the suspect(s), then .30 would reflect the cost.

Canter *et al.*, (2000) provided additional capabilities to the algorithm in order to model the presence, or absence, of a buffer zone. To model the zone, areas represented with constant B-values of 0 (buffer zone), or 1 (no buffer zone), are placed in front of the exponential function. For example, “steps” are used to model the presence of a buffer zone, areas surrounding the haven where criminal activity is non-existent (B-value = 0); and “plateaus” represent the absence of a buffer zone (B-value = 1), an area surrounding the haven where there is the highest likelihood of criminal activity. After a given distance, to a maximum of 4 units, the distance decay curve continues, represented by the family of negative exponential equations (Canter *et al.*, 2000).

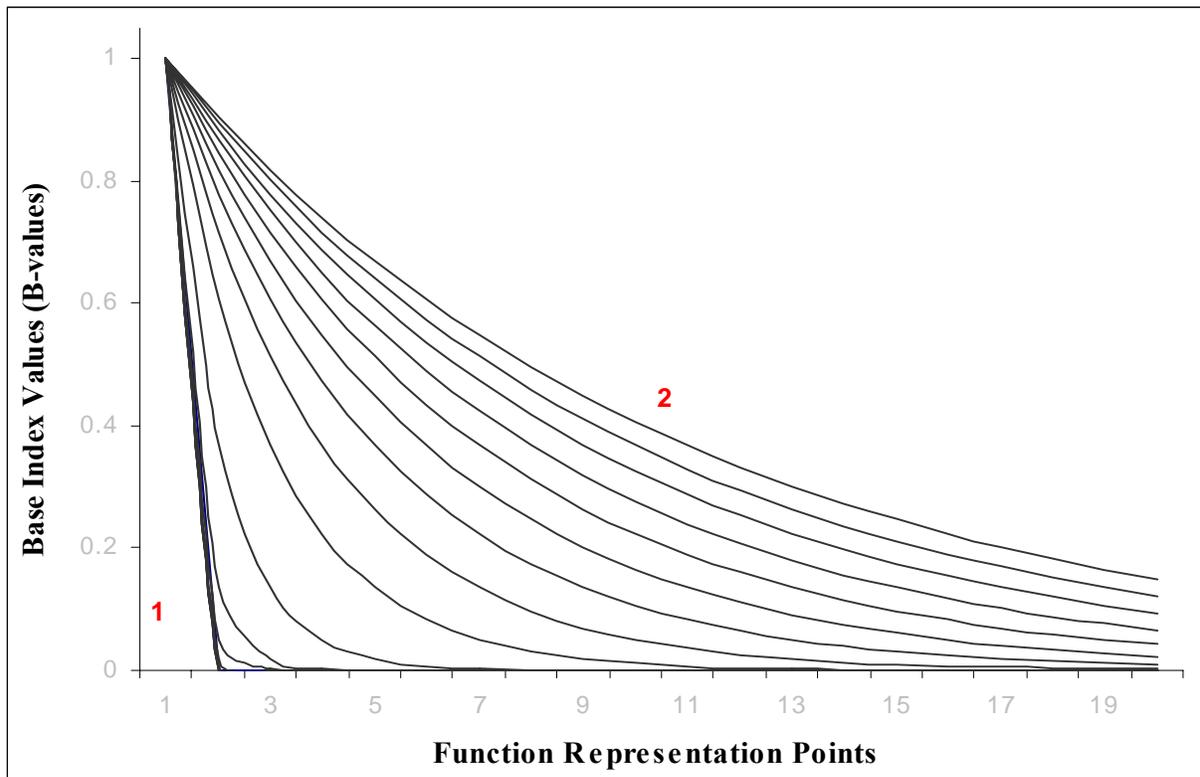


Figure 2.3 Negative Exponential Functions: (1) $\beta = 10$; (2) $\beta = 1/10$ (Canter *et al.*, 2000)

In their analysis of 79 serial killers, the researchers were able to locate 100% of the offenders within the defined search area. Detailed examination of the results found that the QRange normalization parameters provided the most cost effective search. QRange produced a mean search cost of 0.11, or a search of 11% of the original study area before finding offender residency. Additional research cited by Levine (2002a) demonstrated that for three sample populations of burglars, rapists, and murderers, more than half of the offender's residences were successfully identified by Dragnet[®] within 15% of the defined search area.

As noted by Levine (2002a), Dragnet[®] has both strengths and weaknesses that must be considered by investigators. Because the model is relatively easy to implement, and because it provides a consistent process for analyzing offender patterns, it is highly beneficial to law enforcement agencies as an investigative search strategy. Furthermore, it provides a stable quantitative platform on which to model behavior, a process that is significantly more sophisticated than the earlier developed Circle Hypothesis. However, the quantitative model used, negative exponential, is provisionally defined and lacks empirical calibration (Levine, 2002a). While the formula can be adapted (*i.e.* flexible) by implementing 19 possible computations according to the exponent, β , the function may not be the most suitable model for a given population. As cited earlier, most distance decay functions assume isotropic surfaces. As such, the model may only fit well for certain locations, failing in other. While the coefficient is used to ensure that the B-values never exceed 1.0 (to rank the potential costs), Gore *et al.* (2002) and Levine (2002a) note that the calibrated costs are susceptible to distortion as the population of incidents increases. As such, the coefficient value should be calibrated to a known sample population. Finally, the modeling algorithm, like its predecessors, fails to accommodate attraction and intervening opportunities that may exist between the offender's residence and

incident location (Levine, 2002a). While opportunity is inferred by the distribution of incidents, the same opportunity will not exist for different municipalities. As such, the model will need to be recalibrated for each jurisdiction in which it is used. Notwithstanding these problems, Dragnet[®] is a powerful resource available to law enforcement in need of decision support strategies for the investigation of serial offenders. Dragnet[®] represents significant advances for the application of geographic profiling. As an investigative tool, the Dragnet[®] objective to develop a search strategy sets it apart from many of its contemporaries.

Another approach to the profiling construct was developed by Dr. Kim Rossmo of Simon Fraser University and the Vancouver Police Department, Canada. In demonstrating the practical application of geographic modeling, Rossmo's concepts and techniques focus attention on the processes that lead to the specific identification of an offender's haven. By incorporating the subjective and objective elements of a crime defined in Environmental Criminology, Rossmo (2000) developed a process in which geographic models were used to develop probability surfaces indicating the likelihood of an offender living at a particular location. Called Criminal Geographic Targeting (CGT), the algorithm utilizes distance decay functions to describe the criminal hunting process expressed by a serial offender as he or she traveled between haven and crime scene. The mathematics applied by CGT, similar to that of Dragnet[®], represents the formulations defined by the Brantingham's (1981) which proposed a criminal's hunting strategy using an empirically defined distance decay curve that incorporates the theoretical buffer zone surrounding the estimated residence of the offender (Levine, 2002a). In using an empirically defined distance decay algorithm, each location surrounding a crime can be assigned a weighted value that indicates the likelihood of that place as being the residence of the offender. The model

has four steps that generate a probability surface which estimates where the offender likely lives (Rossmo, 2000; see also Levine 2002a):

1. A rectangular study area defines a 40,000 pixel grid within which all crime locations are contained. These locations represent various crime-related sites, such as the target encounter, target disposal site, and any additional sites known to be linked to the offender.
2. For each grid cell, Manhattan distances are measured to each crime site.
3. For each Manhattan distance measured from the grid cell to an incident location, two functions are evaluated:

If the Manhattan distance (Equation 2.1) is less than a specified buffer zone radius, B , then:

$$p_{ij} = k \sum_{n=1}^C \left[\frac{(1 - \Phi)(B^{g-f})}{(2B - |x_i - x_n| - |y_j - y_n|)^g} \right] \quad \Phi = 0 \text{ when } B \leq |x_i - x_n| + |y_j - y_n| \quad (2.7)$$

If the Manhattan distance (Equation 2.1) is greater than a specified buffer zone, B , then:

$$p_{ij} = k \sum_{n=1}^C \left[\frac{\Phi}{(|x_i - x_n| + |y_j - y_n|)^f} \right] \quad \Phi = 1 \text{ when } B > |x_i - x_n| + |y_j - y_n| \quad (2.8)$$

where P is the probability of offender interaction for grid cell, i ; n is the incident number summing to the total, C ; Φ is a weighing factor; k is an empirically determined constant; g is an empirically determined exponent; f is an empirically determined exponent.

4. The values are summed over each grid cell to produce a final score for each point. The higher the score, the greater the probability that the cell contains an offender's anchor point.

Unlike the Dragnet[®] model developed by Canter's group, the CGT model is capable of estimating offender residency for incidents that occur inside and outside a defined buffer zone. The probabilities estimated for inside ($B \leq |x_i - x_n| + |y_j - y_n|$) and outside ($B > |x_i - x_n| + |y_j - y_n|$) the buffer zone requires coefficient, k , and exponents, f and g , that are empirically determined. However, Rossmo does not provide insight into how these values are calculated, nor if the values

are used for each estimation. They are, presumably, empirically enumerated from a population of known offender travel behavior (Levine, 2000). For locations inside the buffer zone, the model uses a curvilinear function designed to fit an increasing distribution of criminal activity as the distance from the haven increases. For those locations outside the buffer zone, CGT uses a classical gravity function characterizing a distance decay curve.

The preferred output is a three-dimensional surface model indicating the likelihood of an offender residing at a particular location. As a probability surface, every cell of the grid is calculated so that it can be represented as an isopleth map, referred to as a jeopardy surface (Rossmo, 2000). Modeling the offender search area using the mathematics of a gravity model is consistent with the concepts proposed by Environmental Criminology. As mentioned earlier, the model is unique in that it distinguished two types of travel behavior – inside and outside the offender’s buffer zone (Levine, 2000a). Furthermore, like Dragnet[®], CGT provides a systematic approach for modeling the travel behavior of a serial offender in order to estimate the likely haven. However, the model does present some problematic elements that may distort its ability to accurately provide haven estimations.

The first problem, as noted by Levine (2000a) is the reliance on Manhattan distance metrics. As discussed earlier, the metric is a speculative measure that can lead to overestimated travel path distances when applied to locations where street networks are irregularly arranged. Additionally, the mathematical stability of the inverted distance decay becomes unstable as the distance between grid-cell and incident approach zero. Also, the model makes no attempt (apart from the Manhattan metric) to accommodate for an anisotropic surface. As such, it assumes that travel impedance is uniform for every direction. And finally, there is no attempt to address intervening opportunities or quantify attraction that any particular location may provide for the

offender's hunting behavior. Like the previous models, the distribution of incidents infers opportunity and attraction without specifically quantifying it.

Building upon the conceptual framework of Canter's Dragnet[®], Dr. Maurice Godwin developed Predator[®], a geographic profiling application that predicts offender residences, presumed, using smallest space analysis (SSA) to represent where an offender resides. However, very little published information has been identified regarding how Predator[®] implements the models. According to Godwin's web site (2003), the application appears to explore the distribution of crime events from angular positions, modeling criminal commutes by employing two location-allocation theories utilizing mean inter-point and straight-line distances between crime sites. Based on these parameters, it appears the Predator[®] attempts to identify the point of minimum distance between distributions of crime sites measured by the unit-less SSA (Godwin and Canter, 1997).

According to Godwin (2003) the advantage of Predator is that it can measure the angular position of a crime. Noting results from an on-going research of approximately one hundred serial killers, Godwin (2003) observes that crime locations were found to occur between 90 and 145 degrees from the offender's residence. As such, this can significantly support how a criminologist can direct its investigative strategies. Godwin further notes that, unlike contemporary geographic profiling applications, Predator[®] does not assume a Buffer Zone but will allow for it when analyzing initial target-offender interaction.

Contemporary techniques and the application of geographic profiling are further championed and enhanced by the contributions and research efforts of dozens of practitioners and scholars that include Snook (1999), Gore *et al.* (2001, 2002). Research continues, integrating the theoretical concepts and modeling techniques from various fields in order to

improve the fundamental application of estimating an offender's haven. These efforts have brought about the development of a group of significantly powerful profiling applications that are available for law enforcement agencies around the world. While the most influential techniques include those already discussed (Dragnet[®], CGT, and Predator[®]), many other analytical methodologies and software applications are gaining popularity, each providing significant value to the investigation of serial crime.

Some research suggests that the concept of a geographic profile should be considered separate from other forms of geospatial criminal investigative analyses (Rossmo, 2000; Levine 2002a). The argument proposes that geographic profiling incorporates sophisticated quantitative and qualitative components that set it apart from the more statistically descriptive approach like that of journey-to-crime. However, it is this author's position that segregating the very tools that ultimately serve the same application is a mistake. The objective of any geographic investigation of crime is to provide a model that can be used to mitigate, and ultimately apprehend, an offender. Levine notes (2002a) that understanding the psychological process associated with an offender's spatial behavior does not necessarily produce better predictions of the haven. Continuing, Levine notes that quantitative models are often provide a more suitable framework for predicting human activity than qualitative models (Levine, 2002a). Accordingly, Rossmo (2000) lists a number of techniques that have been successfully applied as a geographic profile, including temporal distribution analysis, journey-to-crime estimates, mental map interpretation, and Thiessen polygons. These and other subjective and objective methodologies (see Gore *et al.*, 2002; Levine, 2002a, and Snook 2002) demonstrate success because of their application to the investigative process can be customized to fit the needs of a case (Rossmo, 2000). However, both Newton (Newton & Swoope, 1987) and Rossmo (2000) warn that the most appropriate

interpretation of a geographic profile is best provided by an investigator capable of integrating qualities of the offender's characteristics with the quantitative output. Whether the model incorporates complex ecological elements of Environmental Criminology, or quantitative analytical algorithms of journey-to-crime, the ultimate function of a geographic profile remains the same: to provide a process whereby law enforcement is able to extract offender characteristics from offence characteristics. To do this, methodologies must effectively demonstrate flexible approaches to problem solving, capable of meeting the demands of the investigation. As such, geographic profiling should be perceived as a heuristic program for geographically modeling criminal behavior.

2.6 Characteristics of a Serial Offender

Rossmo (2000) warns that not all crime can be geographically profiled. Many different factors and ecological elements must be considered before the construction and subsequent interpretation of a geo-profile takes place. Research by Newton & Swoope (1987), Canter *et al.*, (1993, 1994, 2000), and Rossmo (2000) demonstrates that those criminal characteristics most suitable for geographic analysis typically possess numerous linked crime sites. Accordingly, geographic profiling is primarily constructed for serial crimes, which include serial murder, serial rape and sexual assault, serial arson, serial robbery, serial exposures, kidnapping, and other crimes that possess unusual spatial characteristics (Rossmo, 2000). This is because the distribution of multiple, linked crimes scenes provide the necessary elements for determining the patterns attributable to a single personality (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). 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. However, this does not necessarily confirm the acts of a serial offender. In fact, the event associated with multiple crimes could be entirely circumstantial, which would no longer correspond to a notion of serial offender. Therefore, what defines a serial offender? Most of the definitive research on the subject of serial crime is devoted to serial murder, but can likely be applied to other serial offences. Though arguably simplistic, most experts agree that a serial offender can be defined as an individual (or a collective group of individuals) who (Holmes & Holmes, 1998; Hinch & Hepburn, 1998):

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

Arguably, various elements of the list could be added or removed with relative justification. However, these components represent the underlying subjective and objective characteristics of what defines an offender who commits either personal or property crime.

Once confirmed, a closer examination of the serial offender is needed in order to assess fitness for profiling. Supported by his research, Newton and Swoope (1987) proposed that serial offenders be classified based on the mobility and psychological qualities of their crimes. The

researchers argued that classifying offenders according to type is important because it provides a foundation for distinguishing serial crime from other crimes. As such, classification supports the criminologist by identifying the most appropriate investigative strategy based on the pattern of observable offences. Newton proposed that serial offenders be divided into broad categories: “mobile” (geographically transient) and “static” (geographically stable) (Newton & Swoope, 1987; see also Holmes & Holmes, 1998).

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. For example, in their study of serial rapists, Canter and Larkin (1993) classified an offender as either a commuter - an offender who operates outside his/her awareness space; or marauder - an offender who operates within his/her awareness space. Holmes & Holmes (1998) cites research by Hickey (1997) that classified serial murder based on the mobility characteristics of the offender:

- Local Killers – murders who offend within a certain urban area or single state;
- Traveling Killers – offenders who commit murders while moving through or re-locating to other areas;
- Place-Specific Killers – offender who kill within their own home, workplace or other significant site.

