

Visualising Space Time Patterns in Crime: The Hotspot Plot

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Part of the interest in crime mapping may be due to the relevance of geography in explaining patterns of crime. There is, however, a danger in missing other patterns (temporal patterns most notably) if the spatial domain is given disproportionate focus. A number of recent academic studies have shown reliable and meaningful spatio-temporal patterns of crime; yet their representation remains rather abstract. This article proposes a systematic method of displaying crime hot spots. It combines temporal and spatial information in an effective manner that allows the viewer to intuitively: assess temporal profiles of individual hot spots at the micro and macro levels (i.e. day and year); compare the importance and temporal signature of different hot spots; and relate the results of the first two to baseline measures.

Maps are of time, not place

Henry Reed (1943)

The observation that crime events are spatially concentrated is probably one of the earliest and most consistent empirical findings in criminology (Guerry, 1833; Quetelet, 1835; Shaw and McKay, 1942; Brantingham and Brantingham; 1981). For instance, Sherman et al. (1989) observed that 50 percent of calls to the police in Minneapolis were generated by 3 percent of addresses. Similar results have been found for residential burglary (Bennett, 1995; Townsley et al., 2000), car theft (O'Kane et al., 1994; Rengert, 1997), alcohol related incidents (Block and Block, 1995; Roncek and Maier, 1991), assault and robbery (Jochelson, 1997), fear of crime (Nasar and Fisher, 1993) and all crime (Hirschfield et al., 1995; Hirschfield and Bowers, 1997). The temporal concentration of crime events has been studied less frequently, but generally accepted (Felson and Paulson, 2002; Weisburd et al., 2004). Routine activity theory (Cohen and Felson, 1979) posits that the interactions of everyday movements (or lack thereof) play a non-trivial role in the amount and nature of crime. The potential for an individual criminal event arises when a motivated offender comes into contact with a suitable target/victim in the absence of a guardian. Given that these elements need to converge in space and time together and many activities display temporal concentration (e.g. rush hour), it can be reasoned that certain types of crime are more likely at certain times of the day/week/year than others (Felson and Paulson, 2002). For instance, Rengert (1997) demonstrated that hot spots of auto theft in Philadelphia vary in time. Ratcliffe (2002) presented a more nuanced approach, but generated similar findings for Sydney, Australia.

Over the last decade, interest in the geography of crime, particularly among practitioners, has grown exponentially (Ratcliffe, 2004). Eck and Weisburd (1995) identified the driving forces for this as cheaper and faster computers, police computer-aided dispatch systems, and inexpensive mapping software. However, the temporal nature of crime has been relatively neglected compared to the attention given spatial perspectives. Very little interest has been paid to how crime varies with respect to time (Felson and Paulson, 2002; Ratcliffe, 2004). With respect to hot spots, Weisburd et al. (2004) commented on this paucity and found only two published studies (Spelman, 1995; Taylor, 1999) which examined the longitudinal variation of crime at small areas. Both studies reported relatively high degrees of stability of crime levels in the areas studied. Bennett (1995) and Townsend et al. (2000) examined the stability of hot spots over shorter time frames but found high levels of instability.

At a different temporal scale of resolution, there have been a number of studies that have considered the daily temporal variation of crime within small areas. Both Rengert (1997) and Ratcliffe (2002) showed that hot spots in their respective study areas displayed distinct intra-day variation. The extensive repeat victimisation literature is remarkably consistent concerning the time limited elevated risk experienced by victims in the wake of a crime (Pease, 1998; Farrell, 1995). Repeats also appear to occur at a similar time of day to earlier victimisations (Sagovsky and Johnson, 2007). Ratcliffe (2004) provided an intuitive framework within which to consider the influence of distinct types of temporal concentrations inside hot spots.

The most recent comprehensive study of crime patterns for both space and time dimensions was arguably the trajectory analysis conducted by Weisburd et al. (2004). They took 14 years of recorded crime data for a metropolitan US city and computed crime counts at the street block level by year. Using group based trajectory analysis (Nagin, 1999) street segments were grouped according to shared patterns of crime counts over time. Just over 80% of the city's street segments were considered stable, providing consistent results with the Spelman (1995) and Taylor (1999) studies. However, Weisburd et al. conceded that "these [stable] trajectories overall also had relatively low intercepts [levels of crime]." Thus, the street segments with the highest volume of crime (i.e. hot spots) were those with the least stable levels.

