doi:10.1093/bjc/azh036 BRIT. J. CRIMINOL. (2004) **44**, 641–658
Advance Access publication 7 May 2004

PROSPECTIVE HOT-SPOTTING

The Future of Crime Mapping?

KATE J. BOWERS, SHANE D. JOHNSON and KEN PEASE*

Existing methods of predicting and mapping the future locations of crime are intrinsically retrospective. This paper explores the development of a mapping procedure that seeks to produce 'prospective' hot-spot maps. Recent research conducted by the authors demonstrates that the risk of burglary is communicable, with properties within 400 metres of a burgled household being at a significantly elevated risk of victimization for up to two months after an initial event. We discuss how, using this knowledge, recorded crime data can be analysed to generate an ever-changing prospective risk surface. One of the central elements of this paper examines the issue of how such a risk surface could be evaluated to determine its effectiveness and utility in comparison to existing methods. New methods of map evaluation are proposed, such as the production of search efficiency rates and area-to-perimeter ratios; standardized metrics that can be derived for maps produced using different techniques, thereby allowing meaningful comparisons to be made and techniques contrasted. The results suggest that the predictive mapping technique proposed here has considerable advantages over more traditional methods and might prove particularly useful in the shift-by-shift deployment of police personnel.

Introduction

The proliferation of Geographical Information System (GIS) has increased interest in crime mapping through the identification of locations historically suffering high rates of crime or disorder. While the past is the only basis on which to anticipate the future, the way in which facts about the past are chosen and weighted will determine the predictive power achievable. Crime patterns anticipated using data from even the recent past may be erroneous (Townsley and Pease 2002; Johnson and Bowers 2004a)—or may not be. Some areas have enduring high crime rates, where the allocation of resources represents an efficient resource targeting strategy.

It is almost a truism to note that while the information we have is about the past, it is the future that we need to know about. However, this truism has permeated the content of the literature less than one might suppose. Two recent publications (Gorr and Olligschlaeger 2002; Groff and LaVigne 2002) compare and discuss prediction methods. Their review of previous work and recommendations to practitioners and researchers are evidence-based and extremely helpful. These include abandonment of forecast methods using the same month from a previous year, explore leading indicators (using past values of independent variables that are associated with crime to predict the current value of the dependent variable) and specify minimum crime numbers to constitute a unit for prediction purposes. There is much in common between the recommendations of Gorr and Olligschlaeger and our conclusions. However, our approach derives from

* Jill Dando Institute of Crime Science, University College London, Third Floor, 1 Old Street, London, EC1V 9HL.

different research origins, and (we hope) that merits a separate account of its origins and development, even though some of the conclusions are similar to the leading indicator views of the authors cited here. Attention in this paper is exclusively upon residential burglary.

In their review, Groff and LaVigne (2002) note the distinctiveness of an approach based upon repeat victimization. They write:

> The research on repeat victimization suggests that much more could be learned from further examination of the composition of hot spots and the extent to which repeat victimizations could be used to predict not just future victimizations, but future hot-spot areas. Such studies should explore the question across different sized hot spots as well as different types of crime problems, and should explore the 'near repeat' concept in further detail. Depending on future research findings in this area, repeat victimization has the potential to provide a simple method that could be employed by users of all skill levels. . . . (Groff and LaVigne 2002: 36–7)

At around the time at which those words were written, two of the present authors were submitting for publication three papers which sought to explore the liberalized notion of repeats along the lines suggested (Johnson and Bowers 2004a; Bowers and Johnson 2004; Johnson and Bowers 2004b). The key findings of the research were that the risk of victimization is communicable, with properties within 400 metres and, particularly, on the same side of the street as a burgled home being at an elevated risk for up to two months after an initial event.

As will be explained more fully below, the notion of predictive mapping taken here is event-based rather than area-based. Given what we now know about sequences of burglary events, every such event should revise the predicted probability of burglary for the burgled home itself and for homes on the same side of the street, within 400 metres and of the same design as the burgled home. The essential difference between this approach and those reviewed and researched by Groff and LaVigne (2002) and by Gorr and Olligschlaeger (2002) is that previous work is based upon area incidence and characteristics. The present work, by contrast, is based upon inferences about area patterns yielded by individual events, summed and weighted as their predictive power wanes. For this approach, the crime event is focal and feeds into an ever-changing predictive map.

Making the crime event, rather than an area crime rate, focal has interesting ramifications. For policing purposes, identification of an ellipse defining a hot spot is, of itself, useless. What does a police officer do next, once she finds herself standing in the middle of a designated hot spot? Groff and LaVigne (2002) stress that until one knows what is heating the hot spot, action can be aimless. Operating from the level of individual households, as with the approach reported here, the pattern of risk within the hot spot is clarified by prior research on repeat victimization and near repeats. Because of this, where the police officer goes and what she does is much more evident to her.

While we believe our approach to mapping has both transparency for police practitioners and a more focused immediate application to policing within high-crime areas, it is clear that the predictive power of this approach at the area level must be at least comparable to that yielded by alternative approaches, and the present paper addresses that issue. It uses only a crude approximation of what we know about the communicability of risk from a burgled home. There is, we believe, latent predictive power in the approach which remains to be explored.

Even if the approach taken here proves inferior at the area level, it would remain useful for deployment decisions within hot spots designated by other means. If it proves at least comparable in predictive power to other approaches, it may be that the approach has a case for being regarded as, provisionally, the method of preference in predictive mapping, and research effort directed accordingly.

As a final point, we anticipate the possibility that, aesthetically, the maps based upon this approach will be less pleasing than more conventional maps, on first sight looking more fragmented and incoherent. However, predictive mapping should not be a beauty contest, and the type of map we propose here may just be the ugly ducking of the fairy story.

