



How do offenders choose where to offend? Perspectives from animal foraging

Shane D. Johnson*

UCL Department of Security and Crime Science, University College London, UK

Purpose. Research suggests that offender spatial decision-making is not random. However, little is known about if or how offences in a series influence where an offender will target next. Drawing on concepts and empirical findings from environmental criminology and the ecology literature, in this article I consider what spatial patterns might be expected in the sequential crimes committed by serial offenders and provide an empirical example.

Methods. Data for detected burglars are analysed and patterns in the inter-event distances for sequential offences compared with those signatures typically associated with three types of foraging behaviour – central place foraging, Brownian walks and Lévy walks. Analyses involve the use of a Monte Carlo simulation to derive an expected distribution for central place foraging, while the observed probability density function of sequential inter-event distances is compared to exponential and power law distributions to test for evidence of Brownian and Lévy walks, respectively.

Results. Analyses suggest that patterns in burglar sequential inter-event distances cannot be explained by a simple central place foraging strategy. The distribution of sequential inter-event distances is found to be consistent with both Brownian and Lévy walks.

Conclusions. The findings suggest that there are regularities in the sequential spatial choices made by offenders, and that these are similar to those observed across species. Reasons for why there is evidence of both Brownian and Lévy walks are discussed. The implications of the findings for forensic techniques such as crime linkage analysis, geographic offender profiling and crime forecasting are discussed.

Criminological research concerned with where crimes happen suggests that patterns are far from random (e.g., Block, Dabdoub, & Fregly, 1995; Sherman, Gartin, & Buerger, 1989). Moreover, that offender spatial decision-making can be understood from a rational choice perspective (Clarke & Cornish, 1985), with offenders considering (however, briefly) the costs and benefits of possible choices and making decisions that optimize some expectation of utility. For example, a considerable body of research has examined whether offenders exhibit preferences for committing offences in certain types of areas and why they might do so, with many studies focusing on how far they typically travel to commit offences – the so-called journey to crime (see, Rossmo, 2000). However, little

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*Correspondence should be addressed to Shane D. Johnson, UCL Department of Security and Crime Science, University College London, 35 Tavistock Square, London WC1H 9EZ, UK (email: shane.johnson@ucl.ac.uk).

research has examined the dynamics of offender spatial decision-making and whether there exist patterns in sequential choices. Given the theoretical and potential policy value of understanding such dynamics, this is somewhat surprising. Drawing on theories of animal foraging, and using an empirical example for the acquisitive crime of residential burglary, the aim of the current study was to do so. In the next section, I briefly review existing research on offender spatial decision-making and then discuss the *offender as forager* hypothesis. A set of testable expectations are subsequently articulated and to illustrate the types of analyses that can be used to test them, in the second section of the article I describe a sample of data and a series of methods used to analyse it. After discussing the results, the potential implications of the findings for theory and policy are discussed. Particular emphasis is given to the forensic implications of the research such as crime linkage analysis and geographic profiling. Finally, an agenda for research of this kind is discussed.

Theories of spatial choice

Drawing on theories of human ecology (Hawley, 1950), routine activity theory (Cohen & Felson, 1979) suggests that for a crime to occur, a motivated offender must encounter a suitable target in the absence of a capable guardian, and that this convergence will be a function of the routine activities of offenders, potential victims and guardians against crime. Crime pattern theory (CPT; Brantingham & Brantingham, 1993, 1995) considers how people's everyday activities influence their awareness spaces and, in the case of offenders, how this influences their spatial decision-making when it comes to offending. To explain, as a consequence of engaging in routine activities, people (offenders or otherwise) are believed to form mental maps to represent the routine *activity nodes* they frequent, the *pathways* they must travel to move from one activity node to another, and the areas that surround them (Brantingham & Brantingham, 1993). Routine activity nodes typically include a person's home, place of work, places of recreation, and so on, and it is the environmental backcloth that determines their distribution in space. Some routine activity nodes will be shared by many people (e.g., city centres) and hence encapsulated in their awareness spaces, but others will be more unique to particular individuals (Bernasco & Block, 2009).

According to CPT, it is where offender awareness spaces overlap with suitable opportunities for crime that they are most expected to engage in crime. And, it is where the activity spaces (see Golledge & Stimson, 1997) of many offenders overlap that hotspots of crime are most likely to form. Studies of the journey to crime provide support for CPT, showing that offenders typically commit most of their crimes close to their home location (e.g., Rossmo, 2000; Townsley & Sidebottom, 2010), and do so despite the many and varied opportunities available to them (see Reppetto, 1974). Further support for CPT comes from studies that have examined the influence of factors other than propinquity on offender spatial decision-making. For example, Bernasco (2010) showed that after release from prison, relocated offenders were more likely to target areas in which they had previously resided than alternative locales. Bernasco and Block (2009) showed that robbers were more likely to select areas that contained routine activity nodes such as schools, and Baudains, Braithwaite and Johnson (2013) show the same for rioters, particularly those under the age of 18, for whom such nodes of activity are likely to have the most salience.

According to CPT (Brantingham & Brantingham, 1981), offenders develop cognitive scripts that serve as templates to describe successful offending patterns. Experience

updates the templates, but as far as the author is aware, the theory does not explicitly consider the dynamics of spatial choice, and how one choice might affect the next. Consequently, one could assume little dependency in sequential choices.