Other research integrating space and time patterns has utilised epidemiological techniques for testing disease contagion, and shows that the risk of burglary clusters in space and time. Following a victimisation at one home those nearby experienced an elevated risk of victimisation, which decayed as time elapsed – an extension of the repeat victimisation phenomenon. A recent comparative study showed these near repeat patterns to be consistent across five countries (Johnson et al. (2007); see also Townsend et al. (2003) and Johnson and Bowers (2004) for two different theoretical explanations of this process).

Finally, a recent article by Ratcliffe (2006) examined space-time interactions by considering how movement patterns were constrained by time in conjunction with spatial constraints. This time geography approach (Hägerstrand, 1970) revealed "that temporal constraints, in conjunction with the locations of offender nodes, are a major determinant in spatio-temporal patterns of property crime" (Ratcliffe, 2006).

To summarise, the popularity of crime mapping (particularly among practitioners) has led to increased interest in geographic approaches, but temporal aspects of crime (and their potential for prevention) have been neglected. Typically, crime mapping analyses do not consider temporal trends or concentration of events. A hot spot map may indicate small areas of high crime; but without considering the distribution of events over time, it is unclear whether the map is an appropriate summary of the past. For example, Townsend and Pease (2002) illustrated how

the integrity of hot spot identification could be easily comprised by regression to the mean problems. As for existing methods that incorporate both space and time, the findings from trajectory analysis and the near repeat studies are insightful but not as useful for crime analysts. The observation that most streets had stable crime levels did not apply to those segments experiencing the highest levels of crime. Even if it did, the temporal resolution used by Weisburd et al. (2002) was annual crime counts, so seasonal and daily volatility was outside the analytical remit of the findings.

The Research Problem

The preceding literature review attempted to briefly sketch out current knowledge on the interaction of space and time for criminal events and that these interactions vary at different scales of resolution. The focus of this paper is to propose a method of presenting spatial analysis that allows for the consideration of the temporal distribution of events within hot spots. I call this the hotspot plot. For the purposes of this article, the validity of individual techniques is not considered, only how information should be presented/displayed that allows a reader to effectively isolate interesting or anomalous patterns. Clearly, identifying the “correct” techniques are important but is not the focus of this paper.

The proposed visualisation method needs to be subject to a number of criteria for it to be useful to its intended audience and to allow the communication of information efficiently. These criteria are:

1. It should be able to be used for scanning stage in an operational environment. Spatial analysis is challenging enough without incorporating an additional dimension. The proposal should not aim to replace thorough analytic interrogation, but to allow the elimination/confirmation of basic hypothesis (e.g. is the hot spot (un)stable?).
2. It should not require sophisticated techniques. Requiring the use of techniques beyond the skill level of crime analysts will be self defeating. In terms of assessing long term trends, it would be desirable to filter out seasonal influences, but the majority of practising crime analysts will not be in a position to replicate this, regardless of its justification.
3. It should use an intuitive display of time patterns at different levels of analysis. Many crime analysts can generate hot spot maps, but these need to be used in conjunction with temporal analyses. In addition, the literature review revealed how time varies at two or more levels of granularity, meaning that a series of sub-analyses will be required for each hot spot identified.
4. It should have the ability to compare between hot spots (and to a baseline). Crime mapping is overwhelmingly descriptive in nature and, in many spatial analyses, hot spots are considered in isolation. This could be addressed by allowing comparisons to be made between hot spots and to a baseline measure.

In this article, the hotspot plot will be demonstrated using a sample of crime data. The rest of the article is organised in the following way. The data are described first, then the various elements of the hotspot plot are defined and their respective calculations described. Next, the rationale of the construction of the hotspot plot is outlined, drawing from the empirical research on graphical perception. The hotspot plot for the data sample is then constructed and comments about points of note are made. The article concludes with some suggestions for how the hotspot plot could be used in a broader sense.

Method

The data source used for the analysis presented here is twelve months of recorded domestic burglary in a Basic Command Unit (BCU) in a large UK police force. The data set was selected as a typical sample of observations of crime events. In the time period used, 2050 events comprised the data set. The incidents were geocoded, with 55 incidents (less than 3 percent) located outside the BCU border. The bulk of these 55 incidents possessed meaningless coordinate values (e.g. (0,0)) and were excluded from further analysis. Almost the same number of records (57) contained spurious date values and were similarly excluded.