To restate the central point, our recent work has demonstrated that the risk of victimization can be regarded as communicable (e.g. Johnson and Bowers 2004a), with the risk of victimization increasing for houses within 400 metres of a burgled household for a period of around one to two months, and especially on the same side of the street as a burgled home. Added to evidence about repeat victimization (for reviews, see Pease 1998; Farrell and Pease 2001), this has important implications for predicting where crimes are most likely to occur and opens up the possibility of undertaking prospective mapping. Here, we mean the production of maps which show future risk—not just of previous victims, but of the local neighbourhood. In what follows, we discuss some of the technical issues involved in generating prospective hot spots, how their efficiency may be measured and preliminary results regarding the comparison of the predictive accuracy of prospective and retrospective hot spots. In this process, we use only two related facts about communicated risk, namely its distribution in time and space relative to burglary events. It thus represents about the most basic prospective map possible.

Prospective Mapping Approach

To generate a prospective risk surface, we used a modification of the moving window technique used in hot-spot detection (Bailey and Gatrell 1995). To do this, a two-dimensional grid (with n equally sized cells) is generated and overlaid on the study area. An estimation of the likelihood of crime occurring within each cell—an index of *risk intensity*—is generated using a recursive algorithm. For each cell, every crime event that occurred within 400 metres of the centre of the cell is identified. In traditional hot-spot research, this 400-metre radius would be referred to as the bandwidth of the model. The critical conceptual difference between hot-spotting and the technique developed here is that, for hot-spotting, the bandwidth is relatively arbitrary, or is selected on the basis of the statistical properties of the distribution of the data[1] (see Brunsden 1995), whereas we use this specific distance of 400 metres here, as this is the distance over which we have shown that the risk of burglary is communicable.

A weighting is then given to each crime event. This is derived using information both on the distance of the point to the centre of the cell and the time that has elapsed since the event occurred. For instance, crimes that occurred closest to the centre of the cell

[1] With such approaches, the challenge is seen as producing a map that identifies an optimum number of areas where the density of crime *was* highest. What the optimum number is will vary. Thus, for this approach, the selection of a bandwidth is not informed directly by criminological research.

that occurred most recently are given the greatest weighting. The weightings of each crime event that occurs within the 400-metre bandwidth are then summed to produce the risk-intensity measure. A variety of different equations may be used in the derivation of the weightings, an inverse function being illustrated below.

$$Y(i) = \Sigma 1/\text{distance from cell centre} \times 1/\text{time since event occurred}$$

However, as the resulting risk surface[2] is essentially a series of cells, there is a problem with using a distance weighting that is derived using the coordinates of the centre of the cell. The reason is that risk-intensity values are not generated for individual points (such as the mid-point of the cell) but for the entire cell. For this reason, we present analyses here that use an algorithm that computes a risk intensity for the entire cell rather than the cell mid-point. Thus, a crime event that occurred *within* a cell would have the same weighting, irrespective of where it was positioned within that cell.

Estimating the accuracy of the predictions

An important element of the work involves the evaluation of the accuracy of the predictions made. Nice-looking maps do not equate to an efficient model. One problem with previous crime mapping has been the lack of evaluation of how effective maps are at predicting the location of future crimes (but see Gorr and Olligschlaeger 2002). On first consideration, it appears quite straightforward to do this; you simply use, say, two-years'-worth of data, the first of which is used to define the hot spots and the second of which is plotted on top of the resulting hot spots, to see the extent to which the crimes that 'happened next' have been captured. However, there are several problems with this simple idea—some more severe than others.

First, such exercises are often visual in nature. In other words, the investigator looks to see whether the hot spots capture the new crime incidents or not. This practice is particularly prolific with 'grid'-style coverages, which are raster images (which are, essentially, pictures and hence do not record information about the spatial location of each square) and not vector in format (where the *x* and *y* coordinates of the shapes are known, so they can be spatially located). It is therefore not possible to command the GIS to count the number of new incidents in each grid square, as it cannot spatially intersect the two data sets. This precludes the systematic evaluation of the technique.

Secondly, crime mappers have tended to concentrate on one style of hot-spot mapping at a time (but see Jefferis and Mamalian 1998). Consequently, there is little documentation on comparisons between the effectiveness of different mapping techniques. In order to prove that one has an effective map, you need a method of comparing current methods to others extant. Moreover, as a starting point, the predictive accuracy of a map (or any technique) should also be compared with a random distribution of some kind.

Thirdly, there are a number of different components that should be considered when evaluating map 'effectiveness'. The number of hits that a particular hot-spotting technique makes in terms of new incidents captured is only one of them, and, indeed,

[2] A risk surface is a graphical representation of the estimated probabilities of an event, or series of events, occurring at each of the various locations within a geographical area of interest.

might not be the most important. Some important factors in determining map effectiveness are 1) the 'hit' rate; and 2) the area covered by the hot spot(s). This is crucial—a hot spot that covers the whole area of interest would have a 100-per-cent hit rate, since it would capture all the new crimes—but it wouldn't be any use operationally. Thus, an alternative way of conceptualizing the measurement issue is to consider how efficient the procedure would be in operational terms. For instance, how many crimes could be prevented for every 10 metres-squared patrolled, searched or swiftly targeted with crime-prevention measures. A more sensitive approach then would be to measure the effectiveness of the procedure as a rate of events identified per metre-squared considered—a measure that we will subsequently refer to as the *search efficiency rate*; 3) the number of hot spots identified within a particular area. It is unlikely that, with offence-location data, a hot-spotting procedure will only come up with a single hot spot. However, there will be substantial operational gain to keeping the number of hot spots manageable for operational purposes. It is difficult to say what the optimal number is; too many will create logistical problems, as it will be difficult to deploy resources to all of the areas; too few might perhaps cause too many resources to be concentrated into a limited number of areas; and, 4) the travelling distances between hot spots might be important factors in some cases. Even if the procedure was shown to have a relatively high search-efficiency rate, the effectiveness of the technique in operational policing might be limited if the areas that had high values were randomly distributed across the area considered. Officers would not only have to patrol the areas of high risk, but they would also have to travel between a large number of these, consequently increasing the effort involved and the resources required. For this reason, it may be the case that the shorter the distance between the locations, the better.

