The space/time behaviour of dwelling burglars: Finding near repeat patterns in serial offender data

Derek Johnson

Northumbria University, Ellison Building, Ellison Place, Newcastle upon Tyne NE1 8ST, United Kingdom

Keywords:
Burglary
Clustering
Serial offending
Crime prevention
Repeat

A B S T R A C T

Whilst analysis of crime for tactical and strategic reasons within the criminal justice arena has now become an established need, predictive analysis of crime remains, and probably always will be, a goal to be desired. Opening a window on this over the last 2 decades, prominent research from academia has focused on the phenomenon of repeat victimisation and more recently 'near repeat' victimisation, both firmly grounded in the geography of crime. Somewhat limited to the establishment of near repeat behavioural patterns in whole area data, these can be utilised for crime prevention responses on a local scale. Research reported here however, explores the phenomenon through the examination of serial offending by individual offenders to establish if such spatio-temporal patterns are apparent in the spatial behavioural patterns of the individual burglar, and if so how they may be defined and therefore utilised on a micro rather than macro scale. It is hypothesised that offenders' responsible for more than one series of offences will display consistency across their crime series within time and distance parameters for their closest offences in space. Results improve upon current knowledge concerning near repeat offending being the actions of common offenders. Testing of the extracted data indicates that offenders maintain personal boundaries of 'closeness' in time and space even when actions are separated by significant time spans, creating stylised behavioural signatures appertaining to their use of and movement through space when offending.

Introduction

As spatial analysis and the availability of G.I.S. has blossomed so the relevance of its use, and indeed the concept of an empirical geography of crime, has become embedded within the Criminal Justice System of England & Wales. Chainey & Ratcliffe (2006) devote a number of pages succinctly explaining its use within a variety of functions of such agencies, whilst their book title and potential audience indicates the recognised importance of the subject to practitioners in the crime arena. Introducing an issue of the Professional Geographer devoted to spatial methodologies for studying crime Le Beau and Leitner (2011) set out a time line of developments in the geography of crime together with three claims. Whilst the first two refer to past developments his third considers the future:

"...the academic niche for the geography of crime will very likely be shared with the new fields of environmental criminology, spatial criminology, and crime science." He concludes by asserting an upward trajectory for the geography of crime and in particular for the geographical and spatial analysis of crime due to its importance to society. In the same issue Andresen (2011) reports on empirical research studying crime rates using an alternative measure of the population at risk. Given results showing a marked difference when using these alternative measures he comments on the importance of policy makers remaining current with geographical data sets and geographical analysis in relation to crime to avoid bias in their work. Alternatively Breetzke (2012) considers an aspect of physical geography and how the surrounding terrain may affect risk of victimisation of burglary in South Africa. Rather less contemporary but remaining pertinent, Herbert in 1989 was of the view that the geographers interest in space and place had much to offer criminological research.

Whilst maintaining the theme of geographic analysis of the spatial patterns of crime and criminals this paper reports on the spatial analysis of burglary offences committed by individual offenders. By moving forward with recent research reported within the criminology and crime science literature as suggested by Le Beu, this research indicates a predictability to an individual's offending
behaviour that changes little over time, suggesting that a geography of individual serial offenders can be defined on a micro scale.

**Repeat victimisation**

Predictive patterns of crime in the form of repeat victimisation was a phenomenon perhaps first identified by Johnson, Kerper, Hayes, and Killenger in a 1973 study ‘The Recidivist Victim: A Descriptive Study’. This was furthered by Sparks in 1981 through identifying several key themes that can be linked to what he termed ‘multiple victimisations’; describing views that can be adopted to explain why an individual may become a victim, but more importantly, a victim multiple times (Sparks, 1981, pp. 772–777). In 1993 Farrell and Pease (1993, pp. 6–7) evidenced repeat victimisation accounting for a significant amount of crime in England and Wales. They provided analysis of British Crime Surveys reporting that between seventy-one and eighty-one percent of victims surveyed had suffered two or more victimisations within the twelve months prior to the survey. As a result of these, and other academic explorations U.K. Police Forces began to develop crime reduction processes to counter repeat victimisation; first steps towards prediction of crime events and a suitable preventative reaction. By 1995 the U.K. Home Office were issuing Crime Detection & Prevention Series papers on the topic that were citing 10 or more previous linked papers and Police Forces had annual targets to reduce or at least maintain below target, the number of repeat victimisations in their force areas

**Near repeat victimisation**

Following hot on the trail of successful action to reduce repeat victimisation, studies began to emerge identifying patterns of crime clustering not only in space but also in time. Morgan (2001, p. 87) highlights research conducted in the early nineties by Polvi, Looman, Humphries, and Pease (1990) which showed that the risk of repeat victimisation was heightened over a short time period, but that for the first month, risk of repeat burglary victimisation was twelve times greater than expected. Subsequent research supported this suggesting that between the first and second month risk is temporarily heightened following a residential burglary, but that there are also limits on the spatial risk. Johnson & Bowers term this the spatio-temporal buffer (Bowers & Johnson, 2005; Johnson & Bowers, 2004).