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 (Newton & Swoope, 1987) propose that a minimum of five distinct locations be identified for analysis. This is primarily due to the ecological relationship an offender shares with his or her environment. For instance, when a localized 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 bases 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 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 profiles 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 limiters. In this instance, geographic profiles developed for commuter-type serial offenders represent processes more inline with intellectual speculation (best guess) rather than empirical pattern identification.

CHAPTER 3. MATERIALS AND METHODS

As demonstrated throughout this thesis, the primary function of a geographic profile is to estimate an offender's likely residence. This is achieved by effectively modeling an offender's spatial behavior during his or her journey-to-crime. These models are estimates derived from the patterns associated with the spatial distribution of crime sites. The characteristics of those patterns describe the complex spatial relationship an offender shares with his or her environment. As more information is added to the geographic profiling process, the crime patterns begin to define the activity space in which the offender travels – the offender's geoprofile. By integrating the theoretical concepts of Environmental Criminology, the analytical resources of GIS, and modeling algorithms used in transportation research, the criminologist can use the geoprofile to enhance investigative strategies and possibly identify the offender's haven. Accordingly, police departments have used geographic profiles to leverage existing resources more effectively by prioritizing suspect lists and concentrating patrol efforts for those districts that likely possess the offender's estimated activity nodes. Despite the advantages a geographic profile provides for law enforcement agencies, a number of factors remain unexplored which may contribute to a profile's utility (Snook, 2000; Levine, 2002a).

While it is clear that geographically profiling serial crime offers numerous advantages over the more traditional and intuitive center-of-gravity techniques (see Chapter 2), contemporary quantitative methodologies remain somewhat limited in their ability to accurately model offender mobility. The journey-to-crime modeling algorithms integrated within contemporary geographic profiling applications consistently fall short in their ability to effectively accommodate the objective and subjective qualities of a commuter's travel path. This is because most modeling algorithms traditionally use straight-line (crow-flight) Euclidean

distance measures. Consequently, any interpretation of an offender's commute within their activity space is fundamentally flawed because Euclidean models operate on the assumption that impedance is uniform for every direction. As such, the models cannot accommodate for the inherent distance-variations exhibited by a particular transportation network. A travel route selected by a commuter is almost always determined by a variety of subjective and objective conditions and circumstances that are not easily quantified. As demonstrated by the least effort principle, commuters will optimize their travel in the most effective means possible. Accordingly, it has been observed that commuters will avoid those routes that are overly congested, unattractive, unfamiliar, and too long (Stea, 1969). Therefore, an individual's actual travel path will likely be selected and optimized according their subjective perceptions of the actual landscape. The process of calculating the actual travel path and temporally optimized travel production is achieved utilizing function distance measures.

Of particular interest for this research is the application of functional distance measures as technique for enhancing the predictive effectiveness of a geographic profile. In the context of mobility, a functional distance is a metric used to represent the quantitative distance calculated between two locations (points), weighed by the subjective and objective qualities of the anisotropic landscape between them (measured by impedance). Contemporary methods for measuring distances through urban environments has been traditionally achieved using Manhattan distance measure, discussed earlier (Chapter 1). While it has demonstrated an ability to accommodate for travel within a grid-based network of roads, Manhattan distances are often characterized as providing exaggerated values which overestimate distances (Levine, 2002a). Furthermore, Manhattan distances are often unable to provide a realistic representation of the non-grid transportation network that describes many US and foreign cities. Based on the

assumption that a commuter will optimize travel production for distance and time, this thesis proposes that the application of functional distances measures derived from actual travel-paths available can be used as an effective alternative for geographically profiling serial crime.

The most direct process for calculating functional distances is achieved using network path analysis applications available for most contemporary GIS software packages. However, these complex functions are known to be computer intensive. As a consequence, network path analysis functions are susceptible to application and system failure when executed on systems that do not meet the minimum technical requirements established by the software publisher. Given the number of computations that will be required for this or any similar application, the operating environment will likely be a critical factor for success. As such, an optimal computer configuration will be a determining factor for success when modeling functional distance measures.

Addressing the limitations associated with the conventional use of straight-line Euclidean distance metrics, the practical significance of this thesis will examine the predictive utility and technological prerequisites for using functional distance metrics when estimating the likely residence of a localized serial offender. For the purposes of comparative review, a test sample of *simulated* serial offenders will be geographically profiled using a standard (un-customized) workstation-class personal computer (PC). The simulated offender's haven, the sample subject's residence, will be estimated using straight-line and Manhattan Euclidean, as well as the travel-path and temporal-path functional distance measures. The predictive utility of these methods will be assessed in two ways. First, the distance between the estimated residence and actual residence will be calculated to assess the spatial accuracy (in Euclidean distances). Second, a more meaningful measure will calculate the geographic profile's search cost, defined as the

extent of the total study area that must be searched in order to identify the offender's residence.

Upon examination of the results, this thesis proposes to demonstrate that:

1. Travel-path functional distance measures can be used to effectively predict an offender's residence. By accommodating the anisotropic structure of a transportation network, modeling an individual's likely journey-to-crime (Travel-Path) provides for a more realistic representation of a commuter's distance than either straight-line Euclidean or Manhattan distance measures.
2. Travel-path functional distance measures can be optimized using temporal cost values calculated for all available travel paths. By modeling mobility using the temporal impedance values attributed to all proposed travel-paths, an optimal commuter route (Temporal-Path) can be predicted and attributable to subjective notions of cost savings.
3. The technological prerequisites necessary to accomplish these modeling techniques can be achieved using contemporary workstation-class computer technology, popularly available GIS and statistical software packages, and appropriately attributed transportation data resources.

3.1 Modeling Environment

In order to complete a comparative analysis, it is necessary to identify an appropriate modeling environment upon which this investigation will proceed. Accordingly, different geographic profiling modeling systems were examined in order to identify a suitable technique for this research. Available methodologies varied from simplistic spatial distribution algorithms such as center-of-gravity, Circle Hypothesis, and Thiessen polygons, to more sophisticated models that included variations on the quantitative and qualitative methodologies found in CGT, Dragnet[®], CrimeStat[®] journey-to-crime, and others mentioned earlier. For the purposes of this investigation, an optimal geographic profiling model should meet the following criteria:

- Demonstrate the fundamental utility of a geographic profile;
- Demonstrate the ability to quantitatively model functional distance measures;
- Provide a meaningful output that can be assessed for accuracy.

While it can be argued that there are a limited number of models which are suitable for analyzing the distribution of serial crimes, it has been generally accepted that distance decay

functions represent the most effective technique for modeling criminal mobility characteristics. As examined in Chapter 2, the distance decay algorithm establishes that the number of crimes committed by an offender is inversely proportional to the distance from his or her residence, or haven. Working on the assumption that a relationship exists between crime sites and an offender's haven, distance decay models make statistical predictions about the likely location of the offender's activity nodes. Such predictions are based on the functions that provide the 'best fit' for the observed journey-to-crime characteristics of a known sample of offenders.

Furthermore, distance decay models utilized by traditional journey-to-crime analysis were functionally based on the Newtonian gravity model (see Equation 2.2). A significant problem attributed to the traditional techniques is that as the distance between locations decreases, the mathematical function approaches infinity. Accordingly, criminologists developed more sophisticated models that incorporated various complex functions to ensure mathematical stability and provide improved performance. Because the distance decay observed for human travel behavior is consistently irregular (influenced by numerous subjective and objective factors), selecting an appropriate model requires a pragmatic approach whereby the criminologist selects a function based on trial-and-error. Consequently, little research has been published comparing the measurable effectiveness of any particular function for any particular type of crime data (Canter *et al.*, 2000). For this investigation, three distance decay functions were selected: logarithmic, negative exponential and truncated negative exponential. These three functions were selected based on their ease of implementation and ability to represent the fundamental utility of contemporary journey-to-crime models utilized within geographic profiling applications. While a number of other decay functions could theoretically be utilized by

this investigation, no attempt was made to determine whether or not any one function performed better than another. Such analysis is reserved for future investigations.

In order to obtain the “best fit” distance decay function, each model is mathematically calibrated according to travel characteristics obtained for the study area. When applied using journey-to-crime techniques, the calibrated distance decay functions are used to mathematically assign weight values for all locations within a study area. These weights essentially form a density surface whereby the criminologist can make interpretations (*i.e.* a profile) about an offender, based on those areas predicted as being a part of their activity space. The applications that best matches the requirements listed above include the CrimeStat[®] II journey-to-crime routine by Ned Levine and Associates (2002a), and Kim Rossmo’s Rigel[™] CGT (2000). However, as a proprietary software application associated with specialized prerequisites, including minimum training requirements (the Geographic Profiling Under-Study Program), the Rigel[™] CGT application is placed beyond the economic resources available for this investigation (Rossmo, 2003). Accordingly, the no-cost and easily accessible CrimeStat[®] II application is selected as an appropriate alternative for this research. Accommodating for the complex mathematical and network-path modeling required to complete this analysis, additional applications are needed, which include:

- ESRI[®] ArcView[®] GIS 3.3
- ESRI[®] Network Analyst Extension 1.0b for ArcView[®]
- SPSS[®] 11.0 for Windows
- Microsoft[®] Excel[®] XP (v.10.0)
- Microsoft[®] Access[®] XP (v. 10.0)

All applications are executed using Microsoft[®] Windows[®] XP Professional, Service Pack 1 operating system on an Intel[®] Pentium[®] 4m, 1.70GHz PC workstation with 384 MB of RAM.

3.2 Test Subjects

The sample data typically utilized for an investigation of this nature would normally incorporate crime data specific to both the study area and type of serial offence investigated. As Levine (2002a) notes, geographic profiling models should be calibrated for the unique parameters that characterize specific criminal offences for specific jurisdictions. However, the acquisition of such data can be quite difficult, as noted by Canter *et al.* (2000). Not surprisingly, this research was unable to obtain an adequate sample of serial offence data for its study area in Louisiana. However, an alternative approach was used for obtaining the sample data needed to complete this proof of concept. To secure the necessary data, a travel-diary and commuter survey was distributed among various individuals of differing age, sex, race, education, and social status (Appendices A & B). This alternative approach proved to be advantageous as it allowed this investigation to validate the conceptual procedures needed to analyze the research. Using a controlled sample of *simulated* offenders ensured that all data collected represented the actual travel behavior of an individual participating in a routine activity; data points would be valid; and test subjects could be interviewed for supplemental information (*e.g.* travel survey). These are critical elements that cannot be guaranteed to be as accurate when obtaining data from incarcerated offenders, who often provide exaggerated and often false statements (Hinch & Hepburn, 1998, Canter *et al.*, 2000).

The decision to use non-criminal data is supported by concepts published in popular literature. Canter *et al.* (2000) note that the process of geographic profiling can be applied to any series of activities that possess geographic locations. As noted earlier, a major concept of Environmental Criminology theorizes that crime is an integral component of an individual's routine activities carried out in their daily lives (Felson & Clarke, 1998). Accordingly,

Brantingham & Brantingham (1984) note that crime can be expected to emerge from an offender's non-criminal activities; as opportunities present themselves. Appropriately, the process in which a criminologist investigates a crime, therefore, incorporates the examination of how an offender interacts with their environment. Demonstrated consistently throughout this research are the concepts that reveal how humans consistently express predictable patterns of movement. Therefore, the processes and the decisions associated with movement cannot be expected to differ drastically, regardless of the nature (criminal or non-criminal) of an individual's activity. As Newton notes, the geographic habits expressed by a serial offender are no more or less disorderly than those exhibited by anyone else (Newton & Swoope, 1987). So long as a relationship exists between a point representing an origin and a point representing a destination, a geographic profile can be modeled using some form of distance decay function (Rossmo, 2000).

Meeting the requirements detailed above, a sample of law abiding residents of East Baton Rouge Parish, Louisiana were asked to provide a travel diary for ten commuter destinations (Appendix A). Each destination is assumed to represent a location routinely visited by the offender. As such, the destinations serve as activity-nodes that will define the test subject's routine activity space. Ten locations were selected in order to ensure a sufficient number of incidents from which to build a profile. An eleventh location, the residence (origin), was also recorded in order to measure accuracy and used for calibration. Thirty-five of the seventy-three individuals polled submitted a response. The participating subjects consisted of 13 women and 22 men of varying age, race, and social status. All collected location information was stored within a Microsoft® Access® database, and categorized according to residence and destination. To reduce bias associated with multiple activity nodes, subjects were asked to provide only those

locations in which they chose to travel from their residence. Each subject could include any desirable destination, so long as it met the following criteria:

- Include only those destinations within East Baton Rouge Parish;
- Include only those destinations in which a reasonable alternative existed (to ensure choice of destinations);
- Exclude destinations related to work/school (to prevent multi-node, home locations);
- Exclude all locations contained within a multiple-destination commute (*e.g.* a chain);
- Minimize redundant destinations.

Of the 385 total records, 384 contain valid addresses (35 residences, 349 destinations).

Valid records are address matched using the ESRI[®] ArcView[®] GIS 3.3 and a transportation data layer discussed in the next section. X and Y point coordinates are calculated for the Universal Transverse Mercator (UTM) coordinate system, North American Datum 1983 (NAD83), Zone 15 using meter (Cartesian) and minute (temporal) distance units.

Additionally, subjects were asked to complete a commuter survey to describe their driving behavior (Appendix B). Results are used for assessment against mobility characteristics observed in this research, and will be discussed in the next chapter.

3.3 Data Sets

Three data sets were used for this investigation: a transportation network from which to measure functional distances; test subjects from which to generate a geoprofile; and the study area encompassing the offender's activity space and likely residence.

Geographic Data Technology's Dynamap[®] Transportation road network (GDT-Dynamap[®]) is 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.

For the purposes of generating a geographic profile, test subjects were organized into two groups: a calibration group and test group. In order to establish a sufficient representation for the travel patterns of like commuters, the calibration group must be large enough to ensure reliable calibration parameters. Accordingly, thirty-one of the thirty-five sample subjects were randomly selected to represent the calibration group (Calibration-Sample) of simulated serial offenders from which to empirically derive the most appropriate distance decay models. X and Y coordinates representing each sample's residence (origin) and ten incident locations (destinations) were captured and stored within the Microsoft® Access® database.

The remaining four sample subjects were assigned to represent the test group (Test-Sample) of simulated serial offenders. The X and Y coordinates for each of the Test-Sample point representing the ten simulated incident locations (destinations) were stored inside a database and mapped within the East Baton Rouge study area. The coordinates representing the Test-Sample residence were used to assess accuracy, thus excluded from the geographic profile model.

A study area representing the urbanized portion of East Baton Rouge Parish was defined using the United States Census Bureau's (2001) TIGER® Census 2000 data product. Though it does not encompass the entire parish, the study area represents the majority population, 91%, of all parish residents. This approach was necessary to provide a balance between providing a large enough study area while ensuring consistent computer performance. Preliminary evaluation of the network path functions utilized for this research demonstrated the software's tendency to become unstable, perform inconsistently, and subsequently rendering the computer system unusable (system-crash) when calculating travel paths for large study areas. Accordingly, a reduced study area was determined to provide the most consistent results.

3.4 The Geographic Profile Procedure

The modeling process used to develop a geographic profile is founded on the conceptual application of both the CrimeStat[®] II (Levine, 2002a) journey-to-crime routine and the CGT (Rossmo, 2000) geographic profiling model. The procedure estimates residency by statistically comparing the spatial distribution of the Test-Sample incident locations, with the journey-to-crime patterns exhibited by the Calibration-Sample. Once calculated, a density surface indicating the likely residence is created and mapped for the East Baton Rouge study area. Each location within the study area is scored according to its likelihood of being the Test-Sample's residence. The entire 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 Calibration-Sample of simulated serial offenders. The second part integrates the calibrated decay function within journey-to-crime routines in order to estimate the residency of the four Test-Sample subjects. The resulting geoprofile is mapped for the study area and used to illustrate the probability surface and offender's likely residence.

