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Original Citation

Canter, David V., Hammond, Laura, Youngs, Donna E. and Juszczak, Piotr (2013) The Efficacy of Ideographic Models for Geographical Offender Profiling. Journal of Quantitative Criminology, 29 (3). pp. 423-446. ISSN 0748-4518

The Efficacy of Ideographic Models for Geographical Offender Profiling

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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 employing aggregate distributions across a number of offenders, ignoring the possibility of axially distorted distributions and working with limited probability models. 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 algorithms 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 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 and mathematical models therefore need to take this into account. Such models will improve geographically based investigative decision support systems.

Keywords:

Geographical Profiling - Ideographic Models - Burglary - Dragnet - Criminal Spatial Behaviour

1. 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 standardised 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.

2. 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 their 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. These aspects carry theoretical implications for understanding criminal behaviour. They also offer the possibility of developing decision support systems that provide predictive models of where an offender may be based that can act as an aid to investigations.

A number of studies have shown the power of these decision support systems and have used them as platforms to explore the most fruitful mathematics for encapsulating empirically derived decay functions (Bennell, Emeno, Snook, Taylor and Goodwill, 2009; Canter, Coffey, Huntley and

Missen, 2000; Canter and Hammond, 2006; Hammond and Youngs, 2011; Levine, 2002; 2005; Paulsen, 2005; 2006; Rossmo, 2000). Debate remains rife as to which of a range of different forms of function might most appropriately encapsulate 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, 2009; 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 the earlier 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.

Snook and his colleagues (Bennell, Snook, Taylor, Corey and Keyton, 2007; Bennell, Taylor and Snook, 2007; Snook, Canter and Bennell, 2002; Snook, Taylor and Bennell, 2004; Snook, Zito, Taylor and Bennell, 2005; Taylor, Bennell and Snook, 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 algorithms that model crime locations both as a way of further understanding criminal spatial behaviour and as the basis for enhanced decision support systems.

3. 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. Both Canter and Larkin (1993) and Hammond (2009), for example, show that offenders have typical ranges over which they operate, relating to the resources they have available. There have also been a number of studies showing differences in the distances offenders travel depending on the type of crime (e.g. Townsley and Sidebottom, 2010; as summarised by, for example; Canter and Youngs, 2008a; 2008b; Van Koppen, Elffers and Ruiter, 2011), which geographical profiling methods have typically failed to account for (Levine, 2005). More generally it has been known since Canter and Larkin (1993) first drew attention to the distinction between ‘marauders’ and ‘commuters’ that offenders differ in their offence morphology, differing spatial patterns being characteristic of different offenders. Indeed, a number of authors (Smith, Bond and Townsley, 2009; Van Koppen and De Keijser, 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.

A second weakness is that the morphological models underlying such approaches are very simple. They assume that the opportunities for crime and the directions in which an offender are likely to move are equally probable all around the offender's home/base (Van Koppen et al., 2011). However, there are a number of reasons why this might not always be expected to be the case. Warren, Reboussin, Hazelwood, Cummings, Gibbs and Trumbetta (1998) illustrated what they termed a 'windshield effect', whereby crimes were committed outwards from the home base in specific directions. Indeed, a number of studies have illustrated clear directional biases in serial crime distribution (e.g. Costanzo, Halperin and Gale, 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 GOP algorithm and showed it did improve its effectiveness. 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.

4. DragNetP - Five New Algorithms

In order to test whether more effective inferences of 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 incorporates five different algorithms each working solely with the information available from a particular crime series.

4.1: Ideographic Model 1: Kernal Density Estimation (Density)

Kernel density estimation resembles the nomothetic decay analyses employed by previous GOP systems, but it is based on individual cases. The differences between this form of density calculation and those currently employed in GP systems such as Rigel or Dragnet are that;

(1) Probability distributions are calculated for each individual series, in effect generating a unique *sigma* ( ) 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 probability density function of a random variable. The estimated density is a mixture of kernels centred on the individual training objects (location of offences) (Eq. I):

(I) —

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

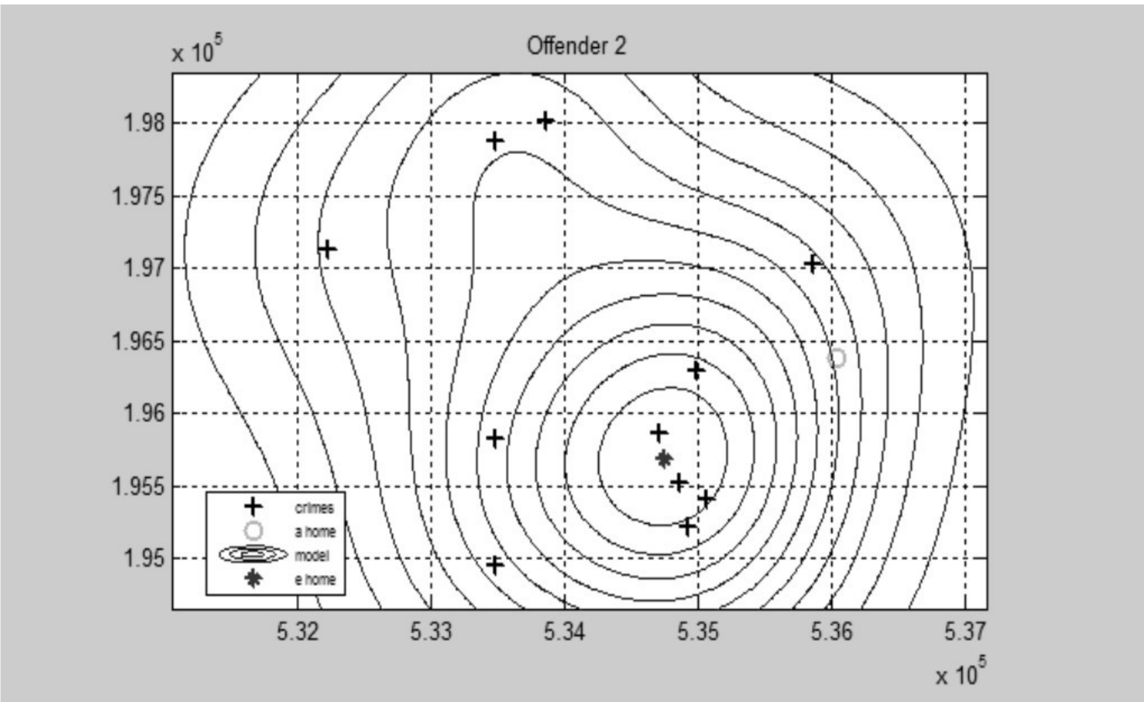
(II) — ——

Training the Parzen density consists of the determination of the width of the kernel . 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 algorithm operates as follows: First for each crime series the width of the kernel is optimised by the maximum likelihood criterion, using the locations of crimes for the 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 on the grid the value of the kernel density estimation is computed. The most likely location of the offender home is assigned to the location with the maximum kernel density estimation (e.g. Eq. III; see Figure 1.):