The fields used for the analysis presented here were the geographical location, the recorded start date and time, and the recorded end date and time of the incidents. The hotspot plot consists of three major components: long term trend in crime volume (e.g. weekly counts); within day temporal trend in crime (e.g. aoristic plot); and hot spot surface (some depiction of spatial concentration of crime). Each of these components is explained below.

The first component is the long term trend in crime volume. Crime analysts' chief concern when identifying hot spots should be regarding the area's temporal stability over time. This relates to whether the hot spot is enduring or is unstable and likely to dissipate regardless of what crime reduction tactics are employed. There are five main types of long term trends that places that are currently deemed hot spots are likely to display:

1. the level of crime has been consistently high for a substantial period of time;
2. the level of crime was once high but is no longer;
3. some time ago a spike in crime occurred but crime levels are now stable (a special case of 2);
4. the level of crime is increasing; or
5. an episodic pattern is operating.

In terms of identifying locations for detailed analysis and potential allocation of prevention activities, analysts should only concentrate on hot spots with long term trends of type 1 and 4. All other patterns indicate that the area is no longer truly "hot" or that it would be difficult to attribute confidently apparent reductions in crime levels to the suite of tactics employed.

Simply plotting the counts of crime events for defined time units (say weeks or months) for individual hot spots would reveal which of 1 to 5 are (im)plausible. The stability of hot spots can be difficult to judge easily, however, if a trend and seasonality are operating. In addition, given the small spatial scale over which crime concentrations exist, the potential for volatility is not trivial. Ideally, seasonal decomposition would be performed on historical crime counts (Cleveland et al., 1990), but this restriction would probably move the proposed technique beyond the current sophistication of many crime analysts.

The purpose of plotting retrospective crime counts is to ascertain whether current crime levels are similar to the long range expectation for that area. A spike in crime several months ago should be obvious, as will a monotonic decline. The insight required, then, is of *relative* change not magnitude. This means that scale of the axis is not of direct relevance, as we are only looking for the consistency of previous levels of crime. This suggests that a plot similar to a sparkline (Tufte, 2006), an "intense, simple, word-sized graphic" that allows a reader to quickly identify deviations from regular behaviour, would be appropriate. For example,  is the sparkline of the Apple stock price for a recent three month period. Even though no value is

given on the y axis, it is possible to anchor the line by providing one or several value (the final value in this series is \$124.63 (USD), represented by the green dot). For a stock price, usually only the current or last value is the most important along with the historic trend. As we will see for the representation of crime a few more “orienting” values will be used.

Sparklines typically have a small aspect ratio (the ratio of the vertical dimension to the horizontal dimension of the plot in physical units). That is, they are normally much wider than they are tall. Interestingly, Cleveland (1993) demonstrated a method of determining the optimal aspect ratio of any data set. In its simplest terms, by allowing the average absolute angle between line segments of the data and the horizontal axis to be 45 degrees (a process Cleveland dubbed “banking to 45 degrees”), the difference between perceived and actual change in data is minimised. It turns out that data that displays high levels of volatility, such as crime counts, are best displayed in plots with small aspect ratios. If this approach is taken, the amount of space required for this information to be displayed is greatly reduced, but also the ability of the reader to discriminate between the longitudinal archetypes is greatly enhanced.

The second element of the hot spot plot relates to temporal patterns during the day. To capture these dynamics, aoristic analysis (Ratcliffe, 2000; 2002) was used. Aoristic analysis is a method of allocating proportions of events to time intervals on a 24 hour clock. Event proportions are allocated as a function of the duration of the event and the time interval used. Specifically, each time period gets a time interval/event duration allocated for every event that spans the associated time interval. So, assuming a time interval of 60 minutes, a burglary occurring between 10 am and 2 pm (240 minutes) would contribute one quarter (60/240) of an event to the intervals 10-11, 11-12, 12- 13 and 13-14 hours. A burglary with an eight hour window contributes one eighth of an event, and so on. Sensible decisions can be made about the maximum allowable time window of the events.