Space-time dynamics of crime

From the above discussion, it should be evident that CPT provides insight as to why the micro-level decision-making of individual offenders should, in the aggregate, lead to the spatial clustering of crime at the area level or at particular places. An increasing body of empirical research provides support for the theory across a range of crime types (e.g., Bernasco & Block, 2011; Kurland, Johnson, & Tilley, 2014). However, much of that research ignores the dimension of time, focusing either on spatial patterns aggregated to some areal unit such as neighbourhoods (e.g., Bernasco & Block, 2009) over some interval of time (such as 1 year) or, on the specific locations targeted by particular individuals (e.g., Townsley & Sidebottom, 2010), without consideration of when those offences were committed.

However, for many crimes, it is evident that the risk of victimization clusters in time as well as space. For instance, considering patterns at the micro level of place, when a repeat burglary victimization of the same home occurs, the elapsed time between events is typically short (e.g., Johnson, Bowers, & Hirschfield, 1997; Polvi, Looman, Humphries, & Pease, 1991), with the risk of further offences typically decaying exponentially over time. More recently, using techniques originally developed to detect disease contagion, scholars (e.g., Johnson, Birks, McLaughlin, Bowers, & Pease, 2007; Johnson & Bowers, 2004; Johnson, Bernasco, *et al.*, 2007; Townsley, Homel, & Chaseling, 2003) have examined the association between the timing *and* location of crimes committed not just against the same target but those nearby. The finding so far consistently observed for crimes including burglary (e.g., Johnson, Bernasco, *et al.*, 2007; Johnson, Birks, *et al.*, 2007; Townsley *et al.*, 2003; Short *et al.*, 2009), theft from motor vehicle (Johnson, Summers, & Pease, 2009), shootings (Ratcliffe & Rengert, 2008), insurgent activity (e.g., Braithwaite & Johnson, 2012; Townsley, Johnson, & Ratcliffe, 2008) and even maritime piracy (Marchione & Johnson, 2014; Townsley & Oliveira, 2013) is that when a crime occurs at one location, others are more likely to take place swiftly nearby. Such events are collectively referred to as near repeats (Morgan, 2001). To be clear, when studied at the area level, it may be the case that some areas are more risky than others, but within (and across) those areas the risk of crime diffuses in space and time with an observable (slippery) regularity.

Why such patterns might emerge, and in particular, how individual offender decision-making might lead to them is the subject of contemporary debate. Two classes of theory have been proposed and according to the first, variation across neighbourhoods (and individual locations) in those characteristics that are time-stable – at least on time scales such as 1 year – that would be appealing to most offenders, can explain observed patterns. Such characteristics would include the location of routine activity nodes, features of the environment that attract or generate crime (e.g., Brantingham & Brantingham, 1995; Johnson & Bowers, 2010), variation in the social fabric of communities that might make crime more or less likely (e.g., Sampson & Groves, 1989), or characteristics of a location that are unobserved by the researcher. This perspective of *risk heterogeneity* (see Johnson, 2008; Nelson, 1980; Sparks, 1981) assumes that offenders select places to commit crimes based on how attractive they are in terms of persistent characteristics. As such, when a crime occurs at a location the future

risk of crime at that location or those nearby does not change. However, it may appear to do so due to an aggregation artefact associated with the statistical methods used to analyse the data (for a detailed discussion, see Johnson, 2008).

Given the finding that (for example) the risk of repeat victimization has a distinct time course, this explanation seems unlikely and a series of studies conducted using computer simulation (e.g., Johnson, 2008; Pitcher & Johnson, 2011), interviews with offenders (Summers, Johnson, & Rengert, 2010) and the analysis of crimes detected by the police (Bernasco, 2008; Johnson *et al.*, 2009) suggest that risk heterogeneity does have a part to play, but that it provides an incomplete explanation of observed patterns.

Considering the second type of explanation, theories of *event dependency* assume a more dynamic process that can be explained in terms of the impact of learning (or experience) on the choices of individual offenders. For example, it is hypothesized that when the conditions at already targeted locations are conducive to burglary, the same offender (or group of offenders), having developed knowledge of that location, will swiftly return to those locations to commit further offences (Pease, 1998).

Offender as forager?

To try to better understand such patterns in terms of individual offender decision-making and to develop a broader conceptual framework, Johnson and Bowers (2004) draw upon theories of animal foraging (for a broader discussion of crime and nature, see Felson, 2006) and propose the *offender as forager* hypothesis (see also, Brantingham & Tita, 2008; Johnson, Bowers, Birks, & Pease, 2008; Johnson *et al.*, 2009). Their motivations for this were two-fold. First, animal foragers and offenders share (at least) some common underlying goals. For instance, both seek to maximize the benefit of their activity, which is to acquire resources, be it food or stolen items (Brantingham, 2013). Both activities involve time spent searching and handling resources (see, Pyke, 1984), and the forager (animal or human) seeks to minimize expended effort and the associated risks; be it the risk of apprehension or of being eaten by a predator. Moreover, both are subject to constraints. For example, both forms of actor can only move so far and so fast per unit time, and both expend effort in so doing. Second, while theories of crime tend not to explicitly consider sequences of offender spatial choices, and how patterns might vary across them, theories of animal foraging do. Building on this earlier research, the aim of the current article is to further refine and test these ideas.

