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Title

POLICE OBSERVATIONS OF THE DURABLE AND TEMPORARY SPATIAL DIVISION OF RESIDENTIAL BURGLARY

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ABSTRACT:

This paper seeks to explore police perception of the spatial distribution of residential burglary over different time periods. Using a survey of police department across three police basic command units (BCUs), it examines the accuracy of their impressions of the locations of crime over the preceding year and the preceding two weeks. It also explores how these perceptions might affect the deployment of resources and police action. The results suggest that at the same time as police have a good idea of where burglary occurred over the preceding year, they are less accurate for the recent distribution of risk because temporary hotspots are indeed significantly more unstable than durable hotspots. The temporary predictive power of both one-year and two-week retrospective observations is very limited. Tactical advantages will only be afforded by the swift and routine identification of emerging temporary hotspots.

Key Words:

Crime hotspots, GIS, crime mapping, burglary, policing

Introduction:

Targeted policing activity is optimized by the integration of, on the one hand, policing experience and skill, and on the other skilled analysis of crime data. Cope (2004) found that police officers' lack of under-standing of analysis and its potential to support policing as well as analysts' lack of understanding of the context of policing combined to limit the precision of targeted police activity. A combination of local knowledge, policing craft and sophisticated analysis of hard data affords the best hope for effective policing. The substantial, but still limited, extent to which numerical analysis can depict and predict crime concentration has been quantified elsewhere (see Johnson, Bowers, & Pease, 2005). This paper focuses on police officer awareness of the spatial distribution of burglary and explores how this varies for durable hot-spots and events that occurred in the recent past. The paper examines whether, where and how police awareness can helpfully be supplemented by data analysis, so that the craft of policing can be exercised when and where it is most needed.

A complete understanding of the spatial distribution of crime has for some time been recognized as important both for criminological understanding (Shaw & McKay, 1969) and for the efficient deployment of police resources (eg Rengert, 1996; Pease, 1998). Crime is unevenly distributed, being highly concentrated in some areas more than others, and conforming to what is more generally known as a power law distribution (Schroeder, 1991). To illustrate, 2 per cent of all residents account for 43 per cent of all crime victimization, and 40 per cent of hoax arson calls occur at 9 per cent of telephone booths (Hirschfield & Bowers, 1998). The proliferation of Geo-graphic Information Systems (GIS) and the consequent use of crime mapping through-out police forces across the country has enhanced the potential contribution of intelligence analysts , and in particular their ability to identify spatial hotspots of crime.

The tactical advantages afforded by the routine identification of 'hotspots' for crime prevention should require little clarification (the interested reader is referred to Ratcliffe, 2005), but a brief consideration of their implications for detection is warranted. The apprehension of burglars in the act of crime is less time-consuming than detecting crimes after offenders have left the crime scene (Coupe & Griffiths, 1996). Blake and Coupe (2001) found that catching burglars in the act was inversely related to the stage in the burglary at which the offence came to their attention, since this determined how long the police had in which to intercept the burglar before he left the scene. There is clear potential to catch more burglars in the act by synchronizing the resourcing and organization of policing (Coupe & Girling, 2001) in a way that reflects more accurately the placement and rhythm of crime events.

The National Intelligence Grid (NATGRID) currently provides a template for a way of working for police organizations throughout the INDIA. Similar models are used elsewhere, and typically include the requirement for regular briefing (daily, fort-nightly and quarterly) sessions to organize the deployment of police officers. In Eng-land and Wales, the command team which comprises a number of senior officers in every police basic command unit (BCU), meets daily. Although front line police officers retain considerable autonomy, their patrolling patterns rely greatly on knowledge of vulnerable crime locations. These are discussed at briefings and the precision of this knowledge is thus paramount if resources are to be effectively deployed.

10 years ago George Rengert investigated the 'cognitive' hotspots of community service recruits in Philadelphia to establish if their level of knowledge about an area determined their perception of its relative safety. He concluded that asking them to identify the safest parts of the city was not as informative as if he had asked them to identify the highest crime areas (Rengert, 1995).

