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Abstract

Objectives Current 'geographical offender profiling' methods that predict an offender's base location from information about where he commits his crimes have been limited by being based on aggregate distributions across a number of offenders, restricting their responsiveness to variations between individuals as well as the possibility of axially distorted distributions. The efficacy of five ideographic models (derived only from individual crime series) was therefore tested.

Methods A dataset of 63 burglary series from the UK was analysed using five different ideographic models to make predictions of the likely location of an offenders home/base: (1) a Gaussian-based density analysis (kernel density estimation); (2) a regression-based analysis; (3) an application of the 'Circle Hypothesis'; (4) a mixed Gaussian method; and (5) a Minimum Spanning Tree (MST) analysis. These tests were carried out by incorporating the models into a new version of the widely utilised *Dragnet* geographical profiling system *DragNetP*. The efficacy of the models was determined using both distance and area measures.

Results Results were compared between the different models and with previously reported findings employing nomothetic algorithms, Bayesian approaches and human judges. Overall the ideographic models performed better than alternate strategies and human judges. Each model was optimal for some crime series, no one model producing the best results for all series.

Conclusions Although restricted to one limited sample the current study does show that these offenders vary considerably in the spatial distribution of offence location choice. This points to important differences between offenders in the morphology of their crime location choice. Mathematical models therefore need to take this into account. Such models, which do not draw on any aggregate distributions, will improve geographically based investigative decision support systems.

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Introduction

Firstly, we begin by detailing existing methods of predicting serial offenders' home locations on the basis of the spatial distribution of their crimes, discussing the relative merits and disadvantages of each. We then introduce a new set of methods, ideographic models of criminal spatial behaviour that have been implemented within a new geographical profiling software package, DragNetP, demonstrating the ways in which they circumvent many of the limitations of existing methodologies. We then test these models on a standard dataset comprising 63 serial burglars from London, U.K., examining their relative accuracy in predicting offender home location. Results from these initial analyses are subsequently compared with those for a range of prediction methods previously reported in the literature. Implications and directions for future research are discussed at the conclusion of this work.

Geographical Offender Profiling

As Canter and Youngs (2009) illustrate in some detail, there are two fundamental aspects of offenders' geographical activities that allow inferences of their most likely home or base location to be derived from knowledge of where they commit their crimes. One is *propinquity*, which is the tendency for the probability of crime locations to reduce incrementally as the distance from the offender's base/home increases, often characterised as an aggregate decay function. The other is *morphology*, which is the tendency for crimes to be distributed around the offender's home or base.

Consequently any attempts to model criminal spatial activity carry implications for our understanding of how they make choices of offence locations. Different mathematical models are, in effect, different hypotheses about the form that offender's crime location choice take. They therefore have consequences for explaining criminal actions.

Furthermore, by exploring different approaches to modelling criminal spatial activity there is the possibility of improving decision support systems that provide predictive models of where an offender may be based. There is now considerable interest in using such systems as an aid to investigations. Therefore any improvement of them can have practical and policy implications.

A number of studies have examined the power of geographical investigative decision support systems. In general these have been based on aggregate decay functions added across crime locations to give probability surfaces. This has lead to the consideration of the most fruitful mathematics for encapsulating empirically derived decay functions (Bennell et al. 2009; Canter et al. 2000; Canter and Hammond 2006; Hammond and Youngs 2011; Levine 2002, 2005; Paulsen 2005, 2006; Rossmo 2000). There has consequently been debate about which of a range of different forms of function might most appropriately summarise crucial features of criminal spatial behaviour (Canter and Hammond 2006; Emeno and Bennell 2011; Hammond and Youngs 2011; Levine 2002; Paulsen 2005, 2006).

As a complement to the use of algorithms based on propinquity and morphology, as discussed by Canter (2009), Levine and his colleagues (Block and Bernasco 2009; Leitner and Kent 2009; Levine 2009; Levine and Block 2011; Levine and Lee 2009) drew attention to the absence of specific geographical information in many existing models of offenders' spatial behaviour and proposed algorithms that drew on existing, specific information about where offenders were based who committed crimes in specific locations. Using Bayesian probabilities they were able to show that the likely area of location of any given offender was reflected in known prior probabilities derived from existing databases for that region. Bennell et al. (2009) also showed that the accuracy of these predictions could be enhanced by calibrating the empirical probabilities using information from established generic decay functions. However, as Canter (2009) has pointed out, Bayesian modelling depends upon the availability of existing data sets for offenders in any given locality and so cannot be applied to crimes where such background information does not exist. So although there are doubtless some practical benefits in certain contexts to utilising the Bayesian approach, these are limited. Also, the fundamentally empirical basis of the work of Levine and his colleagues limits its elucidation of criminal behaviour and the development of theories and explanations to characterise their spatial activities.

In a different approach to geographical offender profiling Snook and his colleagues (Bennell et al. 2007a, b; Snook et al. 2002, 2004, 2005; Taylor et al. 2009) have shown that the basic principles of propinquity and morphology can be taught to naïve judges which enables them to make estimates of offenders' home locations that are, on average, on a par with those achieved by computer algorithms. Of course, as Canter (2009) observes, human judges are not as consistent as computer algorithms. It is only by averaging across a number of human judges that results similar to those obtained by computer algorithms are achieved. Some individuals do not use the principles consistently and some configurations of crime locations do not lend themselves to simple applications of the main principles. Furthermore, human beings cannot be used effectively to search large databases in order to prioritise offenders as Canter and Hammond (2007) have shown computer systems can do very efficiently.

There is therefore continued value in developing and testing other algorithms that model crime locations both as a way of developing the understanding of criminal spatial behaviour and as the basis for enhanced decision support systems.

Weaknesses in Current Geographical Offender Profiling Models

Although there has been some success in geographical offender profiling, whether by human judges or computer systems, this has been limited by a number of factors. Firstly, existing approaches are essentially nomothetic, failing to take into account the notable individual variations that have been demonstrated in studies of offender spatial behaviour. For example, inter-crime and home to crime distances have been shown to be vary considerably between offenders and offence series (Canter and Youngs 2008a, b). Both Lundrigan and Canter (2001) and Hammond (2009) show that offenders have typical ranges over which they operate, relating to the resources they have available. More generally it has been known since Canter and Larkin (1993) first drew attention to the distinction between 'marauders' and 'commuters' that offence series vary in terms of their morphology, differing spatial patterns being characteristic of different offenders. Indeed, a number of authors (Smith et al. 2009; Van Koppen and De Keiser 1997) have argued that distance decay functions do not apply to individual offenders but are general characteristics of populations. As a consequence algorithms based on these general assumptions can only provide crude approximations for any particular crime series. It follows that any improvement in these algorithms needs to develop from calculations that apply directly to a given offence series, without making assumptions drawn from the summary indicated by decay functions or Bayesian probabilities.

