Evaluating the usefulness of functional distance measures when calibrating journey-to-crime distance decay functions

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Abstract

This research evaluates the usefulness of applying functional distance measures to criminal geographic profiles using mathematically calibrated distance decay models. Both the travel-path (i.e., shortest distance) and temporally optimized (i.e., quickest travel time) functional distance measures were calculated based on the impedance attributes stored within a linearly referenced transportation data layer of several parishes in Louisiana. Two different journey-to-crime distance decay functions (i.e., negative exponential, and truncated negative exponential) were mathematically calibrated for “best fit”, based on the distribution of distances between homicide crime locations and offender’s residences. Using the calibrated distance decay functions, geographic profiles were created for a localized serial killer from Baton Rouge, Louisiana. A probability score was calculated for every point within the study area to indicate the likelihood that it contained the serial offender’s residence. A comparison between the predicted
Spatial analysis has long been a valuable tool used within the criminal investigative process. This is especially true for serial offense cases where criminologists apply geographic profiling to model offender mobility and crime distribution patterns in order to estimate a criminal’s likely residence. Yet, traditional analytical methodologies have avoided the utilization of functional distance measures when modeling an offender’s journey-to-crime within a diverse and varied landscape. By substituting straight-line Euclidean distances with travel-path functional distance measures, the predictive utility and technological costs associated with geographically profiling a localized serial killer was assessed using mathematically calibrated distance decay models.

2. Background

The theory and conceptual framework of this research is built upon environmental criminology (Brantingham & Brantingham, 1981). Environmental criminology consists of a number of theoretical concepts, including Routine Activity, Crime Pattern, Rational Choice, and the Buffer Zone postulate that provide an ecological heuristic for understanding the relationship crime has with place. These concepts establish a quantitative and qualitative approach for analyzing the operational, behavioral, perceptual, social, legal, cultural, and geographic factors of a crime (Rossmo, 2000).

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

While Routine Activity theory does support observations that criminal opportunity can exist anywhere within the offender’s awareness space, an offender does not necessarily choose crime sites randomly. Instead, research finds that criminal activity is spatially dependent upon proximity to the offender’s activity nodes, which can include the offender’s residence, place of work, and/or favorite recreation spot (Canter
These activity nodes define an offender’s awareness space. When examined geographically, the processes an offender uses for target selection can reveal patterned structures that describe how an offender operates within his/her awareness space, a concept known as Crime Pattern theory (Brantingham & Brantingham, 1981, 1984; Rossmo, 2000). The Rational Choice theory postulates that criminal behavior is an outcome of decisions that are influenced by rational consideration of the efforts, costs, and rewards associated with a crime (Brantingham & Brantingham, 1984). When examining the geographic characteristics of certain types of crime, Rational Choice theory can describe another environmental criminology concept: the offender’s buffer zone (Brantingham & Brantingham, 1984). The buffer zone represents an area surrounding an offender’s particular activity node, most notably the residence, from which little to no criminal activity will be observed. This buffer zone is seldom observed for spontaneous and/or crimes of passion (LeBeau, 1987). Conversely, research suggests that such a zone will most likely occur for predatory offenses, which can be characterized as pre-meditated (Canter & Larkin, 1993).

3. Journey-to-crime modeling

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

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

The mean and median center, as well as the center of minimum distance use different approaches to measure the center of a distribution of crime sites. The medial circles technique utilizes circle theory to define an area around the occurrences of each offense in order to identify and develop a list of likely suspects. Each circle’s radius is defined by journey-to-crime measures of similar crime types. The mobility triangles approach examines the relationship between offender residence, target location, and crime scene in order to solve a crime. Finally, the most effective technique for journey-to-crime analysis is the distance decay function.
Distance decay functions are quantitatively rooted in the family of gravity models based on Isaac Newton’s fundamental law of attraction. The term “distance decay” characterizes how the attraction between two bodies decreases as the distance between them increases. When placed in the context of modeling travel behavior, the concept characterizes how individuals typically prefer to produce short commutes rather than long trips for the normal travel activities of their every day lives (Harries, 1999). Crime, like pedestrian traffic, shopping, telephone conversations, migration, and a host of other behavioral interactions, is subject to the general class of inverse distance variations formulated as gravity laws (Smith, 1976). Transportation planners typically use distance decay functions within their mathematical models to help simulate human travel characteristics (Beimborn, 1995; Levine, 2002). In terms of its usefulness for modeling criminal mobility, distance decay can be used to represent how a criminal offender travels within his or her awareness space. Capone and Woodrow (1976) investigate the relationship between urban structure and criminal mobility by describing and explaining the distance biases of robbery offenders in metropolitan Miami. Lu (2003) goes beyond the analysis of a criminal’s travel behavior to include journey-after-crime characteristics and finds that journey-after-auto-theft involves both distance and direction biases.