Some general principles concerning animal foraging (for a review, see Pyke, 1984) are particularly worthy of attention, and their relevance to offender spatial decision-making will now be discussed. *Central place foraging* (Orians & Pearson, 1979) refers to instances where a forager has a central base to which it must return at least some of the time. This may be a nest for an animal/insect, or the home in the case of the offender and it is notable that it is this routine activity node that has received the most attention in the criminological literature.

Optimal Patch choice is a complex process concerned with *where* an animal chooses to forage. Assuming an animal does not have perfect knowledge of the quality of patches, targeting choices are assumed to be based on the amount of time available for foraging, past experience and knowledge of the types of patches available more generally (Pyke, 1984). Where sufficient time is available, the forager may spend time sampling alternative locations before deciding where to target. If an animal is aware of the typical quality of patches available, however, it may spend less time sampling from alternatives, and avoid particular patches if they are known to offer less reward (per unit time) than the average

expected (e.g., Pyke, 1984). Of course, those patches that offer the greatest rewards may be those that are the hardest to reach which would mean that their targeting would result in the greatest energy depletion. Thus, with limited resources the forager seeks to optimize their utility by minimizing energy expenditure (which would include time spent searching within and between patches) whilst maximizing their expected benefits (Charnov, 1976).

Considering the distribution of resources in the environment, *patches* that are closer to each other tend to be more similar (see, Fortin & Dale, 2005; consider also Dr Snow's mapping of outbreaks of Cholera in London in 1854) – whether it be in terms of nutritional value in the case of crops, or affluence in the case of residents – meaning that attractive patches are likely to cluster geographically, and hence that targeting new locations near to patches that are already known to be acceptable can be an efficient strategy.

Having selected a patch, *patch departure* rules determine how long a forager spends at a particular location. In cases where the forager knows little about a particular patch, knowledge will be acquired during an episode of consumption that may reveal that the patch is less desirable than others, encouraging it to target alternative locations. Alternatively, as resources are depleted through time spent foraging, a predator may decide to leave a patch when little of value remains. More strictly, according to Charnov's (1976) marginal value theorem (MVT), a predator should leave a patch when the rate of energy intake (or the acquisition of stolen goods for the burglar) drops to the average across the habitat.

Figure 1 provides an illustration of Charnov's model. The panel on the left shows an example of how a forager might move through a habitat that contains different types of patches (two types of patches, A and B are shown). In this example, assume that both types of patches are richer in resources than the average encountered across the entire habitat, but that patches of type A are richer than type B. In line with studies of spatial autocorrelation, both types of patch are shown to cluster spatially. The forager expends resources travelling within and between patches, and time spent in patches of type A will be more beneficial than time spent in patches of type B. The right panel of Figure 1 shows that the rate of net energy intake (given by the slope of the curve) in patches of type A or B

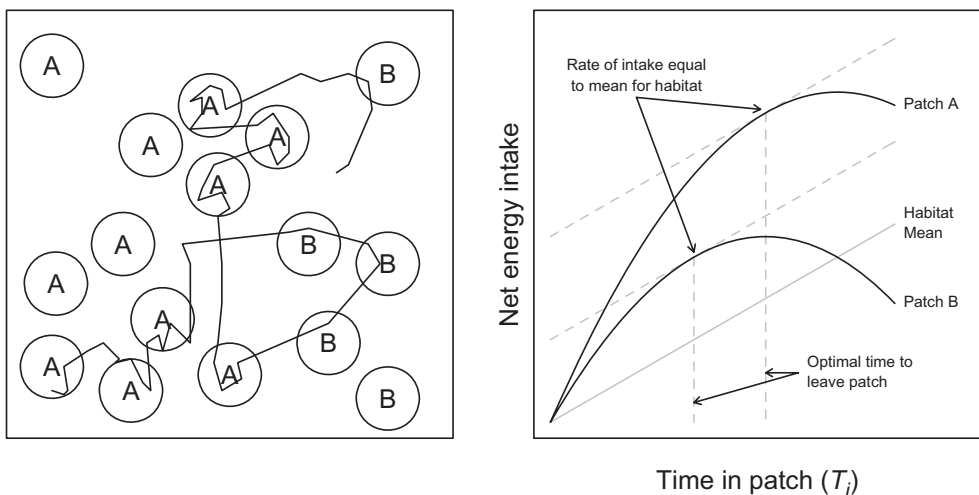


Figure 1. Optimal foraging in a patchy habitat (adapted from Charnov, 1976). Left panel: simulated walk of a forager in a patchy habitat. Right panel: Energy intake for time T spent in patch of type i .

is initially higher than the average across the entire habitat, but that after a sufficiently lengthy bout of consumption, the rate of intake will be equal to or less than the average across the entire habitat. According to MVT, when the rate of intake in a patch drops to the average for the entire habitat (see vertical lines in Figure 1), the forager is expected to leave that patch. In our example, a forager would be expected to spend longer in patches of type A than in those of type B.

Although not included in the MVT, exposure to the risk of predation may also influence foraging bouts at particular locations, with foragers choosing to leave a patch when perceived risks outweigh expected benefits (e.g., Nonacs, 2001). Alternatively, a forager may target patches that are sub-optimal in terms of resources if they offer refuge from other predators (or the police in the case of burglary). For the reasons discussed above, it seems reasonable to suggest that as well as applying to animals, these principles could apply to the offender (as forager).