For the analysis presented here a maximum event duration of 24 hours was selected. This condition removed 301 of the incidents (about 15 percent). Hourly time intervals were used.

The final element is the spatial representation of crime. There are a wide range of methods of representing the incidence of crime over space, each with advantages and disadvantages (see Eck et al. (2005) for an overview). The purpose of this article is not to definitively determine the optimal methods for doing representing crime in space. Nevertheless, for the purpose of this article, Kernel Density Estimation (KDE) was used to depict the incidence of crime spatially. This technique generates intensity surfaces that are fairly intuitive and are analogous in concept to a 2D moving average of relative frequency. Briefly, for a large area with a distribution of crime events, a regular grid of points is overlaid on the study area. For each grid point, the number of crime events within a certain distance (bandwidth) is determined and a weighting function is applied to the crime events – those that are closer are weighted more. These weighted scores are then aggregated (for each grid point) to generate intensity scores. These scores can be binned into intervals and then colour coded. For a more complete treatment, see Chainey and Ratcliffe (2005).

The computation of a KDE surface requires a number of choices by the user. For the purpose of this analysis, the BCU-level surfaces used a grid of points that were 50 metres by 50 metres, and the weighting function selected was an isotropic¹ normal distribution function with a bandwidth of 400 metres. These values were selected on the basis of operational use: the grid cell size is about the maximum extent of a police officer’s line-of-sight in a residential area, and the bandwidth was chosen as it was consistent with the testing and results of an optimal foraging

¹ Extending equally in all directions.

hypothesis of offender target selection (Bowers et al., 2004). At the hot spot level, these parameters were altered to reflect the smaller geographic scale, using 25 metres by 25 metres grids and 100 metre bandwidth.

Another choice for the analyst is that of colour. While an apparently trivial topic, the choice of a colour ramp is critical to how a reader might interpret a map. For reproduction in this journal, a simple greyscale ramp was used to indicate intensity (lighter shades indicating less crime), but there is probably no need for operational analysts to feel restricted in this regard. A wide range of colour schemes are available from Cynthia Brewer's Color Brewer website (www.ColorBrewer.org) featuring colour ramps designed for sequential, diverging, and qualitative variables. In addition, there are useful comments about how appropriate each colour ramp is with respect to red-green colour blindness, photocopying, LCD projectors, LCD computer screens, CRT computer screens, and colour printing.

Having defined the three main elements, it remains to combine them in an effective manner to scan for patterns between and within hot spots. The general approach used here was heavily influenced by the Trellis graphical system conceived by Cleveland (Cleveland, 1993; Becker et al., 1996). This is a method of displaying multivariate data, and is similar to Tufte's concept of small multiples (Tufte, 2001), but is more analytically extensive. At Trellis' core is the principle of multipanel conditioning – a series of plots generated by conditioning the data on a variable of interest. In the simplest case of three variables (A, B and C), several plots of A against B are constructed, each one containing only observations partitioned by the levels of C (or ranges of values of C if continuous). Thus, the plots are of A versus B conditioned by C.