We see it as particularly important that a map's utility is evaluated before it is used in an operational setting. We have therefore endeavoured to design a system for map evaluation that allows comparisons to be made between different hot-spot maps. There are a number of different evaluation criteria that may be produced for each map, and which go a fair way towards quantifying the different measures of effectiveness outlined above. These are:

Hit rate—the number of new crimes that are captured by the defined hot-spot area.

Area—the extent of the hot-spot areas. It is expressed both in terms of total area across all hot spots and average size of hot-spot area.

Search efficiency rate—the number of crimes successfully predicted per kilometre-squared. Using a standardized index allows different procedures and different hot spots to be meaningfully compared.

Number of hot spots—a count of the number of different hot-spot areas produced by the technique.

Area-to-perimeter ratios—the overall and/or the average area-to-perimeter ratio. These are calculated by simply dividing the area of the hot spot by its perimeter. The larger this is, the more 'compact' the area is; in other words, the more area is covered in the shape per length of perimeter. This could be seen as a measure of efficiency of the hot spot in terms of how practical it is to cover the area.

Using measures such as the search efficiency rate has distinct advantages. A police officer can make two mistakes: not be somewhere/do something at a place where a crime happens, or be somewhere/do something at a place where a crime does not happen.

A simple hit (or miss) rate calculation will not capture this, as it assumes that the police are omnipresent within potentially very large hot-spot areas. In reality, they cannot be at every location at every time, which is why it is useful to know the average hit rate per metre-squared across a number of different maps or scenarios. A second advantage is that this approach allows graduated effort on an obviously discernable basis. This allows users to patrol or target harden whatever number of households adds up to the greatest risk within the confines of their operational availability.

Lessons from geographic profiling

Similar issues to those discussed above have been raised in relation to geographic profiling. In this endeavour, the aim is to identify the residence of an offender based on the spatial location of a series of presumably related offences. To do this, a risk surface—sometimes referred to in the literature as a jeopardy surface—is generated. Superimposing this surface onto a cartographic map of the area produces a geoprofile, which represents an optimal search area (Rossmo 1999). The implication for operational policing in respect of offender identification is that the search for the offender's residence should begin where the probability density of the geoprofile is highest (the centre). The aim of the technique is to generate a search strategy that will be more efficient than a random approach. The effectiveness of the approach may be assessed by measuring the total proportion of the target area that must be covered before the offender's residence is discovered. This percentage is referred to as the hit-score percentage. Lower hit scores are associated with optimized search strategies, although these are influenced by the size of the target area identified by the jeopardy surface. Thus, for a single offender, it is possible to generate two different jeopardy surfaces with different-sized target areas. The different surfaces may have different hit-score percentages associated with them. In its simplest form, interpretation of the hit-score percentage should be treated with caution, as it does not take the size of the target area into account—only the proportion which must be searched. Thus, a jeopardy surface may have a 1-per-cent hit-score percentage, which translates into a search area of 28 kilometres-squared, whereas a second may have a hit rate percentage of 10 per cent but a search area of only 2 kilometres-squared. Clearly, then, unless jeopardy surfaces of the same size are to be compared, the hit-rate percentage measure may be misleading. For this reason, to test the effectiveness of a jeopardy surface, the hit-score percentage must be compared with some form of distribution, to determine whether it offers predictivity that exceeds chance. To do this, a series of hit-score percentages are compared with the chance distribution. For a random search strategy, the probability of locating an offender residence at any point is simply the reciprocal of the number of points that can be searched. Thus, for 100 points or locations, the probability would be 1/100. To examine the effectiveness of the jeopardy surface, the number of points that have a risk-intensity score that is equal to or greater than the hit score for the point which identifies the offender's home residence are compared to the total number of points within the target area. The results are then compared with a random distribution using an index of dissimilarity, such as the Gini coefficient (Goodall 1987).

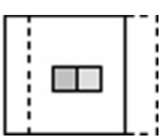
The search for offender locations affords interesting parallels with some of the technical issues confronted here. In particular, it shows that area or scope of search should be accounted for in measures of map efficiency. It also demonstrates that it is difficult to make judgments on efficiency in the absence of any comparison (here, a random distribution). However, the fundamental difference between the two enterprises should be stressed. Here, we are concerned with the proportion of future crime events which can be addressed on the basis of routine prediction based upon past events. This is very different from the search for a single location (an offender residence). In essence, the hot-spot map searches for many high-risk locations simultaneously and the most efficient way of safeguarding these. Therefore, it is not possible to apply geographic-profiling methods directly in the evaluation of offence-based maps.

The issue of calibration

It should be stressed here that the accuracy of any procedure used to generate hot spots or jeopardy surfaces is directly related to the estimation model and any parameters used. To accommodate this, a number of different models have been produced. For some, an inverse distance and time weighting was used (see the equation above), whereas, for others, an inverse exponential function was used. It is, of course, possible to use a constant in any equation. A constant may also be added for some ranges of distances (both in space and time) but not others.

One particular challenge relates to the size of the cells used to generate the two-dimensional grid. The implications of this issue here are similar to those elsewhere, particularly in relation to the ecological fallacy (e.g. Brown 1991). This problem occurs where data of any kind are aggregated up to some areal unit that is larger than the smallest resolution at which it can be measured (e.g. area crime rates vs individuals' experience of victimization). One problem that arises is that an invalid assumption may be made that the average experience for the entire area is common to all. For instance, in areas of high crime, it may incorrectly be assumed that all people are victimized or are at the same level of risk. To avoid this problem, it is important to select the appropriate size of grid. Clearly, this issue is particularly important in the current endeavour.