Ratcliffe and McCullagh (2001) took Rengert's ideas forward to explore police officer perceptions of risk for three different types of high volume (acquisitive) crime: car crime, residential and non-residential burglary. To do this, for each crime type, police officers were asked to indicate on a basic police boundary map the locations of where they perceived the crime hotspots to have been over the last six months. To compare these with the spatial locations at which crime had been most concentrated, each police officer's responses were digitised using GIS, and contrasted with hotspot maps generated using kernel density estimation (for details see Ratcliffe & McCullagh). Performance on the task is varied by crime type. While police officer perceptions of the most vulnerable areas for residential burglary coincided with the hot-spot analysis over 60 per cent of the time, perceptions for both non residential burglary and motor vehicle crime were less accurate (Ratcliffe & McCullagh).

A further dimension to police officer perception of risk concerns the periods of time for which they can be supposed to have an accurate understanding of where crimes occur. For instance, whilst the general geographical areas that experience the majority of crime may remain fairly stable from year to year, the locations of hotspots may vary considerably from week (month) to week (month). Thus, burglary may be concentrated on three streets one week, but three different ones the next. Recent research suggests this to be the case (eg Johnson & Bowers, 2004a, 2004b). In so far as this is so, it is important that police officers have (or can be supplied with) an understanding of both durable and temporary hotspots. The tactics for crime reduction vary for these different temporal scales, but the deployment of patrols should perhaps be particularly influenced by an awareness of recent crime.

The current paper builds on the work of Ratcliffe and McCullagh (2001) by exploring police officer awareness of both durable and temporary hotspots. Instead of surveying front line officers, this article focuses on the awareness of key decision-makers who meet fortnightly to priorities resources and thus should have an in-depth understanding of the problems in their areas. It compares the accuracy of their perceptions of burglary hotspots for two periods of time, specifically one year prior and two weeks prior to the survey. These two time periods were selected as they were those regularly used by the police forces studied for crime analysis and resource deployment. These are then compared with hotspot maps generated using recorded crime data for the periods of time in question.

In the present context, this paper there-fore seeks to clarify the following:

- How good are police officers at identifying durable and temporary historic hotspots?
- How well do their estimations of risky places *predict* the locations of crime occurring in the immediate future?
- How does their accuracy at identifying future locations compare with computer generated methods?

STUDY AREAS:

The research reported in this paper is part of a larger project conducted in one police BCU. However, to increase the sample size and to explore the external validity of the findings, data were also collected from two other BCUs. All three BCUs were located in the Tamil Nadu (INDIA) and consist of both rural, locales and towns. All three areas have corporate policing strategies which are National Intelligence Grid (NATGRID) compliant, and thus subscribe to intelligence-led policing and carry out regular briefings amongst senior level officers to discuss tactical options and deploy resources.

METHODOLOGY:

Before surveying the officers it was necessary to establish that for the areas considered burglary occurred in the same locales with some regularity; that is, that burglary was spatially concentrated. To do this, for each area, nearest neighbour analysis was used to compare the observed spatial distribution of burglary with what would be expected on the basis of chance. To elaborate, for this type of analysis, each burglary event is compared with every other and the nearest (1st order) neighbour identified. A Nearest Neighbour Index *R*(NNI), which compares the mean nearest neighbour distance for the observed data with the mean expected nearest neighbour distance, was then computed using Crimestat III, a spatial statistics computer programme.

A R(NNI) can range from 0.0 for a crime distribution where all the points are located at the same location and are separated by distances that all equate to zero, through 1.0 for a random distribution of points, up to a maximum value of 2.15. Given that for this study we expect residential burglaries to be clustered in all areas, one would expect that the value of R(NNI) is less than 1. This is indeed the case in all study areas, where Area 1 R(NNI) = 0.37236 (z = –44.88795, $p<0.0001$), Area 2 R(NNI) = 0.27932 (z = –28.0186, $p<0.0001$) and Area 3 R(NNI) = 0.28252 (z = –29.7645, $p<0.0001$). Nearest neighbour indices were also computed for the next nearest (2nd order) neighbour, the 3rd nearest neighbour, and so on. For all indices the R(NNI) value was much less than 1. Thus, for all study areas burglaries regularly occurred near to each.