Working in Australia Morgan (2001) conducted research into the repeat burglary phenomenon in Perth discovering the presence of what he termed ‘near repeats’, reject victimisations closely occurring in both time and space to an initial victimisation but not actually at the same (‘repeat’) location. Shaw & Pease reported in 2000 on research of repeat offending in Scotland finding distinct spatial features. On 68% of occasions, if the first dwelling burglary was at a house with an even number, the next property to be burgled was also an even number. This pattern held for odd numbers. Thirty percent of dwelling burglaries on the same street occurred within 6 numbers either side of the first property attacked, the authors referring to this as the penumbra of risk.

In 2000, Townsley, Homel, and Chaseling, again in Australia, considered this further by analysing residential burglary crime for clusters of offences ‘close’ in space and time, near repeat offences in terms of being near to a previous crime event in both dimensions rather than true repeat victimisation of the same location.

This research suggested that, much like disease spreads between people who are classed as potential hosts (those who have the right characteristics to contract a disease) the process translated into dwelling burglary, finding that areas of largely homogenous housing, were far more susceptible to near repeat victimisation than areas of heterogeneous housing.

Johnson, Bowers and Pease invoke Optimal Foraging Theory derived from behavioural ecology as a potential explanation for the behavioural pattern of near repeat offences. Searching for food animals endeavour to maximise resources acquired, simultaneously minimising chances of capture and effort expended. The analogy between animals and offenders is clear. In their search for food animals are likely to learn much about the environment they move through such as high yield locations, escape routes, hiding areas and safe places. If offenders act as optimal foragers it was anticipated that the same would be true; offenders would learn about likely yields, security measures, potential escape routes from their previous actions, using this information for future offending. Extending this they suggest that repeat location offences can then be considered a form of optimal foraging (Johnson, Bowers, & Pease, 2005).

**Policing response**

Academic research activity in this search for predictive analytical power has received significant impetus through work such as that described. Promulgating that the risk of burglary victimisation can be likened to that of a contagious disease, those premises nearest to the initial burglary event being at heightened risk of future attack and such risk decaying both over distance and time, is a useful analogy. Most important from a predictive sense is that parameters from both dimensions can be articulated (Bowers, Johnson, & Pease, 2004; Townsley et al., 2000 and others).

In 2005 Police in Bournemouth, a popular U.K. south coast town, undertook a burglary reduction initiative based on similar near-repeat analysis. Patterns of space/time clusters were evident in the towns recorded burglary data with two dimensional parameters of 200 m and 48 hours for highest risk. Rapid delivery of reduction advice to residents within 200 m of an initial burglary and 48 h of its report resulted in increased crime reduction, but perhaps more significant was an apparent change in offender spatial behaviour in the areas of intervention (Johnson, 2008). Such predictive analysis has now been adopted with significant fanfare by others, particularly Greater Manchester Police. However the proactive Policing response has taken a global approach of establishing near repeat patterns within area based data to intelligently lead the deployment of prevention and patrol resources, refining the original work of Johnson (2008) in Bournemouth.

**Research objectives**

Research reported here explores the phenomenon through the examination of individual offender data to establish if time and space patterns are apparent in the spatial behavioural patterns of the individual burglar. If so it is asked how such patterns may be defined and therefore utilised on a micro rather than meso or macro scale. Such work has the advantage of approaching data from a known situation, namely that a series of crimes were the actions of one individual and therefore display personalised behavioural patterning.

It is hypothesised that offenders’ responsible for more than one series of offences will display consistency across their crime series within time and distance parameters for their closest offences in space. It is suggested that each offender will have personal definitions of ‘closeness’ in space and ‘closeness’ in time in a similar way that we each have our own activity spaces (Brantingham & Brantingham, 1990), although closeness in time may be driven by an individual’s needs and are likely to be more fluid. In addition it was considered that if serial offenders were to display consistent near repeat offending this may create opportunities to develop
predictive analytics utilising these as stylised behavioural patterns akin to crime ‘signatures’.