(III)

Figure 1: Illustration of Density Model Output



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

The most direct way of exploring the possible influence of an axis on the relationship of an offender's home to their offence locations 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 1000 equally spaced points are generated. For each point 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 Figure 2.).

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

As a comparison with these new algorithms, following Canter and Larkin (1993) a prediction of most likely home location is derived using the circle that encapsulates the crime locations. This is in essence the calculation of the centre of the smallest circle enclosing all points , as determined using equation IV:

(I) $-$

where is matrix with elements and is matrix with elements and where **1** is the vector of ones.

Note that non-singularity of a matrix is guaranteed by the non-collinearity of the points .

Figure 2: Illustration of Regression Model Output

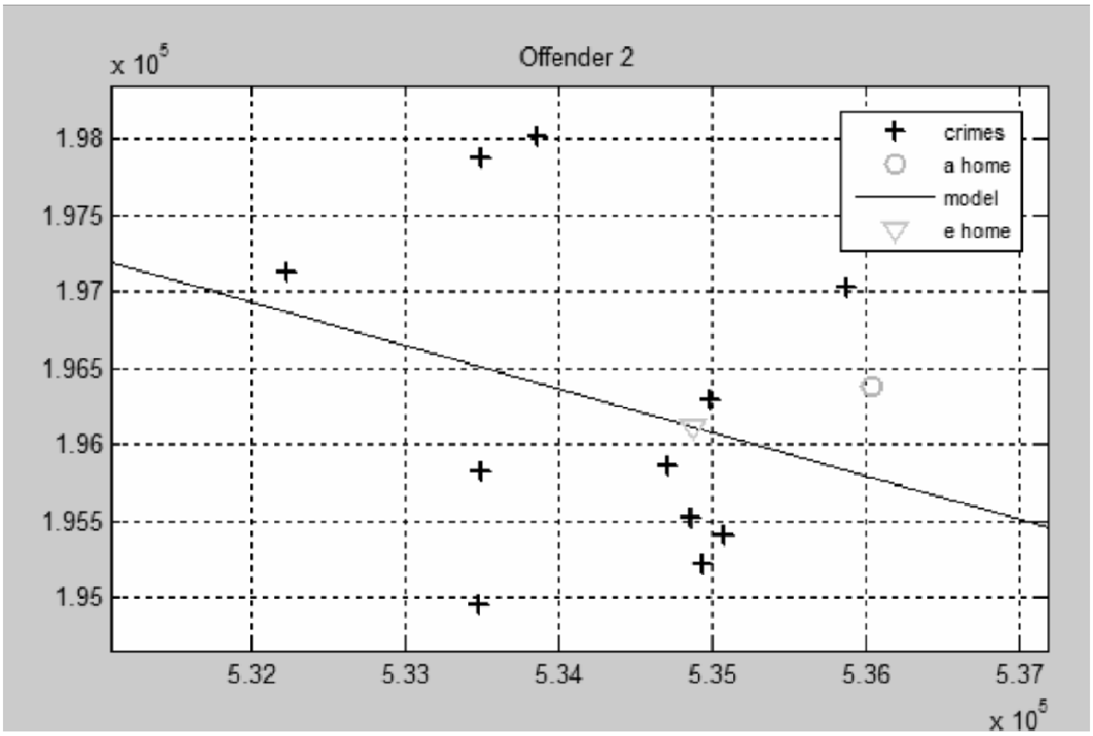
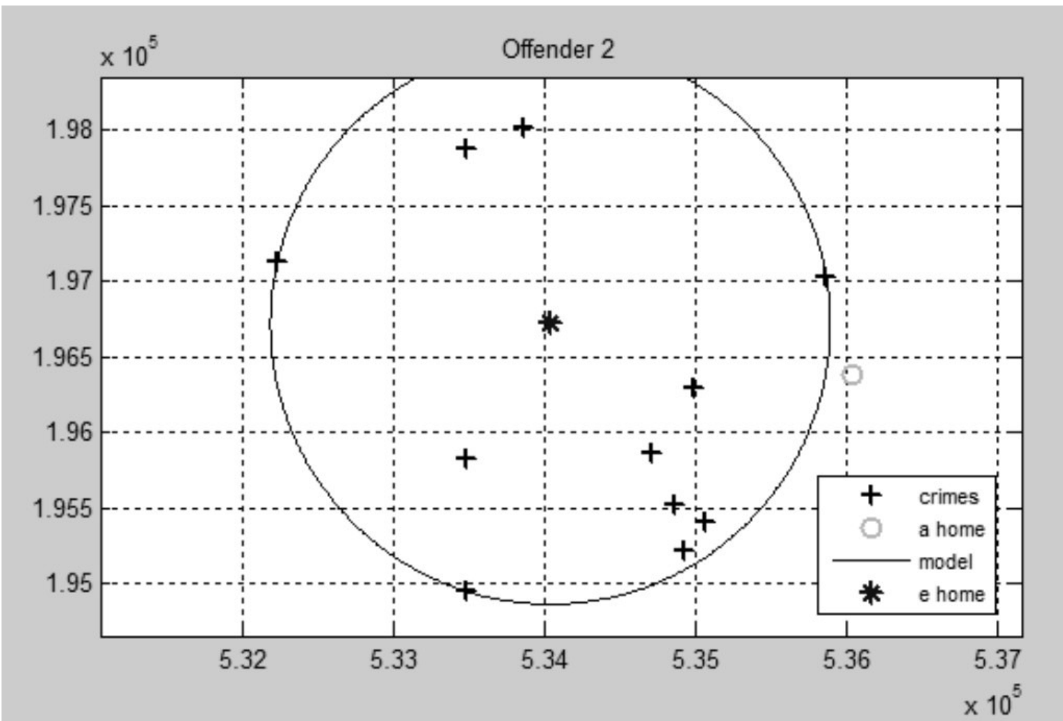


Figure 3: Illustration of Circle Model Output



In the application of this model we compute a circle with the smallest area that encloses all crime locations. Previously the offence circle has been calculated by taking a line between the two crimes that are furthest from each other as the diameter of the circle. This is not necessarily the circle that covers the smallest area incorporating all the crimes, as is the case in the new algorithm (illustrated in Figure 3).