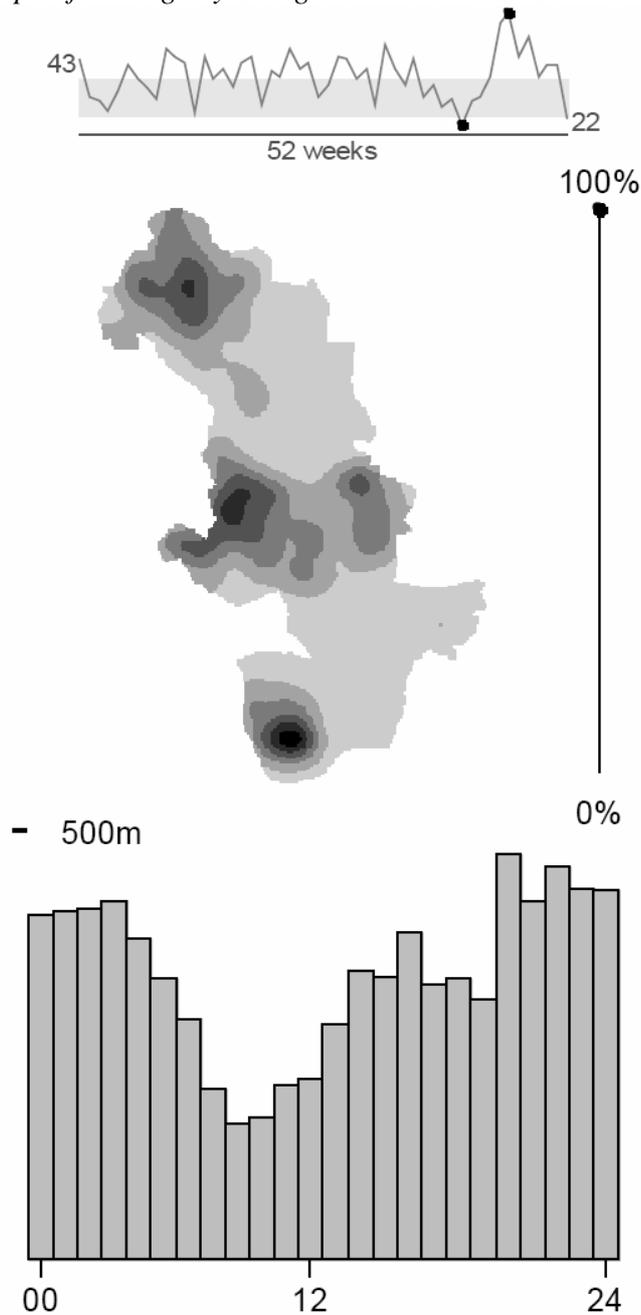
The Trellis system has a number of visualisation features. First, the ranges of the axes stay fixed across each plot, so patterns of particular sub groups in the sample can be easily compared with other sub groups (e.g. whether one group occupies only a small region of the plotting area compared to the others). Second, the individual plots are arranged in a regular grid so their positions can be exploited by the reader for effective decoding; that is, comparisons between plots are made efficiently. Cleveland and McGill (1984) define no less than ten visual tasks used by readers to extract quantitative information from graphs, and theorised that the simpler the visual task required, the more accurate the decoding of that information. To illustrate, if data were encoded in both a pie chart and a bar chart, the graphic requiring the more basic decoding task (in this case the bar chart) should elicit more accurate perceptions from readers. According to Cleveland and McGill's experiments, the most basic task, i.e. the one which had the lowest absolute error, was "position on a common scale".² With respect to the Trellis graphics system, as the associated axes of each plot are identical in scale and they are aligned vertically and horizontally, plot-to-plot comparisons are of the "position on a common scale" variety, and are therefore the least prone to perceptual biases.

All the requisite components have now been defined, so it remains to describe how these components can be utilised to allow a representation of spatial and temporal patterns of crime in one graphic. Figure 1 shows the layout of a graphic containing three plots. The top-most panel contains the long term trend for the area in question, the middle panel is the kernel density surface, and the bottom panel contains the aoristic plot. Thus, in one display, the spatial concentration and the temporal patterns of that space, at different resolutions, are displayed. The column of plots displayed in Figure 1 will be referred to as a plot-triplet. This plot-triplet includes all burglaries for the BCU.

² The full set of visual tasks defined by Cleveland and McGill were: position on a common scale, position on non-aligned scale, length, direction, angle, area, volume, curvature, shading and colour saturation.

For any group of crime data, it is possible, after mapping, to label individual crime events as either within a hot spot area or not. If an analyst infers there are N distinct hot spots in a particular data set, it would be possible to create a categorical variable with N+1 mutually exclusive levels (the additional level accounts for those events not located in a hot spot). This variable will be called the hotspot class variable.

Figure 1
Plot Triplet for Burglary Using the Entire Basic Command Unit



The three plots represent the long term trend, the intensity surface of crime incidence, and the time profile of risk during the day. Lighter shading indicates lower crime incidence.

If Figure 1 can be generated for an entire data set, it would be a comparatively easy task to produce multiple versions of the figure, one for each hot spot. Furthermore, it would be possible to generate a display of plot-triplets conditioned by the hotspot class variable. By arranging these plot-triplets in columns, and ensuring a common vertical alignment, the design features of the Trellis system can be exploited, which allow readers to locate efficiently similarities and inconsistencies between different hot spots areas.