3.4.1 Calibration Routine

The process for calibrating a distance decay function uses the traveled distances measured between each origin and destination stored within the Calibration-Sample data set. The origin represents the test subject's residence while the destination represents the test subject's simulated incident location. The calibration routine is executed in six steps (Levine, 2002a):

1. 340 matched origin-to-destination (O-D) records were obtained from the Calibration-Sample database. The 340 records (31 origins, 309 destinations) are reviewed to ensure that X and Y coordinates for both the origin and destinations were properly referenced.
2. O-D data were imported into ArcView[®] GIS 3.3 as an event theme of point features. Both straight-line and Manhattan distances between each origin and destination were measured using the journey-to-crime routine included within the CrimeStat[®] II software package (Levine 2002a). Travel-path (meters) and temporal-path (minutes) functional

distances were calculated using Shortest Network Path (SNP) functions available with the ESRI[®] Network Analyst extension. Impedance values used to define the network path parameters were calculated from the GDT-Dynamap[®] road data network.

3. Calculated travel distances were collected and stored within the Microsoft[®] Access[®] database according to metric. Cartesian measures were converted from meters to miles, while temporal measures were calculated in minutes. For each metric, values were grouped into distance intervals (referred to as bins). To accomplish this, the distance between each origin and destination were sorted in ascending order. Next, a frequency distribution was applied for each O-D distance, and grouped into .50 mile (Cartesian) and .858 minute (temporal) bins. Both the .50 mile and .858 minute intervals were chosen to ensure computer stability when executing the SNP routines. The .858 minutes distance interval represents the time it would take to travel .50 miles at the averaged speed limit of 35 miles per hour (calculated as the average network speed measured for each SNP utilized).
4. Frequency intervals measured in step-3 are converted into relative frequencies by dividing the frequency values for each interval by the total number of incidents, N , and multiplying by 100. Second, the distance intervals are adjusted to the mid-point of each bin in order to provide a better representation for the bin's contribution for the distribution (McGrew & Monroe, 1993).
5. Using SPSS[®] 11.0 and Microsoft[®] Excel[®], a series of univariate regression equations are executed to model each frequency as a function of the distance. In order to compare various types of activities, the percentage of incidences within each frequency (Pct_i) interval is used as the dependent variable. Three equations are mathematically calibrated to obtain the 'best fit' for the given distributions. Figure 3.1 illustrates the three functions utilized by this investigation.

Logarithmic

A distance model that describes how the occurrence of crime will gradually decrease as the distance from the offender's haven increases. The logarithmic function mathematically calculates a best-fit curved line that describes the rate of change as the data decreases quickly and then levels out. It uses the equation:

$$Pct_i = A + (B \bullet \ln(d_i)) \tag{3.1}$$

where Pct_i is the likelihood that an incident will occur at a particular location, i , d_{ij} is the distance between each reference location and each crime location, j , and A and B are estimated by regression. This function has a tendency to return negative values, which can become problematic for journey-to-crime models that have distances which exceed the parameters of the calibration data set. While not directly utilized by many of the commercially available geographic profiling applications, it does represent an easily

implemented model available within most statistical software packages. This function does not assume a buffer zone around the offender's residence.

Negative Exponential

A slightly more complex function, this model describes how the occurrence of crime is highest near the offender's haven and drops off at a constant rate with distance. The mathematical expression is:

$$Pct_i = A \cdot e^{-C \cdot d_i} \quad (3.2)$$

where Pct_i is the likelihood that an incident will occur at a particular location, i , d_{ij} is the distance between each reference location and each crime location, j , e is the base of the natural logarithm, A is the coefficient, and C is the exponent. This function is most similar to the Dragnet[®] model, except that the coefficient is mathematically calibrated for the observed distribution. Like the logarithmic function above, it assumes no buffer zone around the offender's residence.

Truncated Negative Exponential

This is a complex function consisting of two distinct decay equations: linear and exponential. For locations in close approximation to the residences, a positive linear function is defined (Equation 3.3). Starting at zero (the haven) and increasing to a peak distance, $Max\ d$. Next, the function follows a negatively signed exponential function, declining quickly as the distance increases (Equation 3.4).

$$\text{Linear: } Pct_i = A + Bd_i \quad \text{for } d_{ij} \geq 0 \text{ and } d_{ij} \leq \text{Max } d_{ij} \quad (3.3)$$

$$\text{Negative Exponential: } Pct_i = A \cdot e^{-C \cdot d_i} \quad \text{for } d_{ij} > \text{Max } d_{ij} \quad (3.4)$$

where d_{ij} is the distance from the haven, B is the slope of the linear function, A is the coefficient for the negative exponential function, and C is the exponent. This function is the closest approximation to the CGT model examined earlier (equations 2.7 and 2.8). Furthermore, this model can be used to approximate the often observed Buffer Zone effect surrounding an offender's residence.

6. Once completed, each mathematically calibrated distance decay function can be utilized with the journey-to-crime routine detailed in the next section.

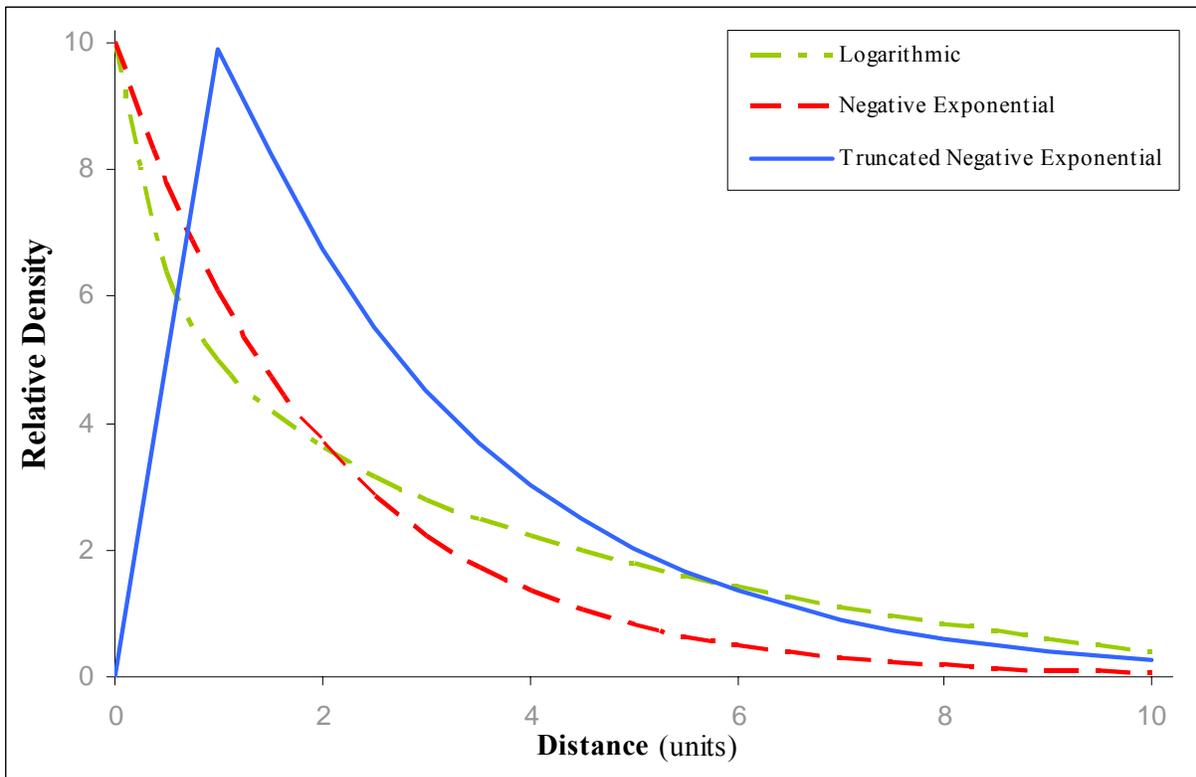


Figure 3.1 Mathematical Calibration Algorithms

3.4.2 Journey-to-Crime Routine

Using the destination locations stored within the Test-Sample data set, residences are estimated based on the mathematically calibrated distance decay function defined for the observed travel patterns of the Calibration-Sample. When applied for each incident, the calibrated function mathematically assigns a value for each point within a study area. Called a “probability-score,” the values are used to indicate the likelihood that any location within the study area is the offender’s likely residence. The procedure is executed in five steps:

1. A study area was constructed from a rectangular matrix consisting of 16,875 grid cells, each measuring 368.86 meters (0.23 mile) wide. The rectangular grid was clipped to match the TIGER[®] 2000 Baton Rouge Urban Area polygon. The result was a study area constructed of a grid consisting of 3,445 cells. The .23 mile cell size was used to ensure computer stability when executing the SNP routines.

2. Both Euclidean and functional distances are measured from each grid cell centroids to each Test-Sample incident location. The straight-line Euclidean and indirect Manhattan distance values are calculated using the journey-to-crime routine within CrimeStat[®] II. To measure the functional distances, SNP analysis routines are executed using ArcView[®] GIS with the Network Analyst 1.0b extension. Each SNP optimizes the commute for distance (travel-path) and time (temporal path). In order to accommodate for one-way access, distances are only measured from the grid cell to each incident location. Impedance values used to define the network path parameters are calculated from the GDT-Dynamap[®] road data network.
3. All three mathematically calibrated distance decay functions are applied to each grid cell-incident pair. The modeled values are summed for each incident. The straight-line Euclidean and indirect Manhattan models were calculated within the CrimeStat[®] II journey-to-crime routine. For functional distance measures, the mathematically calibrated distance decay functions are applied using both Microsoft[®] Access[®] and SPSS[®].
4. For each grid cell-incident pair, a numerical value (probability-score) is calculated to indicate the likelihood that an offender resides at a given cell. Each value is summed over all incidents to indicate the peak likelihood.
5. A density map of each grid cell's probability score is created, indicating the likelihood that a particular location is the offender's residence.

The density surface estimating the likely offender's residence is represented by a density map, termed a geoprofile (Rossmo, 2000). Each grid cell is assigned a z-value (probability score) representing the estimated likelihood for the straight-line and Manhattan Euclidean, and both travel and temporal path functional distance measures. The highest scored grid cell represents the estimated residence (peak likelihood). Because a variety of 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. Error-distance provides a good measure for assessing a geographic profile's spatial precision. For this investigation, the straight-line distance between

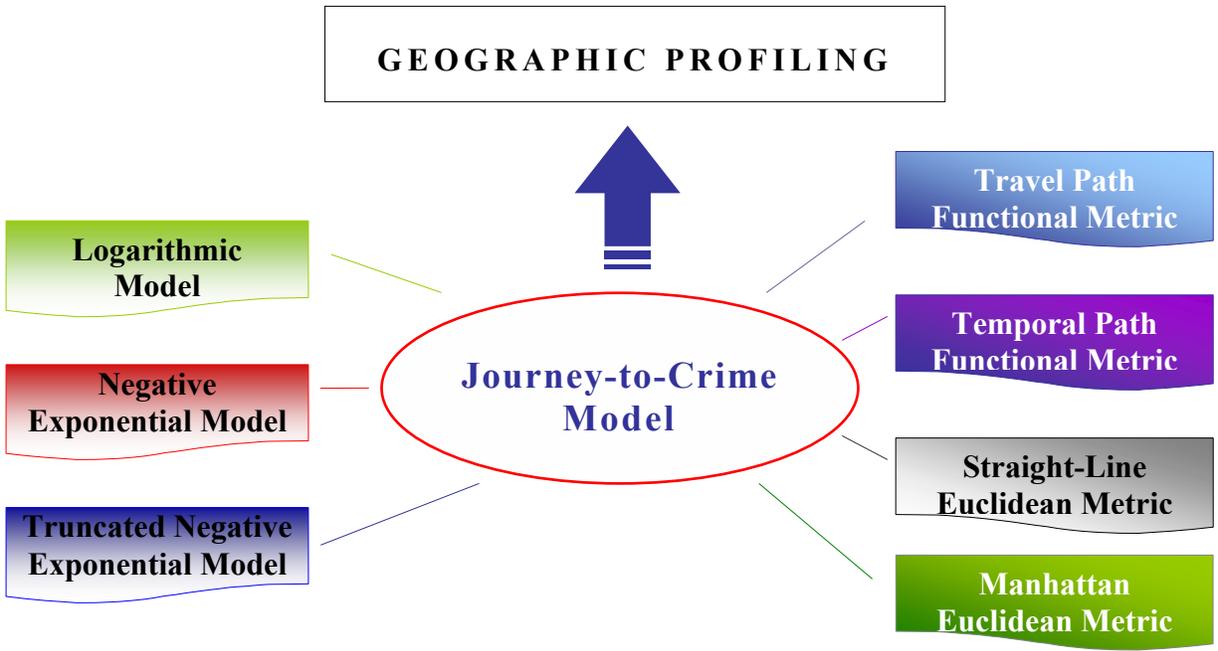


Figure 3.2 Geographic Profiling Metric Calibration Matrix

the grid cell representing the peak likelihood and the grid cell representing test subject’s actual residence (hit-score) is measured. The second method estimates accuracy by identifying the proportion of the area that must be searched in order to successfully identifying the individual’s residence. This search cost is determined by calculating the hit-score percentage: the ratio of the total number of grid cells with a probability score equal-to or higher-than the hit-score, to the total number of grid cells (Rossmo, 2000). A low hit-score percentage indicates a more accurate prediction. The hit-score percentage is the best measure of a geographic profile’s predictive utility. As such, all measures of success will be assessed using the hit score percentage. Figure 3.2 illustrates the association of the various calibration models and distance matrices utilized by this investigation.

3.5 Determining the Best-Fit Distance Decay Model

The three distance decay models utilized by this investigation were mathematically calibrated in order to provide a ‘best-fit’ for the given distribution of stored incidents. Because

mathematical models will inherently demonstrate variable degrees of predictability, some measure of success was needed in order to identify the validity, reliability, and utility of the profiling models used. Using SPSS[®] 11.0, the coefficient of determination, R^2 , is calculated to measure the strength of the regression relationship. R^2 measures how well a model will fit a given distribution by evaluating the extent in which the independent variable, X , can account for the variation in the dependent variable, Y :

$$R^2 = \frac{\sum y_e^2}{\sum y^2} \quad (3.5)$$

where $\sum y_e^2$ is the total explained variation of Y , and $\sum y^2$ is the total variation of Y (McGrew & Monroe, 1993). As a descriptive measure between 0 and 1, R^2 is interpreted as the percentage of variation in the dependent variable that is explained by the independent variable. Analysis of variance (F statistic) is used to evaluate the statistical significance of R^2 .

CHAPTER 4. RESULTS AND DISCUSSION

An examination of the results obtained for this study demonstrates that functional distances are an effective metric for developing geographic profiles. Using both Euclidean and functional distance measures, twelve geoprofiles were created for each of the four Test-Sample data subjects using three unique decay models. As it will be discussed below, the residences of three out of the four test subjects were more precisely identified by geoprofiles created with functional distance metrics than those created with Euclidean metrics. For the purposes of comparative review, each geoprofile is first arranged according to distance metric, and then according to journey-to-crime modeling technique. First, the frequency distributions used to calibrate the modeling algorithms will be examined to illustrate the key characteristics that distinguish Euclidean from functional distance metrics. Next, the top performing geoprofiles will be presented in a manner that seeks to clarify the underlying assumptions and overall effectiveness of each metric used. Assessing the predictive utility of each metric is achieved by calculating the distance-error and the cumulative search-cost. Finally, a summary of this investigation's technological requirements will be compiled in order to identify an optimal operating environment from which to perform similar analysis.