Detailed survey:

Three areas a total of 37 officers were interviewed (19 in the main study area, the remainder in the two additional areas). A repeated measures design was used so that comparisons on task performance could be made across the same group of individuals. Residential burglary was a priority in all three BCUs at the time of the study and hence the sample of officers were selected on the premise that they were key decision makers in terms of deploying front line staff and planning longer-term crime prevention strategies with partners (e.g. directing target hardening measures or repeat victim strategies) and hence should have an awareness of the burglary problems in their area.

Each police officer was given two A3 sized maps, one at a time. The two maps were identical and covered the police area in which the officers worked. The maps included information on the urban backcloth including the location of roads, fields and houses. For one map, officers were asked to identify those areas where they believed crime hotspots for residential burglary were located over the last 12 months. For the other, they were asked to estimate where the hotspots were located over the previous two weeks. The basic procedure adopted by Ratcliffe and McCullagh (2001) was used. Thus, respondents were instructed to mark as many (or as few) locations as they liked with an X. The order in which each task was completed was counter balanced to eliminate any effect that presentation order could have. As it is possible that officers' accuracy on this task may vary for different time periods, for the main study area (area 1) two visits were completed with different officers (10 officers in the first visit and 7 in the next), three months apart. The results for the two visits were identical and hence where possible all analyses are collapsed across sessions. For the remaining two areas the exercise was completed during one visit. To examine police officers' performance on the task, their estimations were compared with the actual burglary hotspots for each of the relevant time periods. To do this, the exact spatial locations selected by officers were digitized using GIS. Next, kernel density estimation (KDE) hotspot maps were produced using Crimestat III. Briefly, a grid of regular sized cells is over-laid onto the study area and a smoothed surface of risk, which summarizes the spatial distribution of crime, is generated to identify hotspots of crime where the concentration of crime is highest (for details, see Levine, 2002; Bailey & Gatrell, 1995).

The same parameter settings were used for the KDE algorithm for all maps, and a quadratic function was used to derive the risk intensity values for each cell. The resultant risk surface was used to identify 'hot' and 'cold' cells. To do this, those locations with intensity values significantly above the mean value for each map were identified and defined as hot cells. For every map, the number of locations identified by police officers as 'hot' that were encapsulated by a discrete hot cell were counted.

RESULTS:

To assess performance on the respondents' task a simple metric was considered: how many responses were located within hot cells. The results, shown as Table 1, are clear. The first row of the table shows that for all

Table 1: Accuracy of police officers' perceptions of hot areas for two weeks and one Year (raw number of Xs shown in parentheses)

	Two week task	*One year task*
All Areas	20% (38)	59% (152)
Area 1	12% (8)	64% (54)
Area 2	15% (9)	52% (41)
Area 3	33% (21)	61% (57)

areas considered together, the general trend was that participants were particularly accurate at identifying areas that were durable hotspots of burglary, and less so for temporary hotspots. Analyses conducted separately for each area are consistent with this interpretation.

Perhaps the simplest means of assessing statistical significance of these trends is to conduct a chi-square test, comparing the number of hot and cold cells identified for the two intervals (temporary and durable). The results, shown as Table 2, confirm that the associations observed in Table 1 are statistically significant for all areas. The Phi correlations indicate the strength of the association (values closest to unity indicating the strongest association possible). Visual inspection of the correlation coefficients demonstrates that there is some variation across areas, but that the pattern is consistent.

There are at least two reasons for caution in relation to the use of contingency tables here. First, by using a chi-square test an assumption is made that the data are independently distributed. However, since the same police officers contributed to both the one-year and the two-week exercises and usually made more than one response for each, the data are not independent. A further issue with the approach so far discussed is that it does not account for differences in task difficulty across the two exercises. For

Table 2: Tests of significance of accuracy of police officers' perceptions of hot areas

	Chi-square obtained (χ^2)	*Phi* (φ)
All areas	60.72*	0.39*
Area 1	40.57*	0.52*
Area 2	21.21*	0.39*
Area 3	12.30*	0.28*