A second weakness is that the morphological models underlying such approaches are based in simplifying assumptions. As Van Koppen et al. (2011) have pointed out, they assume that the opportunities for crime and the directions in which an offender is likely to move are equally probable all around the offender's home/base. However, there are a number of reasons why this might not always be expected to be the case. Warren et al. (1998) illustrated what they termed a 'windshield effect', whereby crimes were committed outwards from the home base in specific directions, creating the fan-like pattern typical of a windscreen wiper on the window of a car. Indeed, a number of studies have illustrated clear directional biases in serial crime distribution (e.g. Costanzo et al. 1986; Goodwill and Alison 2005; Lundrigan and Canter 2001; Lundrigan and Czarnomski 2006). Canter and Hodge's (2000) interviews with criminals, asking them to draw a sketch map of where they committed their crimes also drew attention to the significance of major road routes for many offenders. In another study Canter et al. (2000) used a regression approximation as a normalisation process in their geographical profiling algorithm and showed it did improve its effectiveness.

It is also important to note that Bayesian models omit the possibility of exploring actual geographical distribution of crime series, instead focussing on overall probabilities of relationships between offence and offender home locations, and have thus not been able to explore the impact of dominant axes on the relationship between crimes and offender's base. This is perhaps a surprising omission because such studies are typically characterised as being explorations of the 'Journey to Crime'. Any journey implies a travel route so hypotheses about such routes could contribute to the understanding and prediction of offender spatial behaviour.

DragNetP: Five New Algorithms

In order to test whether more effective inferences of the relationships between offenders' crime locations could be derived from procedures that were based on ideographic models applied to individual series, incorporating analysis of both clustering and axial features of crime distributions, a new version of the frequently studied Dragnet (Canter et al. 2000) software was developed. This incorporated five different algorithms (models), each working solely with the information available from a particular crime series.

The Dragnet software (Canter et al. 2000) was originally developed as a research environment to test different models of offender spatial activity. It allowed the flexible input of any form of decay function in order to generate a probability surface. The resulting tests of different families of decay function (Canter et al. 2000) proved fruitful and allowed the exploration of different theories that might explain the aggregate decay functions explored (Canter and Hammond 2006). It has also been utilised in police investigations (Canter 2007).

In order to explore the issues discussed above an entirely new version of the software was developed that allowed tests of models of criminal spatial activity that did not utilise either aggregate decay functions or Bayesian probabilities. This is referred to as DragnetP. Five algorithms are incorporated into DragnetP that allow the test of different ideographic models, each based on different set of assumptions about a criminal's offence geography.

Ideographic Model 1: Kernal Density Estimation (Density)

Kernel density estimation resembles the nomothetic decay analyses employed by previous geographical profiling systems, which use mathematical functions derived from aggregate distributions of home to crime distances to rank prioritize locations on the basis of distance from crime locations, in that it assumes that offenders will typically choose crime locations around their home and will usually have some typical distance that they travel from their homes to their crime sites. However, kernel density estimation derived predictions as to the likely location of an offender's home are based solely on that particular individual's crime locations (thereby accounting for idiosyncratic variations in crime distribution), rather than the application of aggregate models derived for a sample of offenders committing crimes of a similar nature or operating within the same geographical region.

The key differences between this form of density calculation and those currently employed in geographical profiling systems are that;

1. Probability distributions are calculated for each individual series, in effect generating a unique *sigma* (δ) value for each series
2. Gaussian (i.e. normal) distributions are used for estimating probabilities based on the sigma derived for that series rather than generic decay functions
3. Kernel density algorithms are implemented to combine the probabilities derived from each crime location, rather than adding (as in the original Dragnet) or multiplying (as in Rigel) probabilities.
4. The best estimate of the home/base is given as well as equal density contours.

Many researchers in environmental criminology, especially when deriving 'hotspots' of criminal activity, have used kernel-Parzen-density estimations (Parzen 1962, Yeung and Chow 2002, Nunez-Garcia et al. 2003). This is a non-parametric way of estimating the probability density function of a random variable. The estimated density is a mixture of kernels centred on the individual η training objects (location of offences x_i (Eq. 1):

$$p(x) = \frac{1}{n\delta}\sum_{i=1}^{n} K(x - x_i, \delta) \tag{1}$$

where the most often used kernel is a Gaussian kernel with diagonal covariance matrices (Eq. 2):

$$K(x - x_i, \delta) = \frac{1}{2\pi} e^{-\frac{(x-x_i)^2}{2\delta^2}} \tag{2}$$

Training the Parzen density consists of the determination of the width of the kernel δ. δ can be optimised by maximising the likelihood (Duin 1976). Because this method contains just a single parameter, the optimisation can be applied even with a relatively small training set.

The current algorithm thus operates as follows: First for each crime series the width of the kernel δ is optimised by the maximum likelihood criterion, using the locations of crimes for that particular crime series only. Next for the smallest box containing all crimes, increased by 5 % on each side of the box, a regularly space grid is created containing 2000 locations. These locations represent potential location of the offender home. For each point x in the grid the value of the kernel density estimation $p(x)$ is computed. The most likely location of the offender home x^* is assigned to the location with the maximum kernel density estimation (e.g. Eq. 3). See Fig. 1.

$$x^* \leftarrow \underset{x}{\text{Max}}\, p(x) \tag{3}$$

Ideographic Model 2: Axial Analysis Using a Regression Method (Regression)

The theoretical basis for using regression analyses as a means of predicting likely offender home location stems from the fact that, as discussed above, offenders have often been found to display directional biases in their offence distributions. In other words, there is considerable evidence that the distribution of an offender's crime locations will not be evenly spread around their home/base, but will be distorted in a particular direction. One reason for this is likely to be that they will often operate along major routes, for example into a city centre, or focus their offending towards particular target areas (Canter and Youngs 2008a). Because of this it would be hypothesised that their crime locations will be distributed along an axis on which their home sits (Canter et al. 2000).

One direct way of exploring evidence for an axial relationship between an offender's home and their offence locations for any individual crime series is to treat the crime locations as points in Cartesian Space and to calculate the best fit regression line that moves through those points, as was done by Canter et al. (2000) to establish what they called the Q-Range for normalising their decay functions.

In the present case this allows the kernel density functions to be weighted by the relationship of the crimes to the regression line. To estimate the most likely location of an offender home first all crime locations are used to estimate a regression line using the least squares method (Wolberg 2005). Next, all the crimes are mapped onto the line using a perpendicular projection. From all these projected locations the kernel density estimation (Parzen 1962; Yeung and Chow 2002; Nunez-Garcia et al. 2003) is calculated. Then in the line segment containing all projected locations 1,000 equally spaced points are generated. For each point x the value of the kernel density function is estimated. The point with the maximum value of the kernel density is the estimation of the most likely offender home location (as shown in Fig. 2).

