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RESEARCH ARTICLE

The effectiveness of calibrated versus default distance decay functions for geographic profiling: a preliminary examination of crime type

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This study examines whether a distance decay function calibrated for a particular crime type results in more accurate geographic profiles compared to default functions that are not calibrated for one specific crime type. Decay functions were calibrated for three different types of serial crime (residential burglary, theft, and auto theft) collected from the same geographic region (Glendale, AZ, USA). The two default functions used for comparison purposes (truncated negative exponential and negative exponential) came from *CrimeStat* (v. 3.1), a computerized geographic profiling system. The hypothesis that calibrated functions would possess more predictive power than default functions was not supported. Potential explanations for these findings are provided and implications are discussed.

Keywords: geographic profiling; distance decay; journey-to-crime; serial crime; offender spatial behaviour

Introduction

Rossmo (2000) describes geographic profiling (GP) as 'an investigative methodology that uses the locations of a connected series of crimes to determine the most probable area of offender residence' (p. 1). Investigators often rely on GP as a tool for prioritizing potential suspects, with those suspects living closest to the predicted home location being focused on first (Rossmo, 2000). Although there are different strategies for conducting GP, they all rely on the same underlying assumptions that most serial offenders do not travel far from their home location to commit their crimes and that most serial offenders live within the area covered by their criminal activity. When these assumptions are valid, it should be possible to accurately predict where an offender resides based on the locations of his crimes (Rossmo, 2000).

While there are numerous strategies available for constructing a geographic profile, probability distance strategies are the most common (Snook, Zito, Bennell, & Taylor, 2005). Virtually all of the probability distance strategies currently in use today rely on a distance decay function to model the spatial behaviour of serial offenders (Rengert, Piquero, & Jones, 1999). These functions can take a variety of mathematical forms, including linear, lognormal, negative exponential, normal, and truncated negative exponential functions (Levine & Associates, 2007). However, regardless of form, distance decay functions are used to reflect the fact that an

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offender tends to commit their crimes closer, rather than further away, from their home location.

Graphically, this tendency to commit crimes close to home can be depicted by a curve indicating that the frequency (or probability) of crimes being committed by an offender decreases (on the *y*-axis) as the distance from their residential location increases (on the *x*-axis) (e.g. Canter & Larkin, 1993; Kocsis & Irwin, 1997; Sarangi & Youngs, 2006). However, in the case of GP, the traditional distance decay function is inversed so that the *x*-axis reflects increasing distance from a crime location and the *y*-axis reflects the likelihood of the offender actually residing in locations at those various distances (Rossmo, 2000).

In order to predict the location of an offender's residence using probability distance strategies, some type of distance decay function is applied (using specialized computer software; Canter, Coffey, Huntley, & Missen, 2000; Levine & Associates, 2007; Rossmo, 2000) around each of the crime sites making up an offender's crime series. Locations (pixels) around the offender's activity space are assigned positive real numbers. Where the functions applied to the different crimes overlap, these positive numbers are essentially summed to reflect the overall probability that the offender resides at those locations. When the cells are assigned colours based on their probabilities, the end result is a probability surface that specifies how likely it is that the offender resides in each of the areas within the offender's activity space (Snook et al., 2005). This surface can then be searched in a systematic fashion for the offender's residence (e.g. by starting at the highest point of probability and working outward).

The specific decay function used for GP is expected to take on a different form depending on the assumptions being made about an offender's spatial behaviour, even though it is always assumed that the offender will be living relatively central to his crime site locations (Canter & Hammond, 2006). For example, the negative exponential function predicts that the likelihood of an offender living in a particular location is highest at the crime site and decreases at an exponential rate as the distance from the crime site increases (Canter et al., 2000). In contrast, the truncated negative exponential function, as described by Levine and Associates (2007), predicts that there is likely to be an area around the crime site where the offender is less likely to live (i.e. a buffer zone), and at some optimal distance away from the crime site the probability of a location including the offender's home peaks and then decreases in an exponential fashion (i.e. probability follows a linear function until peak likelihood is reached and then follows a negative exponential function thereafter).

The accuracy of GP systems

Currently, computerized GP systems (e.g. *Rigel*, *Dragnet*, *CrimeStat*) are often used to construct geographic profiles in operational settings and these systems rely on one or more of the probability distance strategies listed above (Canter et al., 2000; Levine & Associates, 2007; Rossmo, 2000). A small amount of research has been conducted to assess the accuracy of the various GP systems that are used. This research usually draws on one of two measures of accuracy: either error distance (i.e. the straight line distance between a predicted home location and the actual home location) or hit percentage (i.e. the percentage of a prescribed area that has to be searched before an offender's home location is found).