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

This is an entirely new approach to considering the probabilities of locations being where the offender's home is. The model attempts to establish if there are sub-sets of crimes that need to be examined distinctly from each other. It therefore gives a result similar to the Density model but organised around groupings of crimes. Conceptually it recognises that crimes may form distinct sub-groups and allows the exploration of that possibility. This can thus be useful for a variety of investigative and crime reduction applications beyond locating an offender's home, such as linking crimes.

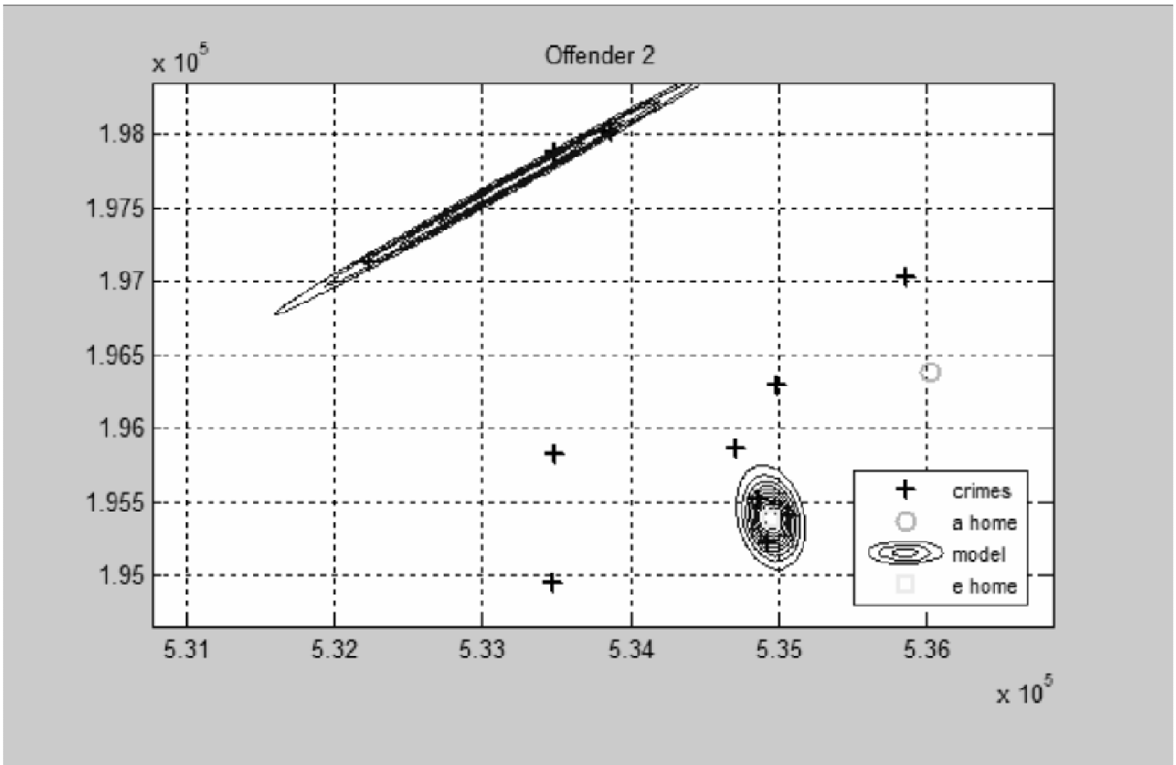
The Mixture of Gaussians model represents a dataset by a set of mean and covariance matrices. Each class is centred at a mean and has a Gaussian distribution which extends as described by its matrix. Each class also has a weight associated with it which is simply its total fraction of points divided 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 Equation V:

(II)

$$L = \prod_{x \in X} \prod_{k} \frac{1}{\sqrt{(2\pi)^d |\Sigma_k|}} \; e^{-(x_k - \mu_k)\Sigma_k (x_k - \mu_k)}$$

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

Figure 4: Illustration of MGauss Model Output



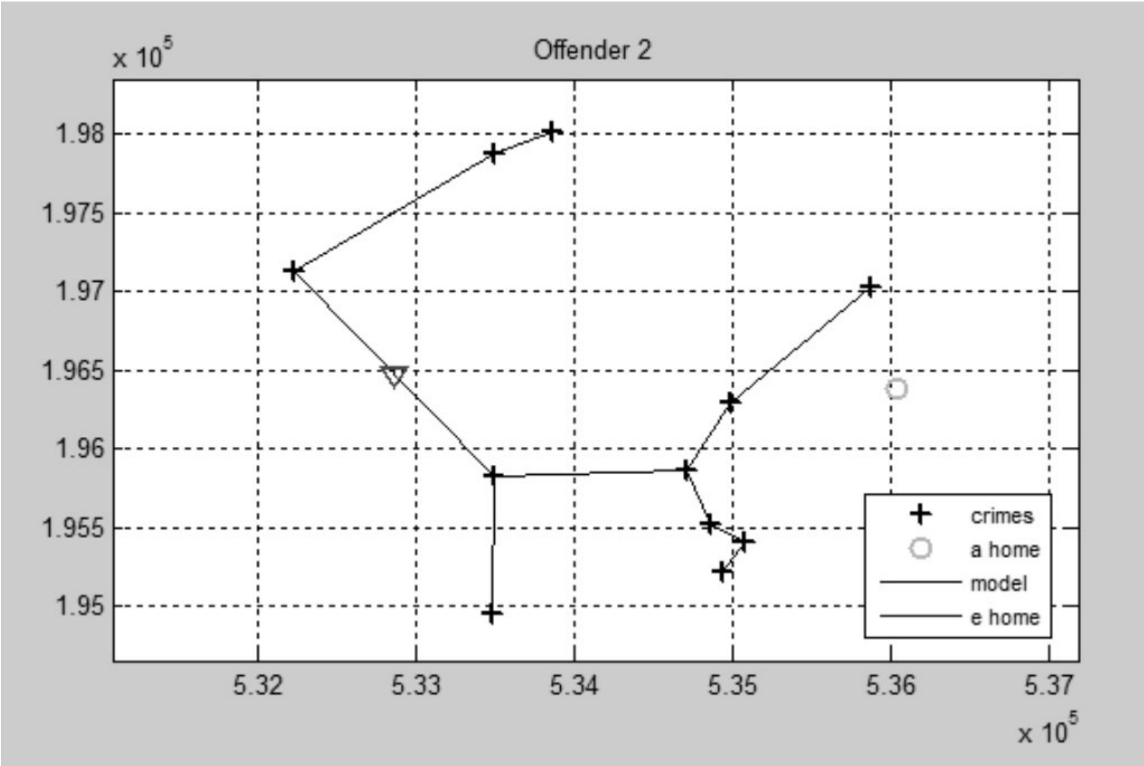
4.5 Ideographic Model 5: A Minimum Spanning Tree Analysis (MST)