Literature on repeat victimisation strongly suggests common offenders for repeat offences (Ashton, Brown, Senior, & Pease, 1998; Hearnden & Magill, 2004; Kleemans, 2001; Pease, 1998; Polvi, 1991; Wright & Decker, 1994) but such studies have tended to rely on victim/crime scene data or interview accounts with offenders. To date little published work on near-repeat burglaries has been undertaken using offender data. Examination of modus operandi facets of burglary has been undertaken on Liverpool data (Bowers & Johnson, 2004) suggesting common offenders are responsible for near repeat offences and the original burglary event, but was based on data with no reference to identified offenders. Bernasco (2008) points out that the theoretical claim that the original and subsequent near repeat offence (in terms of burglary particularly) are the work of the same perpetrator relies on limited evidence. He states that until his work of 2008 no such research had utilised offender data. Bernasco examines Police recorded detected offence data from the Hague and surrounding area over an 8 year period, providing empirical evidence that offences related in time and space are highly likely to indicate same offender activity. However he does not investigate the spatial point patterns of identified individual offenders.

Data for this research was drawn from the English south coast conurbation of Bournemouth and Poole, the first stage involving analysing police recorded burglary data to ascertain whether such near repeat patterns were apparent. Townsley et al. describe using a Knox test to build a non-cumulative table of the number of burglaries actually committed (observed) over various distances and time periods. Such a table allows comparison of the number of burglaries committed with those that may be expected by chance (Townsley et al., 2000). This method was used to establish the presence of near repeat patterns in the Bournemouth & Poole data.

It had been anticipated that it would be similarly effective for identifying such patterns in serial offender data, however, due to comparatively low volumes of offences within serial offending it was found incompatible and a new method was developed.

Material & methods

Police recorded residential burglary crime for the calendar years 2002–2006 inclusive for the coterminous Police divisions were obtained for analysis. Knowledge of the burglary reduction intervention in Bournemouth (Johnson, 2008) prompted the Bournemouth data to be split into two time periods, before and after the intervention start date. No such intervention had taken place in the Poole policing area.

Linked to recorded crime was data enabling the identification of all identified offenders for residential burglary within the extracted crime data set. Further filtering enabled extraction of those responsible for ten or more residential burglaries. Forty-four offenders formed this category but only 14 of those had committed two distinct series of crimes, each having been imprisoned following their first series of crimes for varying terms. Post release a further series had been committed. One offender was responsible for three separate periods of serial offending.

As with most recorded acquisitive crime exact dates and times burglaries occur are rarely known. Time and date fields within the data consisted of ‘from’ and ‘to’ dates and times; when the premises were last known to be in order (‘from’) and when the burglary was discovered (‘to’), so giving a time window when the offence could have occurred. Distributions indicated a prevalence of offences committed within a one day time window indicating that use of the ‘from date’ field in all three data sets as a time reference was valid. Three further data sets consisting of only those offences committed during such a 24 h window were then created so ensuring time accuracy.

The methodology of Townsley et al. (2000) was used in order to establish the presence or otherwise of near repeat offences. This utilises the Knox method where a non cumulative table can be built of the volume of burglary offences within certain time (t) and distance (d) bands. Each cell in the table reports the number of burglaries within t and d parameters such as in Table 1.

By utilising column and row totals the expected values (e) for each cell are also calculated as at formula 1.

\[ e = \left( \sum_{i} \sum_{j} y_{ij} \right) / N \]

Limitations to this methodology are well known, being that time and distance parameters are set by the researcher and should therefore utilise some form of empirical measure. By considering relevant results from previous empirical research integrity can be built in to the Knox analysis through empirically informed categorisation. Time is dealt within previous research concerning repeat burglaries, suggesting a tendency for them to occur soon after previous events and generally within 2 months (Anderson, Chenery, & Pease, 1995; Bowers & Johnson, 2004; Pease, 1998; Polvi, 1991). Concerning Bournemouth the 2005 Dorset Police reduction intervention established high risk at much shorter intervals, certainly being apparent at 7 days from an initial event. Time bands of 7 days were therefore utilised extending over a period of 6 months. Anderson et al. found addresses two doors away from a burgled premise to be at slightly higher risk than those further away (Anderson et al., 1995). A 2002 study also found that houses on the same side of a street were at heightened risk (Eversen, 2002). Actual distances are unknown but a few hundred metres can certainly be inferred. For this research a distance variable of 200 m was chosen extending to 2000 m overall.