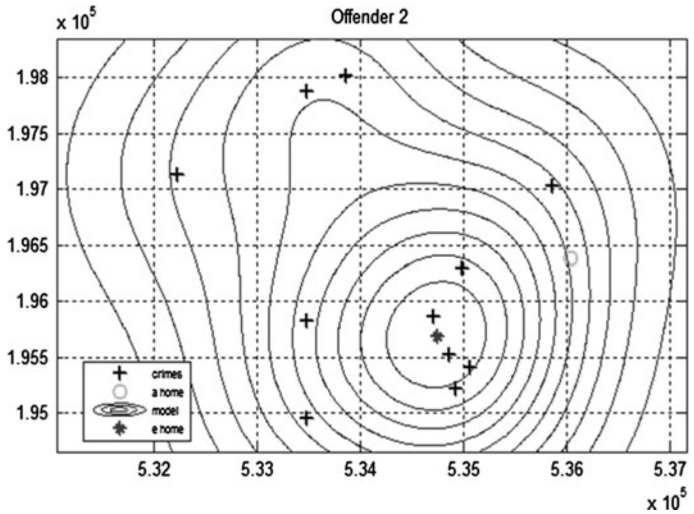

Fig. 1 Illustration of density model output

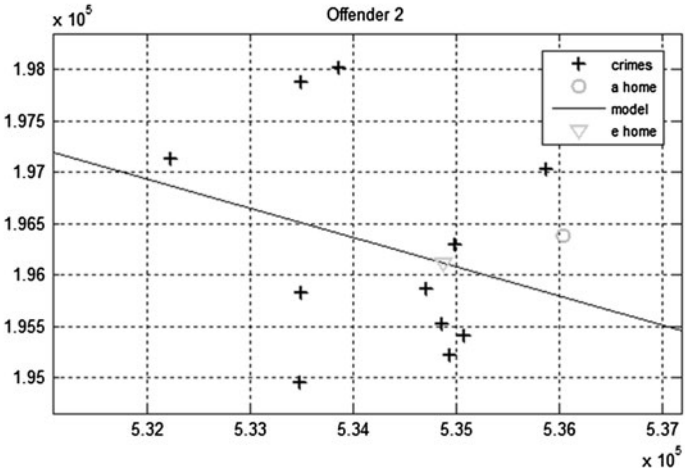

Fig. 2 Illustration of regression model output

Ideographic Model 3: Application of the 'Circle Hypothesis (Circle)

On the basis of consistent findings on the influence of personal factors (such as age, race, resources) on home to crime distances presented within the literature, Canter and Larkin (1993) hypothesised that offenders would tend to operate over fixed, characteristic ranges that were unique to them. They suggested that these would have some discernible, systematic relationship to the offender's home, and might therefore be used as a means of predicting the area of likely offender residence. They tested these assertions on a sample of serial rapes, using a circle (the diameter of which was the distance between the two furthermost crimes) to define the offence area, and found that in the majority of cases offenders lived within the area circumscribed by their crimes (Canter and Larkin 1993). Subsequent studies have replicated this finding (see Canter and Youngs 2008b; for a summary), showing the 'circle hypothesis' to be a useful means of predicting where an offender's residence might be likely to be located (Canter and Hammond 2007, for example, find that in many cases offenders live close to the centre of their offence circle).

In the present work Canter and Larkin's basic circle model has been developed so that a prediction of offender home location can be derived for any given offence series by a) defining the criminal range for that series using the smallest possible circle that encapsulates all of the crime locations, and b) treating the centre of that circle as the most probable location for the offender's residence (see Fig. 3). The formula for deriving this prediction is given in Eq. 4; below):

$$a = \frac{1}{2}\left(X_{-}X_{+}^{T}\right)^{-1}X_{-}\left(1^{T}X_{-}^{T}X^{T}\right)^{T} \tag{4}$$

where X_{-} is $N \times \binom{N+1}{2}$ matrix with elements $(x_i - x_j)$ and X_{+} is $N \times \binom{N+1}{2}$ matrix with elements $(x_i + x_j)$ and where $\mathbf{1}$ is the $\binom{N+1}{2} \times 1$ vector of ones.

Note that non-singularity of a $N \times N$ matrix $\left(X_{-}X_{+}^{T}\right)$ is guaranteed by the non-collinearity of the points x_i.

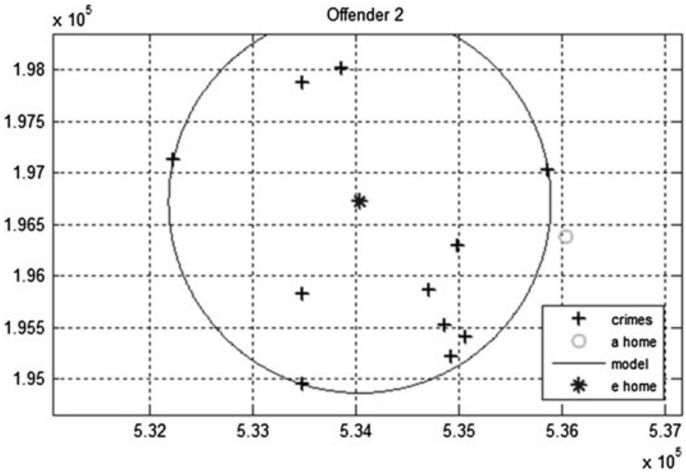

Fig. 3 Illustration of circle model output

The key way in which this model differs from that previously employed for geographical profiling purposes is that the circle here comprises the smallest area incorporating all the crimes, whereas the original method used the two crimes that furthest from each other as the diameter of the circle (i.e. not necessarily the smallest possible circle). This is a subtle but important distinction.

Ideographic Model 4: A Mixed-Gaussian Analysis (MGauss)

Any, even casual, observation of the locations of a series of crimes draws attention to the possibility that the crimes are clustered in some way, not uniformly distributed around a region. Examples of these clustering effects are provided most readily in the analyses of crime 'hotspots' presented by environmental criminologists. However, the implications of this have not been incorporated into any existing model of crime locations. Therefore a somewhat new approach was developed to modelling crime locations within the context of geographical profiling that takes into consideration sub-groupings of offences within a crime series. These sub-groups are then used to weight the predictions as to where the perpetrator of those offences might be most likely to reside.

The model used here delineates subsets of offences to be examined distinctly from one another. It does this by using the degree of propinquity between offences as a means of establishing key 'clusters' within the overall distribution. Kernal density estimations are then made, and these are weighted according the size and positioning of the clusters. The output is therefore similar to that produced by ideographical model 1, but is organised around groupings of crimes (as illustrated in Fig. 4).