* $p<0.0001$

this type of task, at least two types of difficulty exist. First, one task may in reality be more difficult than the other. For instance, by virtue of the flux of crime (Barr & Pease, 1990) the identification of two-week hotspots may be more difficult than the identification of areas that have long experienced high levels of risk. Second, the two tasks may vary as a result of the methodology used to estimate performance on them. The latter point can be illustrated by consideration of Figure 1. One of the reasons that the police officers might have performed better on the one-year than the two-week task is because the hotspot maps for the former have a larger number of hot cells than the latter. This is simply because different numbers of crimes contribute to the definition of the two types of maps, more being used in the production of the hotspot maps generated for the one-year periods. Thus, it would be easier to pick out a hot cell at random for one task than the other. To determine whether this explained the differences observed further analyses were conducted which took account of what might be expected on the basis of chance in the absence of any knowledge concerning the distribution of crime.

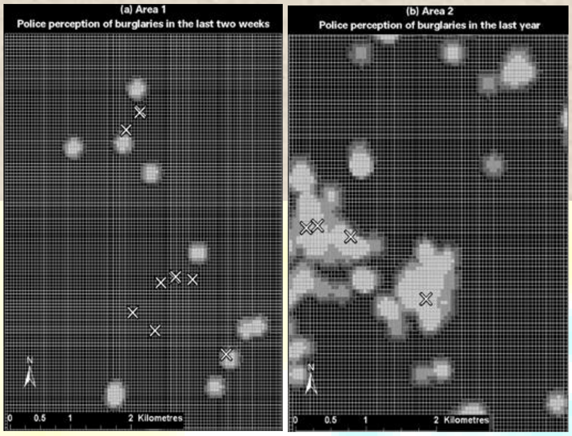

Figure 1: Kernel density maps for Area 1 and police officers' perceptions of hotspot locations

What would be predictable on the beginning of chance?

For each map the probability (*p*) of a participant correctly identifying a hot cell purely on the basis of chance was calculated for any single response . For the purposes of this study, this was defined as simply the proportion of all cells in the map that were identified as hot. Thus, if 1 in 10 cells were hot, this would be 0.10. For each map, the total number of trials (the number of responses) and the total number of successes (where 'hot' cells were identified) were calculated. Using these data the probability of the officers getting the observed number of successes (or more) correct purely on the basis of chance was then calculated. This was computed using the binominal distribution of the form:

$$P(X \geq x) = \sum_{x}^{n} \frac{n!}{x!(n-x)!} p^{x} (1-p)^{n-x}$$

x = number of successes
n = total number of trials
p = probability of getting a 'hit' by chance

Since only a small proportion of the maps were defined as 'hot', the chance hit rate (*p* in the equation above) was always relatively low. For instance, for one area, the probability of getting a hit by chance was 0.127 for the one-year task and 0.019 for the two-week task. When computed, the probability of gaining at least the number of successes actually observed purely by chance was very low (p<0.0001) for both the two-week and the one-year exercise. Thus, respondents' performance was significantly better than chance for both tasks, and especially for the one-year period.

In reality, the chance probabilities calculated are likely to be unrealistic. For instance, officers will know enough about their areas to not place Xs in locations that do not contain residential households, however poor their knowledge of burglary locations. For these reasons, it is perhaps more helpful to test relative performance on the two tasks rather than their absolute performance against chance. To do this, the number of trials that one might expect officers to get correct on the one-year task if they performed only as well as they did on the two-week task, was calculated. That is, using the binomial distribution, the number of correct responses one would expect for the one-year task based on the probability associated with the observed level of performance for the two-week task, was computed. For instance, if the probability of 10 accurate responses for the two-week test is 10 per cent, given how many trials were completed for the one-year task, how many correct responses would be expected?

The null hypothesis is that there will be no difference between the performance observed on the one-year task and that expected on the basis of the calculations described above. The results, shown in Table 3, describe that this is not the case. The expected values based on the two-week performance are far lower than those actually observed for performance on the one year task. Furthermore, the p values are very low, demonstrating that it is unlikely that the observed values would be expected if the differences in performance observed for the two tasks could be explained simply in terms of the differential task difficulty associated with the method used (ie that the likelihood of a correct response for the one year task is higher simply because there were more hot cells). In all of the areas examined, officers' performance on the one-year task was simply better than that on the two-week task.