In support of this, the analysis of crimes detected by the police (Bernasco, 2008; Johnson *et al.*, 2009) indicates that, relative to burglaries that occur close in space but not time, or vice versa, those that occur close to each other in both dimensions (e.g., within a few days and 200 m) are massively more likely to be the work of the same offender(s). The same is true for thefts from motor vehicles (Johnson *et al.*, 2009). Research concerned with crime linkage analysis provides further support for this hypothesis, indicating that offender inter-crime distances are typically short (e.g., Bennell & Canter, 2002; Goodwill & Alison, 2006). Interviews with offenders are also informative, suggesting that offenders frequently return to the same locations (Ashton, Brown, Senior, & Pease, 1998) or those nearby (Summers *et al.*, 2010).

The above findings suggest that offenders return to locations they have recently victimized, or those nearby, but say little about sequential choices in particular, or the longer term patterns of choices observed across an offender's crime series. The aim of the remainder article is to explore these issues conceptually (see also Brantingham & Tita, 2008; Hering & Bair, 2014) and to provide an example to illustrate how they might be examined empirically.

In the case of animal foraging, at least two types of so-called *walks* have been described to characterize animal foraging patterns. The first are *Brownian motion* random walks whereby the 'walker' moves in a random direction at each time step but their step lengths are relatively constant. For such walks, sequential steps are near to each other and the walker may return to the same locations frequently (see Figure 2). More recently, interest has grown in *Lévy walks* (Lévy, 1925; Viswanathan *et al.*, 1999) as an alternative form of foraging strategy. Rather than having a constant length, the step length for each 'trip' (sequential inter crime distances in our case) is selected from a power law distribution of the form $P[l] = l^{-u}$, where $1 < u \leq 3$. For such a distribution, most trips will be short but occasionally trips many orders of magnitude larger than the average will be observed (see Figure 2). In animal foraging, the adoption of a Lévy walk would mean that animals return to the same sites less frequently than if their spatial behaviour resembled a pattern of Brownian motion. One advantage of such a strategy is that locations are less likely to be over foraged (see, Viswanathan, 2010). In the ecology literature (e.g., Humphries *et al.*, 2010), it appears to be the case that Brownian motion is more likely where resources are abundant, but that Lévy walks are adopted where resources are more scarcely distributed (such as the open seas).

In addition to being observed in animal foraging, Lévy walks have been found to characterize patterns of human mobility. For example, Brockmann, Hufnagel, and Geisel (2006) examined human travel patterns indirectly by tracking the movement of bank

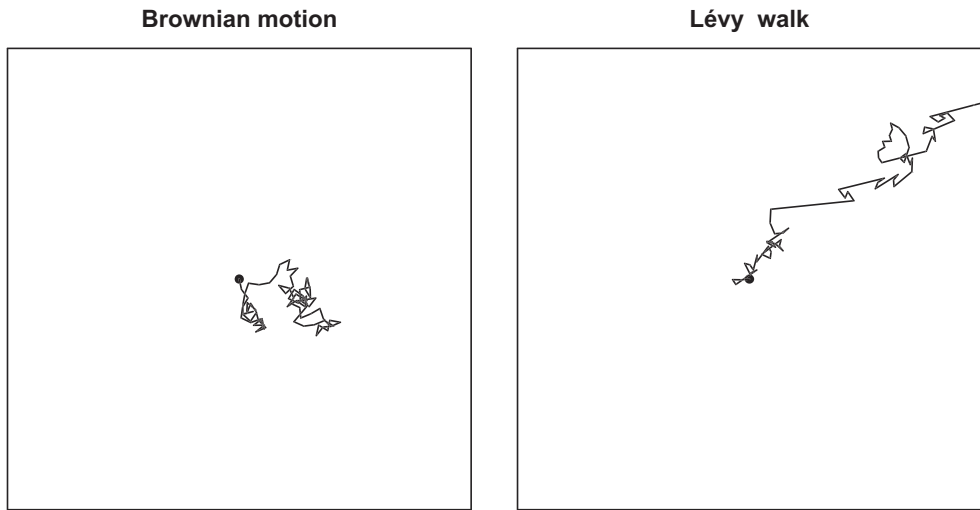


Figure 2. Simulated walks generated for Brownian motion and a Lévy walk (both walks originate from the centre of the plot).

notes in the United States and find patterns of banknote dispersal that are consistent with a Lévy walk (small movements interspersed with scale-free jumps). In a more recent study, using global positioning system (GPS) units, Raichlan *et al.* (2014) examined human foraging behaviour in a sample of 44 human hunter-gatherers in Tanzania, finding that they performed Lévy walks in around 50% of all foraging bouts.

Do sequential 'trips' in offender crime series resemble one of the two foraging patterns described above? If so, which? Or, is there generally little pattern in the sequential choices made, with locations perhaps being targeted purely because of their proximity to the offenders' home locations? Existing empirical research does not shed light on this question. Consider the types of foraging patterns that might be observed, in the case of burglary, targets (homes) are likely to be relatively abundant and so a pattern of Brownian motion might be expected. However, targets will vary in attractiveness and offenders may perceive that continuing to return to the same areas will ultimately attract police attention or lead to over-foraging. For these reasons, the spatial behaviour of offenders may be more in line with a Lévy walk. These are the questions to be considered here.