This is also an entirely new approach to modelling crime locations, although it has parallels to the Regression model. In the most basic of terms, this model finds the shortest direct line set of links between crimes. It allows a calculation of the most likely home location using these links.

Given a connected, undirected graph, a spanning tree of that graph is a sub-graph that is a tree and connects all the vertices together. A single graph can have many different spanning trees. We can also assign a *weight* to each edge, which is a number representing how unfavourable it is, and use this to assign a weight to a 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.

Prim's Algorithm (1957) is used to estimate offender home location for the MST model. Prim's algorithm is a 'greedy algorithm' that finds a minimum spanning tree for a connected weighted undirected graph. This means it finds a subset of the edges that forms a tree that includes every vertex, where the total weight of all the edges in the tree is minimized. The offender's home location estimation is the place on the tree where sum of distances to all crimes along the tree is minimal (Figure 5):

Figure 5: Illustration of MST Model Output



5. Application of Ideographic Models to 63 Burglary Series

5.1 Data

A dataset previously utilised by other researchers (e.g. Leitner, Kent, Oldfield and Swoope, 2007), made available by the London Metropolitan Police Service (Levine, 2005; Harries and LeBeau, 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.

5.2 Measuring GP Effectiveness:

Various measures of GP program output accuracy have been suggested (see, for example; Paulsen, 2004; Rich & Shively, 2004; Rich, Shively, & Adedokun, 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 search 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 may seem at first sight. The distance measures could reasonably be on a Manhattan matrix or the nearest feasible route, both of which could take account of land-use patterns. However, they are open to some arbitrariness because the actual route an offender might take is not known. Indeed, as Canter and Hodge (2000) and Canter and Shalev (2008) have shown through the study of offenders' 'mental maps', there are many reasons why an offender may not use the nearest direct route between home and crime location. The direct 'crow flight' measurement may therefore remain the best estimate of the distance that the predicted home is from the actual home. It is what most previous research has used (e.g. Paulsen, 2005; 2006; Bennell et al., 2009), and is therefore used here.

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, 5km had to be searched, rather than 10% of an arbitrary total area.

6. Results

6.1 Findings on the Efficacy of the Ideographic Models

6.1.1 Summary Descriptions of Efficacy Measures

Two efficacy measures were employed to make comparisons between the five ideographic models presented previously; an error distance measure (shortest ‘crow flight’ distance between actual home an estimated home location) and an area measure (the actual area that would need to be searched to find the home, starting from the predicted home).

Table I gives the summary descriptions of the efficacy measures for the distance from home to predicted home location. Because of the well established skewed distribution of the distances offenders travel the median is the best estimate of the efficacy of the different measures, although other indicators of central tendency are provided for comparison. The results show, interestingly, that the regression model has the lowest median and mean, with the median being close to half a kilometre. Also, a quarter of the sample have a median distance less than a third of a kilometre for the regression model, but also for the Density and Mgauss models, This does show the significance of dominant axes as also reported by Canter et al (2000) with their use of the Q range.

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 I: Descriptive Statistics for Distance Measures (km)

	Mean	S.D.	Median	25 Percentile	50 Percentile	75 Percentile
Regression	1.79	4.088	0.57	0.32	0.57	1.19
Density	1.86	4.129	0.68	0.29	0.68	1.44
MGauss	2.27	4.167	0.79	0.34	0.79	2.51
MST	2.48	4.212	1.25	0.44	1.25	2.82
Circle	2.66	4.078	1.48	0.56	1.48	3.59

Table II: Median Tests Of Differences Between Methods On Distance Measures

		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	.788400
Chi-square	9.854[a]
Df	4
Asymp. Sig.	.043

The area measures, in Table III show a slightly different picture. The MGauss has the lowest median area of less than half a square kilometre. Indeed, in a quarter of case the area that needs to be covered before the offender's base is established is only one tenth of a square metre. This is perhaps to be expected because the MGauss algorithm deliberately identifies sub areas of the general area to be searched and so covers a smaller subset than the other measures. Nonetheless the Density algorithm still gives close results to 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 IV there is a clear statistically significant difference between the models at p<.0001.