The advantage with the approach taken here is that, unlike in traditional hot-spotting, where both bandwidth and grid size are unknowns and often determined by guesswork, or atheoretical statistical criteria, we have a theoretical reason for using a 400-metre bandwidth (this being the distance over which research suggests burglary risk to be communicable). However, the size of the grid squares is still open to debate. To distinguish between the bandwidth and the grid size, consider the illustration below.



On the left of this illustration,[3] the bandwidth and grid size for the two cells are the same. The area which is displayed on the map (the grey shading) is the same size as the area used in the derivation of the grid (the solid and dotted-line boxes). There is no

[3] As noted above, the risk-intensity value is generated by counting how many crimes occur within a specific radius (the bandwidth) of the mid-point of the cell. However, in the illustration presented, the search area for each cell is shown as a square rather than a circle to emphasize the point discussed.

overlap in the data used to derive the grids in these cases. On the right, the bandwidth remains the same. However, in this case, the grid size is a lot smaller and, hence, there is a large amount of overlap in the data used to derive the risk-intensity values for two adjacent cells. The second of these approaches has some significant advantages; first, it predicts crime risk at a more localized level; the smaller the grid size, the more localized the predictions. Secondly, it requires fewer data to produce a sensible picture of risk, because it uses much of the same data in more than one grid. As we explain later, these grids can later be aggregated to defined hot-spot areas. Therefore, we recommend that the smallest grid size be used that is practical within the constraints of computing power and GIS software.

Prospective Hot-Spot Mapping: An Empirical Example

A number of prospective maps have been generated for data available for the county of Merseyside. To generate the maps, we used historic data for the year 1997 (for no particular reason other than its availability to us at the analysis stage). Burglary data were acquired for the 22,704,000-metres-squared grid in South Liverpool, shown as Figure 1. Two levels of resolution have been used to generate the maps. Figures 2 and 3 show maps that use 10,816 cells and grids that are 50 × 50 metres. Other maps have been generated using 10 × 10-metre cells.

FIG. 1 Map of Merseyside and the grid used

For the maps shown here, we used two months' data (1 August to 30 September 1997) to generate the maps, and two (1 October to 30 November 1997) to test their accuracy. In addition to using data for the grid, we used data for a 400-metre buffer zone to minimize edge effects.

As discussed above in relation to calibration, grids of different sizes could, of course, be used to present the data. However, computing power limits the size of the grid and resolution used. For instance, for the same-sized grid, it was only just possible to generate a risk surface for cells that measured 10×10 metres. For Figure 2, the risk-intensity values for each cell were generated by taking the product of the inverse of both time and distance weightings. The distance weighting was derived using the following equation:

Distance weight = 1 + number of complete 1/2 grid widths between event and cell centroid[4]

As indicated earlier, the advantage of using this approach is that it does not artificially inflate the importance of events that happen to be close to the mid-point of the cell, which, after all, is an arbitrary point within the limits of the cell. Events which occurred within 8 cells of a particular cell were considered; those further away were not.[5] The time weighting was computed by simply counting the number of weeks since the event occurred. In this case, this was the number of weeks which had lapsed between the event and 1 October 1997, the date for which the prospective map was generated.

Thus, if a burglary occurred within a cell, one week before the date of the map, it would have a weighting of $1/1 \times 1/1 = 1$; if a burglary occurred two weeks ago and in the neighbouring cell, $1/2 \times 1/2 = 1/4$; and so on. In each map, the cells are shaded to reflect the risk-intensity value. The darker the cell, the greater the risk-intensity value. To allow easy comparisons to be made between the different maps, each cell was assigned to a quantile, depending on the risk-intensity value. Thus, the 20 per cent of cells with the highest risk-intensity values were shaded in black, and the 20 per cent of cells with the lowest values are shaded in the lightest grey colour. Figure 2 also shows burglaries occurring within the next two days (symbolized as stars) and between three days and one week (symbolized as circles) following 1 October 1997. Visual inspection of the risk surface and the location of the burglaries that follow indicates a considerable amount of overlap between the predicted areas of high risk and the burglaries. However, as emphasized earlier, it is important to evaluate this in further detail.

In addition to generating prospective hot spots, we also generated some more traditional hot spots (which do not use temporal weightings), to enable comparisons to be made. Figure 3 shows a hot spot generated using the moving window technique and a quatric kernel algorithm used by Ratcliffe (2000). As suggested by Ratcliffe, we used a bandwidth of 200 metres. When compared, the maps shown in Figures 2 and 3 share a number of features. This is hardly surprising, as crime clusters in space. However, there also exist a number of differences between the two maps. For instance, all of the burglaries occurring within the following week, located within the white dashed grid in the upper left quadrant of each map, are captured in the hottest part of the prospective map but not in the hot-spot map.

[4] The cell centroid is the point at, or *x* and *y* coordinates of, the exact centre of the grid square **for which a risk value is being derived.**

[5] This meant that only events within approximately 400 metres of each cell were considered here.