For example, Rossmo (2000) used information from FBI serial murder cases to evaluate *Rigel*, which relies on a function similar to a truncated negative exponential function (essentially a non-linear increasing function within the buffer zone and an inverse distance function beyond the buffer zone). Case selection was based on whether the crime series matched certain assumptions that are thought to be necessary for GP to be effective (e.g. the offender could not be commuting into his area of criminal activity, but had to live within their area of criminal activity). He found that *Rigel* achieved a mean hit percentage of 6%. In other words, on average across the profiles that were constructed for these cases, only 6% of the total prioritized search area had to be searched before the offender's home location was found. The hit percentages across all of the serial murder cases he examined ranged from 1.1% to 17.8%, with a median of 4.2%.

In a similar study, Canter et al. (2000) examined the GP system, *Dragnet*. Unlike Rossmo (2000), Canter and his colleagues examined a range of distance decay functions to determine which one produced the most accurate profiling predictions and they did not use any formal selection criteria for their test cases. Using the body disposal locations of 79 American serial killers who had each committed a series of 2–24 crimes, they found that several negative exponential functions were capable of producing accurate results (more accurate than truncated negative exponential functions) with the most accurate parameters resulting in an average hit percentage (or 'search cost') across the sample of 11%.

In addition to these formal evaluations of GP systems, a series of studies have also been conducted to examine whether simpler forms of GP (including human-based predictions) are as effective as more complex (i.e. computer-based) forms of GP (e.g. Bennell, Snook, Taylor, Corey, & Keyton, 2007; Bennell, Taylor, & Snook, 2007; Paulsen, 2006; Snook, Canter, & Bennell, 2002; Snook, Taylor, & Bennell, 2004; Taylor, Bennell, & Snook, 2009). Using error distance as the primary measure of accuracy, the results from these studies suggest that simpler forms of GP, such as the use of centroid calculations, are as accurate as more complex forms (Paulsen, 2006), and that human participants, when taught to use basic GP principles, also perform as well as computerized GP systems (Bennell, Taylor et al., 2007).

In sum, the results from formal evaluations of GP systems indicate that these systems are reasonably effective at decreasing the size of the area that needs to be searched in order to identify an offender's home location, although there clearly is still room for improvement (i.e. hit percentages could theoretically be decreased even further). In addition, simple GP methods appear to be as accurate as more complex and less cost-effective GP systems (however, see Rossmo, 2005 for counter-arguments), although this might not be the case if more accurate GP systems are produced.

Improving the accuracy of GP systems through the use of calibrated functions

The accuracy of GP systems can be improved in a variety of ways (Levine, 2009). One method would be to restrict the use of GP to those circumstances where profiles are most likely to be accurate. Rossmo (2000) has indicated that profile accuracy will be maximized when the profile is based on multiple crime sites, when the crimes have been linked to the same offender, when the offender is not commuting into the area of criminal activity, when the distribution of suitable targets is uniformly distributed around the offender's home, and when the offender doesn't move anchor points during his crimes. Unfortunately, there are currently limits on the extent to which we can use these criteria to improve profile accuracy. For example, while it seems clear that profile accuracy will indeed be maximized if profiles are restricted to 'marauding' as opposed to 'commuting' offenders (Canter & Larkin, 1993), there is currently no reliable way of predicting whether an offender is a commuter or a marauder at the time they are committing their crimes (e.g. however, see Paulsen, 2007; Santtila, 2005).

The strategy that will be focused on in this study to improve GP accuracy is to examine the use of calibrated distance decay functions. As highlighted earlier, GP systems currently rely on distance decay functions in order to predict an offender's home location. Most of these functions can be referred to as 'default functions' because they are built into GP systems and have been developed using crimes that sometimes bear little resemblance to the crimes the systems are typically applied to. For example, a default function may have been derived from a sample of American serial homicides (e.g. Canter et al., 2000), but is applied to a sample of UK serial rapes or burglaries.

It is currently unclear whether default functions can be used to accurately profile offenders across a wide range of contexts. It is possible that such functions are robust enough to work well across different contexts. However, there is also evidence that a range of factors influence the form distance decay functions can take (e.g. with respect to their shape and steepness). By incorporating some of these factors into the profiling process (e.g. by creating distance decay functions that are calibrated for different contexts) it may be possible to improve the overall accuracy of geographic profiles beyond what would be achieved by relying on default decay functions.

The list of issues that could potentially be considered when calibrating decay functions is long and varied, and includes variables related to offender attributes, such as age and IQ (e.g. Gabor & Gottheil, 1984; Snook, 2004; Warren, Reboussin, & Hazelwood, 1995), environmental factors, such as land use and population density (e.g. Capone & Nichols, 1976; Kent & Leitner, 2009; Rhodes & Conly, 1981), and offence characteristics, such as the method used to approach the victim and the type of crime committed (e.g. Canter & Gregory, 1994; Laukkanen, Santtila, Jern, & Sandnabba, 2008; LeBeau, 1987). Of course, not all of these variables (e.g. offender attributes) are known to the police at the time of an investigation, and therefore it makes little practical sense to use them to calibrate decay functions. However, this is not true for all of the variables that are included in the categories listed above (e.g. offence characteristics).