Table III: Descriptive Statistics for Area Measures (km^2)

	Mean	S.D.	Median	25 Percentile	50 Percentile	75 Percentile
MGauss	7.72	22.868	0.41	0.10	0.41	4.16
Density	23.42	117.158	0.69	0.12	0.69	2.61
Regression	61.68	329.827	1.02	0.33	1.02	4.46
MST	74.24	327.988	4.88	0.61	4.88	24.93
Circle	73.65	322.582	6.88	0.98	6.88	40.50

Table IV: Median Tests of Differences Between Methods on Area Measure

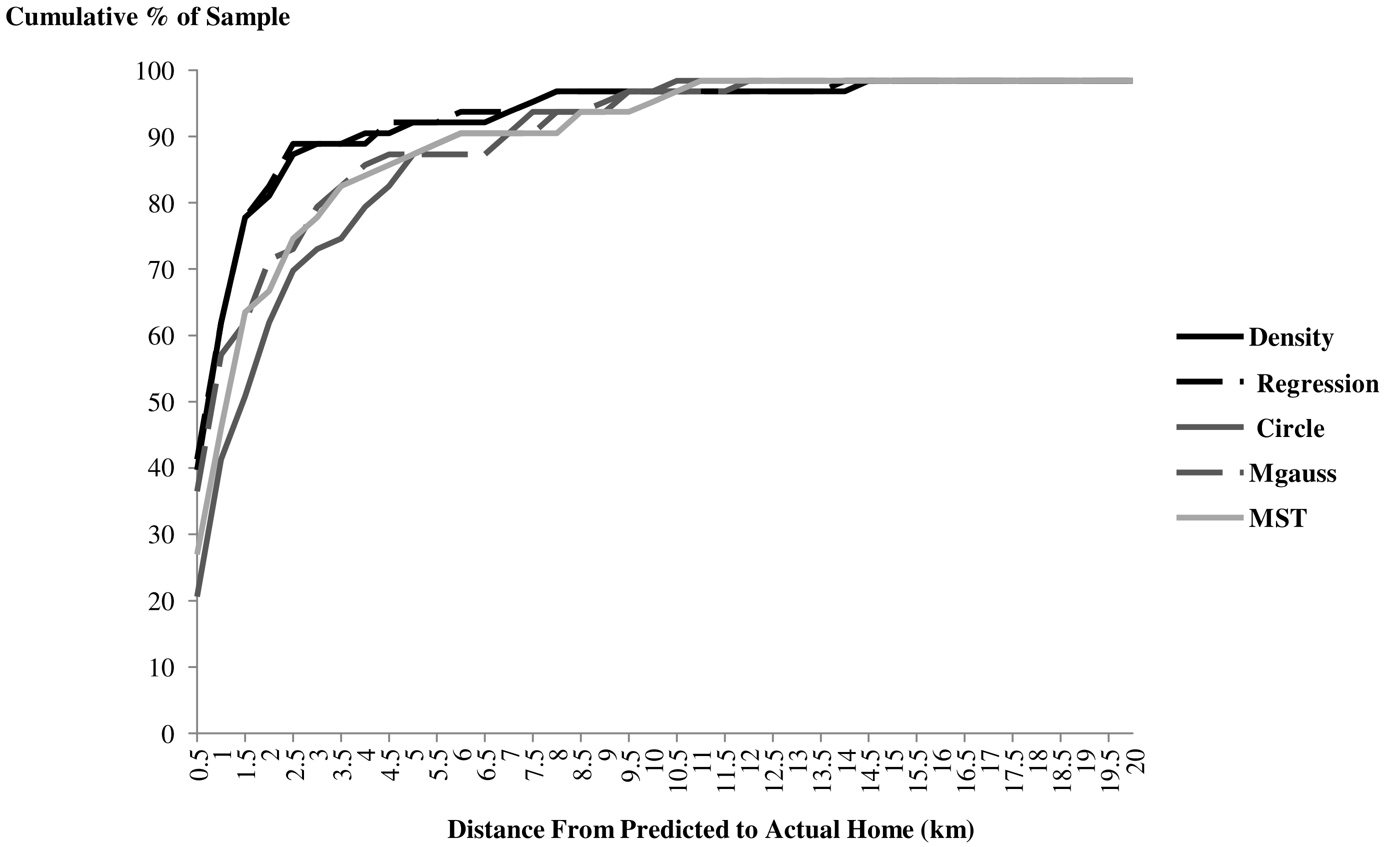
		Method				
		Density	Regression	Circle	MGauss	MST
Area	> Median	23	28	46	21	39
	<= Median	40	35	17	42	24

	Area
N	315
Median	1.454400
Chi-square	29.283[a]
Df	4
Asymp. Sig.	.000

6.1.2 Efficacy Functions for Each of the Models

As Canter et al. (2000) pointed out the utility of geographical profiling models relates in part to the nature of the distribution of their effectiveness. If there is a steady asymptotic increment in the effectiveness of any decision support system then it is difficult to defend its daily use. What is necessary is to demonstrate that there are a substantial proportion of cases in which the algorithm gives useful results. Canter et al (2000) referred to examination of this as a consideration of the ‘search cost function’ for any model. This is most usually a cumulative percentage graph that shows how many cases are achieved at any given estimate of distance or area. For the present study the cumulative proportion of cases that had different error distances or search areas were plotted as in Figures 6 and 7:

Figure 6: Distance Efficacy Functions For Each Of The Models



These show that there is an encouragingly strong ‘elbow’ in each figure. This indicates that there are a reasonable proportion of cases in which relatively small distances or search areas are required.

The error distance graph in Figure 6 shows that there is a not a lot of difference in the error function across the five different measures although it illustrates the finding of the greater efficacy of the regression and density models.

