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Chapter X
Offender Mobility and Crime Pattern Formation from First Principles

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ABSTRACT

Criminal opportunity in most cases is constrained by the fact that motivated offenders and potential targets or victims are not found at the same place at the same time. This ecological fact necessitates that offenders, potential victims, or both move into spatial positions that make crimes physically possible. This chapter develops a series of simple mathematical and agent-based models looking at the relationship between basic movement decisions and emergent crime patterns in two-dimensional environments. It is shown that there may be substantial regularities to crime patterns, including the tendency for crime to form discrete hotspots that arise solely from different movement strategies deployed by offenders.

INTRODUCTION

Foraging theory is the domain of ecology that seeks to model how organisms deploy alternative behavioral strategies to bring themselves into contact with the resources that they need for survival. For stationary organisms such as plants or sessile animals, foraging might mean attempting to establish and control a spatial position within the environment that ensures at least a minimum flow of nutrients past that location. For mobile animals such as large mammalian herbivores or carnivores seeking stationary or mobile prey, foraging may mean developing movement routines that ensure a certain rate of encounter and return from prey items. In exactly

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the same way, criminal opportunity in most cases is constrained by the fact that motivated offenders and potential targets or victims are not found at the same place at the same time. This ecological fact necessitates that the foraging movements of offenders, potential victims, or both intersect in ways that make crimes physically possible (Cohen & Felson, 1979; Felson, 2006).

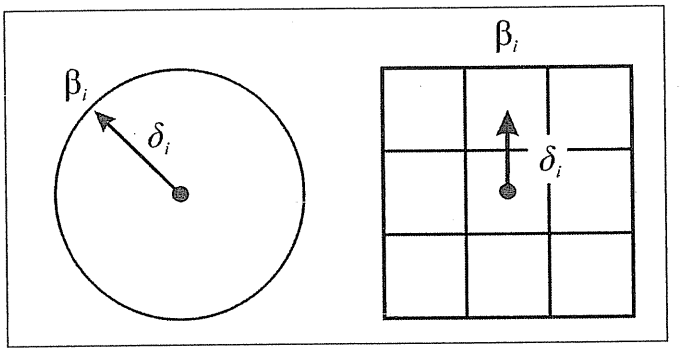
Although formal modeling of the foraging behaviors of nonhuman organisms is routine in ecology (see e.g., Altman, 1998; Stephens & Krebs, 1986; Turchin, 1998), much less attention has been directed at modeling the movement patterns of criminal offenders (but see Brantingham & Brantingham, 1981; Groff, in press; Rengert, Piquero, & Jones, 1999; Rossmo, 2000). What we do know is that offenders appear to concentrate their movement in the immediate vicinity of nodal activity points such as a residence, but they occasionally will travel much farther distances along heavily used pathways (Bernasco & Nieuwbeerta, 2005; Flemming, Brantingham, & Brantingham, 1994). While these observations are crucial to crime pattern studies in a general qualitative sense, a quantitative understanding of how individual level movement choices translate into emergent crime patterns is still lacking. If studies from the physical and biological sciences provide any guide (Camazine, 2001; Koch & Meinhardt, 1994; Topaz & Bertozzi, 2004), then there is a strong possibility that very complex spatio-temporal crime patterns may be the product of relatively simple behavioral processes operating at the individual level. Finding this to be true would be consistent with the perspectives of routine activity theory (Felson, 2002), situational crime prevention (Clarke, 1995) and environmental criminology (Brantingham & Brantingham, 1981).

This chapter develops a series of mathematical and agent-based models looking at the relationship between offender movement decisions and emergent crime patterns in two-dimensional environments. These models rely on the simplest behavioral components and represent a "bottom up" modeling strategy. Section 1 of the chapter examines the minimal behavioral elements necessary to model movement in two dimensions. In principle, all we need specify are the rules describing how offenders choose movement distances and movement directions. In some cases it may also necessary to specify the time intervals at which an offender must return to the origin of movement, generally understood to be an activity node such as a residential location (Brantingham & Brantingham, 1993). Section 2 uses these basic components to build a very general and flexible model of offender movement. The model may be used to describe a continuum of offender foraging strategies ranging from simple random walks (Brownian Motion) through to so-called Lévy flights (anomalous diffusion) (Brantingham, 2006). Section 3 examines the hypothetical crime patterns generated by these movement regimes. We address the possible quantitative regularities in crime patterns that may be linked to movement regimes. Finally, we consider the analytical utility of simulating the emergence of crime patterns from first principles.