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

Levine (2002) provides a detailed list of various theoretical and mathematical modeling functions used by transportation researchers that include linear, negative exponential, normal, lognormal, and truncated negative exponential distance decay curves, among others. Each function possesses various characteristics that can be utilized by journey-to-crime models. For example, the normal, lognormal, and truncated negative exponential are functions that characterize how the spatial distribution of criminal activities reach a peak at a certain distance away from the haven (i.e., the offender’s residence) before exhibiting a decay as the distance from the origin increases. This type of function, most notably truncated negative exponential, is often used to describe the presence of the Brantingham’s proposed buffer zone effect. However, research in spatial interaction modeling points out that parameter estimates used in exponential functions are scale-dependent. In practical terms this means that exponential distance decay functions cannot be transferred from one study area to another, but have to be calibrated anew in order to account for differences between study environments travel distances (Fotheringham & O’Kelly, 1989). Only recently have researchers investigated the effectiveness of the various different distance decay formulae for estimating the offender’s haven (Canter, Coffey, Huntley, & Missen, 2000; Levine, 2002; Taylor, Bennell, & Snook, 2002). This research
tests the effectiveness of the negative exponential and truncated negative exponential distance decay formulae for estimating the offender’s haven.

4. Criminal geographic profiling

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

Criminal geographic profiling is a decision support tool used by law enforcement to make estimates about the likely location of a serial offender’s haven (Godwin, 2003; Rossmo, 2000). Law enforcement can use geographic profiling models to maximize limited resources and create investigative strategies that focus on those locations that possess significant likelihood of being a part of an offender’s hunting area (Canter, 2003; Canter et al., 2000). Rossmo (2000) notes that journey-to-crime estimates, mental map interpretations, Thiessen polygons, and other analytical approaches can be, and have been, successfully applied for the geographic analysis of crime. In certain circumstances, geographic profiling can also be used as a forensic tool capable of verifying the existence of a serial offender (Newton & Swoope, 1987).

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

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

5. Characteristics of a serial offender

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

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

Assessing the suitability for a geographic profile begins when an investigation is reasonably certain that a serial offender is present. In a process commonly referred to as linkage analysis, investigators attempt to connect various crime scene elements
to a single offender through the forensic exploration of evidence (Canter, 2003; 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. Most experts agree that a serial offender can be defined as an individual (or a collective group of individuals) who (Hinch & Hepburn, 1998; Holmes & Holmes, 1998):

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

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

Newton and Swoope (1987) propose that serial offenders be divided into broad categories: “mobile” (geographically transient) and “static” (geographically stable). Mobile offenders commit crimes over large areas that cross cultural and psychological boundaries. These offenses predominantly occur outside the offender’s awareness space and involve complex hunting strategies. A specific characteristic of a mobile offender is that his or her hunting area lacks a definable anchor point from which the offender operates (Rossmo, 2000). Conversely, static offenders commit crimes within a confined area, usually bounded by psychological barriers and landscape features. Furthermore, static offenders typically operate within their awareness space as they travel between activity nodes. As such, the offender will likely have an anchor point (the haven) from which to operate. These characteristics have been observed and are supported by numerous published findings (Canter & Larkin, 1993; Hickey, 1997; Holmes & Holmes, 1998).