Crime type in particular is a variable that can be considered during the investigative phase and may be important to consider when calibrating distance decay functions. Indeed, research indicates that offenders committing different types of crimes travel in different ways, suggesting that the form of distance decay that can be observed across crimes may also vary (e.g. Baldwin & Bottoms, 1976; Gabor & Gottheil, 1984; LeBeau, 1987; Rand, 1986; Rhodes & Conly, 1981; Santtila, Laukkanen, & Zappala, 2007). For example, Rhodes and Conly (1981) found significant differences in journey-to-crime distances between robbers, burglars, and rapists in their study of offenders from Washington, DC. In a similar study, Rand (1986) reported (the now common finding) that offenders committing interpersonal crimes travelled significantly shorter distances than offenders committing property crimes. More recently, Santtila et al.

(2007) found that, even within crime types, different sub-types of offenders can vary with respect to their journey-to-crime distances. Specifically, they found that, when homicides and rapes were examined, offenders travelled longer distances when committing crimes that expressed instrumental aggression (i.e. aggression for ulterior gains) compared to crimes demonstrating expressive aggression (i.e. aggression to harm the victim).

The current study

Based on research that shows differences in spatial behaviour across offenders committing different crime types, the purpose of the current study is to conduct a preliminary test of the hypothesis that distance decay functions that are calibrated for, and then applied to, similar types of crimes will produce more accurate geographic profiles than default functions (i.e. two functions developed on multiple crime types committed in a different geographic region). If this hypothesis is supported it would suggest that police agencies should, whenever possible, rely on calibrated functions when constructing profiles for different types of crimes in order to maximize the accuracy of their profiles (i.e. to reduce the amount of area they need to search in order to locate a serial offender's residence). Of course it is also possible to calibrate distance decay functions on the basis of other factors, such as the environmental factors discussed above. However, these factors were not available for analysis within the current study so the calibration process is restricted solely to crime type.[1]

Method

Data

Data from Glendale, AZ, USA, which is a small suburb in northwest Phoenix, were used to examine the accuracy of calibrated versus default distance decay functions across three different crime types: (1) residential burglary, (2) auto theft, and (3) theft. For the purpose of this study, residential burglary was defined as a crime that occurs when an offender unlawfully enters a residential dwelling with the intent to commit a theft or felony (Federal Bureau of Investigation; FBI, 2006). Theft occurs when an offender unlawfully takes or attempts to take property away from another individual, but the offender has not unlawfully entered a dwelling in order to commit the theft (e.g. shoplifting) (FBI, 2006). The theft of motor vehicles is excluded from this category (FBI, 2006). Auto theft occurs when an offender steals or attempts to steal an automobile, which includes any self-propelled motor vehicle that runs on land, but not on rails (FBI, 2006).

The Glendale data were provided by the Glendale Police Department for the purpose of conducting this research. All of the crimes in the dataset took place between 1 January 1995 and 31 January 2003. During this time period, Glendale had an approximate population of 218,812 persons, an approximate population density of 1517.3/km^2, and an approximate land area of 142.5 km^2 (US Census Bureau, 2010). Given this information, and all the other factors that likely make Glendale, AZ a unique geographic location, it is important to stress that the results obtained in the current study are only applicable to Glendale and may not generalize to the larger metropolitan area of Phoenix, or to other suburbs in the United States.

The data consists of geo-coded *x–y* coordinates for offence and offender home locations across the three different types of serial crimes: (1) 77 residential burglaries committed by 16 offenders, (2) 53 auto thefts committed by 15 offenders, and (3) 585 thefts committed by 131 offenders. Based on the commonly used definition of serial offenders as those who commit at least three crimes (Holmes & DeBurger, 1988), any offender who had moved during their crime series, and had not committed at least three crimes while residing at one particular home location, was eliminated from the study. The average number of crimes included in a series differed across crime types, with residential burglary series being the longest on average (range = 3–24, mean = 4.81, median = 3.50), followed by theft (range = 3–14, mean = 4.47, median = 4.00), and auto theft (range = 3–7, mean = 3.53, median = 3.00).

The proportion of commuters in the sample also varied by crime type. Approximately 25%, 47%, and 44% of offenders in the burglary, auto theft and theft datasets, respectively, were classified as commuters. As previously mentioned, GP will be more effective when applied to marauders versus commuters, which suggests that it would be useful to restrict the use of GP in the analyses below to cases of marauders.[2] However, given that there is currently no reliable method in place for determining whether an offender is a marauder or a commuter at the time of the investigation, it was decided in the current study that all offenders would be included in the analyses (i.e. commuters were not removed).

Procedure

The analysis involved four stages: (1) constructing the calibrated distance decay functions, (2) estimating the parameters of those functions, (3) validating the calibrated functions, and (4) assessing the impact of the calibrated (and default) functions on GP accuracy. Each of these stages will now be briefly discussed.

Constructing the calibrated distance decay functions

CrimeStat (v. 3.1) was used to complete this stage of the procedure (Levine & Associates, 2007). *CrimeStat* is a software program that was developed to analyse the spatial behaviour of criminals. Although *CrimeStat* allows the user to accomplish a wide range of analytical tasks, only the spatial modelling routine was used for this part of the study. This routine allows the user to calibrate distance decay functions based on specific datasets. The process involves several steps (Levine & Associates, 2007).