Before continuing, it is important to discuss a few points of departure between studies of animal foraging and offending. First, when measuring 'trip' distances associated with animal movements, ecologists are often able to record the exact details of each trip using GPS technology or other direct methods of observation. In the case of offenders, or people more generally, this is not typically possible. For example, as noted, the first study of Lévy walks in human mobility (Brockmann *et al.*, 2006) used not GPS traces, but the movement of bank notes to represent observable traces of people's sequential movements. In the case of active offenders, systematic methods of direct observation are currently a little impractical, but observable traces of their mobility can be estimated through the examination of the timing and location of the detected offences that they commit. While imperfect this is the approach adopted here.

Second, in studies of animal foraging, researchers typically collect many observations for every animal sampled, but collect data for only a small number of (say 7) animals (e.g.,

Humphries *et al.*, 2010). In the case of offenders, data will typically be available for many offenders, but the number of jumps for each offender will be rather more limited.

Moreover, even if an offender commits more than one offence per day, traces of their activity – as recorded in crimes detected by the police – will most likely include relatively few ‘jumps’ each day. This contrasts with studies of animal foraging for which hundreds of ‘jumps’ might be recorded for a single foraging bout. However, it is likely that the spatial decision-making of offenders is more deliberate than that for animals, and likely informs actions over longer time scales, making it reasonable to consider sequential decision-making that extends over a number of days (rather than within the same day). For example, relative to animals, offenders may be more likely to engage in rational decision-making (however, briefly) and more likely to draw on their memory of possible spatial choices, associating less uncertainty to those places most recently visited. If this is the case, then even though their sequential choices may be interrupted by the need to return home at the end of each day (central place foraging), it seems reasonable to suggest that they will – with some probability – deliberately return to an area targeted on 1 day (or nearby) on the next. An alternative hypothesis (tested below) is that rather than doing so, offenders return home each day and select an area within which to offend on the next without reference to where they last offended. This would represent the simplest form of central place foraging. In the next section, I describe the data analysed before presenting illustrative results.

Method and results

Police detection data

Data were acquired for all detected residential burglaries committed between January 2007 and December 2012 in one large metropolitan UK police force. The following variables were available for analysis for each offence: a unique identifier for the offender involved; the time and date of the offence; and the address and geographic grid coordinates of the offence (accurate to a resolution of 1 m). A total of 7,713 offences were available for analysis and these were committed by 4,435 unique offenders who each committed an average of 1.7 ($SD = 2.7$, range = 1–63) offences.

For each offender that committed more than one offence (1,037 offenders who committed 4,315 offences), and for which their home address was the same for sequential offences,¹ the Euclidian distance ($d_{i+1} = \sqrt{(x_i - x_{i+1})^2 + (y_i - y_{i+1})^2}$, where i is the i th offence in an offender’s crime series, and x and y are the Easting and Northings of each crime, respectively) between sequential offences in their crime series were computed. Thus, if an offender committed four crimes and lived at the same address across the series, three sequential ‘jump’ distances would be computed for that offender.

Simple central place foraging

As discussed, patterns observed in the distribution of ‘jump’ distances could be explained by offenders starting their trips from a central routine activity node each day and selecting targets nearby, regardless of where they committed their last offence. For the reasons discussed above, the routine activity node considered here is the home location.

¹ Analyzing the distances between offences committed by an offender who had moved residential address would likely distort patterns.

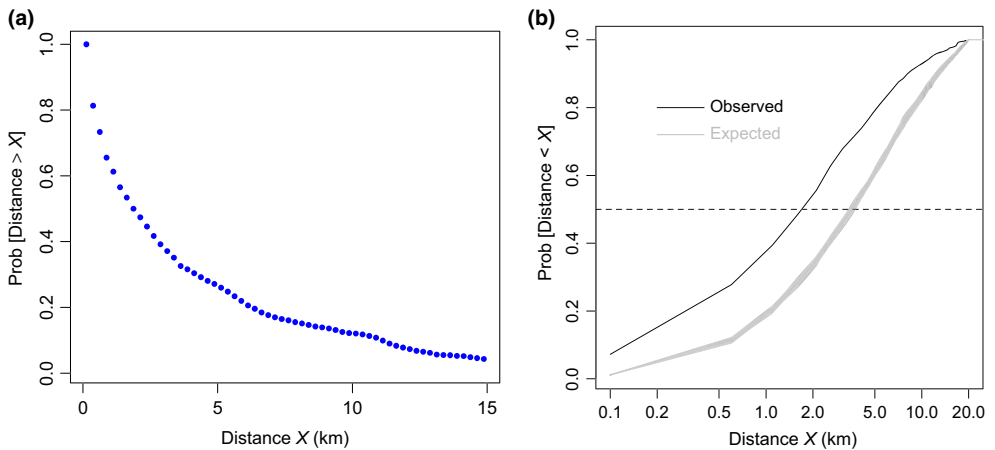


Figure 3. Complimentary cumulative distribution function for the journey to crime (a) and the empirical cumulative distribution function for sequential crime trips (b).

Considering the distance between where offenders live and offend first, as is illustrated in Figure 3A, consistent with previous research, and the idea that there are spatial constraints to offender targeting behaviour, for the sample of offenders considered here, the probability of an offender committing a crime at a particular location decreased the further that location was from the offender's home.