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

When a localized (static) serial offender (marauder) hunts within his or her activity space, he/she does so within a culturally, psychologically, and geographically homogeneous landscape. As such, that landscape upon which the offender basis his or her movement is contextually the same. Therefore, the ability to model that offender’s movement between his or her activity nodes is more easily achieved because there are little variations in the limiting factors that control movement. Conversely, the dispersed (mobile) serial offender (commuter) hunts across various
cultural and psychological environments that result in a collection of continuously complex, heterogeneous landscapes. The activity space in which the commuting offender travels is not contextually consistent, and will often lack definable activity nodes. It possesses dissimilar land-use policies, geographic features, cultural constructs, and so on. As a consequence, the ability to model offender behavior across heterogeneous ecologies is severely handicapped. Any geographic profile created for a non-localized offender will be founded on a diluted collection of crime sites that will most likely lack meaningful patterns due to the variability associated with the mobility of the offender. Consequently, modern and contemporary geographic profiling models yield best results when applied to a geographic stable serial offender, who operates from a definable anchor point (mostly the offender’s residence). These models should not be applied to mobile offenders, who commit crimes over large areas and do not possess a definable anchor point. Canter (2003) discusses the complexities and issues involved in geographically profiling a mobile serial offender. It should be noted, though, that even the “homogenous” landscape of the localized serial offender is still a spatially complex environment where all information cannot be processed simultaneously requiring a degree of hierarchical processing where “like” places are nested together (Fotheringham & O'Kelly, 1989).

6. Study area and data

The study area used by this research is defined by the maximum spatial extent of crime locations associated with the confessed Baton Rouge serial killer, Sean Vincent Gillis. The 2094.75 mile² study area consists of 4175 grid cells and covers the following Louisiana parishes (counties) partially or completely: Ascension, East Baton Rouge, East Feliciana, Iberville, Livingston, Point Coupee, St. Helena, St. Martin, West Baton Rouge and West Feliciana.

The sample data typically utilized for an investigation of this nature incorporates crime data specific to both the study area and the type of serial offense investigated. As Levine (2002) notes, geographic profiling models should be calibrated for the unique parameters that characterize specific criminal offenses for specific jurisdictions. Following these recommendations, two data sets were collected for this research. The first data set was gathered from police reports made available by the Homicide/Armed Robbery Division, Baton Rouge Police Department (BRPD). It includes a total of 497 homicide cases reported over a 7-year period from 1991 to 1997 (Leitner & Binselam, 1998). Of these, 325 had known offender residence locations, of which 301 were successfully associated with a crime location and geo-coded to the road network of the study area. The second data set includes a total of nine crime sites that have been associated with the serial killer, Gillis. Eight of the nine crime sites are body dumpsites and one is a point of fatal encounter. Gillis’s hunting style can be described as that of a typical localized marauder. The locations for all nine crime sites have been reported in detail in the local news media, so was his residence following his apprehension on April 29, 2004. Four of the nine crime sites and the residence of the serial killer are located in Baton Rouge (Fig. 5, Section 8).
information reflects the status of the ongoing investigation at the beginning of August 2004, when this manuscript was revised and resubmitted.

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

7. The criminal geographic profile procedure

The modeling process used to develop a criminal geographic profile is founded on the conceptual application of the CrimeStat® II journey-to-crime routine (Levine, 2002). In order to establish a sufficient representation for the travel patterns of like criminals, the calibration group must be large enough to ensure reliable calibration parameters. Accordingly, the 1991–1997 homicide data represent a suitable calibration group from which to empirically derive the most appropriate distance decay models. The crime locations of the serial killer represent the test group. Gillis’s first known victim was an 82-year-old woman, who was killed more than ten years ago in March 1994. His last known murder was a 45-year-old woman, found in January 2004. This means there is a sufficient temporal overlap between the calibration and test group. In addition, the major arteries of the road network in and around Baton Rouge have not changed since the beginning of the 1990s.

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

Using the crime locations stored within the test group data set (eight body dump-sites and one point of fatal encounter), the serial killer’s residence is estimated based on the mathematically calibrated distance decay function defined for the observed travel patterns of the calibration group (the 301 homicide cases). The calibrated function mathematically assigns a value for each grid cell centroid within the study area. Called a “probability score”, the values are used to indicate the likelihood that any location within the study area is the serial killer’s likely residence.

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

8. Analysis and results

Using direct-path Euclidean, indirect-path Manhattan and two different functional distance measures (shortest travel-path and quickest temporal-path), eight geographic profiles were created using two unique distance decay models. The results of all eight geographic profiles are summarized in Table 2 and only the best and most accurate geographic profile is mapped (Fig. 2).