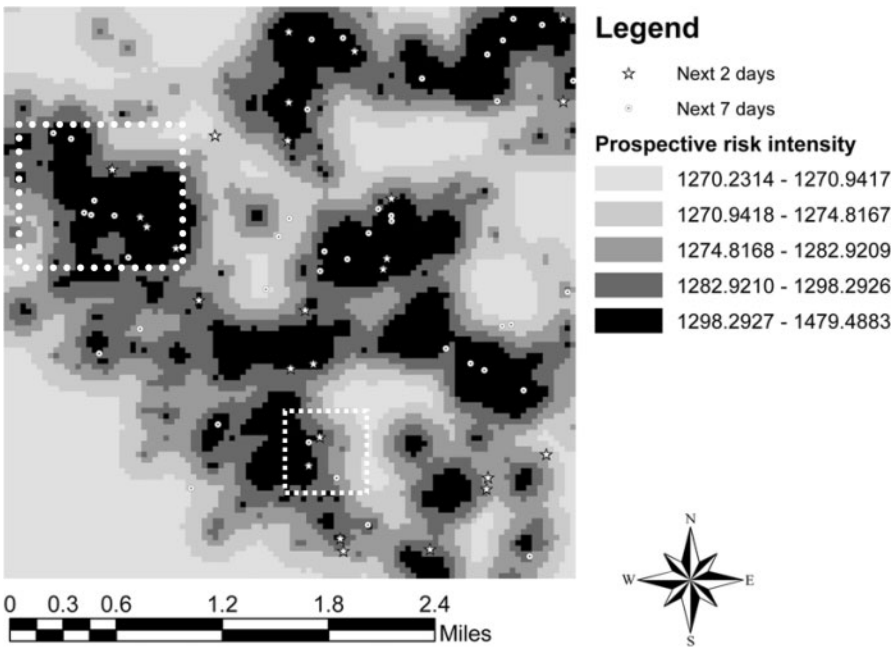


FIG. 2 Prospective hot-spot map using 50-metre grid squares (and the burglaries which occurred within the next week)

Figure 4 shows another commonly used hot-spotting technique. The map has been generated using police beats—an approach commonly employed by the police (see Townsley and Pease 2002). Figure 4 uses the same data that were used to produce Figures 2 and 3. In this case, however, the six police beats with the highest number of burglaries occurring within them have been selected as hot spots. This technique does not incorporate any temporal weighting of incidents; and uses pure counts of incidents to determine high-risk areas. Consideration of Figure 4 suggests that there is some overlap between the designated hot-spot areas and the location of consequent burglaries, but, on first sight, this map does not appear to be as accurate as the maps in Figures 2 and 3.

So far, to compare the accuracy of these maps, we have simply plotted where subsequent burglaries occurred. As the procedure is only intended to be accurate for the immediate future, we chose to plot data for the next two days and the next week. However, to evaluate the map using the procedures suggested above, further processing is required. It is worth noting at this point that GIS packages usually only give the option of producing raster or picture grid coverages, which merely allow the user to visually inspect the relationship between other types of data and the grid. For the current research, it was important to generate a vector grid that would allow the data sets to be spatially related using the GIS. Thus, a FORTAN program was written to generate a vector grid. This was subsequently imported into the GIS.

Hence, using the spatial join command in the GIS, we were able to count how many burglaries occurred within the 20 per cent of cells with the highest risk-intensity values.

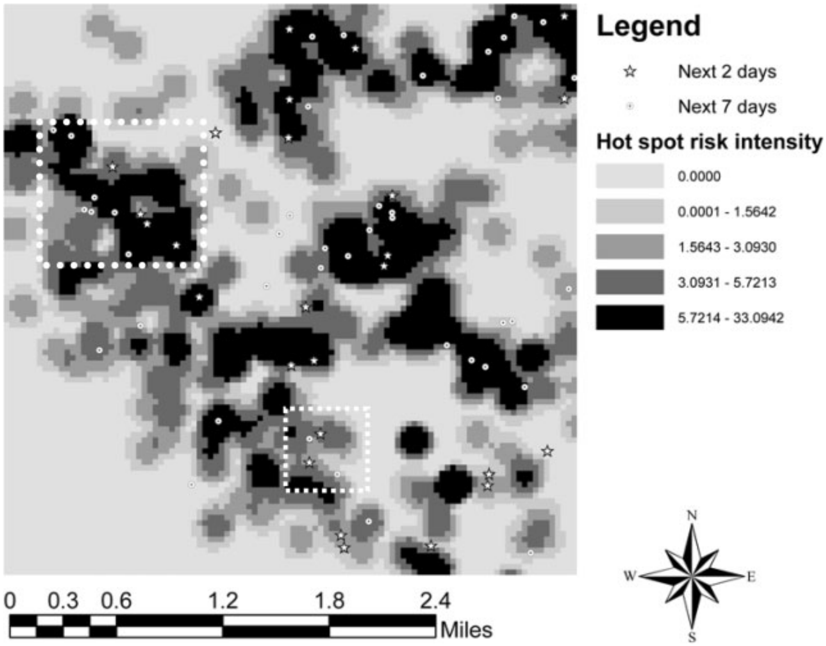


FIG. 3 Hot-spot map using 50-metre grid squares (and the burglaries which occurred within the next week)

Table 1 shows the results. Here, the percentage of incidents captured by the hot spots (or the simple hit rate) is given for each of the three maps shown in Figures 2, 3 and 4 above, along with the total area of hot-spot coverage (in metres-squared). It is clear from Table 1 that the prospective method (Figure 2) is more accurate than both the retrospective hot-spotting technique (Figure 3), particularly for predictions for the next two days. Specifically, the prospective map captured 62 per cent of the burglaries occurring in the next two days, whereas the retrospective map captured 46 per cent of these incidents. Here, compared to the retrospective model, the prospective model correctly predicted an additional 19 per cent of incidents. Expressed in a slightly different way, the prospective model was 35 per cent (= 16/46×100) more accurate. It is important to emphasize that the difference in the level of predictive accuracy for the prospective and retrospective techniques is greatest for predictions regarding the more immediate future (two days). The theory that underlies the prospective approach leads us to anticipate precisely this pattern, and, hence, the rationale for the technique is validated.

Table 1 also shows a calculation of the search-efficiency rate, which, as mentioned above, measures the number of crimes successfully predicted per square kilometre. The advantage of this measure is that it is standardized by area, and, hence, allows easy comparison between maps. The table shows the search efficiency rate for burglaries occurring in the two days following the map production. As with the simple hit rate, this measure shows that the prospective map is the most effective of the three using this criterion. It also emphasizes the inefficiency of the beat model compared to the other two hot-spotting procedures.