The Mixture of Gaussians (MGauss) model calculations are based on a set of mean and covariance matrices. Each class is centred at a mean and has a Gaussian distribution which extends as described by its matrix. Each class also has a weight associated with it which is simply its total fraction of points divided by the total number of points in the dataset. The formula for computing the fitness of a dataset given a model is as defined in Eq 5:

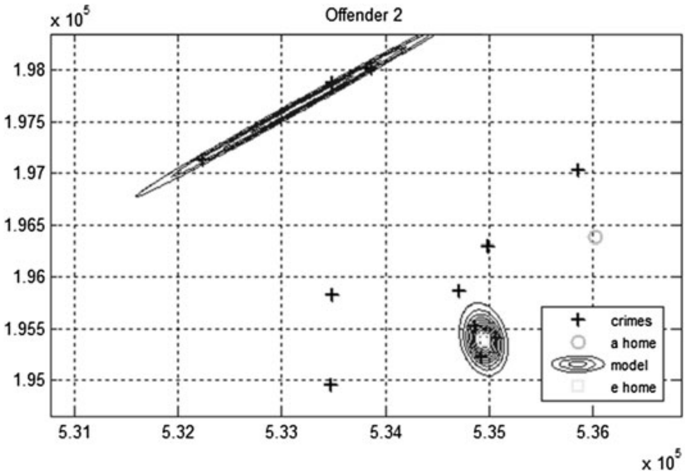

Fig. 4 Illustration of MGauss model output

$$L = \prod_{x \in X} \prod_{k} \frac{1}{\sqrt{(2\pi)^d \left|\sum_k\right|}} e^{-(x_k - \mu_k) \sum_k (x_k - \mu_k)} \tag{5}$$

where μ_k is the mean of cluster k, $\sum_k$ is the covariance matrix of cluster k, d is the dimensionality of the data, and X is the set of test data points.

Ideographic Model 5: A Minimum Spanning Tree Analysis (MST)

The 'journey to crime' conceptualisation of offence location choice does implicitly assume that criminals travel some sort of route to their crime locations. The Regression model (Ideographic Model 2, above) makes the simplifying assumption that this route has some close relationship to a linear axis, but in many contexts this may not be the case. Therefore a new approach to modelling crime locations was developed that explores the possibility of a minimum pathway between points being a possible framework for conceptualising the relationship between crime locations and the offender's home/base.

This innovative approach to modelling crime locations proceeds as follows: for a series of points (in this case crime locations), lines are drawn between every possible combination of points (these lines are referred to as edges). A weight can be assigned to each edge, representing how unfavourable it is (in terms of the distance between the points). Various different 'spanning trees' can then be created, each incorporating different combinations of edges (but always accounting for all points). A combined weight can then be assigned to each spanning tree by computing the sum of the weights of the edges in that spanning tree. A minimum spanning tree (MST) or minimum weight spanning tree is then a spanning tree with weight less than or equal to the weight of every other spanning tree.

Once the minimum spanning tree (MST) for a crime series has been determined, the offender's home location estimation is made. This is the place on the tree where sum of distances to all crimes along the tree is minimal (as illustrated in Fig. 5):

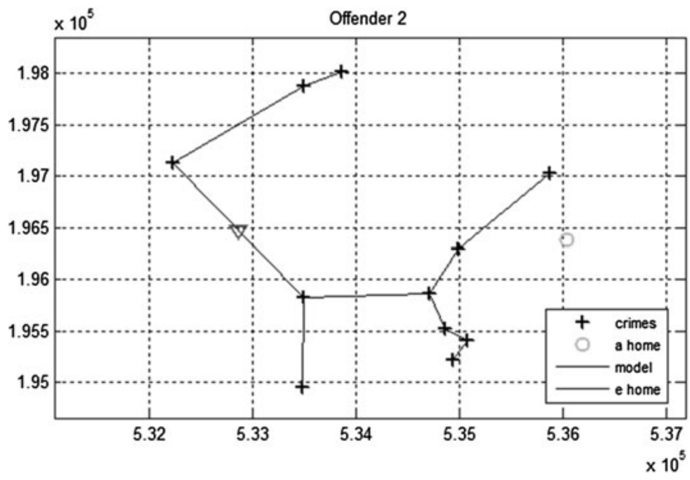

Fig. 5 Illustration of MST model output

Application of Ideographic Models to 63 Burglary Series

Data

A dataset previously utilised by other researchers (e.g. Leitner et al. 2007), made available by the London Metropolitan Police Service (Levine 2005; Harries and Le Beau 2007), was used to test the five new models. This comprised 63 series of residential burglaries committed in London, England, between April 1999 and March 2000, each consisting of at least five offences committed by a known offender who had a known residential location at the time of the offences. This particular data set was used in part because other researchers have shown it to be of value and in part because, unusually for a police data set, very careful searches were carried of the actual home location of the offender at the time of the crimes to ensure the data set was as accurate as possible (Leitner et al. 2007).

Measuring Geographical Profiling Effectiveness

Various measures of geographical profiling program output accuracy have been suggested (see, for example; Paulsen 2004; Rich and Shively 2004; Rich et al. 2004). These generally consist of either the distance from the most probable home location predicted by the algorithm to the known residential base of the offender and/or the area of some putative area that has to be searched, starting from the location indicated as most probable, before the offenders' actual base is reached.

These calculations are not as self-evident or unproblematic as they may seem at first sight. The distance measures make the assumption of a straight-line route between where an offender commits their crimes and where they reside. For many reasons such a direct link would not be feasible (for example, because of physical and topographical barriers or the impact of land-usage). Indeed, both Canter and Hodge (2000) and Canter and Shalev (2008) have demonstrated through the study of offenders' 'mental maps' that offenders rarely use the nearest direct route between their home and crime locations. However, it is impossible to determine the routes taken to offence locations using data of this nature. As

Hammond (2009) discusses, 'crow-flight' distances therefore constitute the best distance measure available as (a) they provide a means of directly quantifying the relative spacing of home and offence locations, and (b) whilst they underestimate the true length of 'journeys to crime', they do so in a systematic manner (meaning variations between individuals, series or offence classes can be quantified reasonably reliably). Moreover, previous research has almost solely employed Euclidean straight-line distances (e.g. Paulsen 2005, 2006; Bennell et al. 2009), and so it is helpful to employ such a measure for the purposes of comparison. For these reasons, the direct distance between the most likely location of an offender's home (as derived from analysis of the distribution of the crime locations) and the actual location of that offender's home is used as a principle measure of geographical profiling effectiveness in the present work.

The problem in calculating the area searched relates to the how the total search area is defined and whether the actual area searched before the home is located is specified or some proportion of the total, defined search area, as in Canter et al.'s (2000) 'search cost'. Rossmo (2000) proposed an area standard that involves the minimum bounding rectangle plus a slight addition and distinguishes this from Dragnet, which increases the minimum bounding rectangle by 20 %. But how that bounding rectangle itself is defined is open to some arbitrariness. In the present work the search area is computed as an area of the circle where a predicted home is the centre of the circle and the true home defines the radius of the circle. For density and MGauss methods the search area is computed along density levels from highest to lowest. Areas are added to the search area until the actual home is located. This is an actual area measure, not a proportion of any notional search area as in previous studies (e.g. Canter et al. 2000; Canter and Hammond 2006; Hammond and Youngs 2011; Rossmo 2000). Moreover, from an operational perspective it is of course of much more value to know that, for example, 5 km^2 had to be searched, rather than 10 % of an arbitrary total area.