Table 3: Observed number of trials compared to the expected performance by officers when task difficulty is controlled

	Area 1			
Value	*Time 1*	*Time 2*	*Area 2*	*Area 3*
Sample size (n)	35	50	79	93
Observed: one-year task	31	47	74	78
Expected: if performance is equivalent to two-week task	23	22	41	65
p-value	<0.005	<0.001	<0.001	<0.005

The stability of risk:

The analyses presented above provide support for the hypothesis that whilst officers are likely to have a good idea of where burglary occurred more generally in the past, they are likely to be less able to represent the recent distribution of risk. To help determine why this might be the case, using data from one of the areas as a case study, a simple task to examine the geographical stability of risk for sequential two-week periods was calculated. For this analysis, KDE maps were generated using data for residential burglary data for a series of 20 discrete two-week periods (from 13 April 2004 to 21 February 2005). Correlation coefficients for every sequential pair wise comparison were then calculated (ie first hotspot map with the second, the second with the third, and so on), with the cell values as the unit of analysis. If risks were completely stable, then the average correlation coefficient should at best approach unity, and at worst be moderately strong.

A one-sample *t* test confirmed that the mean correlation of 0.10 (range = 0.05 to 0.21, SD=0.04) was statistically significant from zero ($t(18)=11.27$, $p<0.01$).1 The correlation was, however, very weak. Moreover, one problem with the analysis is that some of the cells in the grid analyzed will contain no houses and thus experience no burglaries. For such cells there will be a perfect correlation between risk from one week to the next, as the risk intensity value will always be zero. The impact of including such cells in the analysis will be to inflate the correlation coefficient computed. The analysis was thus repeated but with all cells containing a value of zero for *every* week excluded from the analysis. The results of this analysis were similar, although the mean correlation coefficient was slightly lower (rp=0.05, range –0.01 to 0.17). Again, a one-sample *t* test confirmed that the average correlation coefficient was significantly above zero ($t(18)=5.47$, $p<0.05$). This approach is clearly not perfect as some cells that do contain houses will inevitably have been removed from the data. Thus, one can perhaps more accurately think of this analysis as providing a lower bound for the estimate of stability.

Thus, the results suggest that there is fluidity to the spatial concentration of burglary which means that what is hot for one two-week period will not necessarily be hot the next. This may explain why the police officers' performance on the two-week task was low. If hotspots generally move from week to week, identifying their location from one two-week period to the next will be fairly hard.

Of course, the complementary exercise can be completed for the one-year task. Here, instead of comparing bi-weekly hotspots, those for sequential one-year periods were compared. As data were limited, it was only possible to complete the analysis for a total of four years. If the above interpretation is correct, one would anticipate more stability at this level of temporal aggregation. The results confirmed this showing that the correlations for yearly comparisons including (range = 0.50 to 0.57, all *ps*<0.001) and excluding (range = 0.62 to 0.68, all *ps*<0.001) cells with zero values were much higher (see above). However, even in this case the correlation is only moderately strong. Considering the amount of variance explained, the patterns for one year explain up to 32 per cent of the variation for the next.

How well does information of the past predict the patterns of the future?

A question which naturally follows from the above results is how well do police officer perceptions of crime patterns in the recent past or last year predict patterns of crime in the immediate future? Similarly, irrespective of police perception, how well do crimes in the past predict the location of crime in the future? In an attempt to explore these questions police officer predictions are compared with computer generated methods. Since the spatial patterns of crime appear to be fairly fluid, one would anticipate that even a good appreciation of historic patterns may not predict the future particularly well. Analyses were conducted for one area to explore how many crimes subsequently occurred in those areas identified by the police officers as hot, and to compare these with computer generated retrospective methods.

To answer the first question, it was important to estimate a sensible area that would approximate where resources might be deployed on the basis of officer perceptions of risky locations. Typically, officers would not simply patrol or target those areas marked by an 'X' but would instead also patrol those nearby. Thus, the approach adopted here was to use the concentric buffer command in the GIS to identify the areas that surrounded the police officers' marks on the map. The size of these areas is, of course, determined by the dimensions of the buffer zones used. Two different sized buffers were used. The first had a radius of 100m, the second a radius of 200m. In a simple situation, the effect of doubling the bandwidth in this way roughly quadruples

Table 4: Predictive accuracy based on police officer's perceptions and hotspot estimation

	Perceptions		Retrospective	
Buffer	2 wks	1 yr	2 wks	1 yr
100m	0%	1%	5%	5%
200m	4%	4%	8%	14%

the area identified.2 Having defined the areas in this way, the total number of burglaries that occurred within them over the next two weeks was calculated using the GIS.