4.1 Frequency Distributions by Metric

Figure 4.1 illustrates the frequency distribution for each distance measure calculated from the Calibration-Sample data set. Exhibited for each metric, a significant percentage of all destinations, approximately 60%, occur within the first 3.75 miles (the adjusted mid-point between 3.5 and 4.0 mile distance bins), or 3.86 minutes (the adjusted mid-point between 3.43 and 4.29 minute distance bins), from the origin. Figures 4.1A and 4.1B reveal two peak frequencies within the 3.75-mile range, or between 4.0 and 8.0 minutes in Figure 4.1C. As the

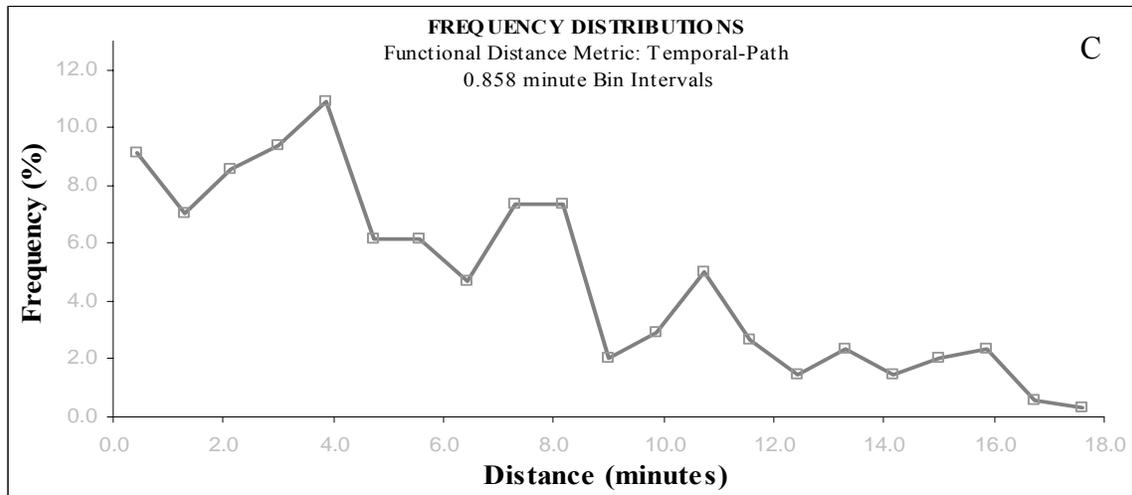
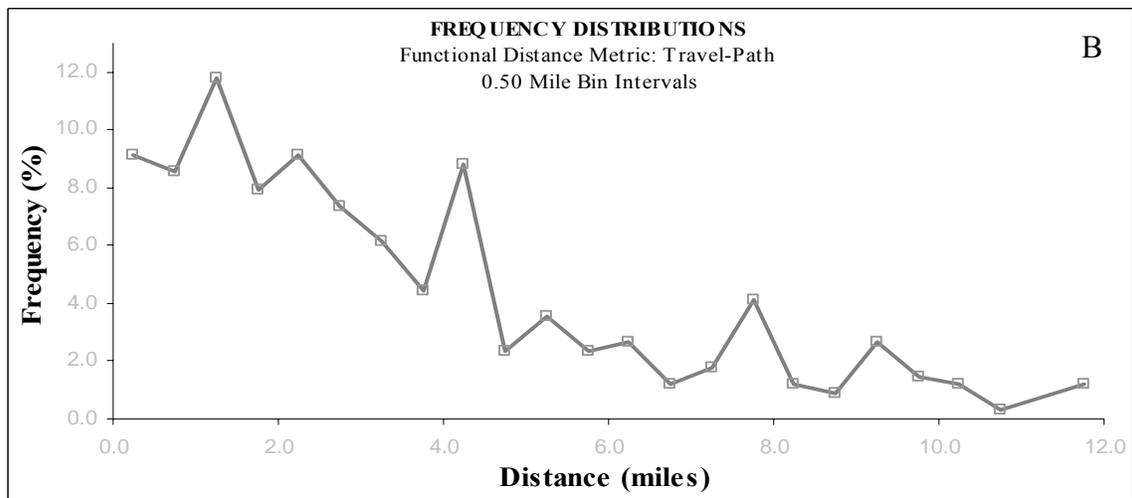
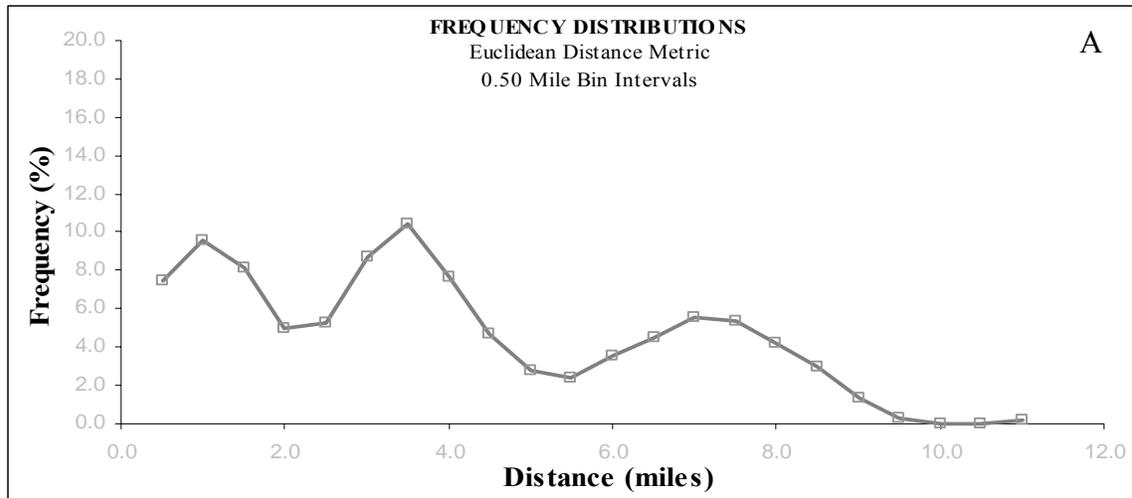


Figure 4.1 Frequency Distributions By Metric: (A) Euclidean Distances, (B) Travel-Path Functional Distances, (C) Temporal-Path Functional Distances.

distance intervals become larger, there is a general decrease in activity for each distance distribution. Additionally, there appears to be a third peak located approximately 7.75 miles (the adjusted mid-point between 7.5 and 8 mile bins), or approximately 9.86 minutes (the adjusted mid-point between 9.44 and 10.296 mile bins), from the origin which is represented by a 6% activity spike. These results correspond significantly with Environmental Criminology research results which indicates that the majority of human activities are performed within a close proximity to their residence (see Chapter 2, Section 2.1 and 2.2).

By inspection, it is clear that the three frequency distributions illustrated in Figure 4.1 illustrate that the maximum cumulative distance traveled by subjects of the Calibration-Sample data set varies according to metric. As illustrated in Figure 4.1A, the measured straight-line Euclidean distance from the origin to the furthest destination is approximately eleven miles. As expected, this measure falls short of the maximum travel-path distance calculated to be approximately twelve miles (Figure 4.1B), or seventeen minutes (Figure 4.1C), from the origin. These differences clearly demonstrate that, for members of the Calibration-Sample group, the distance an individual is willing to travel is not necessarily measured effectively when using straight-line Euclidean metrics.

Another observed characteristic is that the frequencies calculated using the Euclidean distance metric (Figure 4.1A) exhibit the smoothest distribution of activities when compared to the two functional metric distributions. The implication for geographic profiling is that the intermediate travel productions observed for the functional metrics are unidentified within distributions measured using Euclidean metrics. While key activity nodes remain identifiable for all metrics, Euclidean distance measures are unable to account for those destinations that could theoretically provide insight into the activities of a serial criminal.

Another observation is the ‘roller-coaster’ (or serpentine) characteristic exhibited by each of the distributions. The cyclical arrangement of very pronounced peaks and troughs can be attributed to the small calibration sample size. These characteristic may also be attributed to the 0.5 mile (.858 minute) distance interval chosen for this investigation. Furthermore, the pattern may be an artifact of the Baton Rouge commercial landscape. What ever the cause of this condition, some valuable information can be extracted. For example, each distribution exhibits an observed increase in frequencies within the immediate vicinity of the origin. As expected, the frequency decreases as the distance from the origin increases. When modeling criminal behavior, the initial increase in activity near the origin, followed by a general decrease is typically attributed to the proposed Buffer Zone effect (see Chapter 2).

The Buffer Zone represents a condition whereby an offender will intentionally avoid committing crimes within relative proximity to his/her residence for the purpose of avoiding suspicion. Given that the Calibration-Sample group consists of law-abiding citizens, it is unlikely that a deliberate buffer-zone would be purposefully constructed for the normal, everyday activities of the individuals sampled. Therefore, some other characteristic is responsible for the cyclical increase-decrease in activity. One logical explanation is related to the spatial frequency of phenomena shared between the distribution of residential and commercial land-use zones. The observed peak frequencies quite possibly represent activity centers which have been dispersed in a predictable distribution around residential neighborhoods, *i.e.* commercial zoning. Another possible explanation could relate to both the compact size of East Baton Rouge Parish, as well as the possibility that the sample subjects coincidentally live within relative close proximity to activity centers. What ever the cause, this characteristic serves this investigation as

a pseudo Buffer Zone. As it will be demonstrated below, this effect can be modeled with some degree of success by using the truncated negative exponential function.

4.2 Journey-To-Crime Calibration Models

As detailed in the previous Chapter, three distance decay functions were selected to model the frequency distributions observed in Figure 4.1. These functions included logarithmic, negative exponential and truncated negative exponential. Using SPSS® 11.0 for Windows, the 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 three distance metrics used for this investigation: straight-line Euclidean, travel-path functional and temporal-path functional (see also Table 3.1, Chapter 3). 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 (Equation 2.1, Chapter 2). The results of these three models are presented in Figures 4.2 – 4.4. For each model, the coefficient of determination (R^2) is observed to lie between a minimum of 0.542 to a maximum of 0.771, and is considered to be highly significant ($F < 0.05$).

4.2.1 Euclidean Distance Decay Model

Figure 4.2 illustrates the frequency distribution measured by the straight-line Euclidean distances metric. The frequency distribution observed for this model is characterized by a decreasing series of three peaks and two troughs with elevated activity approximately located at 1.25-miles, and again at 3.75-miles from the origin. The logarithmic model demonstrates a shallow curvilinear component for the first 1.5 miles before becoming a more gradual decay. The steep negative exponential model appears to over-estimate much of the first 4.0 miles of the

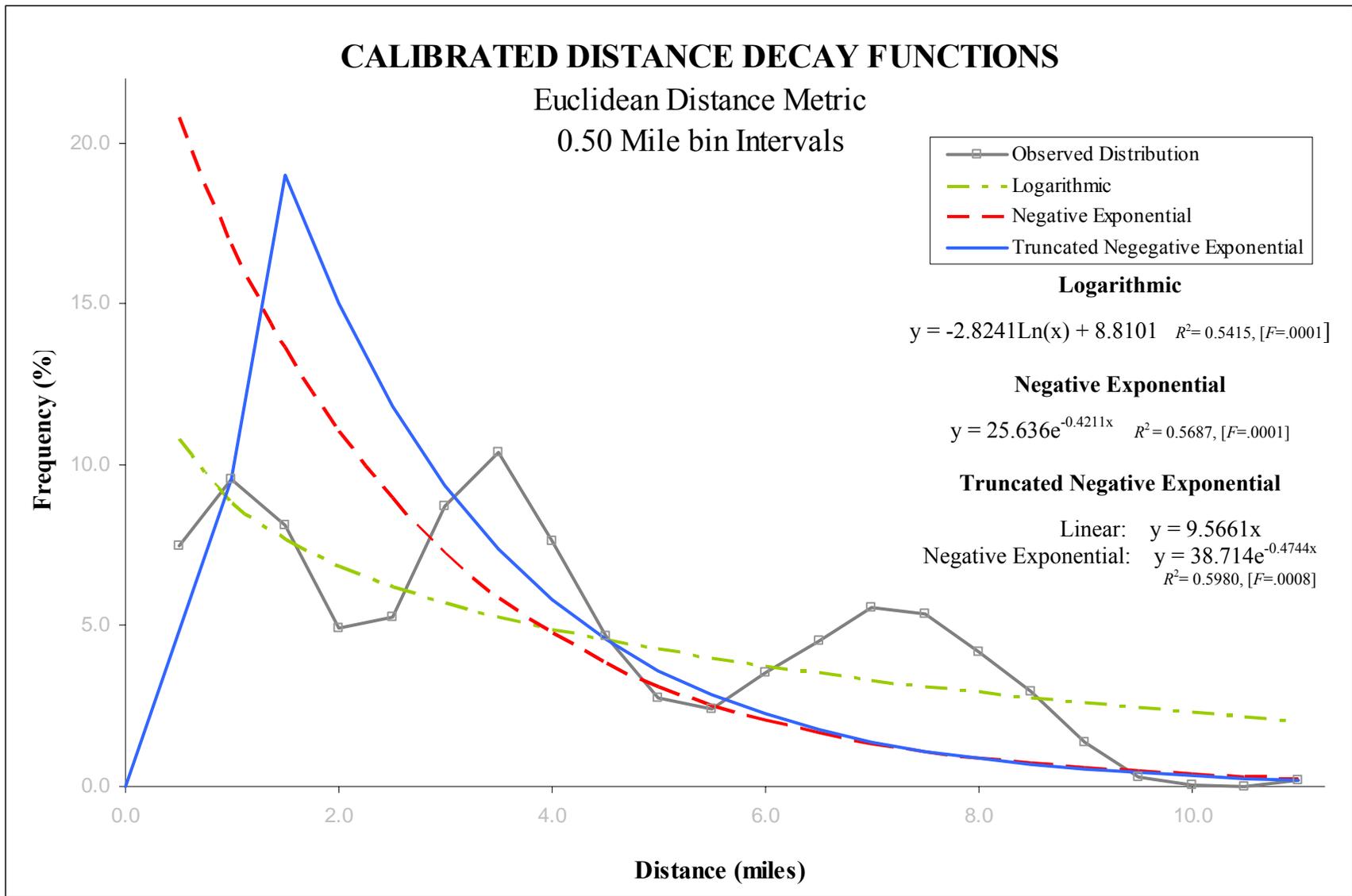


Figure 4.2 Calibrated Distance Decay Algorithms for Euclidean Distance Metrics

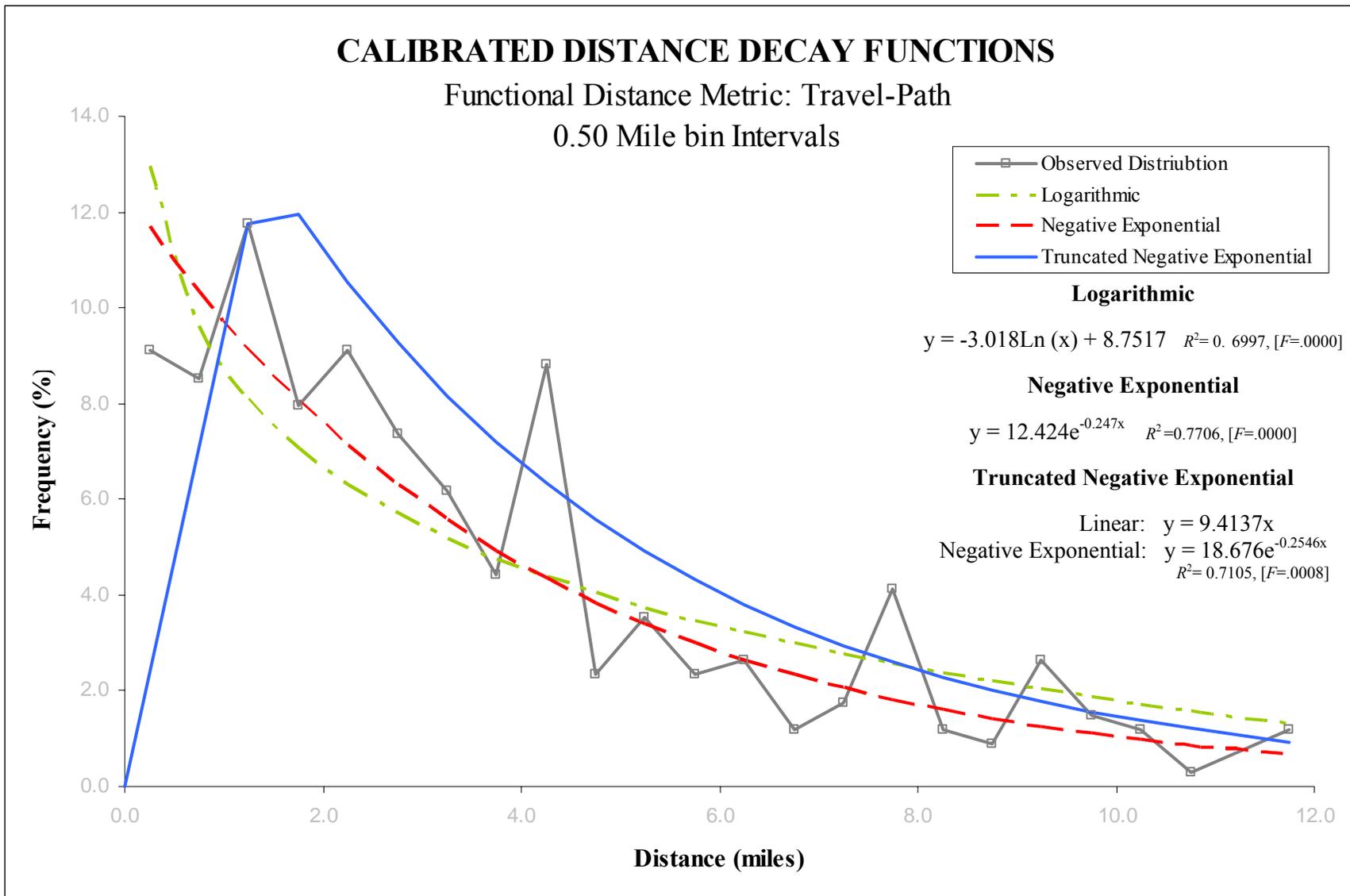


Figure 4.3 Calibrated Distance Decay Algorithms for Travel-Path Functional Distance Metrics