Methods of Analysis

The two measures outlined above (the direct distance from predicted to actual home and the total area needing to be searched, starting from the predicted home, until the actual home was located) were used to make comparisons between the five ideographic models in terms of their prediction efficacy. The lower the values produced, the more effective was the particular model employed within DragNetP.

Firstly, the summated averages for each were determined for all of the five models. This allowed variations in predictive efficacy between the models to be directly quantified. Medians were the main summation measures employed (being the most appropriate measure for non-normally distributed data of this nature), although mean values were also determined to enable comparison with previously reported findings.

However, as Canter et al. (2000) point out; the utility of geographical profiling models relates, in large part, to the nature of the distribution of their effectiveness. It is therefore necessary to determine whether there are a substantial proportion of cases in which an algorithm or model gives useful results. In the present work this was done using cumulative efficacy functions (graphs showing the percentage of the sample achieving any given distance or area range), similar to those used by Canter et al. (2000), Canter and Hammond (2006) and Hammond and Youngs (2011). If these functions show a steady asymptotic increment in the effectiveness of a decision support system when any given model is utilised, then the practical utility of that model likely to be limited (efficacy is not enhanced through the use of that model; rather it increases proportionally with incremental increases in the measured facet). If, however, there is a distinct change in the form and gradient that an efficacy function takes (if, for instance, a distinct elbow presents in the curve of the function), then this may be taken as being illustrative of a positive impact of that model on the efficacy of the system (demonstrating that for a substantial proportion of the sample the model enhanced the effectiveness of the predictions made).

The shape and forms of the cumulative efficacy functions that were produced for the sample when each of the ideographic models was employed were consequently compared in order to assess the likely practical utility of each.

Finally, in order to determine how the ideographic models fared in relation to nomothetic models, Bayesian approaches and human judges, a range of measures that have been used previously to test geographical profiling methods (c.f. Paulsen 2005, 2006; Bennell et al. 2009; Block and Bernasco 2009; Leitner and Kent 2009; Levine and Lee 2009; Levine and Block 2011) were identified and corresponding values determined for each of the five ideographic approaches. These were subsequently compared.

Results

Findings on the Efficacy of the Ideographic Models

Summary Descriptions of Efficacy Measures

Table 1 gives the summary descriptions of the distance efficacy measures for each of the five idiographic models. The results show, interestingly, that the regression model has the lowest median and mean, with the median being close to half a kilometre. This is supports the view that some dominant axis is often an important aspect of crime location choices Canter et al. (2000). However, for the regression, density and MGauss models a quarter of the sample has a median distance less than a third of a kilometre, showing that there is certainly some value to these other models in some cases.

A median test does show that there are statistically significant differences between the different models at $p < .05$. This supports the view that the different models are sensitive to different aspects of the data and are worth considering independently of each other (Table 2).

The area measures, in Table 3 show a slightly different picture. The MGauss has the lowest median area of less than half a square kilometre. Indeed, in a quarter of cases the area that needs to be covered before the offender's base is established is only one tenth of a square kilometre. This illustrates the value of deliberately identifying sub areas of the general area to be searched, as the MGauss algorithm does, thus covering a smaller subset than the other measures. Nonetheless the Density algorithm still gives close results to

Table 1 Descriptive statistics for distance measures (km)

	Mean	SD	Median	25 ‰	50 ‰	75 ‰
Regression	1.79	4.09	0.57	0.32	0.57	1.19
Density	1.86	4.13	0.68	0.29	0.68	1.44
MGauss	2.27	4.17	0.79	0.34	0.79	2.51
MST	2.48	4.21	1.25	0.44	1.25	2.82
Circle	2.66	4.08	1.48	0.56	1.48	3.59

Table 2 Median tests of differences between methods on distance measure

	Method				
	Density	Regression	Circle	MGauss	MST
Distance					
>Median	27	24	40	32	34
≤Median	36	39	23	31	29

Test statistics:

	Distance
N	315
Median	0.79
Chi-square	9.85
Df	4
Asymp. sig.	0.04

Table 3 Descriptive statistics for area measures (km^2)

	Mean	SD	Median	25 ‰	50 ‰	75 ‰
MGauss	7.72	22.87	0.41	0.10	0.41	4.16
Density	23.42	117.16	0.69	0.12	0.69	2.61
Regression	61.68	329.83	1.02	0.33	1.02	4.46
MST	74.24	327.99	4.88	0.61	4.88	24.93
Circle	73.65	322.58	6.88	0.98	6.88	40.50

Table 4 Median tests of differences between methods on area measure

	Method				
	Density	Regression	Circle	MGauss	MST
Area					
>Median	23	28	46	21	39
≤Median	40	35	17	42	24

	Area
N	315
Median	1.45
Chi-square	29.28
Df	4
Asymp. sig.	0.00

MGauss, showing that these models that are based on the general distribution of the crime locations are identifying an important aspect of criminal behaviour. As might be expected the rather crude circle model gives a far larger search area than the other measures. As shown in Table 4 there is a statistically significant difference between the models at $p < .0001$.

Efficacy Functions for Each of the Models

The cumulative proportions of the sample achieving different error distance or search area intervals were plotted for each of the five ideographic models, using the methodology described above (Figs. 6, 7).