CrimeStat III software (Levine, 2004) provides Knox test functionality and reports x values as described in Table 1. To establish which cells in the 3 tables established experienced a greater frequency of events than could be expected by chance adjusted residuals (r) were then calculated for each cell as shown at formula 2.

\[ r = x - e / \sqrt{e(1 - \text{row proportion of } x)(1 - \text{column proportion of } x)} \]

As described by Townsley et al. (2000) “The residual scores measure how many standard deviations the observed frequency is from the expected”. Values &gt;2 reflect a 5% chance of a type I error. To limit this, minimum values of 3 could be utilised thus only 1% of cells will potentially display chance values. The built tables for the
To quantify the time distribution relevant to spatially close offences, those offences close in space, the time distribution relevant to spatially close offences, to quantify the 'closeness' of space relevant to the individual offender and, to quantify the 'closeness' of time relevant to the individual offenders spatially close offences.

Variables for time ($t$) and distance ($d$) now translated into defining what could be considered as 'close' given an individuals' serial behaviour. Literature appertaining to near repeats overwhelmingly suggests small distances of a few hundred m, (Bowers et al., 2004; Johnson et al., 2005, 2007) particularly for Bournemouth (Johnson, 2008). Consequently an aim of establishing the minimum distances within an offenders spatial distribution of crimes was selected.

Straight line distances between crime events were utilised to populate a table of distances between all burglary events and those future to them in the series. For each row of data the minimum distance was extracted. Unlike nearest neighbour analysis which considers events past and future row minimum distances refer to each events future nearest neighbour. Future nearest neighbour distances therefore determine that for each event except the last in the series there is at least one other event that is ‘close’ to it. An assumption is made that events are ordered chronologically.

Table 2 displays the frequency histogram of inter-event distances and Fig. 2 the corresponding histogram of the distribution of future nearest neighbour distances (column ‘Min. Distance’ from Table 2). Table 3 reports descriptive statistics corresponding to the future nearest neighbour distribution. All distances are in kilometres.

For this offender we can conclude that offences cluster at small distances $<\text{median}$ and this can be visualised in Fig. 3, a simple plot of the grid references pertinent to this example.

Skew values for the distribution of future nearest neighbour distances were obtained by using the Pearson coefficient of skewness:

$$\text{skew} = 3 \times (\text{mean} - \text{median})/\text{standard deviation}$$

Skewness is a dimensionless measure descriptive of the relevant distribution. Its descriptive nature is succinctly put by Tabachnick & Fidell (2001, p. 73–77) “If there is positive skewness, there is a pileup of cases to the left and the right tail is too long: with negative skewness, there is a pileup of cases to the right, and the left tail is too long.” Using the Pearson coefficient of skewness secures a guide of significance as values greater than $+1$ can be considered notably positively skewed whilst values less than $-1$ indicate notable negative skewness (Pearson, 1895; Rees, 2001, p. 43).

Skew values for the future nearest neighbour distance distribution describe that distributions tendency or otherwise to cluster towards small or larger distances. Within a skewed distribution median values are representative of the nature of the data sets distribution and central tendency, therefore if an offenders serial offending displayed a positively skewed distribution of future nearest neighbour distances (as with offender D series 2 in Table 2)

Table 1

<table>
<thead>
<tr>
<th>Distance</th>
<th>0 to $d$</th>
<th>$d$ to 2$d$</th>
<th>2$d$ to 3$d$</th>
<th>Totals</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 to $t$</td>
<td>$x_i$</td>
<td>$y_{i-1}$</td>
<td>$y_{i-2}$</td>
<td>$y_{i-3}$</td>
</tr>
<tr>
<td>$t$ to 2$t$</td>
<td>$x_i$</td>
<td>$y_{i-1}$</td>
<td>$y_{i-2}$</td>
<td>$y_{i-3}$</td>
</tr>
<tr>
<td>2$t$ to 3$t$</td>
<td>$x_i$</td>
<td>$y_{i-1}$</td>
<td>$y_{i-2}$</td>
<td>$y_{i-3}$</td>
</tr>
</tbody>
</table>

$d$ represents a distance parameter set by the user e.g. 200 m
$t$ represents a time parameter set by the user e.g. 7 days.
$x_i$ represents the number of burglaries between 0 to $t$ time and 0 to $d$ distance. $y_{i-1}$ represents the number of burglaries between $t$ and 2$t$ time and $d$ and 2$d$ distance. $y_{i-2}$ represents the number of burglaries between 2$t$ and 3$t$ time and 2$d$ and 3$d$ distance.