A MINIMALIST MODEL OF OFFENDER MOVEMENT

Offenders move about their urban environments in response to a complex array of individual and environmental attributes. For instance, the foraging choices of a residential burglar might hinge upon access to private or public transportation, the accessibility of residences, and levels of informal social control or surveillance (Bernasco & Luykx, 2003; Bernasco & Nieuwbeerta, 2005). As demonstrated in ecological studies, however, the simplest possible model of forager movement need only consider two things: (1) the choice of a direction in which to move; and (2) a choice of a movement distance (Brantingham, 2003; Brantingham, 2006; Turchin, 1998). Figure 1 shows how these two essential behavioral variables fit

Figure 1. Minimal components necessary for a model of offender movement. The variable β_i is the bearing for move i in a sequence of i = 1, 2...n moves. The variable δ_i is a distance for move i.



together. Given an initial starting location, a residence for example, we can determine the next spatial location visited by a modeled offender if we know the direction in which that offender is moving and the distance over which he will move. Here we will use the variable β_i to describe the bearing of movement and δ_i the distance for move number i = 1, 2...n in a sequence of n moves. In continuous space β_i is a continuous random variable falling in the interval 1-360° (Figure 1a). On a lattice, β_i is constrained to be in one of the four cardinal directions (Figure 1b). In both continuous and discrete space δ_i may be a fixed, small size, leading to simple random walk models (Turchin, 1998). Alternatively, it may be a random variable drawn on some probability distribution between some minimum δ_0 and maximum δ_{max} possible movement distance. On a lattice, δ_i must be an integer.

For simplicity, we will only describe models where the bearing of movement β_i is a uniform random variable, meaning that all movement directions are equally likely (see Brantingham, 2006; Marthaler, Bertozzi, & Schwartz, 2004; Turchin, 1996). Following a large literature in biology and physics, we model offender movement distances according to the Lévy probability distribution. This so-called Lévy mobility model has been used to study the movement patterns of organisms as different as dinoflagellates (Bartumeus, Peters, Pueyo, Marrase, & Catalan, 2003), bees (Viswanathan, Buldyrev, Havlin, da Luz, Raposo, & Stanley, 1999), albatross (Viswanathan, Afanasyev, Buldyrev, Murphy, Prince, & Stanley, 1996), howler monkeys (Ramos-Fernandez, Mateos, Miramontes, Cocho, Larralde, & Ayala-Orozco, 2004), deer (Viswanathan et al., 1999) and Paleolithic human foragers (Brantingham, 2006). On empirical grounds, therefore, the Lévy mobility model may be expected to provide a good description of offender movement as well.

$$p(\delta_i) = \delta_i^{-\mu} \qquad (1)$$

Equation (1) states that the probability that an offender in one instance i moves over a distance δ_i is simply that distance raised to a negative power μ. Offender move distances thus obey a negative power law with properties defined only by the exponent μ (Viswanathan et al., 1999). The distribution corresponding to equation (1) is concave-up, meaning that short distance moves tend to be very common, but long distance moves also occur with a nonzero probability (Figure 3). For example, with $\mu = 2$, an offender faced with a choice to move a distance of 1 km (if measured in these units) will do so with a probability of $p(\delta) = 1$. Movement over a distance of 100 km will occur with a probability of $p(\delta) = .0001$, a rare event but not unlikely over many moves.

Figure 2. Lévy probability distribution describing the probability that an offender moves a distance δ in a single instance.