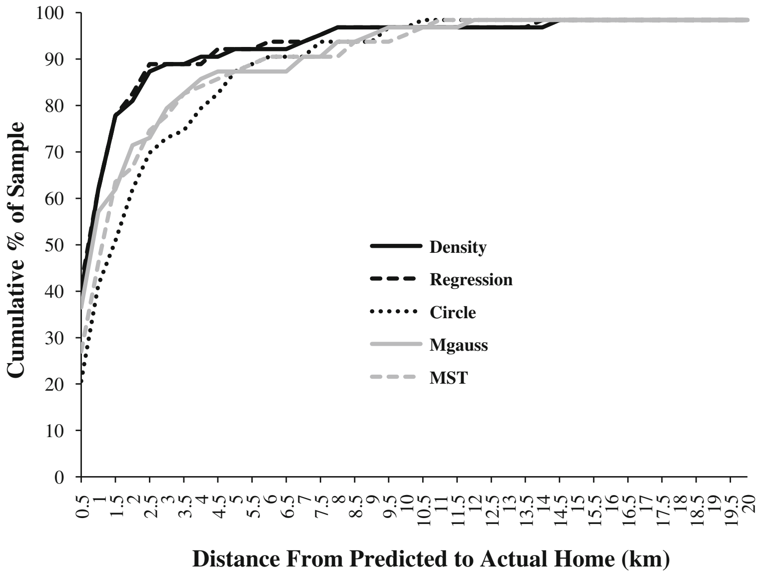

Fig. 6 distance efficacy functions for each of the models

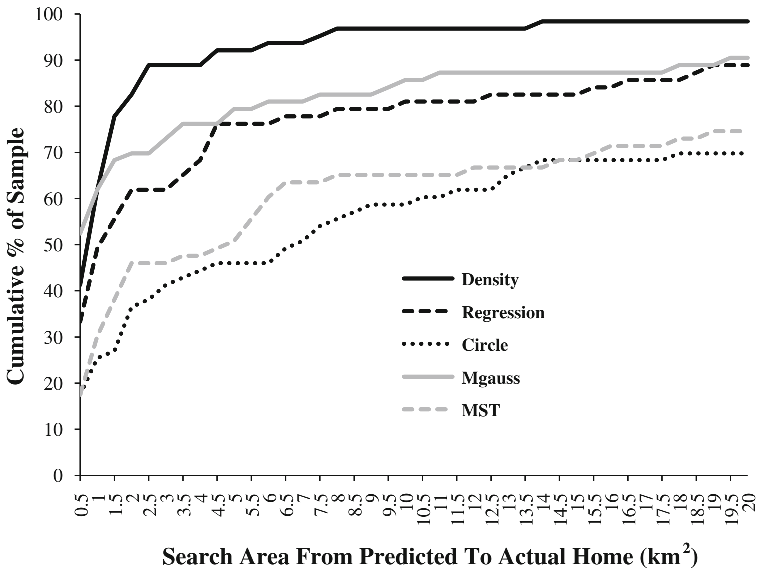

Fig. 7 Area efficacy functions for each of the models

Encouragingly strong ‘elbows’ are evident in the functions produced when each of the models was employed within DragnetP. This indicates that there are a reasonable proportion of cases in which relatively small distances or search areas are required, highlighting the practical potential of each of these approaches.

The error distance graph in Fig. 6 shows that there is not a lot of difference in the error function across the five different measures, although it does mirror the previous finding of greater prediction efficacy for the regression and density models.

Figure 7 shows greater diversity between the different models in terms of the search areas they require. The stronger ‘elbow’ for the Density model shows that it is likely to be the most useful, at least with crimes similar to those in the current data set. The comparison with the MST and the Circle models is also instructive, showing the increased power that comes from the Density algorithm.

Variations in Efficacy of Models for Different Crime Series

The efficacy functions illustrated in Figs. 6 and 7 show that all models have some success with some crime series. Even the worst performing models do have some cases in which they perform well. The question therefore arises as to whether these are the cases that other models perform well with or different cases. Consequently each crime series was analysed in order to determine which model gave the closest distance to home and the smallest search area. Table 5 shows the percentage of cases for which each of the models produced the best results.

Notably, every model produced the best result for some series. For distance all models are best for a similar proportion of cases, although MGauss and Density together account for almost half of the cases. Effectiveness was not so evenly distributed across the measure of search area. Over half the cases produce the smallest search area with the MGauss model and over a quarter with the density model. This supports the impression formed from Fig. 7 that these two models generate a much higher proportion of cases with small search areas than the other three models.

The fact that all five of the ideographic approaches produced the lowest distance and area measures for at least a number of the series comprising the present sample raises a number of important issues for consideration. The efficacy values produced when a model is incorporated into DragNetP are, in essence, a measure of the ‘fit’ of that model to any given crime series; the lower the value, the more effective the prediction and consequently the better the fit of the model to that offence distribution. The fact that each model provided the best ‘fit’ for a subset of the sample supports the proposition of distinct differences in the nature and form of offence morphology across the different offence series studied here. From a theoretical perspective this makes clear the need to develop our understanding of how offenders differ in their selection of crime locations. The models

Table 5 Frequencies and percentages which each method achieved the lowest distance and area scores

	Best distance (km)	% of cases	Best area (km^2)	% of cases
MGauss	1.6	25.4	32	50.8
Density	1.5	23.8	17	27.0
Circle	1.2	19.0	6	9.5
Regression	1.0	15.9	4	6.3
MST	1.0	15.9	4	6.3

Table 6 Descriptive statistics if best method for any series is used

Distance mean	1.26
Distance SD	3.72
Distance median	0.42
Area mean	3.88
Area SD	17.44
Area median	0.16

explored here offer methodologies for studying these variations in offence morphology. In practical terms this indicates that each of the models will be most advantageous under different circumstances.

Table 6 shows the results that are achieved if the 'best' method is used for each case across the whole sample. In essence, this demonstrates what the results would be if the optimum model was used. These values provide a benchmark for comparison with other existing published approaches.

Comparison of Present Results with Previous Findings

A growing body of research reports on the accuracy of different geographical profiling systems (e.g. Canter et al. 2000; Levine 2002; Rossmo 2000), exploring variations in the efficacy of such systems for different crime types (e.g. Emeno and Bennell 2011) and when different mathematical functions are employed (e.g. Canter and Hammond 2006; Hammond and Youngs 2011). More recent studies have begun to compare different geographic profiling models against each other (e.g. Paulsen 2005, 2006), against a range of centrographic measures such as the Centre of Minimum Distance (CMD) (e.g. Paulsen 2005, 2006; Bennell et al. 2009), and against human judges using simple heuristics (e.g. Paulsen 2006; Snook et al. 2002, 2004; Bennell et al. 2009).

Making comparisons between research findings on the efficacy of different geographical profiling models is difficult for a number of reasons. Firstly, different studies have employed samples that differ greatly both in terms of the number of crimes series that they comprise and the nature of the crime(s), as well as the number of crimes in any series. Secondly, they have tended to use different measures of accuracy and efficacy, which as Paulsen (2006) notes makes comparison functionally impossible. Thirdly, many studies have used the mean as a summary statistic of efficacy measures, despite drawing on data that were not normally distributed. This, as Tonkin et al. (2010) discuss, makes comparison difficult as the figures reported will often constitute distorted and biased representations of the true efficacy of geographical profiling models.

Despite these difficulties, basic distance and area efficacy calculations are open to some degree of comparison; those methods that directly measure distances between predicted and actual home locations or evaluate the amount of a prioritised area needing to be searched before the home of the offender is located allow the efficacy of geographical profiling models to be assessed in relative terms.

Comparison of Results with those of Paulsen (2005, 2006)

The studies of Paulsen (2005, 2006) constitute the only independent published evaluations of geographical profiling methodologies that could be found that simultaneously test different methods and systems across a range of measures of accuracy and efficiency. Therefore the findings from these studies offer the most appropriate bases for comparison.