8.1. Frequency distributions of homicides by distance metric

Fig. 1 illustrates the frequency distributions for each distance measure calculated from the calibration group data set (the 301 homicide cases). The frequency distribution for the indirect-path Manhattan metric is not shown here, as it is a computed metric based on the values measured for the direct-path Euclidean distance. Results show that independent of the distance metric used, the frequency distributions look markedly similar. The significant spike (very high frequency) near the offender’s residences corresponds with environmental criminology research results, which indicate that the majority of human activities are performed within close proximity to the home. More than half of all homicides are committed at a location that is within one mile of the offender’s residence. In contrast to environmental criminology research, a buffer zone effect is not observed with any of the distance metrics used. As the distances increase, there is a general decrease in activities for each distance metric. The maximum distance an offender is willing to travel to commit a homicide is almost 12 miles straight-line, approximately 15 miles using the shortest path in the road network and just over 25 min in travel time using the quickest route.

8.2. Journey-to-crime calibration models

Two distance decay functions were selected to model the frequency distributions observed in Fig. 1. These functions included negative exponential (Eq. (1)) and truncated negative exponential. The latter is a joined function consisting of a linear (Eq. (2a)) and a negative exponential (Eq. (2b)) part. Both functions are implemented in the CrimeStat® II journey-to-crime routine (Levine, 2002) and their applicability to geographic profiling has been widely supported in the literature (Section 3). The
Fig. 1. Frequency distributions of homicides by distance metric: (A) direct-path Euclidean distances, (B) shortest travel-path, and (C) quickest temporal-path.
truncated negative exponential function simulates the buffer zone around the offender’s haven where little to no criminal activity can be observed (Section 2). The negative exponential function does not.

\[ y = Ae^{-Rx} \]  \hspace{1cm} (1)

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

\[ y = Cx \quad \text{for } x > 0 \text{ and } \leq 0.5 \text{ miles (0.858 min)} \]   \hspace{1cm} (2a)

\[ y = De^{-Ex} \quad \text{for } x > 0.5 \text{ miles (0.858 min)} \]   \hspace{1cm} (2b)

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

Using SPSS® 11.0 for Windows (SPSS Inc., 2001), both functions were individually regressed for each distribution, thus mathematically calibrated to produce a “best fit” model of the provided distributions. Models were organized according to the four distance metrics used for this investigation: direct-path Euclidean, indirect-path Manhattan, shortest travel-path and shortest temporal-path. The results of all models are visually presented in Figs. 2–4. Calibrations were not specifically required for the Manhattan metric as it measures distances as a function of Euclidean distances between two points. As such, the Manhattan metric uses the same calibration decay model as the straight-line Euclidean. Estimated parameters, standard

![Fig. 2. Calibrated distance decay functions by direct-path Euclidean metric.](image-url)
errors, and coefficients of determination ($R^2$) for all calibrated distance decay functions, with the exception of the Manhattan distance, are summarized in Table 1.

The negative exponential model clearly under-estimates the significant spike at the beginning (the first one mile) of the frequency distribution for each distance metric.
but provides a relatively good fit for the remainder of the distribution. In contrast, the truncated negative exponential model fits the spike in all distributions very well, but mostly over-estimates the distributions beyond a one-mile distance (Figs. 2–4). The truncated negative exponential model with distances measured as direct-path Euclidean provides the overall best statistical fit ($R^2 = 0.851$). The truncated negative exponential model combined with shortest travel-path distances performs the worst, but still captures 72% of the variations in the original frequency distribution. Independent of the calibration model, Euclidean distances provide the best statistical fit, followed by temporal-path and travel-path distances (Table 1).

### 8.3. Best performing geographic profile

All geographic profiles consist of a density surface map measuring 75 columns $\times$ 57 rows completely enclosing all crime locations used in this research. Each individual cell covers an area of 0.49 miles$^2$ (0.7 $\times$ 0.7 miles) and is assigned a probability score indicating the likelihood that it is the residence of the serial killer, Gillis (Fig. 5). The chosen cell size provides a balance between a large enough study area while ensuring consistent computer performance when estimating geographic profiles.

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

### Table 1

<table>
<thead>
<tr>
<th>Distance metric</th>
<th>Calibration model</th>
<th>Parameter estimates (standard errors)</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Direct-path Euclidean</td>
<td>Negative exponential</td>
<td>$11.628$ ($2.624$) $-0.327$ ($0.035$)</td>
<td>$0.819$</td>
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<td>Direct-path Euclidean</td>
<td>Truncated negative exponential</td>
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<td>Negative exponential</td>
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<tr>
<td>Travel-path</td>
<td>Truncated negative exponential</td>
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<td>$0.720$</td>
</tr>
<tr>
<td>Temporal-path</td>
<td>Negative exponential</td>
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<tr>
<td>Temporal-path</td>
<td>Truncated negative exponential</td>
<td>$85.961$ ($3.140$) $14.905$ ($0.016$) $-0.139$ ($0.016$)</td>
<td>$0.785$</td>
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</tbody>
</table>