Figure 7: Area Efficacy Functions For Each Of The Models

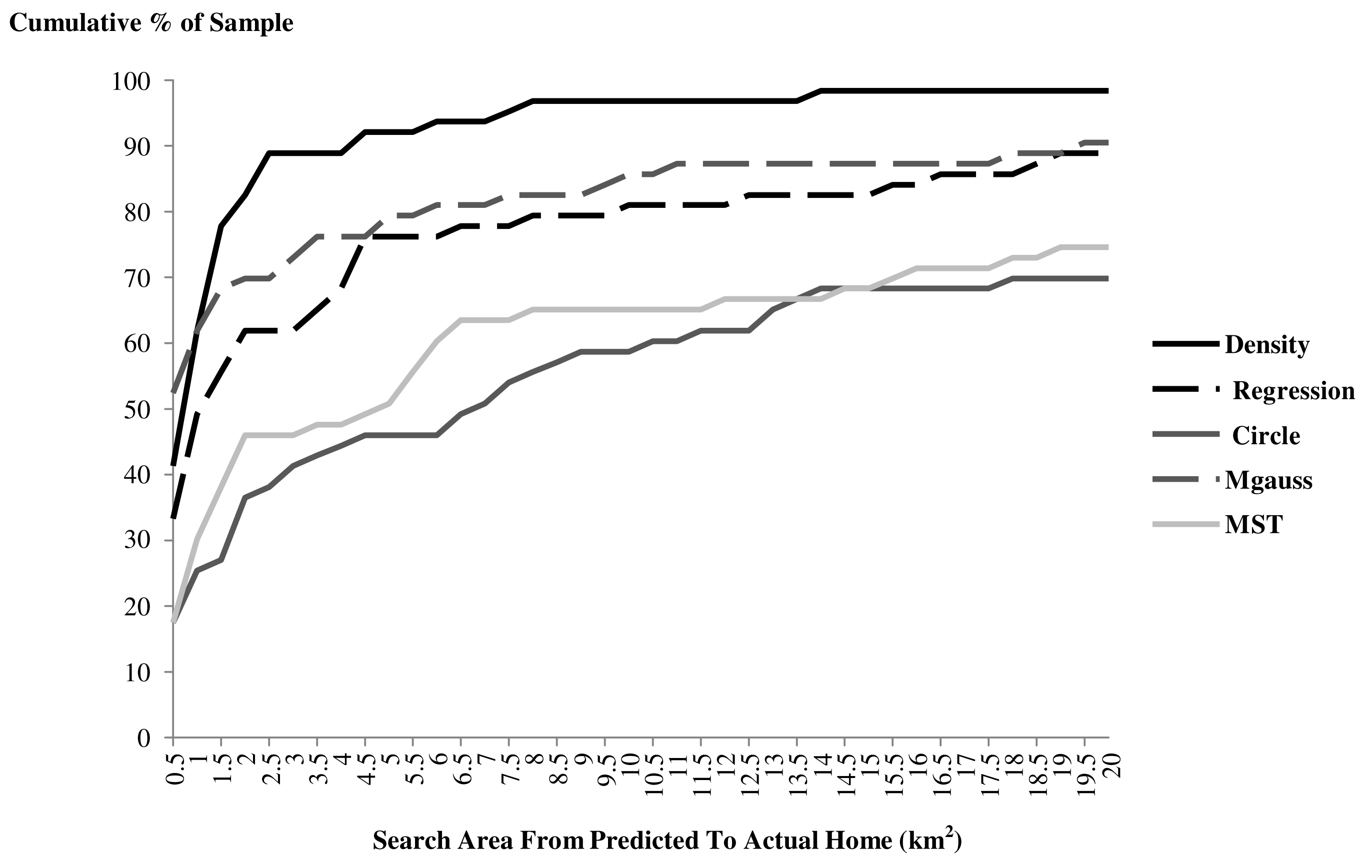


Figure 7 shows greater diversity between the different models in terms of the search areas they require. The stronger 'elbow' for the Density model shows that it is likely to be the most useful, at least with crimes similar to those in the current data set. The comparison with the MST and the Circle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

6.1.3 Variations in Efficacy of Models for Different Crime Series

The efficacy functions illustrated in Figures 6 and 7 show that all models have some success with some crimes. 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. Examination was therefore made of every crime series to determine which model gave the closest distance to home and the smallest search area. Table V shows the percentage of cases for which each of the models produced the best results. Quite remarkably 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.

Table V: Frequencies And Percentages With Which Each Method Achieved The Lowest Distance And Area Scores

	Best Distance	**% of Cases**	**Best Area**	**% of Cases**
MGauss	16	25.4	32	50.8
Density	15	23.8	17	27.0
Circle	12	19.0	6	9.5
Regression	10	15.9	4	6.3
MST	10	15.9	4	6.3

Effectiveness is not as evenly distributed across area as it is across error distance. 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 Figure 7 that shows these two models having a much higher proportion of cases with small search areas than the other three models.

Table VI 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. This provides a benchmark for comparison with other existing published approaches.

Table VI: Descriptives If Best Methods Are Used

Distance Mean	=	1.26
Distance S.D.	=	3.722
Distance Median	=	0.424
Area Mean	=	3.88
Area S.D.	=	17.440
Area Median	=	0.164

6.2 Comparison of Present Results with Previous Findings

A growing body of research is reporting on the accuracy and success of individual 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, Canter, & Bennell, 2002; Snook, Taylor, & Bennell, 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 works 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 efficiency, 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.

6.2.1. 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 VI presents key results[4][5][6] from Paulsen's (2005; 2006) studies with equivalent figures for the five ideographic models under consideration in the present work for comparison.

The results show very clearly that on all of Paulsen's measures the optimum models in the present study do considerably better. Even looking at the models on their own the results are considerably better. This supports the central hypothesis of the present study that ideographic models capture more of offending behaviour than general aggregate models.

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

[5] Paulsen's (2006) sample also consists of a range of crime types; however, only five residential burglary series were included in the sample 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 VII.

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

Table VII: Comparison of Present Results With Those of Paulsen (2005; 2006)

Method	**Profile Accuracy**	**Mean Error Distance (km)**	**Mean Profile Error Distance (km)**
Paulsen (2005)*			
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)*			
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.

* figures converted from values presented in Miles in the original work

6.2.2. 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 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 VIII details the results for the error distance measures of published evaluations of Bayesian methods using various models with equivalent figures for the five ideographical 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 efficiency 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 VIII 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).

Table VIII: Comparison of Present Results With Those Published For Bayesian Methods – Distance From Predicted to Actual Home (km)

Method	Levine & Lee (2009)	Leitner & Kent (2009) Multiple Crime Series*	Leitner & Kent (2009) Single Crime Series*	Block and Bernasco (2009)	Levine and Block (2011) Baltimore Data*	Levine and Block (2011) Chicago Data*	Bennell et al. (2009)*
Journey to Crime	2.86	4.30	4.86	1.82	4.47	3.20	-
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	4.60	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	-	-	-	-	-	-	4.30
Calibrated	-	-	-	-	-	-	4.10
DragnetP							
Regression	1.79						
Density	1.85						
MGauss	2.45						
MST	2.48						
Circle	2.66						
Optimum	1.26						

*Measures converted to km from the Mile values originally reported

Table IX: Comparison of Present Results With Those Published For Bayesian Methods – Percentage of Offenders Living Less Than 1km From Predicted Home

Method	Levine & Lee (2009)	Leitner & Kent (2009) Multiple Crime Series	Leitner & 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	50.0
CMD	43.27	38.94	32.59	35.5
DragnetP				
Regression	61.9			
Density	61.9			
MGauss	52.4			
MST	46.0			
Circle	41.3			
Optimum	61.1			

Nonetheless, it is clear that the distance from home to predicted home is much smaller for the models tested here than for the Bayesian studies. It is only for the Block & 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 proportion of offenders living within any given distance from the predicted cell. These percentages are given in Table IX with comparisons from the present study.