Paulsen (2005, 2006) uses four different measures of model efficacy;

(a) 'Profile Accuracy'; a simple dichotomous (yes/no) measure of whether the home of the offender fell within the top profile area created by the different strategies.
(b) 'Error Measurement'; the crow-flight distance between the estimated home location and the actual home location of the offender
(c) 'Profile Error Distance'; the crow-flight distance between the actual home of the offender and the nearest part of the top profile area.
(d) 'Top Profile Area'; the size of the top profile area created by different profiling methods.

Table 7 presents key results[1,2,3] from Paulsen's (2005, 2006) studies with equivalent figures for the five ideographic models under consideration in the present work for comparison.

On all of Paulsen's measures the optimum models in the present study do considerably better than both nomothetic decay models and human judges. Even looking at the models on their own the results are substantially better.

Findings therefore provide tentative support for the central hypothesis of the present study that ideographic models, tailored to the particular characteristics of any given crime series, will be more effective in modelling and predicting home-crime relationships for serial offenders than methods that rely on generic theory and aggregate models.

However, for the reasons stated previously, it is difficult to draw any firm conclusions from the material presented here. Variations between the previous and present methods might have been (and in all likelihood were) due to the differing nature and characteristics of the samples employed for each of the three sets of analyses. These were drawn from different offending contexts, within which target availability and distribution are likely to vary considerably. Moreover, it is not possible to ascertain how the samples differ in terms of their personal attributes (e.g. age, race, gender)—given that these have been shown within the literature to impact upon the offender mobility and the spatial patterning of serial crime (e.g. Canter and Larkin 1993), the possibility that the large differences observed may have been governed, at least to an extent, by the individual characteristics of the offenders cannot be ignored.

Thus whilst initial indications point to an advantage for ideographic models over nomothetic approaches in deriving predictions of likely offender residence, and understanding criminal spatial behaviour, it is clear that more work is needed to establish the true degree of variation between these methods using directly comparable samples.

Comparison of Results with those for Bayesian Methods

Bayesian methods indicate general areas or 'cells' in which an offender may have a base. They do not identify specific locations for likely offender residence, and so their efficacy

[1] Paulsen (2005) provides findings for a number of different crime types; in Table 7 the findings obtained for the residential burglary series in his sample are used (being more directly comparable to the sample in the present study).

[2] Paulsen's (2006) sample also consists of a range of crime types; however, only five residential burglary series were included and this was deemed too small a number of cases against which to make comparisons. Therefore findings for the whole multiple crime type sample are provided for comparison in Table 7.

[3] 'Top Profile Area' is not included in Table 7, as it was not deemed useful for comparison given that the ideographic models being evaluated do not generate profile areas.

Table 7 Comparison of present results with those of Paulsen (2005, 2006)

Method	Profile accuracy	Mean error distance (km)	Mean profile error distance (km)
Paulsen (2005)[a]			
Residential burglary (N = 51)			
RIGEL	11 (22 %)	6.61	4.54
DRAGNET	10 (20 %)	6.82	5.55
Neg. exponential	16 (31 %)	7.45	5.13
Normal	5 (9 %)	7.50	6.07
Lognormal	3 (6 %)	7.77	6.13
Linear	15 (29 %)	7.21	5.07
Tr. neg. exponential	4 (8 %)	7.52	6.02
CMD	22 (43 %)	6.98	5.70
Median centre	22 (43 %)	7.07	5.76
Mean centre	20 (39 %)	6.81	5.44
All strategies	13 (25 %)	7.16	5.54
Paulsen (2006)[a]			
All crime types (N = 25)			
Human prediction	(11 %)	6.08	4.47
RIGEL	3 (12 %)	5.68	3.96
Dragnet	2 (8 %)	5.73	4.41
Neg. exponential	4 (16 %)	5.87	4.33
Normal	1 (4 %)	6.15	4.14
Lognormal	1 (4 %)	6.20	4.26
Linear	6 (24 %)	5.86	3.46
Trun. neg. exp	1 (4 %)	6.23	4.15
CMD	8 (32 %)	5.94	4.43
Median centre	7 (28 %)	6.26	4.57
Mean centre	6 (24 %)	6.58	4.86
DragNetP (N = 63)			
Regression	49 (78 %)	1.79	1.66
Density	49 (78 %)	1.85	1.15
MGauss	40 (64 %)	2.45	1.54
MST	41 (65 %)	2.48	1.15
Circle	35 (56 %)	2.66	1.52
Optimum	52 (83 %)	1.26	0.76

NB. For strategies producing a single point rather than a top profile area Paulsen (2005, 2006) creates a top-profile area using a one-mile radius circle, the centre of which is the point indicated by any given method as having the highest likelihood of containing the home of the offender. To enable comparisons this method was employed for the five ideographic models utilised within DragNetP

[a] Figures converted from values presented in miles in the original work

has been tested by researchers using various forms of error distance measure reflecting the distances between the cell predicted to contain the offender's home and the cell that actually contains the offender's home (e.g. Block and Bernasco 2009; Leitner and Kent 2009; Levine and Block 2011; Levine and Lee 2009).

Table 8 Comparison of present results with those published for Bayesian methods—distance from predicted to actual home (km)

Method	Levine and Lee (2009)	Leitner and Kent (2009) Multiple crime series[a]	Leitner and Kent (2009) Single crime series[a]	Block and Bernasco (2009)	Levine and Block (2011) Baltimore data[a]	Levine and Block (2011) Chicago data[a]	Bennell et al. (2009)[a]
Journey to crime	2.86	4.3	4.86	1.82	4.47	3.2	–
General	11.26	10.06	10.06	1.76	13.32	6.41	12.04
Conditional	2.78	3.93	4.39	1.23	5.18	3.14	4.22
Product	2.73	4.07	4.6	1.41	4.26	2.99	4.01
Bayesian risk	2.75	4.31	4.88	1.68	5.07	3.11	4.63
CMD	2.45	3.85	4.46	1.77	4.22	3.04	3.78
Default	–	–	–	–	–	–	4.3
Calibrated	–	–	–	–	–	–	4.1
DragnetP							
Regression	1.79						
Density	1.85						
MGauss	2.45						
MST	2.48						
Circle	2.66						
Optimum	1.26						

[a] Measures converted to km from the mile values originally reported

Table 8 details the results for the error distance measures of published evaluations of Bayesian methods using various models with equivalent figures for the five ideographic models under consideration in the present study.

To reiterate; accuracy and efficiency measures of Bayesian methods use the distance from the cell predicted to contain the offender's home to the cell containing the offender's actual home. In contrast, for the ideographic models incorporated within DragNetP accuracy and efficacy measures reflect the distance from the point location predicted to contain the offender's home to the point of the offender's home. The findings presented in Table 8 will therefore be biased in favour of the Bayesian methods (systematically underestimating the true distance between the predicted and actual home locations for Bayesian methods by taking the measurement from the edges of their surrounding cells).