Table 2

<table>
<thead>
<tr>
<th>Min. Distance</th>
<th>Event:</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.752</td>
<td>1</td>
<td>1.54</td>
<td>3.72</td>
<td>0.75</td>
<td>2.43</td>
<td>2.38</td>
<td>1.52</td>
<td>10.39</td>
<td>8.10</td>
<td>1.51</td>
<td>1.81</td>
<td></td>
</tr>
<tr>
<td>0.390</td>
<td>2</td>
<td>4.62</td>
<td>2.03</td>
<td>3.78</td>
<td>3.83</td>
<td>0.39</td>
<td>9.66</td>
<td>8.40</td>
<td>0.57</td>
<td>3.01</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.878</td>
<td>3</td>
<td>2.97</td>
<td>1.88</td>
<td>2.31</td>
<td>4.30</td>
<td>9.03</td>
<td>4.82</td>
<td>4.13</td>
<td>1.97</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.067</td>
<td>4</td>
<td>1.76</td>
<td>1.80</td>
<td>1.87</td>
<td>10.06</td>
<td>7.43</td>
<td>1.78</td>
<td>1.07</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.446</td>
<td>5</td>
<td>0.45</td>
<td>3.58</td>
<td>10.46</td>
<td>6.69</td>
<td>3.46</td>
<td>0.84</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.101</td>
<td>6</td>
<td>3.67</td>
<td>10.88</td>
<td>7.12</td>
<td>3.57</td>
<td>1.10</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.187</td>
<td>7</td>
<td>9.34</td>
<td>8.01</td>
<td>0.19</td>
<td>2.78</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6.352</td>
<td>8</td>
<td>6.35</td>
<td>9.22</td>
<td>9.90</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6.628</td>
<td>9</td>
<td>7.82</td>
<td>6.63</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.649</td>
<td>10</td>
<td>2.65</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Bournemouth and Poole data contained 280 cells each and therefore residual values of 3 and above were deemed significant, limiting the number of cells displaying Type I error values to a maximum of 3.

Ultimately when used with offender data the Knox method becomes unstable with low values, high residual scores showing significance against observed values of only one burglary. Given such instability with low values of serial offending a second methodology was developed to identify near repeat patterns in serial offending and a number of requirements for the analysis were formulated, namely to identify within a series of burglary crimes:

- Those offences close in space,
- The time distribution relevant to spatially close offences,
- To quantify the ‘closeness’ of space relevant to the individual offender and,
- To quantify the ‘closeness’ of time relevant to the individual offenders spatially close offences.

Fig. 1. Histogram of Inter-event distances.
it shows a tendency to commit offences close in space. These Median values provide a cut-off measure at which events with inter event distances ≤ to this distance can be selected. Such events represent those that have taken place at close distances with respect to the overall spatial distribution, thus identifying offences within a burglary series that are ‘close’ in space. Time spans for these spatially clustered events were then calculated and by utilising the same methodology of selecting those with a time span ≤ median time span a simple matrix was compiled of offences close in both time and space.

If an offenders’ behaviour is such that, in chronological sequence, his/her closest future nearest neighbour offences always follow the immediately previous offence such a matrix would show populated cells across the diagonal. Such time/space patterning can be summarised by the simple proportion of populated cells in this diagonal where the total number of possible nearest time/space neighbours = n (No of offences in series) – 1. This proportion can be seen as an index score for time/space nearest neighbours.

Such a sequence can be imagined as a series of clustered events on a straight line, perhaps a single street, where chronologically events move along the street from left to right or vice-versa. Other configurations can be imagined but in every case events move along a time line and are further away from the event prior to the immediately preceding event. In this case the index score obtained would equal 1 and these closest nearest neighbours could be referred to as first order time/space neighbours. Second order time/space neighbours would relate to the next offence but one i.e. offence 3 to offence 1, offence 4 to offence 2 and so on. Again an index can be calculated. High index scores for k order space/time neighbours will indicate a repeating pattern of behaviour. The relevance of the k order neighbour is however dependent on the number of crimes in the series. Crime opportunities available = n – k therefore the 8th order neighbours in a series of 11 events only represents three possible crime opportunities.