Again Block and Bernasco (2009) achieve the highest percentage for their 'conditional' model with 64% of their offenders within one kilometre of the cell designated by the Bayesian analysis, but most of the other studies and models show much smaller figures, typically in the region of 40% or less. By contrast the optimum result for the present study is 61%, with even the simple circle model giving 41% of the offenders within one kilometre of the highest probability designated location.

Discussion and Conclusions

Existing explorations of how an offender's base may be related to where he or she commits crimes have all 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 likelihood surface can be applied to each individual crime series. However, growing empirical evidence supports the commonsense perspective that each offender is likely to use surroundings in a unique 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 related 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 entirely dependent on a particular data set of a number of crimes and criminals from a specific location. It is 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.

The results of applying these models to a set of 63 burglary series in London showed that each was optimum for some series, but none was optimum for all series. The density models had the highest number of series in which they were optimum giving median distances of close to 1 kilometre between the predicted home and the actual home. This indicates that these offenders did tend to operate in an area that encompassed their home. However, the models that drew on dominant axes or routes were also optimum for some series raising the prospect of some important differences between offenders in the structure of their crime searches.

Comparisons of the results from the present study with those from the nomothetic models showed that in virtually all cases the ideographic models out-performed them. For this data set at least the density 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. Such an understanding will also increase the effectiveness of geographical investigative decision support tools.

References

Bennell, C., Emeno, K., Snook, B., Taylor, P. & Snook, B. (2009) The Precision, Accuracy and Efficiency of Geographic Profiling Predictions: A Simple Heuristic Versus Mathematical Algorithms. *Crime Mapping: A Journal of Research and Practice*, 1 (2); p.65-84.

Bennell, C., Snook, B., Taylor, P. J., Corey, S., & Keyton, J. (2007). It's No Riddle, Choose the Middle: The Effect of Number of Crimes and Topographical Detail on Police Officer Predictions of Serial Burglars' Home Locations. *Criminal Justice and Behavior*, 34 (1), 119-132.

Bennell, C., Taylor, P., & Snook, B. (2007). Clinical Versus Actuarial Geographic Profiling Strategies: A Review of the Research. *Police Practice and Research*, 8(4), 335–345.

Block, R. & Bernasco, W. (2009) Finding A Serial Burglar’s Home Using Distance Decay and Origin Destination Patterns: A Test of Empirical Bayes Journey-to-Crime Estimation in the Hague. *Journal of Investigative Psychology and Offender Profiling*, 6 (3); 187-211.

Canter, D. (2009). Developments in Geographical Offender Profiling: Commentary on Bayesian Journey-to-Crime Modelling. *Journal of Investigative Psychology and Offender Profiling*, 6; 161-166.

Canter, D., Coffey, T., Huntley, M. & Missen, C. (2000). Predicting Serial Killers’ Home Base Using a Decision Support System. *Journal of Quantitative Criminology*, 16, 4; 457 – 478.

Canter, D. & Hammond, L. (2006) A Comparison of the Efficacy of Different Decay Functions in Geographical Profiling for a Sample of U.S. Serial Killers. *Journal of Investigative Psychology and Offender Profiling*, 3; 91-103.

Canter, D. & Hammond, L. (2007) Prioritising Burglars: Comparing the Effectiveness of Geographical Profiling Methods. *Police, Practice and Research*, 8(4); 371-384.

Canter, D. & Hodge, S. (2000). Criminal's Mental Maps. In L.S. Turnball, E. Hallisey-Hendrix & B.D. Dent (Eds). *Atlas of Crime*. Oryx Press; 187-191.

Canter, D. & Larkin, P. (1993). The Environmental Range of Serial Rapists. In Canter, D. & Alison, L. (Eds.). *Criminal Detection and the Psychology of Crime*. Aldershot, Dartmouth: Ashgate.

Canter, D. & Shalev, K. (2008). Putting Crime in its Place: Psychological Process in Crime Site Location. In D. Canter & D. Youngs (2008*) Principles of Geographical Offender Profiling. Aldershot*, Ashgate.

Canter, D. & Youngs, D. (Eds.) (2008a) *Principles of Geographical Offender Profiling*. Aldershot, Ashgate.

Canter, D. & Youngs, D. (Eds.) (2008b) *Applications of Geographical Offender Profiling*. Aldershot, Ashgate.

Canter, D. & Youngs, D. (2009) *Investigative Psychology: Offender Profiling and the Analysis of Criminal Action*. Chichester: Wiley.

C.M. Costanzo, W.C. Halperin, and N. Gale (1986). Criminal Mobility and the Directional Component in Journeys to Crime, in R. Figlio, S. Hakim and G. Rengert (Eds.) *Metropolitan Crime Patterns*. Monsey, N.Y.: Willow Tree Press.

Duin, R. (1976). On the Choice of the Smoothing Parameters for Parzen Estimators of Probability Density Functions. *IEEE Transactions on Computers*, C-25(11); 1175–1179.

Emeno, K. & Bennell, C. (2011) The Effectiveness of Calibrated Versus Default Distance Decay Functions for Geographic Profiling: A Preliminary Examination of Crime Type. *Psychology, Crime & Law,* DOI:10.1080/1068316X.2011.621426

Goodwill, A.. & Alison, L. (2005) Sequential Angulation, Spatial Dispersion and Consistency of Distance Attack Patterns from Home in Serial Murder, Rape and Burglary. *Psychology, Crime & Law*, 11(2); 161-176.

Hammond, L. (2009) *Spatial Patterns in Serial Crime: Modelling Offence Distribution and Home-Crime Relationships For Prolific Individual Offenders*. Unpublished Doctoral Thesis: University of Liverpool.

Hammond, L. and Youngs, D. (2011) Decay Functions and Criminal Spatial Processes: Geographical Offender Profiling of Volume Crime. *Journal of Investigative Psychology and Offender Profiling*, 8; 90-102.