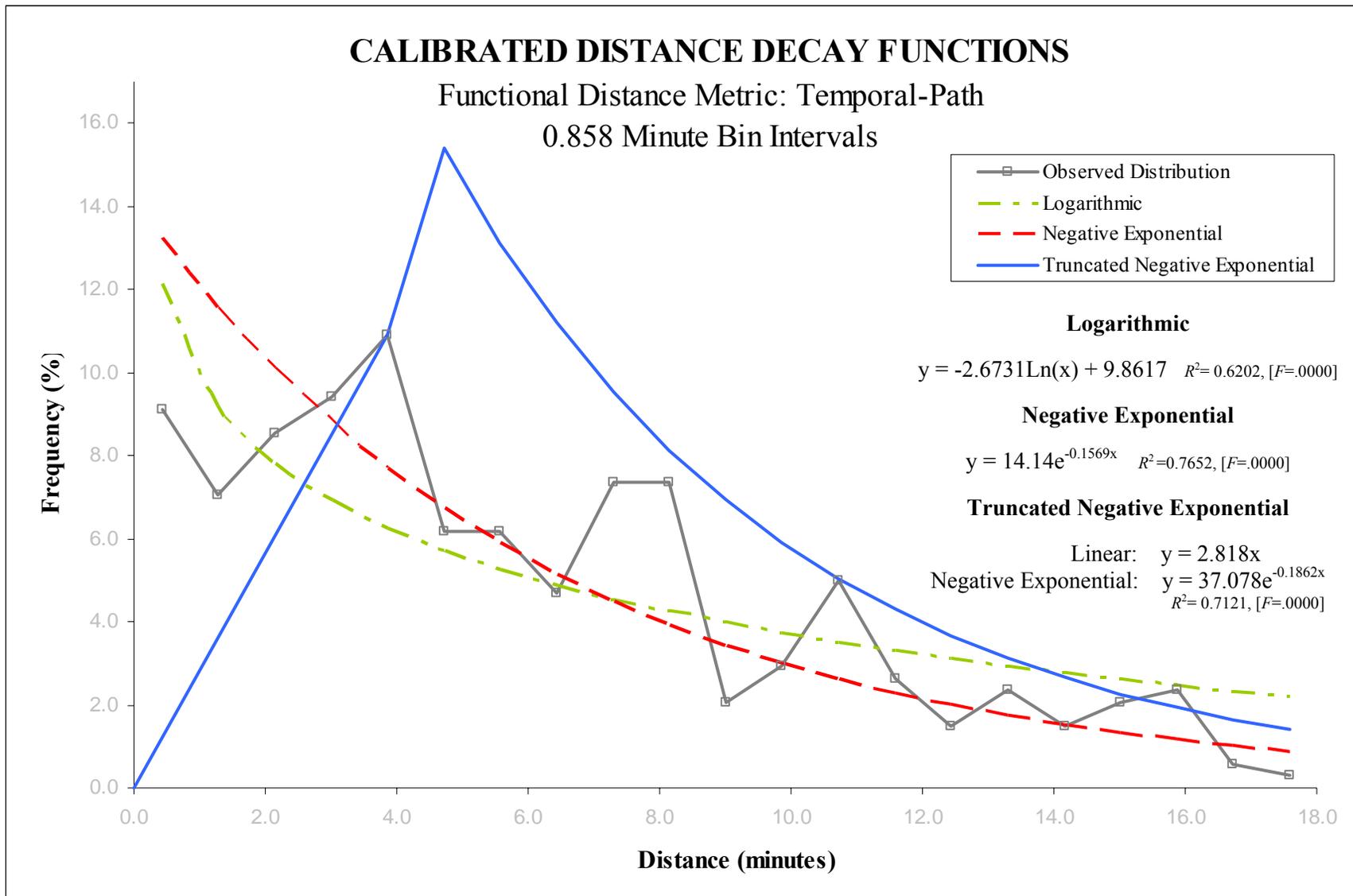


Figure 4.4 Calibrated Distance Decay Algorithms for Temporal-Path Functional Distance Metrics

distribution before underestimating the remaining frequencies. Of the three models applied to the distribution, the truncated negative exponential provides the best statistical fit ($R^2 > 0.5980$). Represented by the blue line (solid), the linear portion of the function overestimates most of the first observed peak frequencies, while the negative exponential component provides a better fit for distances beyond 1.75-miles. Geoprofiles created from these models were automatically generated using the CrimeStat[®] II Journey-to-crime routine.

4.2.2 Travel-Path Distance Decay Model

Figure 4.3 illustrates the frequency distribution measured by the actual travel-path distance metric. Like the Euclidean frequency distribution of Figure 4.2, the pattern is characterized by a decreasing series of peaks and troughs with elevated activity approximately located at 1.75 miles, and again at 4.25 miles from the origin. The logarithmic model appears to underestimate the distribution within the first four miles, whereby it appears to overestimate the distribution through the remainder. However, the logarithmic function exhibits a rate of decrease that is very similar to the general decay observed for approximately the first 4.25 miles. The mathematically calibrated negative exponential function (red, dashed line) is observed to provide the best statistical fit ($R^2 > 0.7706$) across the whole distribution. However, the linear component of the truncated negative exponential model can better represent the steep increase in frequency between 0.75 and 1.25 miles while matching a similar decay rate. Geoprofiles using travel-path models are manually constructed for each grid cell using Microsoft[®] Access[®] and ESRI[®] ArcView[®] GIS.

4.2.3 Temporal-Path Distance Decay Model

Figure 4.4 illustrates the frequency distribution exhibited by the temporally optimized travel-path (temporal-path) functional distance metric. Similar to the distribution characteristics

observed for the previous two models, the distribution pattern is characterized by a decreasing series of peaks and troughs with a maximum occurrence of destinations at approximately 4 minutes from the origin. The logarithmic function appears to underestimate the distribution between the 2nd and 4th minute from the origin, whereby it appears to provide a good estimation until approximately the 11th minute. Of the three decay functions implemented, the negative exponential model (red, dashed line) statistically provides the best fit across the whole distribution ($R^2 > 0.7652$). While possessing a relatively strong coefficient of determination, the truncated negative exponential model appears to over-estimate nearly all frequency measures. Once again, geoprofiles created with these values are manually constructed for each grid cell using Microsoft[®] Access[®] and ESRI[®] ArcView[®] GIS.

4.3 Assumptions

Specifying conditions attributed to this investigation, the following assumptions have been made when developing a geographic profile:

- All travel production originated from the sample subject's residence;
- A relationship exists between each incident location and a sample subject's residence, which can be modeled using some form of distance decay function;
- Members from both sample groups have optimized their travel when commuting from their residence to each destination. Such optimization can be measured in terms of the commuted distance (miles) and time of travel (minutes).

4.4 Best Performing Geoprofiles

Reviewing the parameters established in Chapter 3, all geoprofiles used for this research consists of a density surface map of 3,445 grid cells representing the Urban Area of East Baton Rouge Parish, Louisiana (US Census Bureau, 2000). Each grid cell is assigned a z-value (probability-score) indicting the likelihood that it is the Test-Sample's residence. Probability-scores are determined for each Test-Sample by measuring the distance between each grid cell

and each incident location. The distances (Euclidean and functional) are modeled according to the mathematically calibrated distance decay algorithms discussed in Section 4.2.

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 will measure the straight-line distance between the grid cell representing the predicted residence (peak likelihood) and the grid cell representing test subject’s actual residence (hit-score). 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 test subject. Accordingly, this investigation will assess precision using the hit-score percentage.

Assessing the generated geoprofiles based on the parameters detailed above, Table 4.1 illustrates the most precisely modeled geographic profiles by Test-Sample ID. Each geoprofile is

Table 4.1 Geographic Profiling Results: Best Performing Geoprofiles

SAMPLE ID	METRIC	MODEL	HIT SCORE %	SEARCH COST MILES ²	ERROR DISTANCE
1	Temporal Path	Truncated Negative Exponential	1.11%	2.00	2.72
2	Travel Path	Truncated Negative Exponential	0.53%	0.97	0.73
3	Manhattan	Truncated Negative Exponential	1.31%	2.36	1.32
4	Travel Path	Truncated Negative Exponential	0.56%	1.02	1.94
AVERAGE:			0.88%	1.59	1.68

organized in ascending order according to Test-Sample ID, and lists the metric and calibration model used. As detailed in the table, geoprofiles created with functional distance measures more precisely predicted the residences for three of the four Test-Samples. Cumulatively, these top performing geoprofiles were able to identify all of the actual residences within a mean error-distance of 1.68 miles, for an averaged search cost of 0.88% (approximately 1.6 miles²) of the 181.01 square-mile study area of East Baton Rouge Parish. Figures 4.5 – 4.8 illustrate a density map for each of these top performing geoprofiles.

Upon examination of these results, some key characteristics can be observed. First, all of the geoprofiles listed in Table 4.1 were modeled using the truncated negative exponential function. This observation corresponds to the findings indicated in Section 4.2 whereby the truncated negative exponential model consistently provided a best statistical fit for each frequency distribution. This finding also supports the earlier observation (Section 4.1) that some kind of Buffer Zone is affecting the frequency of activities based on a regular distribution of activity nodes. This suggests that the journey-to-crime model selection has a significant impact on the way travel distances are represented when generating a geographic profile. A second observation notes that the travel-path functional distance metric performed well, providing the best residency estimation for Sample ID 2 and 4. A third observation notes that the temporal-path functional distance measure did not perform as well as expected. A number of circumstances may account for this and will be addressed later in the discussion. Accordingly, the results obtained for this investigation clearly demonstrate that functional distance metrics can be used to create effective geographic profiles.

While Table 4.1 illustrates that three of the four best performing geoprofiles were created using functional distance metrics, a more detailed examination of the geoprofiles generated for

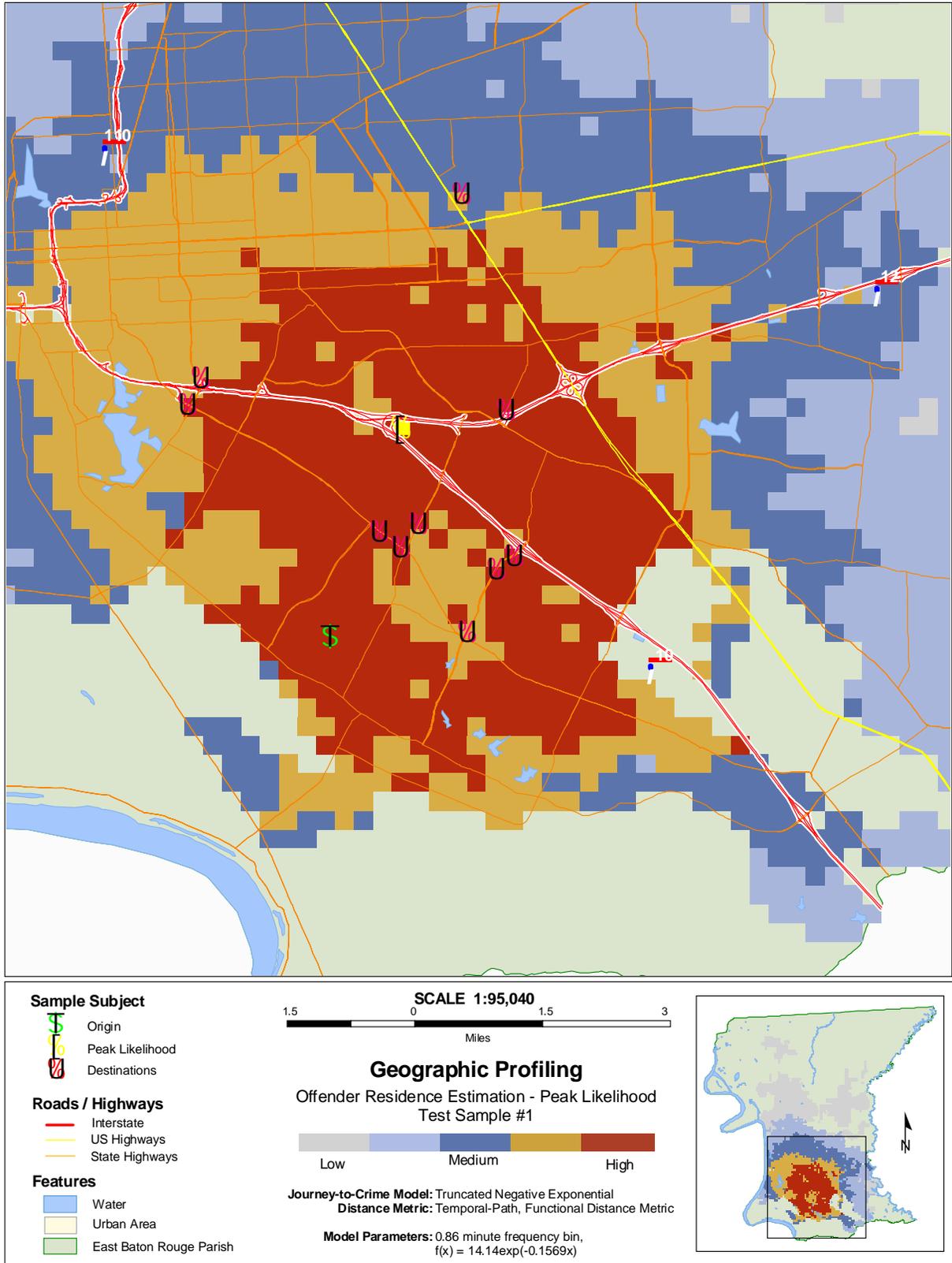


Figure 4.5 Geographic Profiling Results: Best Performing Geoprofiles – Test-Sample 1