First, the Glendale data were sorted into three sub-samples of crimes (residential burglary, auto theft, and theft) and saved as separate files. Next, the offenders in each data file were randomly divided into two separate data files to form a development sample and a test sample. The development sample was used to develop a calibrated distance decay function for a particular crime type and the test sample was used to validate the calibrated function. Finally, the development sample data files were read into *CrimeStat*, where a calibrated function was produced. One function was calibrated for each of the three crime types in the Glendale data.

Estimating the parameters for the calibrated functions

Although *CrimeStat* can be used to estimate the parameters of a calibrated function, the nonlinear regression routine in *SPSS* (v. 16.0) was used for this purpose because it is more user-friendly and provides more information. This stage consisted of several steps.

First, data from the development samples were used to create frequency distributions where the distance (in miles) between the offender's home location and the offence location formed the *x*-axis and the number of records in the data file that were characterized by particular journey-to-crime distances formed the *y*-axis. Second, for each development sample, distances along the *x*-axis were grouped into distance intervals, or bins, of 0.25 miles (Levine & Associates, 2007). Third, for each development sample, a new file was created that included only the frequency distribution of the distances (i.e. the number of journey-to-crime distances belonging in each bin). In order to compare the frequency distributions across the different types of crimes the frequency of distances in each bin was then converted to a percentage (i.e. the percentage of crimes in a particular dataset falling within each bin).

Based on these distributions, all of the calibrated functions were classified as being either: (1) negative exponential, which is a particular type of parametric function, or (2) truncated negative exponential, which is a particular type of mixed function. A calibrated function was classified as being negative exponential if the first bin contained the greatest percentage of crimes (which suggests that a buffer zone is *not* present). On the other hand, a calibrated function was classified as being truncated negative exponential if the first bin did not contain the greatest percentage of crimes (which suggests that a buffer zone *is* present). Within *SPSS*, the nonlinear regression routine was then used to determine parameters for each calibrated function. R^2 values were provided as part of the *SPSS* output for each calibrated function as were graphs representing the actual frequency distributions and the predicted frequency distributions (using the estimated parameters).

Validating the calibrated functions

The next stage of the procedure involved validating the functions using their corresponding test samples, a method referred to as split-half validation (Efron, 1982). Specifically, the calibrated functions were applied to data in each of the relevant development and test samples, and error distance and hit percentage were calculated for each offender's crime series. While it should be expected that calibrated functions will result in more accurate predictions (smaller error distances and hit percentages) when applied to data in the development samples, significant increases in error distances and hit percentages when moving from the development sample to the test sample would indicate problems with generalizability. If split-half validation is successful then the development and test samples can be pooled.

The impact of calibrated and default functions on GP accuracy

The real test of the usefulness of calibrated distance decay functions is to determine whether they ultimately result in the development of more accurate geographic profiles (compared to default functions). To examine this issue, *CrimeStat*'s spatial modelling routine was used to examine the differences in GP accuracy that occurred when using calibrated versus default functions.

First, data files consisting of x–y coordinates for all of the offenders' homes and crime site locations from each crime type were read separately into *CrimeStat* and a rectangular grid was overlaid on top of the area of criminal activity. The size of the grid was specific to each data file. *CrimeStat*'s interpolation routine was then run in order to develop a grid for each data file with the outputs provided by this routine being saved as shape (.shp) files. *ArcMap* (v. 9.2) was then used to open the .shp files and calculate the x–y coordinates of the centroid of each cell.

Next, the .shp files (including the centroids) were used within *CrimeStat*'s spatial modelling routine to predict the cell in the grid where the offender was most likely to reside based on his crime locations. Within the spatial modelling routine, the user can choose to use a default distance decay function that is already incorporated into *CrimeStat* or they can manually input parameters from an empirically derived function. In the current study, parameters related to the three empirically derived functions were used, in addition to two default functions: a negative exponential function and a truncated negative exponential function, both of which were constructed using a dataset derived from 11 different types of crimes committed in Baltimore County, MD between 1993 and 1997 (Levine & Associates, 2007). Negative exponential and truncated negative exponential functions were selected for inclusion in the current study because they are the most commonly used functions in GP systems (Canter et al., 2000; Rossmo, 2000). See the Appendix for the parameters that define *CrimeStat*'s default functions.

The calibrated function and the two default functions were applied to each of the three crime types and *CrimeStat* provided, as output, the error distance (in miles) and hit percentage for each offender in the data file. As previously mentioned, error distance is the direct distance (in miles) between the offender's predicted home location (as specified by *CrimeStat*) and their actual home location, whereas hit percentage refers to the proportion of the entire search area that needs to be searched before finding the offender's home location. While many potential GP accuracy measures exist (Rich & Shively, 2004) error distance and hit percentage are the two most commonly used measures.[3]

Inferential statistics were then used to compare the error distances and hit percentages of the calibrated and default functions across each of the three crime types. If significant differences were found, *post hoc* analyses were conducted to compare the calibrated function to each of the two default functions and to compare the two default functions to one another. These comparisons were determined to be of the most practical importance because both of these default functions are currently used in naturalistic settings, and the calibration of functions is being proposed as a means of improving those functions. Again, it was expected that error distances and hit percentages would be significantly smaller when calibrated distance decay functions were used to construct geographic profiles.