The analysis presented in this paper was performed entirely in the statistical programming language R (R Development Core Team, 2006). It contains, among other features, sophisticated graphics capabilities, allowing the user a fine degree of control over plotting parameters. The temporal trend plots were programmed directly using basic frequency and plotting functions, the KDE surfaces were generated using the spatstat package (Baderly and Turner, 2005). The aoristic analysis required writing functions to compute the time profile (in essence, this required a series of small functions to determine which time intervals each crime event spanned and the corresponding event fraction to allocate to each). The grid package (Murrell, 2006), a distinct graphics system within R that allows complex layouts of plots to be defined, was used to create the layout of multiple plots in a single plot-triplet graphic. In principle, the analyses could be performed in a GIS environment.

In the example presented in the results section, hot spots are selected according to areas corresponding to concentrations of crime. That is, rectangular sub-regions of interest might be defined and all events located within this sub region are selected. No attempt was made to systematise this, although there would be merit in doing so. For example, LISA-type statistics like G_i^* could be used to identify clusters of cells with significantly high counts of crime (Getis and Ord, 1996; Chainey and Ratcliffe, 2005).

Results

Figure 1 contains the plot-triplet for the entire BCU. Looking at the kernel density surface, there are some fairly clearly distinguished hot spots located at the top, middle, and bottom of the BCU. The two temporal plots show clear patterns as well. The long term trend is fairly well behaved, although there is a spike toward the end of the time window. The plot of the long term trend is different from Tufte's sparkline concept. It is larger in size than a single word. Sparklines are designed to be included within paragraphs of text with the surrounding lines of text serving as reference points, but this is clearly not possible here. The time frame of the data used to construct the plot is included, along with the observed crime counts for the first and last time periods. In addition, to highlight the extremes of the series a shaded band indicating the interquartile range of the data series is shown.

The aoristic plot indicates that the typical day can be partitioned into four time periods, each with a different level of associated risk. The hours with the lowest risk profile are 0900 to 1400 hours approximately. The hours of 1400 to 2000 have a relatively moderate level of risk, with 2000 to 0500 hours associated with the highest risk period. The 0500 to 0900 hours display burglary risks in transition and is very different from the consistent risks displayed in the other time periods. Apart from this time period, all changes are fairly pronounced.

Figure 1 contains two other graphical features designed to assist in making comparisons between hot spots. The first is the percentage line to the right of the KDE surface, and is simply a modified dot chart (Cleveland, 1982). This indicates what percentage of the data set contributes

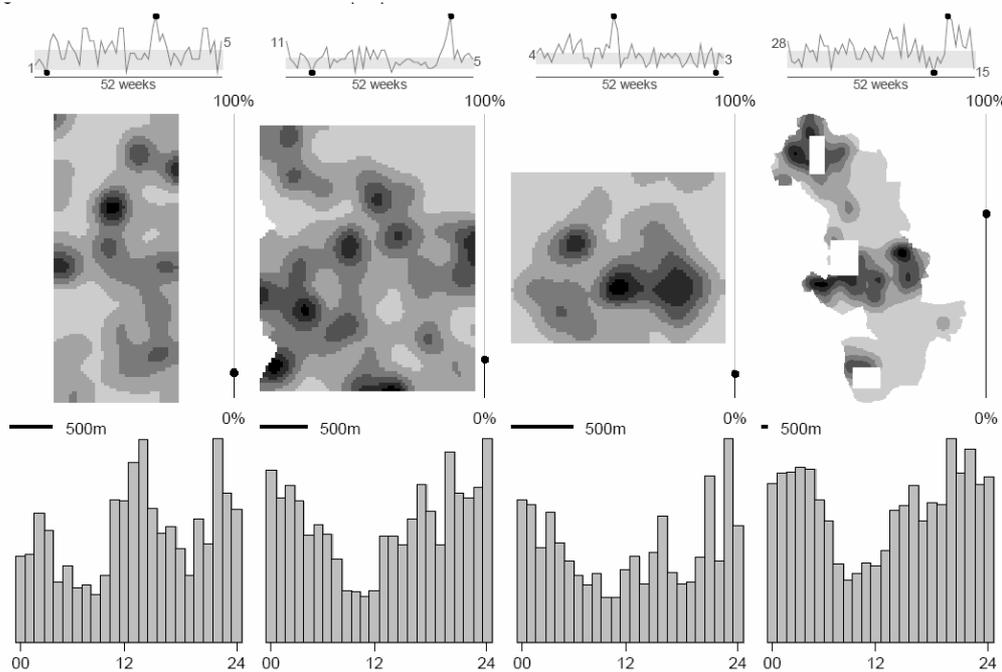
to the data in the three plots, indicated by the black dot. The second feature is the scale bar to the bottom left of the KDE surface. The extent of the line indicates the scale of the KDE surface, in this case the magnitude of 500 metres. As Figure 1 contains the entire BCU, i.e. all the data over a large area, neither of these reveal much, but they do serve a purpose when comparisons are to be made.