Within an offenders’ data the future nearest neighbour distance data sets from their series of crimes were compared using a Fisher exact test on the median values. The data sets of the two series of each offender were amalgamated and a combined median value calculated. A 2 × 2 table was constructed (Fig. 4).

 Fisher’s exact test calculates the exact probability that a table could be obtained that differs from the expected values as much as or more than the actual table of values by effectively generating all possible tables given the margins of the observed values. Unlike a chi-squared test the Fisher exact test can utilise small values (<5) hence its preferred use in this case. The null hypotheses (H0) state that the medians of future nearest neighbour distances for each series of crimes with a common offender are the same. This same method was applied to the tables of time spans between events where the inter event distance ≤ median future nearest neighbour distance. In all cases a double sided p-value was sought as direction was unknown. In each instance the alternative hypotheses states that the medians would be different as an individual offender maintains no personal concept of ‘closeness’ in terms of distance or time between offending locations.

**Results**

**Area results**

Knox analysis showed significant time–space clustering in the data from both towns. A marked difference between the two Bournemouth data sets was observed, the post intervention analysis showing a considerable decline in such clustering.

Poole data returned significant residual scores at 14 days up to 400 m. All residual values greater than three were sourced from observed values of actual burglaries that were at least 20 offences greater than their respective expected values. Bournemouth data provided a considerable contrast against that for Poole. Given that they reflect different time periods and that such crime had been noticeably falling comparisons are however jeopardous. High scores (>8) were reported at 200 m up to 21 days, similar to parameters set by the analysis undertaken for the Police reduction initiative (Johnson, 2008). Observed values for the first 14 days at 200 m were at least 100 offences greater than expected. For the period post April 2005 in Bournemouth risk remained high at

<table>
<thead>
<tr>
<th>Table 3</th>
<th>Future nearest neighbour distribution.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Q1</td>
</tr>
<tr>
<td>Min. Distance</td>
<td>0.523</td>
</tr>
</tbody>
</table>

**Fig. 2.** Histogram of future nearest neighbour distances.

**Fig. 3.** x/y plot of offences.

**Fig. 4.** Fisher exact test: 2 × 2 table.
200 m but for only 7 days. As this data reflects the reduction intervention it is interesting to note the considerable change.

**Offender data analysis**

Offenders with multiple series were required in order to facilitate comparison between series. All selected offenders were lone offenders; data did not reflect others being proceeded against for the same offences. Only one had committed more than two series of crimes (offender F, 3 series) leaving potential comparisons limited.

Table 4 reports time and distance parameters for each offender and respective series of crimes. These values were concluded by reference to the skew value obtained, the median or mean value as appropriate and frequency distributions. Unless the skew value indicated a distribution close to symmetrical the median value was concluded as the better descriptor.

'Close offences' provides the parameter for those offences determined as close in space and close in time for the individual series of offences being examined, whilst the 'All offending' value reports a similar statistic for the distribution of all crimes within the series. This table also reports the results from the Fisher's exact test carried out on each pair of crime series. This test sought to establish if the 'Close offences' parameter in relation to one series was statistically the same or significantly different from the 'Close offences' parameter in a second series of offences.

**Discussion**

There are a number of caveats to consider when using Police recorded crime data, notably that not all crime is either reported or recorded. For the whole area research under reporting/recording of crime was not considered problematic due to the volume of data obtained, however exploring individual offending and relying on recorded data may create bias. There are two issues, the potential for the offender to have committed offences that went unreported (or reported but unrecorded) and/or the potential for the offender to have to committed more offences than are known to have been his responsibility. In many ways these are limitations that are forced upon researchers, there probably is no better available data to work with.

Regarding offences simply not reported to the police domestic burglary is one that routinely shows a high reporting/recording rate. The 2010/11 British Crime Survey (Chaplin, Flatley, & Smith, 2011) reported that "over eight in ten burglaries where something was stolen (82%) and over three-quarters of burglary with entry were reported (79%)."

In this case detected offences were considered those offences where an offender had been brought to justice as opposed to being arrested for it without further action being taken. In all cases offenders were prosecuted for a sample of the offences in their series of offending and asked the court to then take the remaining offences into consideration (TIC). Whilst not foolproof personal knowledge of relevant investigative procedures and methods indicate to the author that the technique of detecting offences by way of confession and 'TIC' is reasonably robust. In the majority of cases offenders accept that they have little to lose once formally charged with a sample of substantive burglary offences and that it can help their case by showing a willingness to cooperate. During the period when this data was collected it was common practice for an offender to be driven around an area and be asked to point out premises attacked. If an indicated address had no associated recorded crime an enquiry would be made with the householder, recording a detected burglary offence rather than an undetected one obviously being more favourable.