Results

Calibrated functions

Figures 1–3 are graphic representations of the distance decay functions calibrated for each development sample (burglary, auto theft, and theft). The solid line in each figure represents the observed relative frequencies for the development sample (the dashed line represents the relative frequencies predicted by the calibrated function, as discussed below). It is important to note that the observed frequencies are only for the data file's development sample (i.e. the sample used to develop the calibrated function).

As previously mentioned, all of the calibrated functions were classified as being either a negative exponential function or a truncated negative exponential function based on the distribution of frequencies across the journey-to-crime distance bins. Based on the distribution of frequencies across the distance bins, the data files for burglary and auto theft are best represented by negative exponential functions, whereas the data file for theft is best represented by a truncated negative exponential function. Parameters for each calibrated function and their corresponding R^2 values are presented in Table 1, and the predicted frequencies are presented in Figures 1–3 (represented by the dashed line). Based on the R^2 values, all of the calibrated functions fit their corresponding development sample moderately well (R^2 values range from 0.64 to 0.78).

As indicated in Table 1 and Figures 1–3, the R^2 value is slightly lower for the theft data file than for the other two data files and the theft function is the least well-fitting of the three calibrated functions. One possible explanation for this poorer fit is the considerably larger sample size of the theft data file (sample size: burglary = 77; auto theft = 53; theft = 585). As a result of a larger sample size, the theft data file contains more commuters than the other two data files (number of commuters: burglary = 4; auto theft = 7; theft = 57), which would result in greater fluctuation in journey-to-crime distances (variance in journey-to-crime distances: burglary = 30.12; auto theft = 93.91; theft = 161.63). As well, the range of journey-to-crime distances is

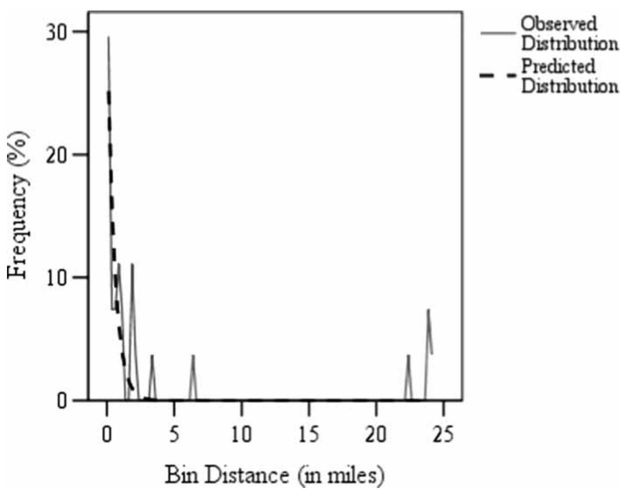

Figure 1. Calibrated function for Glendale: burglary.

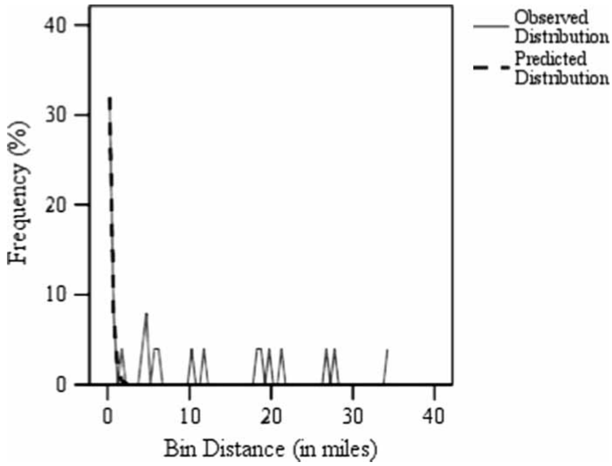

Figure 2. Calibrated function for Glendale: auto theft.

much greater for the theft data file (range (in miles): burglary = 0 − 24.35; auto theft = 0–34.36; theft = 0–91.10).