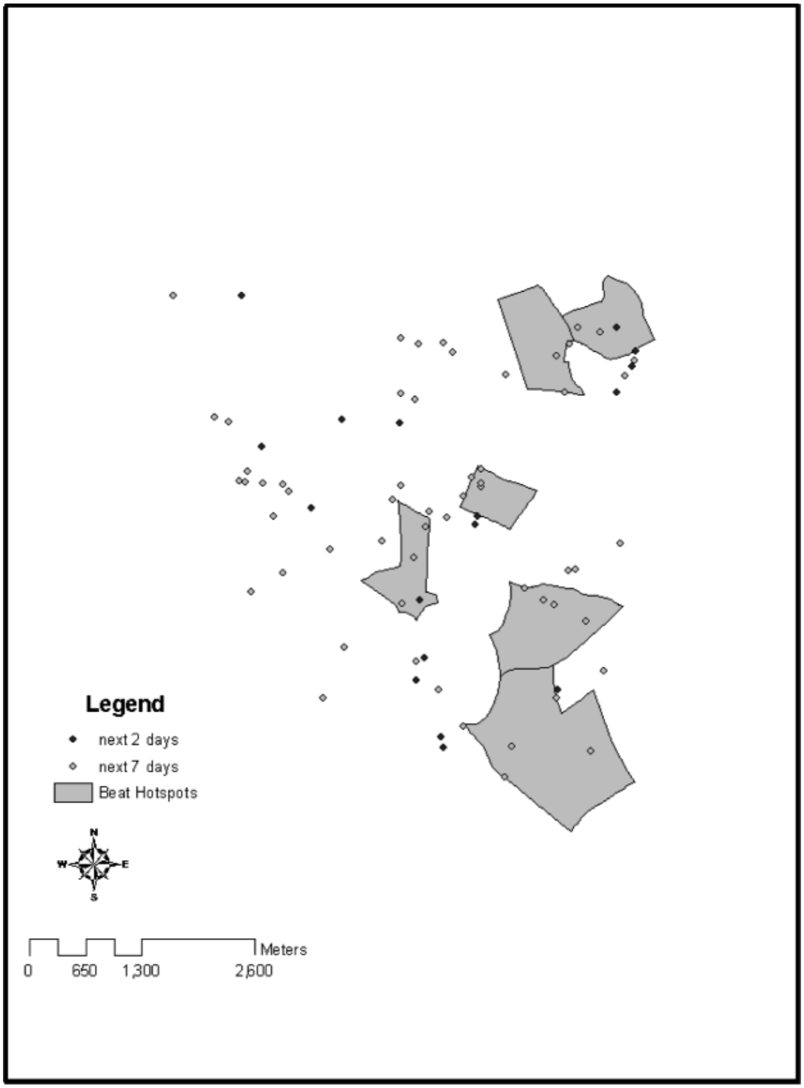


FIG. 4 Hot-spot map using police beats (and the burglaries which occurred within the next week)

TABLE 1 *Relative predictive accuracy of the different techniques*

	2 days (26)	1 week (70)	Area covered	Search efficiency (2 day per km^2)*
Prospective	62%	64%	5,405,000	2.96
Retrospective	46%	56%	5,405,000	2.22
Beat	12%	24%	5,083,886	0.59

* Scaled by a factor of 1,000,000 to ease interpretation.

One point which requires further discussion is the specific procedure used to generate the retrospective hot spots. To standardize the comparisons between the prospective and retrospective methods, the same historic data were used for each technique. Thus, we used two months' historic data for every method. Since our past research has shown that victimization has an impact over 400 metres and for around two months, the algorithm used to generate the prospective maps weights each burglary event by the amount of time that elapsed since the event occurred and the date on which the map was produced. Retrospective hot-spot maps do not do this. However, because we only used two months' historic data here, this may increase the accuracy of the hot-spot maps, as events that occurred close in time (within two months) were effectively weighted in the analysis, as these were the only data points used. A second point is that, to generate the retrospective hot spot using the moving window technique, we used a bandwidth of 200 metres and an equation that weighted events on the basis of propinquity. The reason for using a bandwidth in retrospective hot-spotting is essentially to produce a smooth risk surface. As far as we are aware, there exists no (theoretical) reason for selecting this bandwidth other than the fact that it produces nice-looking maps. Thus, under the conditions in which we tested the retrospective hot-spotting techniques here, burglary events were essentially weighted both spatially and temporally. The reason for this, however, was entirely atheoretical. One way of testing the accuracy of the various methods more systematically would be to use longer periods of historic data, e.g. one year. Additionally, it will be necessary to repeat the current exercise using different geographical areas and different periods of time.

Area-to-perimeter ratios

As discussed above, an alternative and complementary index that may be used to evaluate hot-spot efficiency involves the comparison of the area and perimeter of the hot spots produced. Using the following method to calculate these ratios also results in the production of another simple measure that can be used in determining map efficiency, namely the number of hot spots produced by different hot-spot measures. To explain the area-to-perimeter ratio measure in more depth, let us take two examples:

1. In this case, the shape is long and thin; the area is 9 square units; the perimeter is 20 lengths:

□ □ □ □ □ □ □ □ □

area/perimeter = 9/20 = 0.45.

2. Here, the shape is more compact; the area is still 9 square units but the perimeter is only 12 lengths:

□ □ □
□ □ □
□ □ □

area/perimeter = 9/12 = 0.75.

The second of these shapes has a higher area-to-perimeter ratio and therefore may be seen as more efficient in operational policing terms, in that a patrolling journey of any given length will traverse a greater number of vulnerable places.