Considering sequential 'jumps', Figure 3B shows the empirical cumulative distribution function (ECDF) for the observed distances for the entire sample of offenders. It is apparent that most sequential jumps were short but that they were as large as 20 km. How does this compare with what would be expected if offenders adopted very simple central place foraging patterns? To generate such an expected distribution, for each offender I simulate their targeting choices (the number of simulated offences being equal to the number observed) assuming that each trip originates from their home location, that the distances they travel are constrained, that they select a direction in which to offend at random, and that sequential choices are independent. To do this, for each offender and for each simulated offence, the angular direction of travel from their home location is selected at random using a uniform random number generator (range 0–360). The jump distance from their home location is also selected at random (without replacement), but this time it is selected from the vector of journey to crime distances for that offender (rather than a theoretical distribution). Having simulated the data in this way, an ECDF can be computed for the simulated sequential jump distances as before, which can then be compared with the observed distribution. Doing this many times represents a Monte Carlo simulation that can be used to compute the probability with which the observed distribution can be explained by the simulated process.

The grey lines shown in Figure 3B illustrate the expected distribution for 999 realizations of this process. While formal methods (North, Curtis, & Sham, 2002) could be used to estimate the probability with which this explains the observed distribution, it is clear that it does not. The observed distribution never overlaps with those simulated, and the expected sequential inter-event distances are consistently much larger than those observed. For example, while about 10% of the observed jump distances were around 100 m, almost none of those expected were.

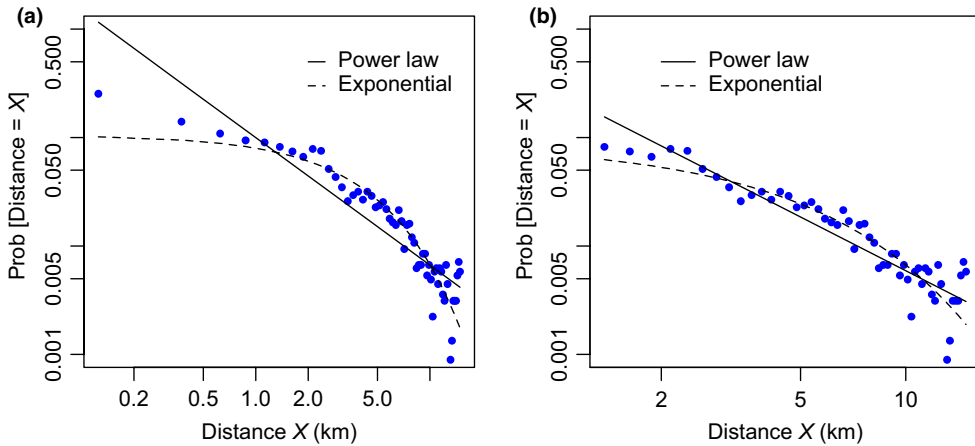


Figure 4. Log-Log plots of the probability density function for the observed inter-event distances for different ranges of the observed inter-event distances.

Lévy walks or Brownian motion?

Having established that a simple central place foraging strategy does not appear to explain offender spatial choices for the current sample, I explore the inter-event distances in more detail. Figure 4 shows a Log-Log plot of the probability density function (PDF) for the entire sample of data. As noted above, in the event that the inter-event distances are consistent with a Lévy walk, the PDF should have a power law distribution which, on a Log-Log plot would resemble a straight line.

Figure 4A suggests that a power law provides a relatively good fit to the data. However, visual patterns can be illusory and so more formal testing is necessary. There exist different approaches to measuring the extent to which an observed distribution fits a particular distribution (e.g., Clauset, Shalizi, & Newman, 2009) and for estimating the parameters that best describe it. Here, I take a simple approach, estimating parameters using a linear model in the *R* package. Two distributions are considered. The first is a power law distribution. In the event that the data fit a power law distribution, the linear model $\log_{10}N(x) = u\log_{10}x$ should describe the data well. For the current sample, the R^2 of .78 suggests a good fit to the data. Moreover, the estimate value of u of 1.17 is in the range of $1 < u < 3$, associated with a Lévy walk (e.g., Viswanathan, 2010).

The second probability function considered is an exponential of the form $\log_{10}N(x) = x$. Such a distribution is expected if foraging patterns are more consistent with Brownian motion (e.g., Humphries *et al.*, 2010). With an R^2 of .85, this provides a slightly better fit to the data, but the differences in model fit are not large. Moreover, a known issue with this type of analysis is that only part of an observed distribution is likely to fit a power law. Consequently, it is common practice to estimate the minimum (x_{\min}) and maximum (x_{\max}) values of the distribution for which the data are consistent with a power law (e.g., Clauset *et al.*, 2009). For instance, the tail of a distribution will usually contain many zeros (for which the logged value is negative infinity) that cannot be included in the analysis. Sensitivity analyses of the current data indicate that as the minimum value of X considered increases, the two functions rapidly converge in terms of the amount of the variance explained. For example, in Figure 2B with x_{\min} and x_{\max} values of 1.25 and 24.5 km, the power law (with an estimated value of u 1.65) and exponential distributions provide an equally good fit to the data with R^2 values of .81.