Harries, K. & Le Beau, J. (2007) Issues in the Geographic Profiling of Crime: Review and Commentary. *Police Practice and Research*, 8 (4); 321-333.

Leitner, M. & Kent, J. (2009). Bayesian Journey to Crime Modelling of Single and Multiple Crime Type Series in Baltimore County, MD. *Journal of Investigative Psychology and Offender Profiling*, 6; 213-236.

Leitner, M., Kent, J., Oldfield, I. & Swoope, E. (2007). Geoforensic Analysis Revisited – The Application of Newton's Geographic Profiling Method to Serial Burglaries in London, U.K. *Police Practice and Research*, 8 (4); 359-370.

Levine, N. (2002). *Crimestat II: Spatial Modeling*. Report for the U.S. Department of Justice, August 13th, 2002.

Levine, N. (2005). CrimeStat III. *Crime Mapping News*. 7(2), Spring. 8-10.

Levine, N. (2009) Introduction to the Special Issue on Bayesian Journey-to-Crime Modelling. *Journal of Investigative Psychology and Offender Profiling*, 6 (3); 167-185.

Levine, N. & Block, R. (2011) Bayesian Journey-to-Crime Estimation: An Improvement in Geographic Profiling Methodology. *The Professional Geographer*, 63 (2); 213-229.

Levine, N. & Lee, P (2009). Bayesian Journey-to-Crime Modelling of Juvenile and Adult Offenders by Gender in Manchester. *Journal of Investigative Psychology and Offender Profiling*, 6; 237-251.

Lundrigan, S. & Canter, D. (2001). Spatial Patterns of Serial Murder: An Analysis of Disposal Site Location Choice. *Behavioural Sciences and the Law*, 19; 595-610.

Lundrigan, S. & Czarnomski, S. (2006). Spatial Characteristics of Serial Sexual Assault in New Zealand. *The Australian and New Zealand Journal of Criminology*. 32 (2); 218-231.

Nunez-Garcia, J., Kutalik, Z., Cho, K.-H., and Wolkenhauer, O. (2003). Level Sets and Minimum Volume Sets of Probability Density Functions. *Journal of Approximate Reasoning*, 34(1); 25–47.

Parzen, E. (1962). On the Estimation of a Probability Density Function and Mode. *Annals of Mathematical Statistics*, 33:1065–1076.

Paulsen, D. J. (2004, March). *Geographic profiling: Hype or hope? – Preliminary Results into the Accuracy of Geographic Profiling Software*. Paper presented at the UK Crime Mapping Conference, London, UK.

Paulsen, D. (2005). Connecting the Dots: Assessing the Accuracy of Geographic Profiling Software. *Policing: An International Journal of Police Strategies and Management*, 29 (2); 306-334.

Paulsen, D. (2006). Human vs. Machine: A Comparison of the Accuracy of Geographic Profiling Methods. *Journal of Investigative Psychology and Offender Profiling*, 3(2); 77-89.

Prim,R.J. (1957) Shortest Connection Networks and Some Generalizations. *Bell System Technical Journal*, 36; 1389–1401.

Rich, T. & Shively, M. (2004). A Methodology for Evaluating Geographic Profiling Software: Final Report. Cambridge, MA: Abt Associates Inc.

Rich, T., Shively, M., & Adedokun, L. (2004). *NIJ Roundtable for Developing an Evaluation Methodology for Geographic Profiling Software*. Cambridge, MA: Abt Associates.

Rossmo, D.K. (2000). *Geographic Profiling*. Boca Raton, FL. CRC Press, LLC.

Smith, W., Bond, J.W. and Townsley, M. (2009). Determining How Journeys-to-Crime Vary Measuring Inter- and Intra-Offender Crime Trip Distributions. In D. Weisburd, Bernasco, W., Gerben, J. & Bruinsma, N. (Eds). *Putting Crime in its Place*. London: Filiquarian Publishing.

Snook, B., Canter, D. V., & Bennell, C. (2002). Predicting the Home Location of Serial Offenders: A Preliminary Comparison of the Accuracy of Human Judges with a Geographic Profiling System. *Behavioural Sciences and The Law, 20*, 109-118.

Snook, B., Taylor, P. J., & Bennell, C. (2004). Geographic Profiling: The Fast, Frugal, and Accurate Way. *Applied Cognitive Psychology*, 18, 105-121.

Snook, B., Zito, M., Bennell, C., & Taylor, P.J. (2005). On the Complexity and Accuracy of Geographic Profiling Strategies. *Journal of Quantitative Criminology*, 21 (1); 1-26.

Taylor, P.J., Bennell, C., & Snook, B. (2009). The Bounds of Cognitive Heuristic Performance on the Geographic Profiling Task. *Applied Cognitive Psychology*, 23, 410-430.

Tonkin, M., Woodhams, J., Bond, J.W. & Loe, T. (2010). A Theoretical and Practical Test of Geographical Profiling With Serial Vehicle Theft in a U.K. Context. *Behavioral Sciences and the Law*, 28; 442-460.

Townsley, M. & Sidebottom, A. (2010). All Offenders Are Equal, But Some Are More Equal Than Others: Variation in Journeys to Crime Between Offenders. *Criminology*, 48 (3); 897-917.

Van Koppen, P.J. & De Keiser, J.W. (1997). Desisting Distance Decay: On the Aggregation of Individual Crime Trips. *Criminology*, 35 (2); 505-513.

Van Koppen, M.V., Elffers, H. & Ruiter, S. (2011) When to Refrain From Using Likelihood Surface Methods for Geographical Offender Profiling: An Ex Ante Test of Assumptions. *Journal of Investigative Psychology and Offender Profiling*, 8 (3); p. 242-256.

Warren, J., Reboussin, R., Hazelwood, R.R., Cummings, A. Gibbs, N., and Trumbetta, S. (1998). Crime Scene and Distance Correlates of Serial Rape. *Journal of Quantitative Criminology*. 14 (1); 35-59.

Wolberg, J. (2005) *Data Analysis Using the Method of Least Squares: Extracting the Most Information from Experiments*. Springer: ISBN 3540256741.

Yeung, D. Y. and Chow, C. (2002). Parzen-Window Network Intrusion Detectors. *Proceedings of the Sixteenth International Conference on Pattern Recognition*, 4; 385–388.