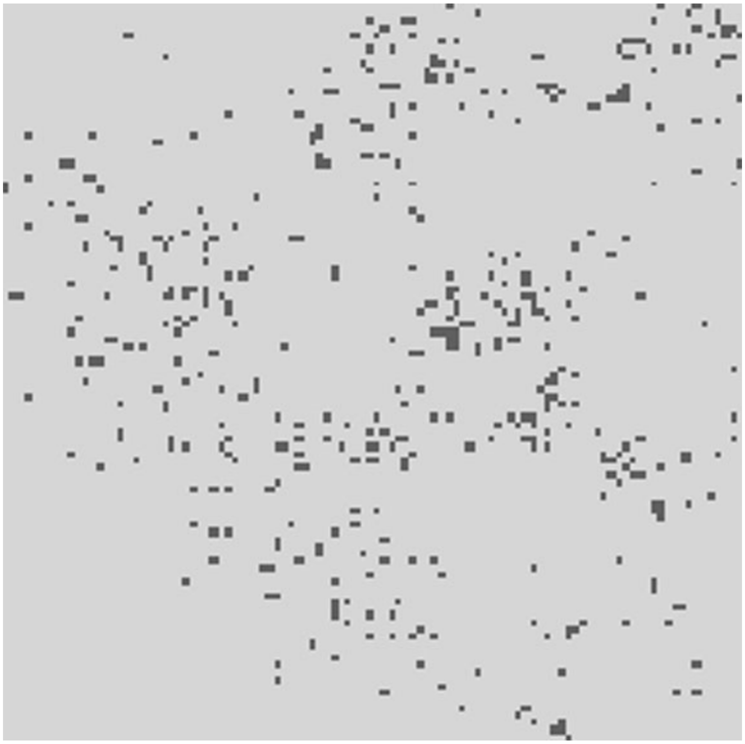


FIG. 5 Hot-spots from aggregating burglaries to grid squares

For the purposes of illustrating the area-to-perimeter ratio technique, a further form of hot-spot mapping is introduced here. Figure 5 shows the results of a simple grid aggregation using the same data as have been used in the production of the maps shown above. In this case, hot areas are identified by simply adding up the number of burglary offences that fall into each of the 50-metre grid squares. Every square that contains a burglary offence has been defined as a hot area in this case.

The two maps in Figures 2 and 5 look dramatically different. There are many more coloured grids in Figure 2 than in Figure 5 and the 'hot' grids are far less dispersed in Figure 2 than in Figure 5. It is useful to examine a refined version of Figure 2, which becomes more easily comparable with Figure 5 by selecting a subset of the 'hottest' squares—specifically, the top 447 of the 10,816 grid squares displayed. The reasons for selecting these cells are twofold: first, this displays an equal number of squares to those defined as hot from simply aggregating the burglary data (Figure 5), which enables easier visual comparison. Figure 6 is, therefore, directly comparable to Figure 5 in terms of the number of squares that it defines as hot. Secondly, this produces defined 'hot-spot' areas from the prospective map in Figure 2, which is necessary for the production of area-to-perimeter ratio calculations.

The next step is to identify the number and boundaries of distinct shapes or 'hot spots' shown in Figures 5 and 6. The figures themselves make this procedure look deceptively straightforward—to the beholder, the 'blobs' already look as if they are

FIG. 6 Top 447 'hot grids' from prospective mapping function

distinct shapes. In reality, in the GIS, these are still a series of coloured grids that are sometimes located next to, but independent of, each other. We have not yet found a GIS function that enables us to define these as distinct shapes easily (it is possible to do this by manually digitizing the areas, but this is time-consuming and impractical for operational policing purposes). The only procedure we have found to date involves converting the information from the likes of Figures 5 and 6 to raster grids and then converting them back into shape (or vector) files! The disadvantage of this fairly clumsy procedure is that the resulting shapes are approximations (and not exact replications) of the hot spots in Figures 5 and 6 above. The advantage of the new representations is that they represent distinct shapes, and hence their areas and perimeters are known. Summary data for these are displayed as Table 2.

TABLE 2 *Summary area–perimeter (AP) statistics*

Map evaluation criteria	Prospective mapping function	Aggregate grid squares	Hot-spot function
Mean area	12,778 m^2	2,400 m^2	56,502 m^2
Mean perimeter	377 m	219 m	925 m
Number of hot spots	79	330	19
Mean AP ratio	19	10	51

A number of patterns are evident from Table 2. First, the prospective mapping technique identifies 79 discernible areas of high risk—considerably less than the number identified using the aggregate-grid-squares approach (330). However, the traditional hot-spotting method yielded a lower number of discernible areas than the prospective function (19). For operational policing, a smaller number of defined areas may offer an advantage, as these will be more manageable to visit and police. It is a certainty more practicable to distribute resources across 19 (or even 79) areas, rather than 330. Secondly, the mean area-to-perimeter ratio is almost twice as high for the prospective technique than it is for the aggregate grid squares, thereby indicating an operational advantage of this technique. However, the hot-spot function has a higher area-to-perimeter ratio than either of the other techniques. This indicates that the traditional hot-spot shapes, followed by the prospective shapes, are more 'efficient' in terms of the length that would need to be patrolled to cover the same area. The aggregate squares are not as efficient as the other two methods in these terms.

With the current models, therefore, the prospective model outperforms the other two by having a high search-efficiency rate. At present, the hot-spotting technique offers some advantage in terms of hot-spot shape efficiency. Interestingly, other prospective models, generated as part of the research but not reported here, yield different search-efficiency and shape-efficiency levels. Early indications suggest a reciprocal function linking the two indices of efficiency. In other words, increasing shape efficiency might decrease search efficiency and vice versa. More research is required to determine the nature of this relationship. However, in the meantime, it will suffice to say that it is likely that there will be a trade-off between the accuracy and the functionality of prospective maps, which will require the careful balancing of needs.

What Next?