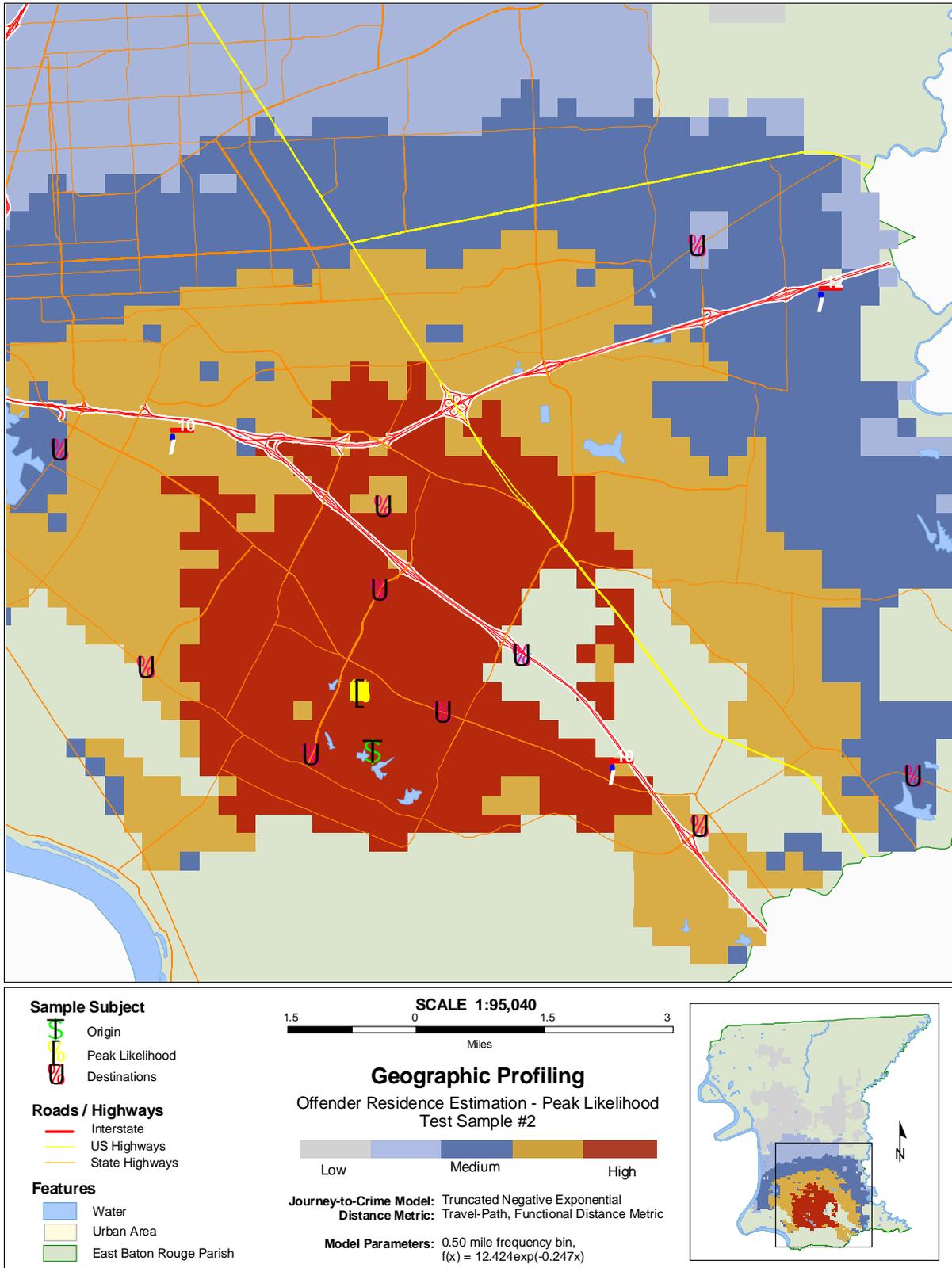


Figure 4.6 Geographic Profiling Results: Best Performing Geoprofiles – Test-Sample 2

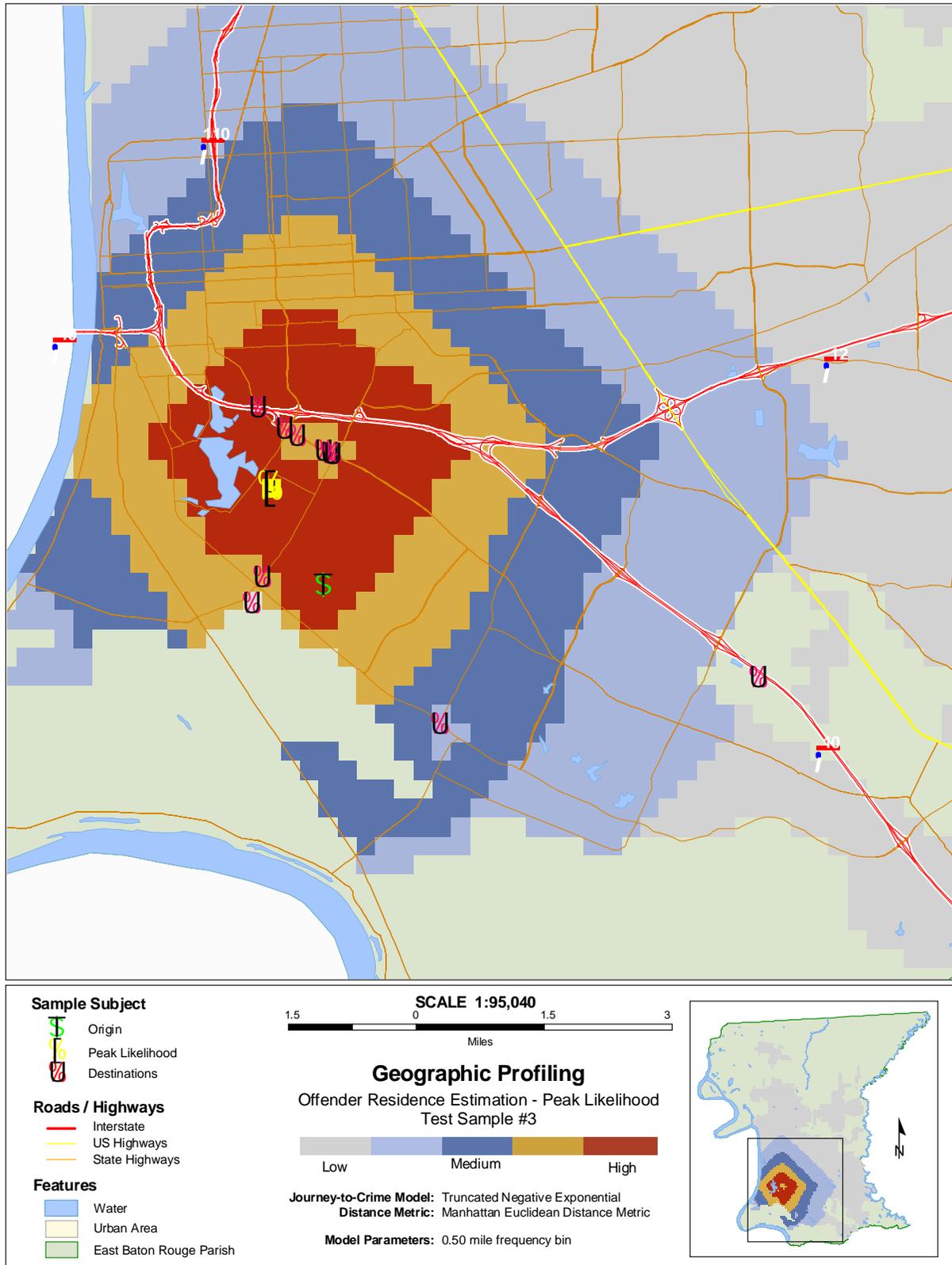


Figure 4.7 Geographic Profiling Results: Best Performing Geoprofiles – Test-Sample 3

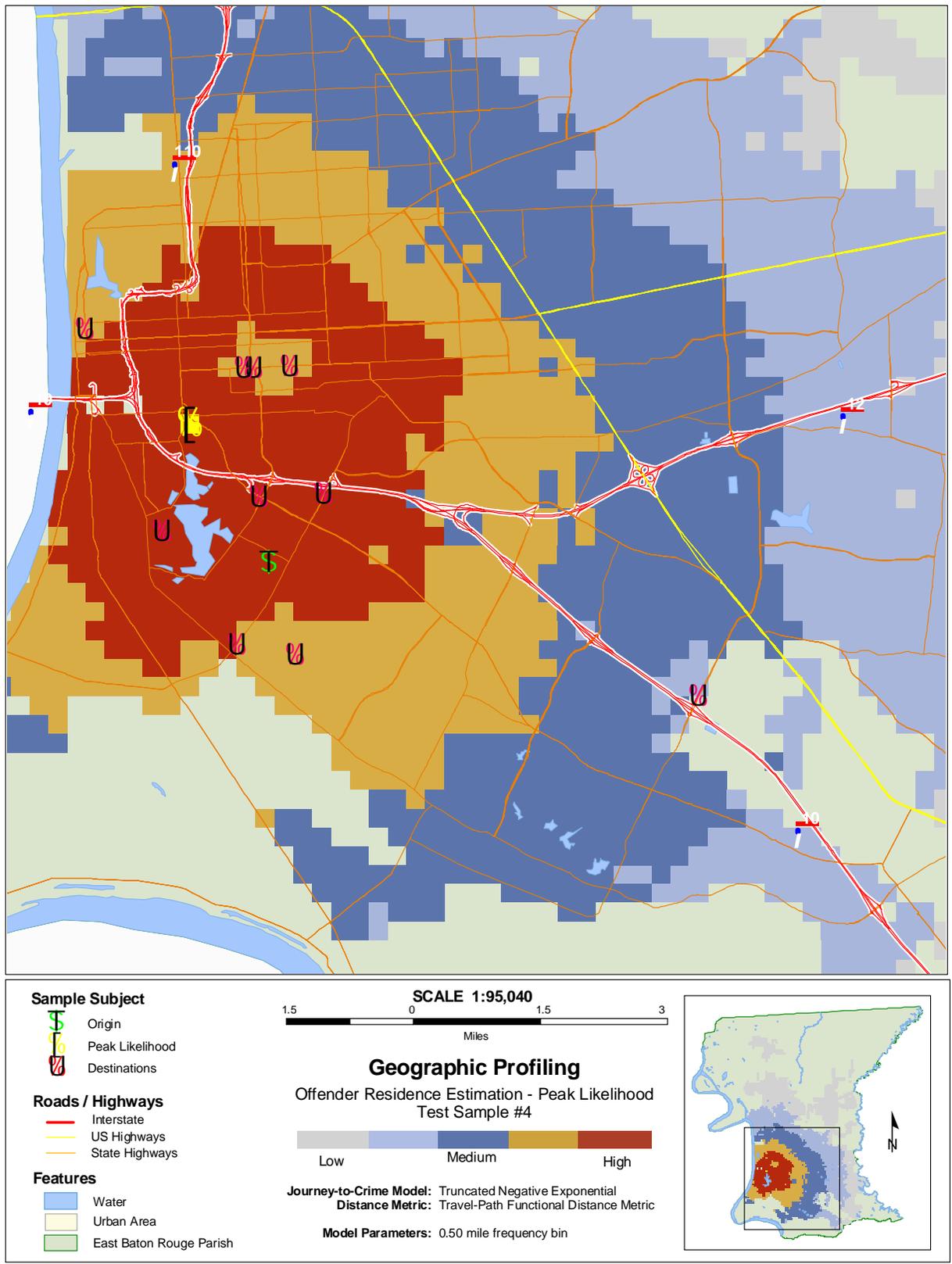


Figure 4.8 Geographic Profiling Results: Best Performing Geoprofiles – Test-Sample 4

this investigation is in order, for the purpose of clarifying the underlying characteristics and overall effectiveness of each metric used. Accordingly, the following text will present in detail all twelve geoprofiles generated by this investigation (4 test subjects x 3 modeling metrics = 12 geoprofiles), organized by metric. Cumulative scores will also be presented in order to assess the overall effectiveness of the metric examined.

4.5 Geographic Profiles by Euclidean Metric

The geoprofiles using both straight-line and Manhattan Euclidean distance metrics identified all four Test-Sample residences within a mean error-distance of 1.78 miles from the predicted location, representing a cumulative search cost of 4.15% (approximately 7.51 miles²). The sections detailed below examine independently calculated results for both the straight-line and Manhattan Euclidean distance measures, which are organized in Table 4.2 and 4.3.

**Table 4.2 Geographic Profile Results
Direct Path Euclidean Metric**

MODEL	SAMPLE ID	HIT SCORE %	SEARCH COST MILES²	ERROR DISTANCE
LOGARITHMIC				
	1	8.27%	14.97	1.8
	2	15.15%	27.43	2.71
	3	3.16%	5.73	1.65
	4	2.29%	4.15	2.41
NEGATIVE EXPONENTIAL				
	1	7.69%	13.92	1.63
	2	3.51%	6.36	1.87
	3	3.08%	5.57	1.65
	4	2.06%	3.73	0.99
TRUNCATED NEGATIVE EXPONENTIAL				
	1	5.98%	10.82	2.61
	2	2.76%	4.99	0.98
	3	1.48%	2.68	1.29
	4	0.72%	1.31	1.63
AVERAGES:		4.68%	8.47	1.77

4.5.1 Straight-Line Path Distances

As detailed in Table 4.2, geographic profiling models using straight-line Euclidean distances measures identified all four residences of the Test-Sample data set within a mean error-distance of 1.77 miles from the predicted locations, representing a cumulative search cost of 4.68% (approximately 8.5 miles²) of the total study area. Highlighted in bold is the model that provided the best prediction in terms of search cost.

4.5.2 Manhattan Distance

Geoprofiles generated using Manhattan distance metrics cumulatively performed the best overall, accounting for the most precisely predicted residences. As detailed in Table 4.3, all four residences of the Test-Sample data set were geographically profiled within a mean error-distance of 1.79 miles from the predicted locations, representing a cumulative search cost of 3.62% (approximately 6.6 miles²) of the total study area. The model that provided the most

**Table 4.3 Geographic Profile Results
Manhattan Euclidean Metric**

MODEL	SAMPLE ID	HIT SCORE %	SEARCH COST MILES ²	ERROR DISTANCE
LOGARITHMIC				
	1	9.20%	16.66	2.45
	2	3.60%	6.52	1.87
	3	2.44%	4.41	1.67
	4	1.80%	3.26	2.41
NEGATIVE EXPONENTIAL				
	1	8.74%	15.82	1.63
	2	2.06%	3.73	1.18
	3	2.44%	4.41	1.67
	4	1.68%	3.05	2.41
TRUNCATED NEGATIVE EXPONENTIAL				
	1	8.16%	14.76	2.45
	2	1.13%	2.05	0.97
	3	1.31%	2.36	1.32
	4	0.87%	1.58	1.49
AVERAGES:		3.62%	6.55	1.79

exact prediction in terms of search cost is highlighted in bold. The map provided in Figure 4.7 illustrates the results of the Manhattan Euclidean distance metric for Test-Sample 3, modeled with the truncated negative exponential function.

4.6 Functional Distance Measures

Geoprofiles using functional distance metrics identified all four Test-Sample residences within a mean error-distance of 1.73 miles from the predicted location, representing a cumulative search cost of 4.53% (approximately 8.2 miles²). The sections detailed below examine the independently calculated results for both the travel-path and the temporal-path functional distance measures, which are provided in Table 4.4 and 4.5.

4.6.1 Travel-Path Distances

As detailed in Table 4.4, residences of the Test-Sample data set were geographically profiled within a mean error-distance of 1.66 miles of the predicted locations, representing a

**Table 4.4 Geographic Profile Results
Travel-Path Functional Distance Metric**

MODEL	SAMPLE ID	HIT SCORE %	SEARCH COST MILES ²	ERROR DISTANCE
LOGARITHMIC				
	1	8.62%	15.61	1.48
	2	1.96%	3.54	0.91
	3	5.81%	10.51	1.67
	4	2.34%	4.24	2.41
NEGATIVE EXPONENTIAL				
	1	8.24%	14.91	1.48
	2	1.62%	2.93	1.2
	3	5.81%	10.51	1.65
	4	1.68%	3.05	2.41
TRUNCATED NEGATIVE EXPONENTIAL				
	1	6.79%	12.28	2.64
	2	0.53%	0.97	0.73
	3	4.12%	7.45	1.43
	4	0.56%	1.02	1.94
AVERAGES:		4.01%	7.25	1.66

cumulative search cost of 4.01% (approximately 7.25 miles²) of the total study area. The model that provided the best prediction in terms of search cost is highlighted in bold. The geoprofile maps provided in Figure 4.6 and 4.8 illustrates the results using the travel-path functional distance metric measured for Test-Sample 2 and 4, respectively; both modeled using the truncated negative exponential function.

4.6.2 Temporal-Path Distances

As detailed in Table 4.5, all four residences of the Test-Sample data set were geographically profiled within a mean error-distance of 1.80 miles of the predicted locations, representing a cumulative search cost of 5.06% (approximately 9.16 miles²) of the total study area. The model that provided the best prediction in terms of search cost is highlighted. The geoprofile map provided in Figure 4.5 illustrates the results using the temporal-path functional distance metric measured for Test-Sample 1, and modeled using the truncated negative exponential function.