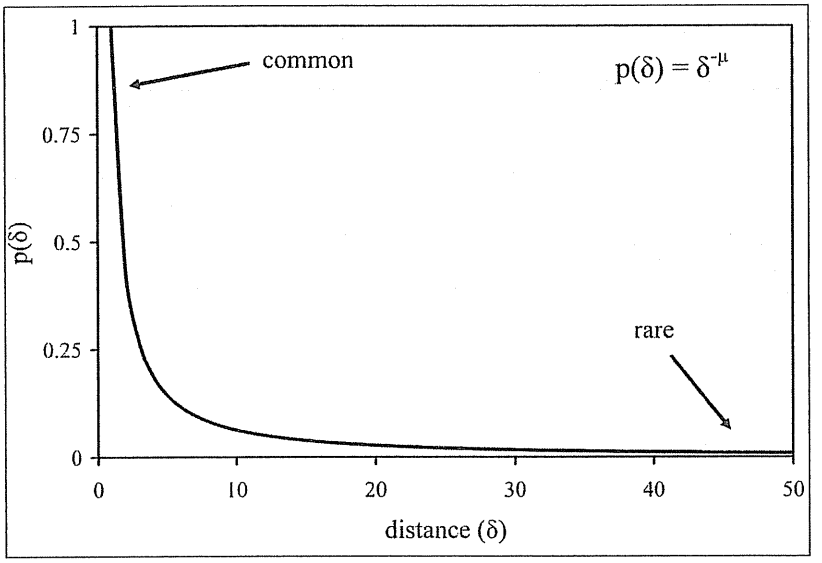
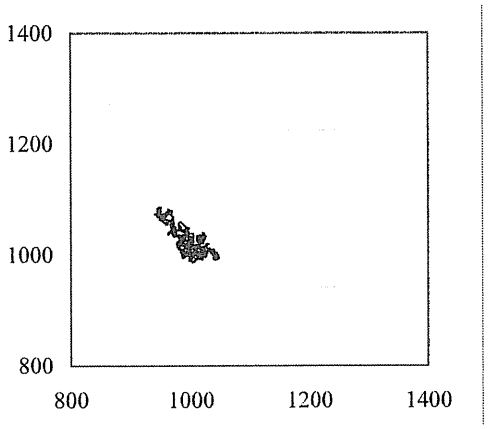


Figure 3. The path followed by of a offender in a continuous 2D environment over 2000 discrete moves. Movement directions are uniformly distributed and movement distances are from equation (1) with μ = 3.5.



Physical (Nakao, 2000; Shlesinger, Zaslavsky, & Klafter, 1993) and biological (Viswanathan, Bartumeus, Buldyrev, Catalan, Fulco, Havlin, 2002; Viswanathan et al., 1999) studies have shown that qualitatively different forms of behavior appear when $1 < \mu \leq 3$. As μ approaches 3, the probability distribution shown in Figure 2 becomes increasingly concave, meaning that most of the moves that the offender makes will be of short distance. When $\mu \geq 3$, then the average move length is equal to the minimum move length and the pattern of movement is equivalent to a simple random walk (Brownian Motion) (Figure 3) (Viswanathan et al., 1999). At an analytical level therefore values of μ = 3.5 or μ = 7.5 lead to the same behavior. As μ approaches unity, the Lévy distribution develops a "fat tail" and longer distance moves become common (Figure 4). If μ = 1 then there is a finite probability that an offender moves along a path of infinite length, producing a so-called ballistic movement trajectory. When μ = 2, the associated movement pattern displays clusters of short distance moves interspersed with occasional long distance moves (Figure 5). It is reasonable to consider the range of movement routines represented by different values of the Lévy exponent μ as corresponding to the range of movement options available to an offender (see Bernasco & Nieuwbeerta, 2005; see Groff & McEwen, 2006; Wiles & Costello, 2000). Of-

fenders who travel solely on foot such as a teenager, might best be represented by a movement model with $\mu \geq 3$, since this would generate movement patterns dominated by short distance moves. By contrast, offenders who have access to a car such as an experienced commercial burglar might best be represented by a movement model with $\mu \rightarrow 1$ since this would generate movement patterns that show more regular long distance moves.

The movement patterns simulated in Figures 3-5 illustrate cases of unconstrained offender movement. This is typical behavior for foraging animals who do not return to a central place or home base except stochastically (Brantingham, 2006; Ramos-Fernandez et al., 2004; Viswanathan et al., 1996). In the present context, this is the drifter who moves about a city or between cities with no fixed address for any significant period of time. In a technical sense, an offender who commits only one crime from an anchoring address before moving to a new anchor point is itinerant from the perspective of crime pattern formation. The two parameters of the movement model are sufficient to specify the locations of the turning points, strung together end-on-end, along a movement path (Figure 6a).[1] At the other extreme, an offender might return to an activity node such as a residence, place of work or a bar after each individual move (Brantingham & Brantingham, 1993). This is the ideal behavior of a central place forager (see also Canter & Larkin, 1993; Stephens & Krebs, 1986). The two parameters of the current model are sufficient to describe the end points of each individual movement path (Figure 6b). Of course, between these extremes are movement regimes where an offender can string together a number of individual moves end-to-end before returning the origin. For example, Figure 7 illustrates a case where a mobile offender follows ten unique paths each of which strings together 20 individual moves end-to-end before returning to the origin.