The parameter notations ($A$–$E$) refer to the same parameter notations used in Eqs. (1), (2a) and (2b). No standard error for the parameter of the linear part of the truncated negative exponential model was estimated, but directly calculated from the original frequency distribution of homicides. All $R^2$ values are highly significant at $p < 0.01$. 


actual residence of the serial killer. Search cost is determined by calculating each geographic profile’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

Fig. 5. Best performing geographic profile overall.
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 identifying the offender (i.e., the number of grid cells to search before apprehending the suspect).

Eight geographic profiles combining each distance metric with each distance decay model are shown in Table 2. Overall, geoprofiles created with the negative exponential distance decay function more accurately predict the residence of the serial killer. Of all distance metrics, indirect-path Manhattan distances performed slightly better than direct-path Euclidean. In contrast, geographic profiles created from the two functional distance metrics estimate the residence of the serial killer rather poorly. This is good news, because geographic profiles based on functional distance metrics, and especially shortest travel-path are time-consuming, computational intensive and costly to create. In contrast, geoprofiles created from Euclidean and Manhattan distance metrics are readily available in existing software packages.

The straight-line distance between the predicted and the actual residence (error distance) measured a very low distance of 0.49 miles for all eight geoprofiles. Of those, three geoprofiles are able to identify the actual residence of the serial killer with an averaged hit score of 0.05%, approximately 0.98 miles$^2$, of the 2094.75 miles$^2$ study area. Relative to the size of this large study area, this is an extremely low hit score and a very small area to be searched (Table 2).

Fig. 5 illustrates a density map for one of the three best performing geoprofiles, combining the Euclidean distance metric with the negative exponential distance decay function. The main map shows a portion of the study area with six of the nine crime sites. The inset map in the lower right corner shows the entire study area including all nine crime sites. The actual residence of the serial killer clearly falls

<table>
<thead>
<tr>
<th>Distance metric</th>
<th>Calibration model</th>
<th>Hit score (%)</th>
<th>Accuracy (%)</th>
<th>Grid cell count</th>
<th>Search cost (miles$^2$)</th>
<th>Error distance (miles)</th>
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<tbody>
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<td>Direct-path Euclidean</td>
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<td>Indirect-path (Manhattan)</td>
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<td>2</td>
<td>0.98</td>
<td>0.49</td>
</tr>
<tr>
<td>Indirect-path (Manhattan)</td>
<td>Truncated negative</td>
<td>0.05</td>
<td>99.95</td>
<td>2</td>
<td>0.98</td>
<td>0.49</td>
</tr>
<tr>
<td>Travel-path</td>
<td>Negative exponential</td>
<td>0.19</td>
<td>99.81</td>
<td>8</td>
<td>3.92</td>
<td>0.49</td>
</tr>
<tr>
<td>Travel-path</td>
<td>Truncated negative</td>
<td>0.22</td>
<td>99.78</td>
<td>9</td>
<td>4.41</td>
<td>0.49</td>
</tr>
<tr>
<td>Temporal-path</td>
<td>Negative exponential</td>
<td>0.24</td>
<td>99.76</td>
<td>10</td>
<td>4.9</td>
<td>0.49</td>
</tr>
<tr>
<td>Temporal-path</td>
<td>Truncated negative</td>
<td>0.26</td>
<td>99.74</td>
<td>11</td>
<td>5.39</td>
<td>0.49</td>
</tr>
</tbody>
</table>
within the two grid cells with the highest probability scores. These two cells cover a mostly residential neighborhood in the southern part of the city of Baton Rouge with single-family houses, apartment complexes, retail stores, and some gas stations.

9. Discussion of results

The geographic profiles created in this research predicted the actual residence of a Baton Rouge serial killer extremely accurately. The error distance for all geoprofiles was within 0.49 miles of the actual residence and the three best profiles estimated an averaged hit score of 0.05%, defining a search area of 0.98 miles$^2$. These results strongly support the notion that geographic profiles should be created and used as often as possible when a criminal investigation involves a serial offender. The results also indicate that a geographic profile cannot identify the exact location of the residence of the serial offender. However, from a practical point of view, law enforcement can focus their limited resources and investigative strategies to the search area identified by a geographic profile.

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

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

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

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

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