**Table 4.5 Geographic Profile Results
Temporal-Path Functional Distance Metric**

MODEL	SAMPLE ID	HIT SCORE %	SEARCH COST MILES²	ERROR DISTANCE
LOGARITHMIC				
	1	9.87%	17.87	1.48
	2	1.96%	3.54	0.91
	3	7.46%	13.50	1.67
	4	2.45%	4.43	2.41
NEGATIVE EXPONENTIAL				
	1	9.51%	17.22	1.48
	2	3.60%	6.52	2.13
	3	7.28%	13.18	1.65
	4	1.60%	2.90	2.06
TRUNCATED NEGATIVE EXPONENTIAL				
	1	1.11%	2.00	2.72
	2	7.19%	13.02	2.57
	3	7.12%	12.88	0.5
	4	1.60%	2.90	2.06
AVERAGES:		5.06%	9.16	1.80

4.7 Further Discussion

A number of key observations have been made from these results which support the proposition that functional distance measures be effectively used when creating a geographic profile. First, in terms of obtaining the most precise estimation of residency, functional distance metrics provided the three most accurate geoprofiles (Table 4.1). Additionally, travel-path functional distance measures ranked second in predictive performance when compared to the results obtained for each metric (Table 4.6). However, temporally optimized functional distances did not perform as well as anticipated. Upon examination of Table 4.5 (see also Table 4.6), temporal-path distance measures were observed to have the lowest predictive performance of all three metrics examined. It must be noted, however, that the degree of precision measured for all metrics (48 total geoprofiles) varied marginally; where search-cost estimates ranged from a low of 0.56% to a high of 15.15% (mean = 4.34%, standard deviation = 3.32). There are a number of possibilities that could explain the poor results exhibited by temporal-path geoprofiles, including sample size, and path analysis techniques. The small sample size used by this investigation clearly had an impact on results, as indicated by the variations exhibited for all frequency distributions. As such, the calibrations used for this investigation are assumed to provide only a marginal representation of the travel characteristics of East Baton Rouge Parish.

Table 4.6 Geographic Profiling Results: Cumulative Results by Metric

METRIC	MODEL	AVG. HIT SCORE %	AVG. SEARCH COST MILES²	AVG. ERROR DISTANCE
Direct Euclidean	Truncated Negative Exponential	4.68%	8.47	1.77
Manhattan	Truncated Negative Exponential	3.62%	6.55	1.79
Travel-Path	Truncated Negative Exponential	4.01%	7.25	1.66
Temporal Path	Truncated Negative Exponential	5.06%	9.16	1.80
AVERAGE:		4.34%	7.86	1.76

Accordingly, future research should include larger calibration and test sample groups for different locations. Another possible source of error attributed to the temporal-path's poor performance may relate to network path analysis.

As detailed in Chapter 3, Shortest Network Path (SNP) analysis was used to derive the functional distance measures (travel-path and temporal-path) for both the Calibration-Sample and Test-Sample data sets. Despite its name, the SNP routines may not necessarily take the shortest network path when optimizing time. This is primarily attributed to the fact that SNP routines are not flexible decision systems. That is, SNP routines make measurements based on the specific parameters indicated by the impedance characteristics (speed, distance, and direction) associated with the underlying road network. The implication is that a route calculated by an SNP routine may not be as optimized as a route taken by an individual who will often behave outside of these parameters.

This can be explained by examining Figure 1.2 (Chapter 1), where two routes are available to the commuter. When optimizing travel-time, the commuter is expected to take the beltway to reach the destination (Figure 2.1B). For this example, the commuter simply exits the beltway, and arriving at the destination. However, network path analysis may interpret the path quite differently. For this circumstance, SNP will follow the specific parameters of speed, direction, and distance when optimizing the route. Referring back to Figure 1.2, the SNP path may be forced to exit the highway to the right of the preferred destination, whereupon it will travel away from the destination before turning around 180 degrees before completing the commute. While the path may remain temporally optimized when compared to the alternative route, it will inherently require more time to travel. As a result, the distance measure for such a route is no-longer a realistic representation of the actual commute.

Yet another possible explanation for the poor results of the temporal-path model may be attributed to the commuters surveyed for this investigation. Specifically, test subjects simply may not have optimized their routes based on time. For most circumstances, a travel production will present a commuter with an opportunity to select either a direct route (which will result in a long production) or an optimized route (which will result in a short travel production). The route a commuter selects is ultimately dependent upon two conditions: 1) awareness of the optimal route; and 2) an individualistic perception of the route. To some degree, traffic congestion will impact a travel production, but is considered a subjective element for this research as the commuter is afforded the opportunity to avoid congestion by traveling at a different time. The awareness of a route is a condition of the commuter's mental map: a concept discussed in Chapter 2 which states that a commuter bases his or her travel primarily on their direct and indirect knowledge of the immediate surroundings. In terms of optimizing a route, if the commuter is unaware of alternative paths to a destination – the path is not selected. For conditions when the commuter is aware of alternate routes, he or she will choose to take or avoid the alternate routes based on conditions set-forth by Stea (1969) (see also Section 2.1). As Rossmo (2000) recognized in an examination of trail systems, individuals do not simply follow the shortest path. Instead, they minimize their travel effort. Existing routes may not be the most effective, but optimizing travel using an undesirable route requires that the commuter disregard inherent biases. As such, a compromise between convenience and distance is made.

Whatever the condition of reason, the commuters surveyed for this investigation most likely did not optimize their travel production. This is supported by the commuter survey (Appendix B) which indicates that approximately 60% of the participants in this investigation would not necessarily choose to temporally optimize their commute when traveling to their

selected destinations (Table 4.7). Instead, the participants indicated a preference to travel a direct route to their destination even when provided an opportunity to optimize. Consequently, this negates a primary assumption of this investigation, that the temporally optimized route is the preferred path for each travel production. As such, this may provide an explanation as to why travel-path functional distance measures performed better than temporal-path.

A second observation from this investigation is made with regard to the truncated negative exponential model. While no attempt was made by this investigation to identify those distance decay models that could provide the best possible performance, the analysis for this investigation finds that the truncated negative exponential model consistently perform the best for both travel-path and temporal-path functional distance measure. Conversely, the logarithmic model performed the worst of the three. As discussed in Sections 4.1 and 4.2, there are a number of reasons that can explain this finding. It is likely that the dynamic nature of the model (i.e. the combination of both linearly increasing and exponentially decaying models) may have provided the advantage needed to accommodate the various spatial characteristics attributed to the data.

A third observation from this investigation is made with regard to the size and resolution of the study area. As noted by Barry (1998), both network and grid-based analyses such as journey-to-crime, consistently struggle with the effects of artificial edges. For this investigation,

Table 4.7 Commuter Survey Results

ROUTE SELECTION	TRAVEL OPTIMIZED ROUTE	TEMPORAL OPTIMIZED ROUTE	CONGESTION AVOIDANCE	CONVENIENCE
DIRECT PATH (8.6%)	ALWAYS (2.9%)	ALWAYS (8.6%)	UNFAMILIAR ROUTE (14.3%)	CLOSE (62.9%)
INDIRECT PATH (8.6%)	MOSTLY (20%)	MOSTLY (31.4%)	FAMILIAR (54.3%)	FAR (37.1%)
COMBINATION (82.9%)	SOMETIMES (62.8%)	SOMETIMES (48.6%)	DIFFERENT TIME (31.4%)	
	RARELY (14.3%)	RARELY (11.4%)		

only the urbanized area of East Baton Rouge Parish was selected to serve as the study area for the journey-to-crime routines. As a result, portions of the Parish were excluded from analysis, potentially eliminating locations that may have influenced the geoprofile's results. For two test subjects, destinations were positioned outside the study area (Figure 4.9). While the models were able to account for the location's influence over the entire distribution, many of the grid

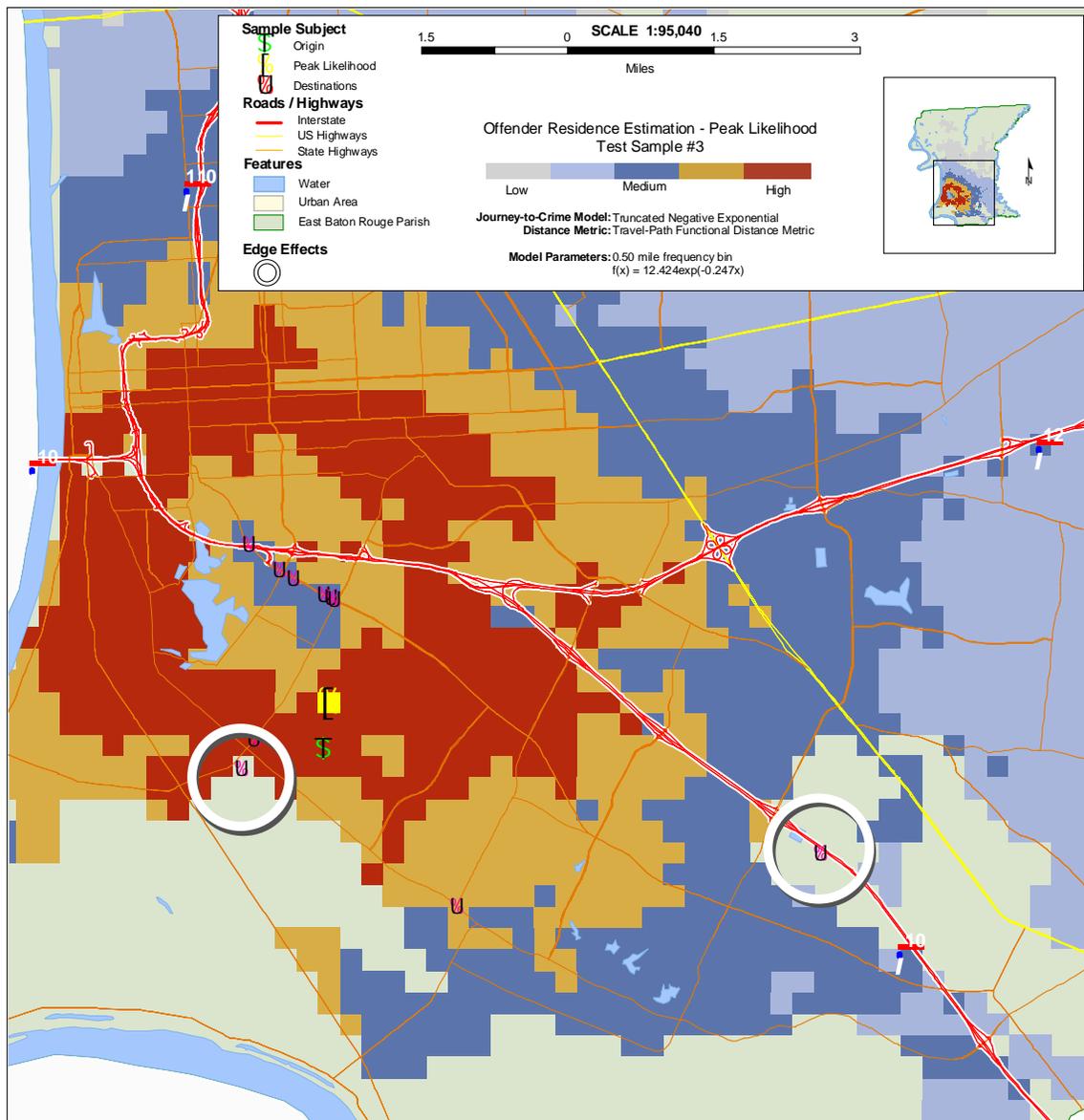


Figure 4.9 Potential Edge Effects When Using Artificial Boundaries

cells attributed to the points were lost, and not calculated for the final results. Conversely, portions of the Parish that are un-inhabitable (*i.e.* lakes and rivers) were not excluded from the analysis. It is not clear to what extent this may have influenced the results.

Additionally, the large grid cell size used by this investigation, .23 miles, may have permitted false network connections when calculating distances; whereby the centroid of a grid cell may have been aligned with an inappropriate network feature segment (such as a park's path, a farm road, or other competing paths of different directions). In such a circumstance, a path could have been selected that would not accurately represent a realistic condition of travel, thus altering distances used by both the calibration and journey-to-crime models.

Of course this last observation is a consequence of the technological limitations placed on this analysis. As stated earlier, the technological pre-requisites for this investigation has only recently been achieved for "off-the-shelf" resources. And while the operating environment from which these results were obtained can be considered typical, the technological costs remained high. Numerous tests had to be performed in order to identify the analytical parameters that produced results without a hardware or software malfunction or instability. As a result, the study area utilized for this research had to be reduced from a rectangular area consisting of over 35,000 grid cells, to a study area consisting of 3,445 grid cells clipped to match the shape of the urbanized area of the parish.

As stated earlier, each geographic profile was generated using an Intel Pentium 4, 1.2GHz PC-Workstation computer, utilizing 384 MB of RAM memory, operating on the Microsoft® Windows® XP Professional operating system. Given the large processing capacity attributed to the computer, SNP analysis routines used to calibrate the thirty-one test subjects (340 points) – a process that measured the distance between each of the 3,445 grid cells and the

340 Calibration-Sample points – required approximately one-hour and forty-five minutes to complete. The SNP analysis routines used to measure the distance between each of the ten Test-Sample destination points to the 3,445 grid cells required approximately one-hour to complete for each test-subject. Clearly, a more accurate geographic profile would result if analyzed over a much-higher resolution investigative surface. However, the investigation must weigh the error and potential inaccuracies associated with large grid cells, to the technological requirements needed to develop better models. Fortunately, hardware and software technology is increasingly becoming more powerful. Since the origination of this investigation, processor speeds have doubled, approaching 3.5GHz processor speeds in a relatively short timeframe. As such, the reader can anticipate an environment in which these functions become common-place, if not antiquated.

CHAPTER 5. SUMMARY AND CONCLUSIONS

The last one hundred years of the criminal investigative process has been marked by a steady increase in the use of geographic mapping applications to display, analyze, and model criminal activities. Beginning in the early 1900s, few criminologists and sociologists were interested in exploring crime spatially, relying on wall-sized pin maps to survey the occurrence of crime as it related to the prevailing environment. Today, GIS is used by thousands of law enforcement agencies across the U.S., and around the world, to model real-time trends and predict criminal activity using personal computers and hand-held devices. Technology has empowered the criminal investigator by providing a meaningful method of disseminating sophisticated geographic information using intuitive processes. In no other aspect of the criminal investigative process has the relevance of geospatial information been more profound than for localized serial offences.

Serial crime incorporates a complex set of psychological and ecological phenomena that requires specialized investigative tools and strategies that extend beyond the traditional criminal investigative processes. Geographic profiling provides such a strategy. By utilizing the existing intelligence/evidence obtained from traditional investigative strategies, geographic profiling examines the characteristics associated with the distribution of crime scenes in order to obtain key characteristics of an offender's spatial behavior. Building upon the theories established in Environmental Criminology, geographic profiles attempt to identify key components of an offender's behavior by analyzing the quantitative and qualitative relationship the criminal and his/her targets share with the immediate landscape. In doing so, these characteristics emerge that are used to identify how the offender perceives his/her environment, and how the offender behaves within their activity space. When coupled with journey-to-crime modeling techniques

used to quantitatively describe the travel behavior of criminals, geographic profiling can be used by the criminologist to develop new, and enhance existing, investigative strategies and potentially predict the offender's residence, or haven.

Geographic profiles are created by applying a variety of geo-analytical techniques that model travel behavior. One of the most significant techniques available to the criminologist is the distance decay model used to quantitatively measure an offender's journey-to-crime. By measuring the distance decay from any point on a map to each crime scene, the geographic profile can make estimates about where an offender initiated his/her travel. However, a number of circumstances conspire against the predictive effectiveness of such analysis. One such handicap is the distance measure used to model journey-to-crime. Traditionally, geographic profiling models measured crime patterns using straight-line Euclidean distance measures. Yet, these measurements are consistently distorted by various physical and psychological factors that ultimately handicap the model's ability to accurately predict offender residency. Accordingly, if a geographic profile is to become an effective investigative tool, it must be able to accommodate for the anisotropic landscape in which crime occurs.

In an effort to address these issues, this thesis proposed, as a proof of concept, two alternative distance measures to accommodate both the physical and psychological elements associated with travel: the actual travel-path, and the perceived travel cost in terms of time. Using processor intensive network path analysis functions, both travel-path and temporal-path distances measured the wheel-distance (miles) and travel time (minutes) between the origin and destination locations stored within both a calibration sample and test sample data set. This investigation proposed two theories. First, by measuring distance according to the travel-path (the wheel distance), a modeling application would more accurately account for the inherent

impedance factors which ultimately dictate the direction and route an individual can travel when commuting between two locations. Second, in accounting for the least effort principle, the temporal-path measures the time it would take for an individual to travel between an origin and destination when optimizing the commute to conserve time. To test the theory, the residence of four test sample subjects were estimated using geographic profiling models created with straight-line Euclidean, Manhattan, and both the travel and temporal path functional distance measures. Each resulting geoprofile was assessed for error-distance (used to determine spatial precision) and search-cost (the area that needed to be searched in order to identify the residence).