This paper seeks to present a method of hot-spot designation which is distinctive in being event-derived, i.e. in being generated from individual crimes, rather than from areal crime rates. The closest it comes to previously suggested methods is with leading indicators. In one sense, the method uses each crime event as a leading indicator, modifying area predictions on the basis of individual risk—both the direct risk of repetition and referred risk to nearby places and imminent times. The results are very promising, in that the prospective method, crude as it is in not incorporating some known patterns of repetition, outperforms a traditional, more sophisticated method. Of particular interest is the fact that the superiority of the prospective approach is greatest in the two days following a crime event, which is the time horizon for which police briefings apply. The research needs now to develop by making comparisons with a wider range of conventional hot-spotting procedures, and by refinement to incorporate more dimensions of communicated crime risk.

On this last point, we know, for example, that the extent to which space–time clustering is evident varies across different types of area. For instance, space–time clustering is greatest in more affluent areas (Bowers and Johnson 2004a). Thus, it is likely that the manipulation of the parameters used in the modelling process will increase the predictive accuracy of the risk surface across different areas, available for refinement to release latent predictive power. The refinement of the algorithm for areas with different characteristics represents one of the next steps in this research.

There is further work to be done on assessing the optimum time periods and prospective algorithms in the production of the predictive-risk surfaces. For instance, maps could be produced using a year's historic data rather than two months', or inverse exponential weightings rather than reciprocal ones. Furthermore, there are important judgments to be made concerning the geographical area used to define the maps, as the use of different areas. And, the size of the grid squares that contribute to the definition of the prospective hot spots requires consideration.

We also aim to refine the technique further to increase its utility in operational policing. For instance, it would be useful to explore the advantages of generating a series of maps on a daily basis—one for each police shift. For each shift, this could be done by adding the previous shift's burglary incidents to the historic data and removing the data for the most historic shift and analysing the consequent data-set. Assuming a daily pattern of three shifts (daytime, evening and nighttime), doing this for, say, six shifts would allow a comparison of the maps generated for the equivalent shifts over two consecutive days. This would allow us to see whether the maps for different shifts showed similar trends or whether they differed. In the case of the former, this may mean that a single daily map would suffice for policing purposes. In the case of the latter, this would suggest that it would be wise to generate one map for each shift, in the way described.

A final comment on the prospective approach taken here is that it assesses risk at the direct neighbourhood level. This is distinct from concentrating solely at the level of the individual or of the community. There are direct advantages of this. For instance, it may help to realize the goal of neighbourhood-level crime prevention, which has largely eluded practitioners to date. It also balances the aims of identifying those most at risk and the need to minimize the geography that requires special attention. In relation to this point, traditionally, hot spots have been defined as larger areas. Part of the appeal of the prospective approach is that it offers the potential for within-hot-spot differentiation. In other words, it informs the allocation of police resources in terms of where to go within more traditional hot spots. Take two scenarios: in an undifferentiated hot spot, an officer might be able to visit *n* households at random; they might also to be able to visit the same number of households within prospective hot spots. However, it is likely that the ratio of visits/burglaries (for both historic burglaries and for future locations) will differ for the two approaches, as the latter areas will be defined by local levels of risk.

Notwithstanding the considerable research agenda which remains, we believe that a trial of the present system in police briefings is not premature. Indeed, in so far as operational experience will shape the research agenda, it seems urgent.

References

Bailey, T. C. and Gatrell, A. C. (1995), *Interactive Spatial Data Analysis.* Harlow: Longman.

Bowers, K. J. and Johnson, S. D. (2004), 'Domestic Burglary Repeats and Space–Time Clusters: The Dimensions of Risk', *The European Journal of Criminology,* in press.

Brown, P. J. B. (1991), 'Exploring Geodemographics', in I. Masser and M. Blakemore, eds, *Geographic Information Management: Methodology and Applications,* 221–58. London: Longman.

Brunsden, C. (1995), 'Estimating Probability Surfaces for Geographical Points Data: An Adaptive Kernel Algorithm', *Computers and Geosciences,* 21: 877–94.

Farrell, G. and Pease, K. (2001), *Repeat Victimisation.* Monsey, NY: Criminal Justice Press.

GOODALL, B. (1987). *The Penguin Dictionary of Human Geography*. Harmondsworth, Middlesex: Penguin.

GORR, W. and OLLIGSCHLAEGER, A. (2002), *Crime Hot Spot Forecasting: Modelling and Comparative Evaluation*. Final Report to the National Criminal Justice Reference Service (NCJRS).

GROFF, E. R. and LAVIGNE, N. G. (2002), 'Forecasting the Future of Predictive Crime Mapping', in N. Tilley, ed., *Analysis for Crime Prevention (Crime Prevention Studies Vol. 13)*. Monsey, NY: Criminal Justice Press.

JEFFERIS, E. S. and MAMALIAN, C. A. (1998), *Crime Mapping Research Center's Hot Spot Project*. The Second Annual Crime Mapping Research Conference, December, Arlington, VA, USA.

JOHNSON, S. D. and BOWERS, K. J. (2004a), 'The Burglary as a Clue to the Future: The Beginnings of Prospective Hot-Spotting', *The European Journal of Criminology*, 1: 237–255.

JOHNSON, S. D. and BOWERS, K. J. (2004b), 'The Stability of Space–Time Clusters of Burglary', *British Journal of Criminology*, 44: 55–65.

PEASE, K. (1998), *Repeat Victimisation: Taking Stock*. Crime Detection and Prevention Series, Paper 90. Home Office: London.

RATCLIFFE, J. (2000), 'Aoristic Analysis: The Spatial Interpretation of Unspecific Temporal Events', *International Journal of Geographical Information Science*, 14(7): 669–79.

ROSSMO, D. K. (1999), *Geographic Profiling*. Washington, DC: CRC Press LLC.

TOWNSLEY, M. and PEASE, K. (2002), 'Hot Spots and Cold Comfort: The Importance of Having a Working Thermometer', in N. Tilley, ed., *Analysis for Crime Prevention (Crime Prevention Studies Vol. 13)*. Monsey, NY: Criminal Justice Press. Table 1: Percentage of burglaries correctly predicted using the three different hotspotting techniques (actual number of burglaries in parentheses).