From this figure, a new variable hotspot class was created. Three rectangular regions were defined that correspond to the hot spots at the top, middle, and bottom of the KDE surface in Figure 1. Every observation in the data set was classified on this basis as either “hot spot 1,” “hot spot 2,” “hot spot 3” or “not a hot spot.” The analyses for the long term pattern, aoristic plot, and kernel density were performed for each category of hotspot class. Following this analysis, the plot-triplet conditioned on hotspot class was constructed. Figure 2 contains the results.

The first three columns are the plot-triplets for the three hot spots identified in Figure 1. The final column is the plot-triplet for the remainder of the BCU less the observations within the three hot spots (indicated by the holes in the KDE surface). The purpose of displaying this information is to serve as a baseline for the individual hot spots.

Figure 2 contains information about the amount of burglary in this BCU at different spatial scales and different temporal scales. The magnitude of information available in this figure allows multiple comparisons to be made inter- and intra- hot spots. Much of this is assisted through the layout of the plots, which make comparisons efficient.

*Figure 2
Hotspot Plot of BCU Burglary Events*



Plot-triplets conditioned by hotspot area with non-hotspot burglaries acting as a baseline measure. Lighter shading indicates lower crime incidence.

With respect to the long term trend in each area, the top row of plots, there is considerable variation between hot spots. The first hot spot area (leftmost column) displays quite

volatile crime counts: for most of the time frame, the crime count oscillates from relatively low to moderate crime counts, with a spike at about the three quarter mark. This is very different from the second hot spot area, which displays stable levels of crime for most of the year but a very sudden elevation in burglary towards the end of the time window. The long term trend of the third hot spot is somewhat similar to the second hot spot in that crime levels are relatively stable apart from the spike in the middle of the time frame. The final column of plots pertains to the entire BCU less those observations located in a hot spot area. The long term trend in non hot spot burglaries is fairly consistent, but an increase toward the end of the time frame can be observed.

Moving to the KDE surfaces of the hot spots, a number of features are obvious. First, the percentage bar to the right of each KDE indicates the fraction of the sample contained in each area. It is clear that the hot spots cumulatively account for about one third of the BCU's burglary events.³ The fraction existing within each individual hot spot can also be estimated. Comparing across the hot spots, each accounts for roughly the same proportion of events with the second hot spot having slightly more than the first and third (implying the crime counts per week in the long term trend plot are broadly comparable). The scale bar relates the degree of spatial magnification for each area. It is possible this information can be inferred from the size and shape of the holes in the KDE "remainder" column, but it was decided to display this directly. For these data, the scale used for each hot spot area is similar.

The KDE surface of the hot spots are dissimilar. This is to be expected, as the underlying geography is different for each. It may be useful to include appropriate land use information in these plots, even at the scanning stage.⁴ There is one comment about the KDE surface which is worth pointing out explicitly. Observe the KDE surface of the non-hot spot area (the rightmost column) and compare this to the KDE surface displayed in Figure 1. Equivalent parameters were used for the computation of both surfaces, yet there are some striking differences. The reason these surfaces are so different is that the "remainder" surface is computed without those observations located in areas of high concentration. Whenever relative measures (such as KDE surfaces) are calculated, the effect of excluding outliers will be to make values that were previously moderate more extreme in relative terms. Here, previously cool spots have become hot by virtue of an absence of any areas that are hotter.

Finally, it is possible to look at differences in burglary risk during the day through the aoristic plots shown in the bottom row of Figure 2. Here, within each plot, the range of the aoristic values has a common minimum value of zero but will have different maximum values due to the number of events that contribute to each hot spot area. For this particular data set, this difference is likely to be minor as the hot spots have similar proportions, but it is likely to be an issue for other data sets. A solution is to compute the aoristic values so they represent relative proportions rather than relative frequencies so that they all conform to a common scale.