5.1 Conclusions

Upon final examination of the results obtained from this proof of concept, there are a number of conclusions that have been identified. First, functional distance measures can be used to produce accurate geographic profiles. When modeled using both travel-path and temporal-path functional distance metrics, all four residences of the sample population of simulated serial offenders were successfully identified within an averaged error-distance of 1.73 miles from their estimated locations (Tables 4.4 and 4.5). More significantly, the average hit-score was calculated to be 4.53% of the total study area, or a search cost of 8.21 miles² of East Baton Rouge Parish (Tables 4.4 and 4.5). These values performed quite well when compared to the cumulative average error-distance of 1.76 miles, and an average hit-score percentage of 4.34%, or 7.86 miles² (Table 4.6). Of the two functional distance metrics, travel-path measures performed the best, predicting each test subject's residences within an average error distance of 1.66 miles, or 4.01% of the total study area, approximately 7.20 miles² (Table 4.6).

A second conclusion finds that, for any distance metric, model selection is the most critical component for determining the overall effectiveness of a geographic profile.

Specifically, journey-to-crime models using the truncated negative exponential function consistently performed better than either the negative exponential and logarithmic functions (see Table 4.1). Though discussed in detail in Chapter 4 (Section 4.7), a few possible reasons for this can be attributed to the inherent travel characteristics of the sample data sets, the structure of the model (a combination of linear and negative exponential functions), the land use characteristics of East Baton Rouge Parish, and the limited sample size of the calibration and test data sets.

Third, temporal-path functional distance measures do not significantly improve a geographic profile's effectiveness. Of the four metrics used, temporal-path functional distances produced the least accurate predictions, averaging an error-distance of 1.96 miles, or 5.06% of the total study area (approximately 9.20 square-miles). While temporal-path values were not significantly different from the travel-path value (see Table 4.5 in Chapter 4), this unexpected result may be attributable to a number of key characteristics already identified by this research. The most significant factor is that the law-abiding residents surveyed for this investigation did not optimize their travel productions according to time. When given the opportunity to select between a commute optimized for distance (travel-path) and a commute optimized temporally (temporal-path), the majority of those surveyed chose to take the most direct travel path (see Table 4.7). The implication to the criminal investigative process is unclear. Because the sample data sets included only those origins and destinations of law abiding citizens, no conclusive statement can be made for the actual travel behavior of a serial criminal, and thus warrants further investigation.

Fourth, the size of the study area is a significant factor for reducing error. As noted earlier, network and grid-based analyses consistently struggle with the effects of artificial edges. Because only the urbanized area of East Baton Rouge parish was selected to serve as the study

area, a large portion of the parish was excluded from the analysis. As such, the exclusion of potentially valuable portions of the study area most likely would have altered the outcome of these results. For two test subjects, destination locations were positioned outside the study area (see Figure 4.9). While the models were able to account for the location's influence over the distribution, many of the grid cells attributed to the points were lost, and not calculated for the final results. To what extent this may have influenced the results is undetermined.

Furthermore, grid cell resolution played a significant role during the network path analysis routines. As indicated in Chapter 3, because technological limitations restricted the analysis to a grid cells size of 0.23 miles, false network connections are certain to have occurred. That is, the centroid of a given grid cell may have been improperly associated with a particular road or path, or may have randomly selected any one of the possible feature segments that intersected the cell. In such a circumstance, a path could have been selected that would not accurately represent a condition of travel, thus altering distances used by both the calibration and journey-to-crime models. While the size of the study area and resolution of the grid cells were selected as a direct result of the technological limitations of the investigation, it is clear that these parameters are a significant factor for the effective application and predictive ability of a geographic profile.

A final conclusion of this investigation notes that the technological prerequisites needed to complete the processor-intensive network path analysis functions can be achieved using "off-the-shelf" computer and software resources, without the expense of a customized configuration. And while the processing time was extensive, in one instance lasting over two-hours, the results presented by this thesis demonstrate the feasibility of applying functional distance measures to future investigations. The only significant expense that remains is the acquisition of an

appropriate transportation network data set compatible with the chosen GIS platform. As a strategy for obtaining this data, law enforcement organizations are encouraged to participate with local and municipal governments that may have the data, or would be willing to entertain a cooperative partnership to acquire the data. Such collaborative relationships are common, easy to implement (politically), and should be encouraged in order to offset the expense of the data sets needed to obtain the desired information.

5.2 Recommendations

No matter how effective functional distance measures are for enhancing the predictive capabilities of a geographic profile, the true value of any criminal investigative technique can only be assessed by its practical application. This research found that functional distance measures can be successfully calculated and integrated within a geographic profile using easily off-the-shelf technology as well as conventional statistical and GIS software applications. While this research is inherently a theoretical construct, the process of geographic profiling of modeling criminal behavior to identify the haven remains the same. Accordingly, the processes executed by this research can be easily applied to a serial criminal investigation without a great deal of effort. And as would be the case for any modeling application, reliability is only as good as the assumptions made, the techniques utilized, and the meaningful interpretations derived. Accordingly, more needs to be done if this research is to find a practical application. Briefly discussed below are some recommendations that may aid in this objective.

The findings of this research clearly demonstrate that measuring functional distances within geographic profiling is theoretically founded and procedurally sound. However, a larger sample must be employed to demonstrate this conclusively. At best, these conclusions serve only as hypothesis for future studies. Only by modeling a large sample of like-serial criminals

can this methodology be assessed accordingly. Never-the-less, the results and conclusions presented here are done so as a feasibility study and proof of concept to initiate the first steps necessary to achieve that goal.

Another recommendation of this research can be attributed to the operational techniques used by this investigation. A significant amount of time was needed to successfully perform the network path analysis functions needed to obtain the functional distance measures. For study areas that incorporate larger and higher resolution (more dense) distribution of grid cells, the computations could, theoretically, require more than 24 hours of processing. Once completed, a grueling series of calculations between various statistical, GIS, and database software applications are executed. Complicating the situation even more, additional software becomes necessary, solely for the purpose of managing the output. The tediousness of these processes become magnified when it is intentionally repeated for the purpose of recalibration (required every few years), or created anew for each individual police jurisdiction. Therefore, if a geographic profile is to distinguish itself from other investigative techniques, it must demonstrate its utility as a cost-effective tool that can be easily implemented in a meaningful and intuitive way. Clearly, the complexities associated with the manual implementation of the methods presented in this research do not meet these criteria. Accordingly, a geographic profiling applications enhanced by functional distance measures must be accessible as a package, combining all the necessary functions, models, and techniques within one, intuitive interface capable of providing a meaningful output.

A third recommendation serves as a cautionary note for the criminal investigative process. As discussed in Chapter 3, the effectiveness of a geographic profile is dependent upon the primary assumption that the crime sites associated with a localized serial offender share a

direct relationship with the offender's activity space. However, investigators looking to utilize the enhanced resources of functional distance measures must also accommodate a second assumption, that the offender will optimize his or her travel when commuting between residence and crime scene. Only by certifying these two assumptions can the criminologist expect to develop an effective geoprofile. But no matter how many assumptions are made, or how similar an offender's travel behavior matches that of a law-abiding citizen, the predictive effectiveness of a geographic profile remains vulnerable to the vagaries of the serial offender's behavior. Because geoprofile models are calibrated to the spatial behavior of like-offenders, a serial criminal that demonstrates atypical travel characteristics/patterns will likely lead an investigation in the wrong direction. Only the insight of an experienced investigator can determine if the pattern is typical or not, and thus the effectiveness of the tool. As such, geographic profiling must be considered a supplement to existing techniques, not a substitute.

5.3 Further Topics of Study

The combined efforts of the Brantingham's, Newton, Canter, Rossmo, Levine, and countless others have been instrumental for the development of contemporary geographic profiling techniques. The extensive body of work established by these researchers continues to expand and inspire others to develop new techniques and strategies that will ultimately enhance its application. As the very nature of this thesis indicates, new methodologies are continuously being proposed and tested for validity. While there are numerous quantitative and qualitative techniques that can be applied to this study, three specific areas of research stand-out in their potential to utilize functional distance measures: competing destination and intervening opportunities; transportation modeling between traffic analysis zones; and micro-level geographic profiling of offender probability surfaces.

As demonstrated by both Rational Choice and Crime Pattern theory (Chapter 2), criminal activity occurs in specific (*i.e.* non-random) locations, specified by the various objective and subjective characteristics attributed to that location. Research examining how individuals perceive their geographic surroundings indicates that spatial information is cognitively stored and processed within hierarchical structures. How these structures are evaluated represents a critical component for the decisions an individual will make as he or she travels from one location to another (Curtis, 1995). By incorporating this concept of spatial choice within geographic profiling models, it may be possible to account for how a criminal evaluates and selects a potential crime site. Of the various formulations available, competing destination models has been proven to be an effective method for quantifying an individual's spatial choice (Fotheringham, 1988). Characteristics that include distance, path, availability, size, and spatial configuration (*i.e.* how much information is available for a particular area) can be enumerated within a journey-to-crime model, quantifying how an offender evaluates the prevailing landscape when initiating a crime. Such a model would represent a more comprehensive foundation for understanding offender hunting behavior and site selection.

Evaluating the quality of a destination can also be achieved by using travel demand models. However, these techniques are notorious for their limited ability to accommodate for spatial choice. As Levine (2002a) notes, existing travel demand models utilized by transportation planners are overly simplistic measures that are not capable of accommodating the variety of conditions and circumstances that are observed for 'real life.' Briefly discussed in Chapter 2 (Section 2.4), the probability that an offender will commit a crime at a particular location is conditionally dependent upon an individual's assessment of both the travel cost and the attractiveness for that destination when compared to any intervening opportunities (Stouffer,

1940, Guldman, 1999). Any travel model that can allocate offender trip behavior according to origin, destination, distance, mode, and path will stand out in its ability to account for the available opportunity a particular destination has over another potential destination.

Accommodating for these travel characteristics are techniques that expand on existing transportation modeling algorithms to look at criminal journey-to-crime between traffic analysis zones (TAZ), a GIS data layer available through the U.S. Census Bureau. Criminologists can use transportation models to look at the aggregated volume of crime trips produced-by and attracted-to each TAZs in order to estimate how journeys-to-crime are allocated according to origins, destinations, distances, and the routes between them (i.e. network path). Trip-production (origin) and trip-attraction (destination) values are calculated from variables associated with each zone (i.e. demographics, income, land use, etc). Each trip is then distributed to every other zone using an empirically calibrated distance decay model. As such, a zone with a large number of trip-productions will receive a greater number of trip-attractions (which decreases with distance). The resulting calibration measure represents the predicted travel attractiveness between each origin zone and each destination zone. Those values are assigned to particular network routes using shortest network path algorithms. In the context of geographic profiling, it identifies the most likely zone from which the perpetrator originated, and the commute most likely used based on the attractiveness of that zone. As noted by Levine (2002a), because these models are simultaneously calculated over the entire field of study, all intervening opportunities are accounted for within the model.

Another possible topic of study is the utilization of offender residency probability surfaces (ORP), and incident based ORP surfaces for predicting the likely perpetrator by assessing the rank of potential offenders from a police-generated suspect list. Proposed by

researchers Gore and Tofiluk (2002), the process utilizes various distance decay curves to model the aggregated travel behavior of a sample group of like offenders for a given area. The distance decay models are used to rank the suspect list as an investigative time-savings strategy. Gore and Tofiluk's (2002) results find that incident based distance decay curves (distance decay curves applied to a defined hot spot of criminal activity) have an advantage over traditional journey-to-crime decay curves because they are not affected by sub-structural or domain characteristics usually attributed to models that extend over a large urban area. Incorporating these methods within a geographic profiling routine may enhance the results obtained for this investigation by improving predictive accuracy and reducing the time needed to perform the processor intensive network path analysis.

All told, the findings of this thesis support the utility of functional distance measures for the criminal investigation of a serial crime. Despite the small sample size, the results of this investigation demonstrated the theory's conceptual validity as well as the procedures suitability. As illustrated in Figures 4.5 – 4.8, the mere fact that each geoprofile density surface was able to illustrate the underlying structure of the East Baton Rouge urban landscape is in itself a clear indicator that functional distance measures can model an individual's travel behavior. Accurately identifying three out of four residences within 0.73% (1.33 miles²) of the total study area provides the proverbial "icing on the cake," demonstrating that these metrics can perform. However, the extent from which a geographic profile's effectiveness is enhanced for predicting the residence of a localized serial offender remains uncertain, and exists as the subject of future research.

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APPENDIX A TRAVEL DIARY QUESTIONNAIRE

If you live in East Baton Rouge parish, please provide, with confidence, ten (10) locations within East Baton Rouge parish in which you CHOSE to travel from your home. Examples can include gas stations, grocery stores, a mall, a park, a friend's house, bar/restaurants, etc.

Please limit your list for only those places in which you wanted to travel. Examples must NOT include work related places or those locations that you would not have normally chosen to travel from your residence (for example: a store near a friend's house). Preferred destinations are those that you would normally use to complete routine activities from your home.

The logic behind these CHOSEN locations is that you could have opted to visit some other destination that would fulfill the same need. But, for what ever reason, you selected one location over another (due to its attractiveness, convenience, etc.).

Finally, please provide your home address.

To participate, please include the following:

List 10 locations you recently drove to, anywhere in East Baton Rouge parish. Provide your home address last.

Below are answers to frequently asked questions:

- Provide a street address. If unknown, cross-streets will do.
- Provide the place name, especially if it can help determine the location (i.e. Albertsons on Bluebonnet).
- Must be in East Baton Rouge parish.
- Can be any place in which you would normally travel from your residence.
- Can be a friend's house, gas station, grocery store, fitness center, etc.
- Keep redundant instances to a minimum.
- Best if those locations are not in a chain (i.e. do not include those destinations where you traveled from one place to another to another).
- Cannot be work, or school related.
- Do not include unique locations that do not have alternatives (Examples include a circus, concert, Mardi Gras parade/ball, or other unique location).

	Location Name	Address	Description
1			
2			
3			
4			
5			
6			
7			
8			
9			
10			
11			RESIDENCE

APPENDIX B COMMUTER SURVEY

To complete the survey, please choose the answer that BEST describes a condition of your driving/travel behavior. You may indicate your answer (a,b,c,d,e) next to the question.

Please note that these questions only refer to trips to locations within this parish. Please do not consider long-distance travel in this survey.

- 1) How often do you drive?
 - (a) Daily
 - (b) Every other day
 - (c) A few times a week
 - (d) Rarely / only as needed

- 2) How many destinations do you typically make on an average commute/drive?
 - (a) One
 - (b) Two
 - (c) Three
 - (d) More than three

- 3) When you drive to a location, is distance (miles) to destination a factor in planning the commute?
 - (a) Always
 - (b) Most of the time
 - (c) Some of the time
 - (d) Rarely
 - (e) Never thought about it

- 4) When you drive to a location, is the time (minutes/hours) to destination a factor in planning the commute?
 - (a) Always
 - (b) Most of the time
 - (c) Some of the time
 - (d) Rarely
 - (e) Never thought about it

- 5) I consider myself a/an
 - (a) Defensive driver
 - (b) Aggressive driver

- 6) Do you consider traffic/congestion a problem?
 - (a) Yes
 - (b) No

- 7) If given the opportunity to avoid congestion, you would:
 - (a) Take a less-congested and familiar alternate route
 - (b) Take a non-congested and unfamiliar alternate route
 - (c) Travel at a different time
 - (d) Accept the congestion
 - (e) None of the above

- 8) Considering your driving preferences, how would you categorize your driving style:
 - (a) Direct path traveler (fewest turns, often use major arteries)

- (b) Indirect path traveler (many turns, often use "back-streets")
- (c) Hybrid (combination of A and B, depending on traffic conditions)
- (d) Other

9) When choosing between two super markets to purchase equally available products, you would most likely:

- (a) Travel to the closest market, with slightly higher prices
- (b) Travel further to the market with slightly cheaper prices

10) How many licensed drivers reside at your address?

- (a) One
- (b) Two
- (c) Three
- (d) More than three

VITA

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