For this research the results obtained indicate that data sets utilised were probably consistently accurate with regard to these non recording/non detecting issues. Consistent results such as those obtained would not be anticipated had there been non recording issues apparent in individual offender's data sets.

Another important issue concerning offender data is that it only represents those offenders brought to justice. Whilst the offender data examined appears representative of the most prolific offenders it only concerns a proportion of total offending. In this case 21.29% of all burglary offences in the data set were marked as detected, whilst the offences committed by the selected prolific offenders amounted to 5.87% of all offences.

**Table 4**

<table>
<thead>
<tr>
<th>Offender</th>
<th>Series 1</th>
<th>Close offences</th>
<th>All offending</th>
<th>Series 2</th>
<th>Close offences</th>
<th>All offending</th>
<th>Fisher's exact test between series</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>n t n_c r</td>
<td>km Days</td>
<td>km Days</td>
<td>n t n_c r</td>
<td>km Days</td>
<td>km Days</td>
<td>p distance</td>
<td>p time</td>
</tr>
<tr>
<td>A</td>
<td>39 155 38 0 0–0.4 0–28 2–4 0–5</td>
<td>12 14 14 0 0–0.6 0–12 1–3</td>
<td>0.320</td>
<td>0.000023**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>22 90 17 0 0–0.4 0–10 0–2</td>
<td>6 10 2 0 0–0.6 3–4</td>
<td>0.280</td>
<td>0.485</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>14 114 8 0 0–0.6 0–28 0–1</td>
<td>15 46 11 0 0–0.8 0–5</td>
<td>0.449</td>
<td>0.369</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>13 39 11 0 0–0.65 0–15</td>
<td>11 34 8 0 0–1 0–25</td>
<td>0.669</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>9 79 7 0 0–0.4 0–30</td>
<td>10 53 7 0 0–1.1 0–10</td>
<td>0.153</td>
<td>0.286</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>8 125 4 0 0–0.8 0–40</td>
<td>15 85 18 0 0–0.6 0–32</td>
<td>0.659</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>G</td>
<td>12 125 5 0 0–0.5 0–8</td>
<td>9 27 6 1 0–0.4 0–10</td>
<td>0.592</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H</td>
<td>6 34 3 0 0–0.5 0–8</td>
<td>6 1 0–0.2 0–4</td>
<td>0.310</td>
<td>0.361</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>J</td>
<td>15 313 25 0 0–0.7 0–25</td>
<td>17 40 15 0 0–0.4 0–15</td>
<td>1.000</td>
<td>0.000774**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>K</td>
<td>20 142 14 0 0–0.5 0–10</td>
<td>17 33 12 1 0–0.4 0–11</td>
<td>1.000</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L</td>
<td>11 44 7 2 0–0.2 0–1</td>
<td>10 95 5 1 0–0.2 0–15</td>
<td>1.000</td>
<td>0.00126**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M</td>
<td>28 92 28 0 0–0.9 0–12</td>
<td>17 47 5 0 0–0.4 0–1</td>
<td>0.004**</td>
<td>0.048*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>7 98 4 1 0–0.8 0–10</td>
<td>9 21 5 1 0–1 0–2</td>
<td>1.000</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P</td>
<td>39 56 41 0 0–0.3 0–3</td>
<td>38 30 40 0 0–0.3 0–3</td>
<td>1.000</td>
<td>0.822</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Significance level * – p < 0.05, ** – p < 0.01.

n – volume of offences.

n_c – number of future nearest neighbours with inter event distance ≤ the median future nearest neighbour distance.

r = number of repeat offences in series.
All offenders selected, bar one, had committed the majority of their offending in either Bournemouth, Poole or both towns, but there were instances of some offenders travelling considerable distances (tens of kilometres) to commit one or two offences. It is suggested that the most likely scenario concerns visits by offenders’ to associates, committing burglaries whilst ‘en route’. Such activity would be representative of crime pattern theory (Brantingham & Brantingham, 1990) and entirely expected. In the context of this research such distant offending has the effect of literally skewing the results in that offenders with such patterns will potentially generate high skew values in relation to distance over their entire offending. Should the distant offence be a lone event in time, such as one offence preceded and followed by offences in Bournemouth, it will be recorded as one of the future nearest neighbour distances and could therefore significantly skew the future nearest neighbour distance distribution. Such activity was present in the data for 3 of the series of crimes examined (D1, J1, E1).