Split-half validation

It was determined that the error distance and hit percentage results for all three data files (i.e. burglary, auto theft, and theft) were not normally distributed. As a result, a series of non-parametric Mann–Whitney U tests were run to compare the error distances and hit percentages from the development samples to the error distances and hit percentages from the test samples when the calibrated functions (developed using the development samples) were applied to these samples. These tests revealed no significant differences suggesting that the calibrated functions can be used with sufficient accuracy when applied to data beyond that which was used to derive them

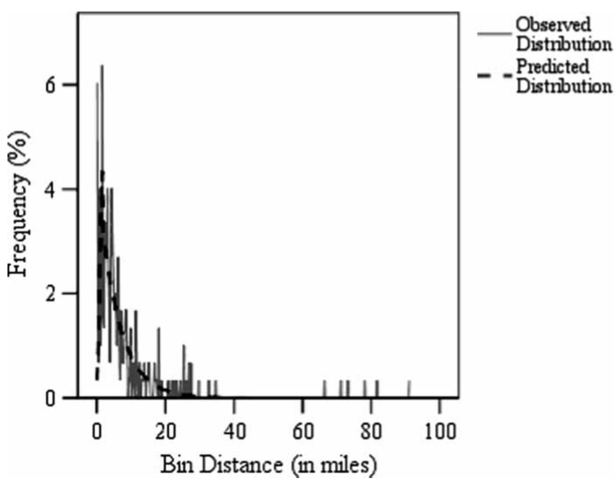

Figure 3. Calibrated function for Glendale: theft.

Table 1. Parameters and R^2 values for the calibrated functions.

Dataset	Function	Parameters			Distance of peak frequency (in miles)	R^2
		A	B	C		
Glen: burglary	negative exponential	31.68	1.85	–	–	0.72
Glen: auto theft*	negative exponential	65.19	2.85	–	–	0.78
Glen: theft	truncated negative exponential	4.31	0.17	2.67	1.625	0.64

Note: the parameter notations (A, B, and C) in this table refer to the same parameter notations used in the equations in the Appendix. * indicates that the parameters in this row are for 0.50 mile bins instead of 0.25 mile bins due to the low number of crimes in the development sample for this data file.

(but still from the same crime type). Since the split-half validation was successful, the development and test samples were pooled for all further analyses.

Accuracy of calibrated and default functions

Mean and median error distances (in miles) and hit percentages are presented in Table 2. Given the non-normal distribution of data, non-parametric Friedman tests were conducted to examine overall differences in accuracy that exist when using calibrated and default functions. If these tests were significant, Wilcoxon signed rank tests were run to compare the accuracy of: (1) the calibrated functions to that of the negative exponential function, (2) the calibrated functions to that of the truncated negative exponential function, and (3) the default negative exponential function to that of the default truncated negative exponential function. A Bonferroni correction was used for these comparisons such that the alpha level was set to 0.02 ($\alpha_{\text{planned}} = \alpha_{\text{per contrast}}$/number of planned contrasts $= 0.05/3 = 0.02$).

Glendale: burglary

The Friedman test found a non-significant difference in error distance when applying the calibrated versus default functions, $\chi^2(2) = 2.32$, $p = 0.33$. Similarly, a non-significant difference in hit percentage was also found, $\chi^2(2) = 3.50$, $p = 0.19$.

Glendale: auto theft

For the auto theft data file, the Friedman test found a non-significant difference in error distance when applying the calibrated versus the default functions, $\chi^2(2) = 0.33$, $p = 0.86$. For hit percentage, however, a significant difference was found between the three functions, $\chi^2(2) = 10.13$, $p = 0.01$. The follow-up Wilcoxon signed rank tests found non-significant differences in hit percentage between the calibrated function and both default functions (negative exponential function, $Z = -0.23$, $p = 0.84$, $r = 0.06$, observed power $= 0.02$; truncated negative exponential function, $Z = -0.74$, $p = 0.49$, $r = 0.19$, observed power $= 0.04$). However, the negative exponential function did

Table 2. Mean and median error distances (in miles) and hit percentages.

		Function applied to:					
		Burglary		Auto theft		Theft	
Function applied:		Mean (SD)	Median	Mean (SD)	Median	Mean (SD)	Median
Truncated negative exponential	error distance	3.03 (6.39)	0.46	8.33 (9.42)	3.67	7.18 (13.13)	2.74
	hit percentage	15.05 (17.71)	7.83	26.08 (27.43)	13.17	7.74 (16.65)	1.91
Negative exponential	error distance	3.10 (6.52)	0.62	8.32 (9.50)	4.09	7.14 (13.10)	2.79
	hit percentage	6.56 (16.61)	0.16	17.93 (27.27)	1.77	7.29 (17.00)	1.15
Calibrated	error distance	3.20 (6.51)	0.62	7.39 (9.64)	3.38	7.84 (12.80)	4.03
	hit percentage	10.83 (32.46)	0.12	23.30 (32.56)	1.27	8.23 (17.77)	2.27

result in a significantly lower hit percentage than the truncated negative exponential function, $Z = -3.35$, $p < 0.001$, $r = 0.86$, observed power $= 0.72$.

Glendale: theft

For the theft data file, there was a significant difference in error distance depending on the function that was applied, $\chi^2(2) = 11.57$, $p = 0.003$. Follow-up comparisons using the Wilcoxon signed rank test found significant differences in error distances when applying the calibrated function to both default functions (negative exponential function, $Z = -3.07$, $p = 0.002$, $r = 0.27$, observed power $= 0.75$; truncated negative exponential function, $Z = -3.15$, $p = 0.001$, $r = 0.28$, observed power $= 0.78$), with both of the default functions resulting in lower error distances than the calibrated function. However, the error distances were not significantly different when comparing the two default functions ($Z = -0.04$, $p = 0.97$, $r = 0.003$, observed power $= 0.02$).