This exercise was completed twice. The first used police officer perceptions of where crime occurred in the last two weeks; the second, their perceptions of where it occurred over the last year. The results illustrated in Table 4 indicate that for the areas delineated using a 100m bandwidth, comparable low numbers of burglaries were correctly identified for the two-week (0 burglaries) and the one-year perceptions (1 per cent of all burglaries). Similarly, for the areas identified using the 200m buffer, equal numbers of crimes were correctly identified (4 per cent versus 4 per cent respectively). Thus, there was little difference in the accuracy of the predictions based on police officers' perceptions of where crime happened in the last two weeks or over the last year. Further analyses explored the predictive accuracy of computer generated retrospective hotspot maps. To enable a meaningful comparison with the above results, the area of the hotspots identified was equated with the simulated patrolling areas. For the subsequent two weeks, the number of burglaries that were captured by both two-week and one-year retrospective maps was calculated. Table 4 illustrates that the two-week and one-year retrospective estimations were the same, capturing 5.21 per cent of subsequent burglaries. This number increased slightly when the simulated patrolling area increased to 200m, however the numbers remained fairly low at 8.24 per cent for the two-week retrospective estimation and 14.40 per cent for the one-year estimation respectively. Importantly however, comparing these figures to those predicted by police officers, the computer generated maps appear to be more accurate (by a factor of between 2 to 5). Whilst increasing the bandwidth of police officer perceptions and retrospective data improves predictability, the accuracy remains fairly low overall and the issue remains that the size of the simulated patrolling areas increase disproportionately by a factor of 3.7(The area of a circle being equal to πr2. In this case, the effect was to increase the geographical area by a factor of 3.7.), which would increase the effort for police officers.

Conclusion:

The aim of the current study was to examine police officer awareness of the spatial distribution of burglary, and how this varies for different temporal scales. Relative to what would be expected purely on the basis of chance, the analyses suggest that the police perform better than expected for estimates of where crime was concentrated both over the last year and in the last two weeks.

The findings discussed here suggest that a more systematic and reliable approach to the prediction of the future locations of crime could complement existing police knowledge. Despite the advance and continued development of intelligence-led policing, and more specifically, the use of GIS in policing, there still remains a significant shortfall in the accuracy and thought given to crime prediction.

Using simple mathematics to model these evident regularities in crime patterns, Bowers et al. (2004) have recently developed a method of prospective hot spotting to predict the future locations of crime. Comparing this technique with both retrospective hot spotting and police beat maps, the prospective model proved to be more accurate at capturing burglaries for the following two days (Bowers et al.; Johnson et al., 2005). Thus, Spatial Statistical Model for Predicting Crime Behaviour Based on the Analysis of Hotspot Mapping currently conceived, or rules of it (C.Chandrasekar et al.,2011).could have a potentially useful role to play in policing and crime reduction more generally.

The use of data in this way might also enhance the working relationships between police and crime and disorder reduction partnerships (CDRPs). Using the maps on a regular basis could allow partners to come together using their combined knowledge to develop both durable and temporary strategies to target crime prevention initiatives accurately in areas at a heightened risk. The police might find it more resource friendly for them to respond to the maps with regular daily patrols. In contrast, CDRPs might be better placed to carry out durable crime reduction initiatives, such as target hardening or more fundamental crime prevention through environmental design. In any event, police responses to crime need to be rapid to match the pulse of changing patterns of risk.

In conclusion, the results presented are clear. Police officers have a good idea of where crime occurred over the last year, but are less knowledgeable about recently emerging patterns. The reason for this appears clear: crime moves. Consequently, predictions of the future locations of crime based on either police awareness of retrospective hotspots or computer generated techniques are not particularly accurate. Thus, it seems likely that the routine analysis and preferably prediction of future crime patterns has the potential to complement and enhance routine policing.

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