FROM MOVEMENT TO CRIME PATTERNS

Very different spatial activity patterns are generated by the above models simply by: (1) varying

Figure 4. The path followed by of a offender in a continuous 2D environment over 2000 discrete moves. Movement directions are uniformly distributed and movement distances are from equation (1) with μ = 1.2. Scale is the same as in Figure 3.

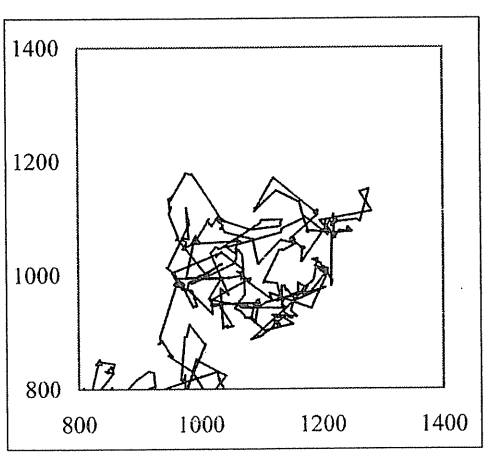
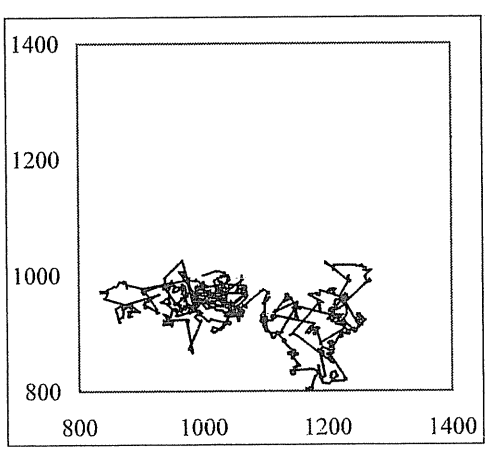


Figure 5. The path followed by of a offender in a continuous 2D environment over 2000 discrete moves. Movement directions are uniformly distributed and movement distances are from equation (1) with μ = 2.0. Scale is the same as in Figure 3.



the parameter μ, which controls the relative frequency of movements of different lengths; and (2) imposing different constraints on when a modeled offender must return to the origin of movement. Depending upon the degree of complexity sought, it is relatively straightforward to examine the impact of how these different movement models might lead to different crime patterns. Here we assume that crime opportunities are ubiquitous in the environment and, as a consequence, that crimes occur at the distal end point of each move. An alternative would be to assume that crimes occur at any point along movement paths including both the endpoints and all of the intermediation locations between (see Brantingham, 2006). In the case of an offender that is unconstrained to return to the origin there are dramatic differences in both the overall spread and the local clustering of simulated crime incidence locations (Figure 8). When offender movement patterns are modeled using equation (1) with the exponent $\mu = 3.5$ (Brownian Motion) then crime locations tend to be relatively close to the origin of movement and tend to form dense continuous clusters (Figure 8a). Increasing $\mu = 2$ means that longer distance moves become more common. As a result, crime incidence locations are spread over a much larger area and crime clusters tend to be smaller and isolated (fragmented) (Figure 8b). With $\mu = 1.2$ the spread of crime incidence locations away from the origin of movement is even greater and there is a tendency for crime clusters to be even smaller and more isolated (Figure 8c).

A similar pattern is repeated in the case of an offender that is constrained to return to an origin of movement at some set interval of time. Figure 9 shows the density of crime locations for an offender that returns to the origin after each sequence of 100 moves. In each case, crime locations are mapped in arbitrary space and kernel densities are calculated for the same arbitrary grid size and search radius to ensure comparability of patterns across different simulations. Several general patterns are immediate apparent. When $\mu = 3.5$ and the offender moves out each time from the origin following approximately a simple

Figure 6. The two extreme types of movement topologies an offender might deploy. (a) Itinerant search where the offender is not constrained to return to an origin. (b) Central place movement where the offender returns to an origin after each move.