The Friedman test also found a significant difference in hit percentage across the three functions, $\chi^2(2) = 21.14$, $p < 0.001$. The follow-up tests found non-significant differences in hit percentage between the calibrated function and the truncated negative exponential function ($Z = -1.82$, $p = 0.07$, $r = 0.16$, observed power $= 0.29$). However, the negative exponential function resulted in a significantly lower hit percentage compared to the calibrated function ($Z = -4.39$, $p < 0.001$, $r = 0.38$, observed power $= 0.98$) and the truncated negative exponential function ($Z = -3.99$, $p < 0.001$, $r = 0.35$, observed power $= 0.94$).

Discussion

At present, a common procedure for constructing geographic profiles is to use default distance decay functions that are incorporated into computerized GP systems. Given research that suggests that crime type may limit the extent to which default distance decay functions generalize, the primary purpose of the current study was to determine whether decay functions calibrated for crime type produce more accurate profiles than default functions. In addition to providing a preliminary examination of the impact of calibrated functions, the current study also compared the degree of GP accuracy that could be achieved using different types of default functions, namely the negative exponential and truncated negative exponential function. Given that these two functions are commonly used in naturalistic settings this comparison was considered to have practical implications.

The major hypothesis that was being tested in this study was not supported to the extent that was expected. Specifically, the results indicated that calibrated functions did not result in significantly smaller error distances or hit percentages than the default functions. In fact, in the case of theft, which represented the largest sample tested in the current study, the opposite was found; both default functions resulted in more accurate profiles with respect to error distance than the calibrated function and the negative exponential function was found to outperform the calibrated function with respect to hit percentage. In addition, across all three of the data files, the two default functions also did not differ significantly from one another with respect to GP accuracy as assessed by error distance, although the negative exponential function did result in significantly smaller hit percentages than the truncated negative exponential function across two of the three data files (auto theft and theft). This finding suggests that, for these two samples of crimes, there is no evidence of an obvious buffer zone.

Overall then, the results from this study provide preliminary evidence indicating that calibrating for crime type does not result in significantly better fitting distance decay functions for use in GP systems. In addition, the results suggest that neither default function is significantly more accurate than the other in terms of GP accuracy when measured by error distance, although the negative exponential function may lead to more accurate geographic profiles in terms of hit percentage. However, it should be reiterated that the results from the current study are preliminary in nature and do not offer concrete evidence that GP accuracy cannot be influenced by selecting one function over another.

Explaining the lack of a calibration effect

It was predicted that calibrating functions based on crime type would result in more accurate profiles because previous research has shown that the spatial behaviour of offenders differs depending on the type of crime being committed. However, in the current study, while crime type varied across the Glendale sub-samples, each of the sub-samples represented only one broad class of crimes – property crimes. Therefore, a potential explanation for why the calibrated functions did not result in more accurate geographic profiles was because the spatial behaviour of different types of property offenders is relatively similar. If the crime types examined in the current study had varied more dramatically, for example by including samples of interpersonal offenders *and* property offenders, the results of the study may have been different (e.g. Rand, 1986; Rhodes & Conly, 1981). This will be an important avenue for future research.

As previously mentioned, the two default functions examined in the current study were developed from an analysis of multiple crime types (Levine & Associates, 2007). In total, there were 11 crime types included in the samples used to generate the default functions, with larceny, burglary, and motor vehicle theft being included as three of the sub-groups. In fact, 47.8%, 11.3%, and 6.2% of the crimes used to calibrate *CrimeStat*'s default functions can be categorized as larceny, burglary, and motor vehicle theft, respectively. Given that the three crime types examined in this study (i.e. burglary, theft, auto theft) were similar, if not identical, to three of the crime types used to develop the two *CrimeStat* functions, it is possible that the accuracy of the default functions examined in this study was improved as a result. Thus, if a sample of crimes was examined that differed to a greater extent from the crime types used to develop the default functions then it is possible that significant findings may have emerged.

It is also important to highlight the fact that the Glendale data file spanned a wide temporal period, including crimes that occurred over a period of 8 years. It is highly probable that significant environmental changes, such as new residential developments, the construction of roadways, and changes in population density, occurred during those 8 years and these changes would likely have an effect on the spatial behaviour of offenders operating in this area. Indeed, if an offender's spatial behaviour is determined in part by their routine activities (e.g. Cohen & Cantor, 1980; Sherman, Gartin, & Buerger, 2006) such environmental changes would likely have a large impact on the behaviour of offenders committing crimes at different times in the same geographic area. Thus, the fact that the data sets could actually consist of different sub-samples of crimes based on 'temporal period of offending' could have masked the impact of 'crime type' on offender spatial behaviour. Unfortunately, the Glendale data could not be restricted to a shorter time period due to the limited data available. If larger samples can be collected in the future, this should be done.