Within offender analysis there is a degree of dependency in the data. This concerns distances for future nearest neighbour events and those that occur at a distance ≤ the median measure of that distribution, as one data set is a derivation of the other. However derived data sets are not formally compared nor tested against their origins but used only as tools to gather further descriptive information, namely time spans between close events in space. Similarly Fisher’s exact test is conducted on data sets derived from different series of offender’s crimes. The offender is a common factor but the crime series from which the two sets of data originate are temporally independent. Offender data analysis sought to establish if near repeat patterns could be observed within a series of burglary crimes and therefore within individual offending behaviour, and a methodology was devised to achieve this. A second question asked was whether such ‘near repeat’ spatial and temporal patterns could be considered a ‘signature’ of the individual offender. Patterns in offender data generally reflected the parameters established by the area analysis. Of 29 series of offences 18 displayed spatially close offences taking place within 14 day time spans and a further three within 15 days. Distances did not reflect the area results quite so well with only 11 series reporting small distances <400 m. This may be because the offender data only accounts for a relatively small proportion of the data used for the area analysis. It is plausible, given low detection rates, that offender data for burglary does not accurately represent all offenders.

Stylising offender space—time behaviour could advantageously provide investigative opportunities for undetected series of offences. Results in this research suggest many maintain a spatial and temporal approach to offending, even when such acts are separated by significant time periods. Results show little differentiation in the ‘closeness’ of time or distance between offenders with regard to their minimum distances and time lags. Testing between inter event distances across different offenders’ serial burglaries may be more informative. This would tend towards a fuller description of their spatial offending behaviour. As it is results suggest small scale spatial and temporal offending features are aspects that could add to undetected serial crime analysis of modus operandi features.

Index scores for space—time k order nearest neighbours also indicate a tendency for the majority to commit burglary offences at their individualised shortest distances in space and time. With almost all offenders committing, at some point, future nearest neighbour offences that were actually consecutive in time (1st order space/time nearest neighbours) the importance of the time element is highlighted within offender decision making, perhaps giving an indication of the needs of the offender at that particular time. Establishing the offenders’ yield at an initial offence may be informative of offences which become a ‘seed’ offence to a near repeat.

**Conclusion**

Area analysis confirms near repeat residential burglaries in the two towns, suggesting such patterns should also be discernible in offender data. Fisher’s exact tests between offender’s series only led to the rejection of H₀ in five cases, 4 rejections being in respect to time only. For only one series was H₀ rejected for both time and distance, thus suggesting offenders particularly maintain distance ‘mental maps’ over significant periods with respect to ‘close’ offending.

This research adds to existing literature expressing the view that crime reduction work should follow quickly in the footsteps of offenders and take on a targeted ‘small area approach’ as well as focussing on an attacked premise (Farrell & Pease, 1993; Polvi et al., 1990, 1991; Townsley et al., 2000). Whilst future risk at burgled premises is significant there is now substantial evidence to suggest that current repeat victimisation policies focussing solely on an attacked home would benefit from an expanded approach. Offender analysis upholds this view and provides further evidence that serial offenders commit spatially and temporally clustered crimes.

Merry considers the ability to link both past and present offences with common offender(s) to be the “essence of operational crime analysis” (Merry, 2000) and such work is a core activity of the operational crime analyst. Considerable literature exists concerning methods to link offences to common offenders, although it is perhaps most prevalent concerning sexual and serious violent offending rather than volume property crime. By far the most common approach used by Police analysts (barring evidence such as DNA or fingerprints) is examination of behavioural modus operandi features from crime scenes. However research indicates the preferred approach would utilise spatial information concerning crime locations as well (Ewart, Oatley, & Burn, 2005; Goodwill & Alison, 2006). This research provides further evidence of the importance of spatial consideration when searching for linked crime events but emphasises the need to consider space/time relationships in doing so.

**Acknowledgments**

The assistance of Dorset Police in the provision of data which made this work possible is acknowledged, together with the always constructive encouragement and proof reading of Dr M. Barke of Northumbria University Geography. The insightful and constructive comments of two anonymous reviewers are greatly appreciated.

**References**