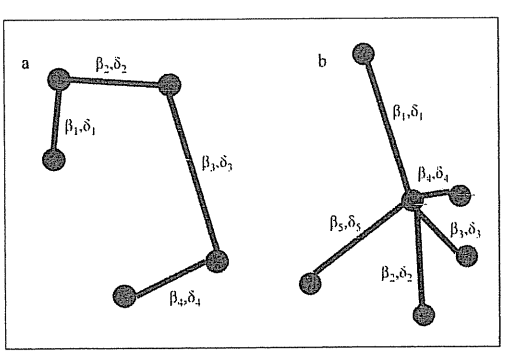
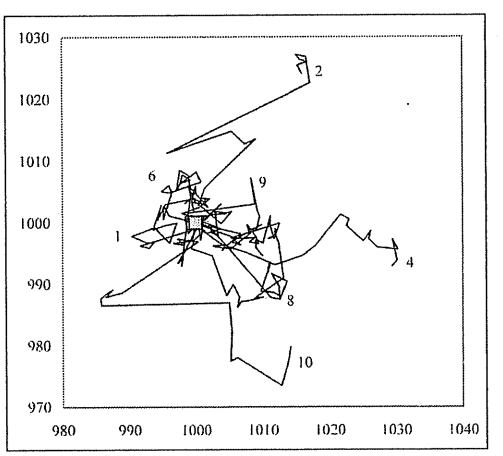
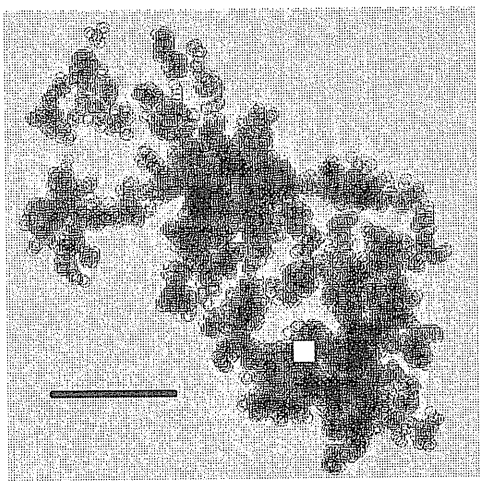


Figure 7. Ten separate paths followed by of a offender in a continuous 2D environment. The offender returns to the origin after each set of 20 discrete moves. Movement directions are uniformly distributed and movement distances are from equation (1) with $\mu = 2.0$. The origin is at 1000, 1000, shown as a gray box.

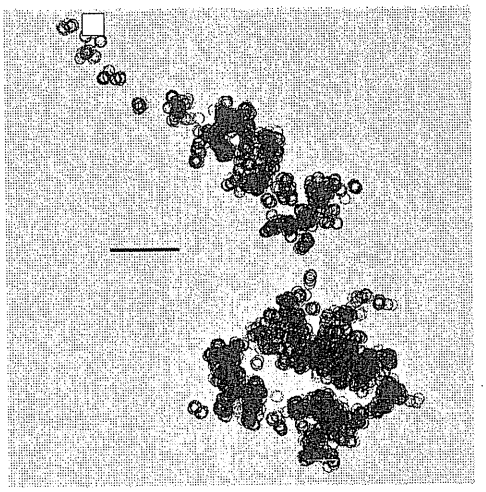


random walk (Brownian Motion) the density of crime locations is very high and compact around the origin and displays a sharp edge that takes the form of a "disc" (Figure 9a). In other words, all areas within this disc are repeatedly victimized a large number (and approximately equal) of times, while areas outside of this disc are victimized rarely. With $\mu = 2$ there is still an area of high

Figure 8. Simulated crime locations for a spatially unconstrained offender in a continuous 2D environment. In all simulations crimes are assumed to occur at the distal end point of each move. Offender movement directions are uniformly distributed. (a) Movement distances are from equation (1) with $\mu = 3.5$. (b) Movement distances are from equation (1) with $\mu = 2.0$. (c) Movement distances are from equation (1) with $\mu = 1.2$. Each simulation consisted of 10,000 individual moves. The origin is at 1000, 1000, shown as a white box. Scale bar in (a) is 50 arbitrary units. Scale bar in (b) and (c) is 200 arbitrary units.



(a)