In addition, the current study was limited to the relatively small geographical region of Glendale, AZ (land area = 142.5 km^2; US Census Bureau, 2010), which could also be a potential explanation for why the analyses failed to reveal significant differences between some of the distance decay functions. More specifically, focusing on a small geographical area would restrict the range of possible error distances that can be observed. This in turn would limit the variation in error distance values and decrease the probability of finding differences between any type of distance decay function, at least when relying on error distances. We do not believe that the same argument can be applied to hit percentage values. Thus, replicating this study over a larger geographical area may impact the findings, especially when GP accuracy is assessed by error distance.

Other possible explanations also exist to explain the lack of a calibration effect. One of the most obvious has to do with the relatively small sample sizes that were available for analysis in the current study. While small sample sizes are not uncommon in research of this type (e.g. Paulsen, 2006; Snook et al., 2002, 2004, 2005), often due to difficulties in obtaining sensitive data from the police, the size of the burglary and auto theft samples used in this study are cause for concern, especially for identifying small effects (as indicated by the reported power analyses). Clearly, collecting larger samples for future research must be a high priority. Furthermore, it could be that crime type is simply not an issue that needs to be considered when calibrating distance decay functions. If this turns out to be true, this does not in any way suggest that other issues (e.g. environmental factors) should not be considered when calibrating decay functions.

Conclusions

While it is difficult to know for sure what the non-significant results found in the present study actually mean, it appears that calibrating distance decay functions for crime type may not be a consistent and effective way of improving GP accuracy, as assessed by either error distance or hit percentage. In addition, while the default negative exponential function occasionally outperformed the truncated negative exponential function with respect to GP accuracy (with respect to hit percentage) this finding was not consistent across all three crime types and there were no significant differences between the two default functions when error distance was used to assess GP accuracy.

Thus, the preliminary evidence presented in the current paper suggests that it may not be worthwhile for police departments to calibrate GP functions for property crime type and that major differences between the negative exponential function and the truncated negative exponential function should not be expected when examining these types of crimes. However, future research is clearly needed before solid conclusions can be drawn. This future research should focus on addressing the limitations present in the current study, particularly the relatively small size of the samples and the sole focus on property offenders/offences.

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Notes

1. Although many, if not the majority of, serial offenders commit multiple types of crime (e.g. Leitner & Kent, 2009), almost all of the GP research to date has used a single crime type in their analyses (e.g. Bennell, Emeno, Snook, Taylor, & Goodwill, 2009; Canter et al., 2000; Paulsen, 2006; Rossmo, 2000; Snook et al., 2005). Thus, the current study will focus on single crime types as an initial step in assessing calibrated versus default functions.
2. While the size of the sub-samples prevented us from running formal inferential tests, a visual examination of the means for both error distance and hit percentage indicated that the profiles generated in this study were more accurate for marauding offenders compared to commuting offenders. This trend was consistent across all three data files and for each of the three functions examined. Please contact the first author if you are interested in seeing these results.
3. Interestingly, there has also been a lot of debate about the relative merits of these two measures, especially error distance. While some argue that error distance is an appropriate measure of GP accuracy (Levine & Associates, 2007; Snook et al., 2005), others disagree, typically pointing out the fact that measures such as error distance do not reflect how GP systems are often used (i.e. error distance focuses on one single location or point of prediction, rather than on an area that can be searched, as is produced by GP systems; Gorr, 2004; Rossmo, 2005).

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Appendix : *CrimeStat*'s default negative exponential and truncated negative exponential functions (Levine & Associates, 2007)

The two default functions examined in this study include the negative exponential and truncated negative exponential functions currently used in *CrimeStat*. The following is the default negative exponential function used in *CrimeStat*:

$$f\left(d_{ij}\right) = A * e^{-B_* dij}$$

where f(d_{ij}) = the likelihood that the offender will commit a crime at a particular location, i (defined here as the centroid of a grid cell); e = base of natural logarithm; d_{ij} = the distance between the offender's residence location, j, and crime location, i; A (coefficient) = 1.89; and B (exponent) = 0.06.

The default truncated negative exponential function in *CrimeStat*, unlike the default negative exponential function, assumes that the offender's home location will be surrounded by a buffer zone. Thus, the function is a linear one up until peak likelihood is reached, whereupon it switches to a negative exponential function. The following is the default truncated negative exponential function used in *CrimeStat*:

Linear : $$f\left(d_{ij}\right) = C^* d_{ij} \qquad \text{for } 0 \le d_{ij} \le d_p$$

Negative exponential : $$f\left(d_{ij}\right) = A^* e^{-B_* d_{ij}} \qquad \text{for } d_{ij} > d_p$$

where f(d_{ij}) = the likelihood that the offender will commit a crime at a particular location, i (defined here as the centroid of a grid cell); d_{ij} = the distance between the offender's residence location, j, and crime location, i; d_{p} (distance of peak likelihood) = 0.4 miles, C (slope of linear function) = 34.5, A (coefficient) = 14.22, and B (exponent) = 0.2.