Nonetheless, it is clear that the average distance from predicted to actual home is much smaller for the ideographic models tested here than for the Bayesian approaches. It is only for the Block and Bernasco (2009) study that the average distances are at all close to those from the present study. Their best result is for their 'conditional' condition of 1.23 km. That is close to the optimum value for the present study of 1.26 km. However all the other values from the other studies are much higher.

The variations in values across the different Bayesian studies are likely to be a direct function of the distribution of crimes and criminals in any particular city. This is because Bayesian analyses draw directly on the actual locations of offenders' bases to develop their probabilities. In order to counteract this problem measures are used that consider the

Table 9 Comparison of present results with those published for bayesian methods—percentage of offenders living less than 1 km from predicted home

Method	Levine and Lee (2009)	Leitner and Kent (2009) Multiple crime series	Leitner and Kent (2009) Single crime series	Block and Bernasco (2009)
Journey to crime	45.03	41.88	35.47	40.3
General	1.17	1.06	1.06	35.5
Conditional	42.69	36.35	31.65	64.5
Product	46.78	41.53	34.47	51.6
Bayesian Risk	49.12	42.35	33.88	50
CMD	43.27	38.94	32.59	35.5
DragnetP				
Regression	61.9			
Density	61.9			
MGauss	52.4			
MST	46			
Circle	41.3			
Optimum	61.1			

proportion of offenders living within any given distance from the predicted cell (e.g. Block and Bernasco 2009; Leitner and Kent 2009; Levine and Lee 2009). Table 9 shows the percentages of offenders living within one km of the home location predicted by both Bayesian methods and the current models.

Once more, Block and Bernasco (2009) report the best results of those employing Bayesian methods; the highest percentage of offenders residing within one km of the predicted home that they report is for their 'conditional' model (64 %). Their other models produced much lower percentages, typically less than 40 %, which are more in line with those reported by the other studies utilising Bayesian methods.

In contrast, the optimum result for the present study is 61 %, with even the simple circle model placing 41 % of the offenders within one kilometre of the highest probability designated location.

Again, then, findings support the proposition that approaches to modelling offender home location that rely solely upon the attributes of that particular crime distribution will be more effective than aggregate models of offending spatial behaviour.

However, as above, these findings must be taken with a degree of caution, given the variations between the samples employed in the different analyses and the ways in which these are likely to have impacted upon the figures produced.

Discussion

Existing explorations of how an offender's base may be related to where he or she commits crimes have drawn on general trends across a number of offenders. The dominant process has been to apply geometric models based on aggregate probability distributions. These assume that the same likelihood surface can be applied to each individual crime series. However, growing empirical evidence supports the common-sense perspective that each offender is likely to use surroundings in a characteristic way.

An emerging approach that differs from the use of likelihood surfaces uses Bayesian probability modelling. This relies on geographical examination of the actual locations in particular cities of the areas in which offenders reside relative to where they commit their crimes. This implicitly takes account of differences in land use patterns and so can be more sensitive to local issues than aggregate likelihood surfaces. However, it is dependent on a particular data set of a number of crimes and criminals from a specific location. It thus also is essentially nomothetic in dealing with general trends across a number of offenders.

In contrast to these existing approaches a number of models have been explored in the present paper that are essentially ideographic, in that they only draw on information about the location of the crimes in a unique crime series. Indeed, one of the earliest models of serial crime distribution, often known as the 'circle' model (Canter and Larkin 1993), was ideographic, utilising only the two crimes furthest from each other to predict the base of the offender. A stronger mathematical formula has been placed on that model in the present study and others have been added that use density, dominant axes and routes applied to any specific crime series.

By taking account of variations in the nature and form of offence distributions (for example; in terms of inter-crime distances, criminal range and directional/axial biases) and deriving predictions based solely on the spatial characteristics of a particular offence series, the ideographic models presented overcome many of the weaknesses of previous geographical profiling methods (e.g. nomothetic algorithms and Bayesian approaches). The initial findings presented here suggest that taking such an individualistic approach to modelling home-crime relationships is likely to enhance the accuracy of geographical profiling predictions.

Prediction efficacy was, however, found to vary considerably between the ideographic models. This suggests that the crime series comprising the present sample differed greatly in terms of the ways in which offences were distributed in relation to the home. Detailed consideration of such variations in prediction efficacy across offence series offers an enriched understanding of the factors that impact upon the strength and nature of the home-crime relationships, thereby facilitating the development of our theoretical understanding of offender spatial decision-making. Further, the present models demonstrably offer a more comprehensive and reliable repertoire of methods for characterizing different forms of crime distribution than those that have previously been available to researchers.

Comparisons of the results from the present study with those from nomothetic models showed that in virtually all cases the ideographic models out-performed existing geographical profiling methods. For this data set at least the models tested here gave consistently and distinctly shorter distances to crime and consistently and distinctly higher proportions of offenders within one kilometre of the designated most probable base location.

These results of course need to be tested further with other data sets dealing with other sorts of crimes in other locations, but the results strongly indicate that offenders need to be modelled individually if our understanding of their crime location choices is to be improved.

Enriched understanding would, in turn, enable geographical investigative decision support tools to be developed and refined, through the incorporation of more reliable and robust methods of characterizing and predicting home-crime relationships. The findings of the present study suggest that this would enhance their overall efficacy, and increase their practical utility in the investigation of serial crimes.

Limitations and Directions for Future Research

The main limitations of the present work stem from its reliance on a single, relatively small dataset and a lack of suitable figures against which to make comparisons. Future research certainly needs to directly examine the effectiveness of these models relative to existing geographical methods using the same dataset(s), rather than attempting to make comparisons across samples (as in the present study).

Moreover, the efficacy of the ideographic models presented here should be examined for samples of a different nature and for different crime types. Rossmo (2000) discusses in detail how different samples are likely to be subject to varying personal, social, contextual and environmental influences and constraints. Canter and Larkin (1993) and Snook (2004) show that individual offender characteristics impact upon offender travel patterns. Further, both Hammond (2009) and Hammond and Youngs (2011) show that the spatial patterning of serial crime depends greatly on the nature and type of offence, as well as the availability, suitability and distribution of targets.

It is therefore likely that the proportions of cases in which the different approaches generate the best predictions are likely to vary greatly between different samples. Measuring and accounting for such variations would facilitate the development of theory on the factors and psychological processes underlying the decision of where to offend.

In addition, the ways in which different aspects or characteristics of the crime series themselves (for example; the number and selection of crimes included or distribution attributes such as average inter-offence distances, size of offending area and offence dispersion, including areas of no-activity) impact upon the prediction accuracy of different models should be explored. For it is only by establishing when and under what conditions different models are likely to provide the best approximations for different forms of crime distributions that the predictive accuracy of any of these approaches be reliably assessed, and ways of enhancing their overall operational utility proposed.

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