Discussion

The discussion and analyses presented here provide a more complete picture of offender sequential spatial targeting patterns than have been explored hitherto. In the main, previous empirical research has examined the distance from an offender's home location to where they offend, but has ignored regularities in their sequential offences. In the few notable exceptions (Bennell, Snook, Macdonald, House, & Taylor, 2012; Bernasco, 2008; Johnson *et al.*, 2009; Lammers, 2014) that inter-event distances have been examined in empirical studies, in all but one study (Hering & Bair, 2014) sequential patterns have been ignored. The aim of the current paper was to consider the dynamics of burglar spatial decision-making with a specific focus on whether observed patterns resemble those identified across animal species. In what follows, I discuss the results of the empirical example presented and consider what these might mean for theories of offender spatial decision-making and for those forensic applications that are most likely to be informed by them (crime linkage analysis, geographic offender profiling, and crime forecasting).

The results suggest that when analysed in the aggregate, for the current sample at least, burglar sequential inter-crime distances cannot be explained by a very simple type of central place foraging strategy, and hence a more complex strategy is likely. The data were tested for evidence of two other types of foraging behaviour: Lévy walks and Brownian motion. Both, rather than one distribution, provided a relatively good fit to the data, and this was particularly evident for increasing values of x_{\min} . There are a number of reasons why one specific distribution might not provide an unequivocal best fit to the data. The first is that it is possible that rather than adopting one strategy exclusively, offenders may switch from one strategy to another. For instance, as has been observed in studies of animal foraging (Humphries *et al.*, 2010), one strategy may be more effective in some areas than it is in others – a walk based on Brownian motion may be particularly effective in areas where good opportunities are abundant, while a Lévy walk may be optimal where resources are sparse. Alternatively, offenders may vary their foraging strategy based upon their perception of the risk of apprehension. For example, a more complex Lévy walk may be the most sensible where offenders perceive the risk of detection is high. Summers *et al.* (2010) provide examples that are consistent with this in their interviews with burglars:

If this area I didn't get caught in, I earned enough money to see me through the day then I'd go back the following day to the same place. If I was in, say, that place and it came on top, and by it came on top I mean I was seen, I was confronted, I didn't feel right, I'd move areas straight away ... (P02)

Summers *et al.* (2010)

A second possibility is that burglars are relatively consistent in the strategy they adopt but different offenders prefer different strategies (most of the time). For example, those more established in their criminal careers may be more likely to adopt a Lévy walk, while others may favour a strategy more consistent with Brownian motion. Moreover, opportunistic offenders may adopt very little strategy at all, perhaps engaging in central place foraging unintentionally. In a recent study, Hering and Bair (2014) found that a sample of burglars in the United States differed in the extent to which their offences clustered spatially. Many (around 60%) committed offences near to each other, but others appeared to avoid doing so. Future research might systematically explore these possibilities further, perhaps starting with an exploration of whether certain types of strategy are more apparent in certain types of areas or for particular types of offenders.

A third possibility is that offenders might adopt a different strategy to those considered above. Many strategies are possible, but an issue not so far discussed concerns bias in the direction of travel offenders might take. In the case of Lévy or Brownian walks no attention is given to this, with the focus being on trip lengths. Research concerned with the journey to crime has often also ignored directional bias. However, research on this is growing, with studies suggesting that for many offenders their direction of travel does tend to be biased (e.g., Goodwill and Alison, 2005; Frank *et al.*, 2011; Rengert & Wasilchick, 2000), and may be oriented towards nodes of activity such as shopping malls (e.g., Frank *et al.*, 2011). However, this is not always the case, and it appears that some offenders prefer to commit offences around their home location (e.g., Canter & Larkin, 1993) and that patterns may vary across offence types (e.g., Meaney, 2004).

Of course, such research considers directional bias as measured relative to the offender's home location. Thus, the consideration of angular variation in sequential *inter-crime trips* would complement these findings by examining patterns in the vector of travel from one crime to the next (not from the home location to each crime). In conducting such research, if biases emerge researchers might explore if activity nodes or other factors might explain observed regularities. They might also consider angular variation relative to the offender's home base and their last offence simultaneously to see if (for example) the former constrains the latter. Other targeting strategies may exist and researchers are encouraged to articulate and test for evidence of them.

Considering the approach to model fitting adopted here, as with many studies that have examined such issues, a simple and easy to articulate method was taken. However, in future research, scholars who examine some of the suggested lines of enquiry discussed here are advised to adopt Maximum Likelihood approaches to model fitting, such as those described in Clauet *et al.* (2009). Such approaches have been shown to provide less biased parameter estimates than other methods and hence will be the preferred approach.

A further point concerns the data analysed here. As noted, the data considered were for burglary offences detected by the police and these represent an incomplete picture of offender movement. First, the data are for crimes detected by the police and it is possible that patterns of offending differ for those who are and are not detected. For example, those who commit crimes close to each other may be more easy to detect than those who do not. However, in a recent study, Lammers (2014) examined this issue using data for a sample of offenders who were either apprehended by the police or were not apprehended but whose crimes were linked together using DNA samples. Lammers found no differences in the distribution of the inter-event distances for such offenders, suggesting that the two groups could not be differentiated – and hence that detection data are unlikely to be systematically biased – in this respect.

A second issue concerns the fact that the data do not provide a complete record of movement for those who *are* detected by the police. They only detail the timing and location of detected offences. Using an alternative method, in a recent study, Rossmo, Lu, and Fang (2011) mapped the sequential movements of a sample of 14 offenders required to wear GPS trackers as a condition of their parole. Such analysis – not without its own biases – provides a richer picture of offender mobility and could and should be analysed in the ways presented here. More generally, a better understanding of offender mobility will be gained through the triangulation of findings from studies that use different sources of data.