The first hot spot (leftmost column) appears to have two high burglary risk times of the day, around 1200 and 2200 hours. Outside these times, there is a considerably lower risk of burglary. The aoristic plots for the second hot spot and the "remainder" (second and fourth

³ The hot spots' area makes up less than five percent of the total area of the BCU. This estimate is slightly misleading as some parts of the BCU are non-residential, so hot spot areas probably account for a greater component of the residential area of the BCU.

⁴ This was not done here as it lies outside the remit of this article. The purpose of this paper is to propose an effective method of displaying patterns, not their calculation. As such, decisions as to what to include are left to the analyst.

columns) are quite similar and match that of the daily risk profile of the entire BCU. The third hot spot displays markedly different risk profiles across the day. From 2200 to 0400 hours, there is a relatively high risk of burglary but quite a low risk outside this time.⁵

The method set out here does not, of course, tell analysts what to do, and should only be used as a scanning or exploratory data analysis guide. Prevention opportunities are unlikely to be identified from a map. What it does indicate is which areas/hot spots deserve additional analytic attention, and it provides a preliminary indication of the analytical direction to take. It allows a number of rudimentary hypotheses to be tested quickly, such as whether a hot spot is a stable or unstable concentration of crime. It also tells the reader how exceptional each hot spot is by displaying a baseline measure.

Conclusions

Whenever a map or graph is constructed, information is encoded by the designer to be decoded by the viewer. The proposed “hotspot plot” is a systematic, intuitive approach to displaying crime patterns in two dimensions (space and time) simultaneously, designed for efficient decoding of information.

This article has presented a method for visualising spatial and temporal patterns of crime at different levels of spatial and temporal resolution. The Trellis-like trait of vertical and horizontal alignment of plots allows efficient decoding of information by the reader, specifically:

- comparing the long term levels of crime within each hot spot (as well as similarities between hot spots);
- comparing the intra-day time signature of each hot spot;
- the relative spatial and numerical magnitude of each hot spot; and
- the production of a baseline to use against the observed hot spot patterns.

The hotspot plot demonstrates that, for the data used here, there exists considerable variation in the temporal distribution between hot spots at different levels of resolution: within year and within day. These differences are located effectively due to the careful design of the plot. Moreover, the construction of a baseline measure provides a useful frame within which to make comparisons. By doing so, this creates an environment in which crime mapping could evolve from mere descriptive to inferential analysis.

There are two qualifiers to the analysis and method presented here. First, only 12 months of data were used. It would be useful to use a longer time frame to consider the effect of seasonal effects on crime volumes at hot spot locations. In developing the hotspot plot, a high priority was placed on practitioner utility, so no effort was made to incorporate seasonal decomposition. Second, no attention was placed on the validity of the analytic methods used for each component of the hotspot plot. The approach here was to view crime analysts as rational professionals who are best placed to determine the strengths and weaknesses of individual techniques. As long as analysts are aware a variety of techniques exist, there is no need for the method outlined here to be fixated on a false lure of the “one-and-true technique.”

⁵ For reasons similar to those for the long term trend, relative change in the aoristic profile is of greater importance than magnitude. Given each hot spot has very similar magnitude of crime events, the point is moot for this application.

There are a number of ways the proposed method could be enhanced. First, the choropleth plots could be conditioned by monthly time periods (or seasons, quarterly reporting periods) to investigate whether the daily rhythm of criminal events has changed historically. Second, plots of other variables could be incorporated in the plot-triplets. For instance, suppose it is possible to classify burglaries according to information about method of entry (forced, distraction, opportunistic). This could be represented as a series of graphs conditioned by the hotspot class variable. The resulting plot could be inserted in the associated column. Third, plot-triplets could be conditioned on a variable other than hot spots. For instance, communities or housing estates could be used as a conditioning factor for performance management purposes to summarise a larger jurisdiction. Alternatively, the conditioning variable need not be geographic in nature. A separate plot-triplet could be generated by the method of entry classification suggested above. For these non-area conditioned plots, the baseline plot-triplet (“remainder”) could be replaced by the aggregate plot-triplet (i.e. “all events”).

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