Turning to possible applications of the findings, consider crime linkage, or comparative case analysis (Grubin, Kelly, & Ayis, 1997). This analytic technique is used to identify a series of offences committed by a single perpetrator out of a pool of

unsolved crimes (Woodhams, Hollin, & Bull, 2007). If completed correctly, it can play a major role in the detection of prolific offenders. While linkage analysis can sometimes be achieved using physical or other identifying evidence (e.g., fingerprints, DNA, witness statements), such evidence is often unavailable (Davies, 1991). Consequently, linkage is often attempted using other forms of crime scene evidence, such as an offender's *modus operandi*. If successful, crime linkage allows for the centralization and rational allocation of investigative resources (Godwin, 2001). For the crime of burglary at least, recent research on linkage analysis suggests that the distance between offences is one of the best predictors of whether two crimes were committed by the same offender (e.g., Bennell & Canter, 2002; Bennell & Jones, 2005; Bouhana, Johnson, & Porter, 2014; Goodwill & Alison, 2006; Tonkin, Santtila, & Bull, 2011). This is, of course, completely consistent with the current findings and the theory articulated. However, what should also be clear from the current findings is that while most offences committed by the same offender may tend to be near to each other, others will be a long distance from each other. Considering Figure 2, this suggests that if an offender adopts a foraging pattern that resembles Brownian motion, crime linkage based on distance will work well and should lead to many pairs of offences being correctly linked to each other. However, where offenders adopt a Lévy walk, while geographic clusters of offences will be correctly linked to each other, offences from one spatial cluster are unlikely to be linked to those of another. This does not challenge the validity of methods of crime linkage based on propinquity, but does highlight an issue that scholars might want to try to address in future research.

A related methodology is that of geographic profiling (e.g., Rossmo, 2000). This technique is intended to assist law enforcement agencies investigating a crime series focus their efforts geographically. Informed by CPT, and specifically the finding that most journeys from an offender's home-to-crime location are short, the approach essentially assumes that offenders are central place foragers who typically begin their journeys to crime from a specific routine activity node that could – but need not be – their home location. The approach is not intended to pinpoint the exact location that an offender may be found, but rather to direct police resources to those locations where investigative effort might most profitably be focused (e.g., Rossmo, 2000). To over simplify the analytic technique that underlies the approach, an assumption of existing models is that given a set of crime locations that are known (or assumed) to have been committed by a single offender, using a simple (isotropic) density estimator it is possible to estimate the residence of the offender, or at least an important anchor point.

In those cases, where offenders employ a Brownian motion search strategy, for the current sample this technique is likely to be effective at least some of the time. However, where offenders employ a Lévy walk search strategy, it is unlikely to generate optimal predictions, having the potential to be grossly inaccurate some of the time. The extent to which the current findings are generalizable remains to be seen, but assuming they are they suggest directions that future research of this kind might explore.

A similar issue can be discussed with respect to spatial methods of crime forecasting. Inspired by the research on near repeats, one contemporary approach (e.g., Bowers, Johnson, & Pease, 2004; Johnson *et al.*, 2008; Mohler, Short, Brantingham, Schoenberg, & Tita, 2011) assumes that the risk of crime in an area is the function of two things. Time stable risk associated with features of the environment, and, a more dynamic process whereby, after successfully targeting one location, offenders target others nearby. Mathematical models have been developed to mimic such processes and have been shown to be more accurate at predicting the future locations of crime than more

traditional methods of crime mapping (e.g., Bowers *et al.*, 2004; Johnson *et al.*, 2008; Mohler *et al.*, 2011).

However, such models assume that the risk of crime spreads in space and time according to pattern known in statistical physics as a diffusion pattern (e.g., Barthelemy, Bertolotti, & Wiersma, 2008). For such a process, and in the case of offending, we assume that the average squared distance travelled by an offender (referred to as displacement) increases linearly with time spent foraging. That is, sequential crimes will tend to be committed close to each other. Where offender foraging patterns resemble a Brownian walk, the mathematics associated with predicting the diffusion of risk will be simple. However, in the case of a Lévy walk, the average squared displacement is known not to increase linearly with time spent foraging and instead leads to a different pattern of *superdiffusion* (Viswanathan, 2010). Modelling such a process is more complicated and hence future research on crime forecasting might consider how to model such a process, or a mixture of them.

To conclude, the aim of this article was to explicitly consider regularities in offender spatial decision-making that has not received attention in the literature hitherto. The theoretical perspective offered, and the empirical example presented, suggest that space–time patterns of burglary (at least) may be explained by offenders adopting foraging strategies not unlike those observed across animal species. The results also suggest that one foraging strategy is either not adopted by all offenders, or is not adopted all of the time, and hence suggestions were made regarding the future directions that research might take to further enhance understanding of offender spatial decision-making.

Acknowledgements

I would like to thank West Midlands police and in particular Alex Murray for supporting the work reported in this article. I would also like to thank Kate Bowers, Toby Davies, Paul Ekblom and Paul Taylor for comments on an earlier draft of this article.

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Received 24 June 2013; revised version received 22 May 2014