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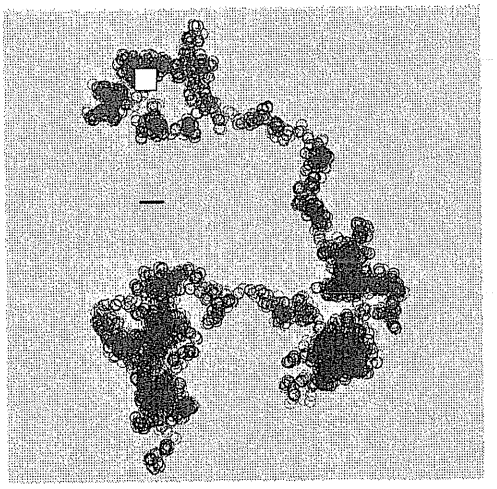
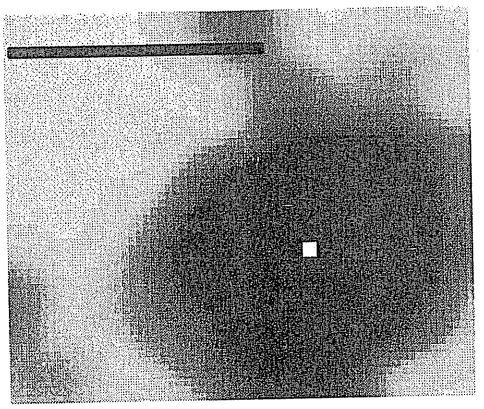
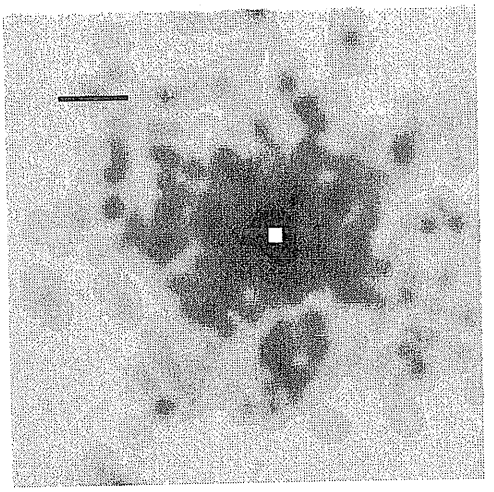


(c)

Figure 9. Density of crime locations for a spatially constrained offender in a continuous 2D environment. In all simulations, the offender was forced to return to the origin after every 100 moves and crimes are assumed to occur at the distal end point of each move.. Movement directions are uniformly distributed. (a) Movement distances are from equation (1) with $\mu = 3.5$. (b) Movement distances are from equation (1) with $\mu = 2.0$. (c) Movement distances are from equation (1) with $\mu = 1.2$. Simulation consisted of 10,000 individual moves. The origin is at 1000, 1000, shown as a white box. Scale bar in each panel is 50 arbitrary units.



(a)



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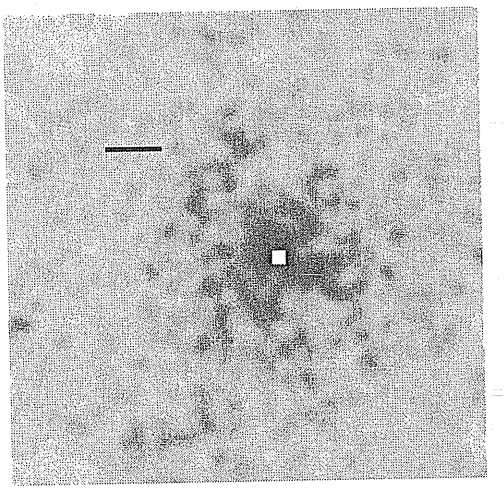


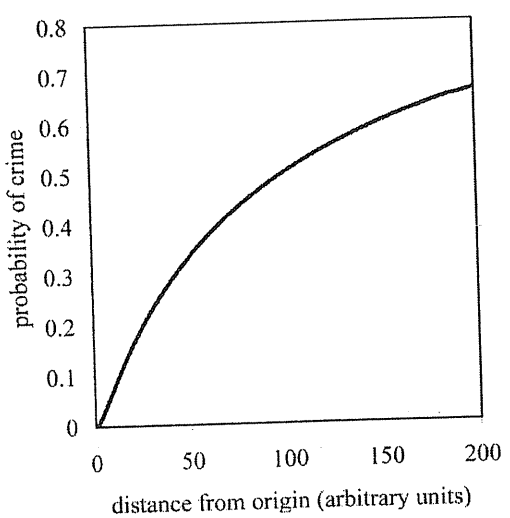
(c)

density crime close to the origin that is both "disc-like" in shape and approximately the same size as with the simple random walk case (i.e., $\mu = 3.5$) (Figure 9b). However, beyond this central region the exterior contours of crime densities become increasingly "rough" with growing distance from the origin until ultimately there are well-formed, discrete crime "hot spots" isolated from the central crime area by regions with relatively little or no crime. The maximum distance of crimes from the origin is about three times greater than in the simple random walk case. With $\mu = 1.2$ these patterns are even more pronounced with a

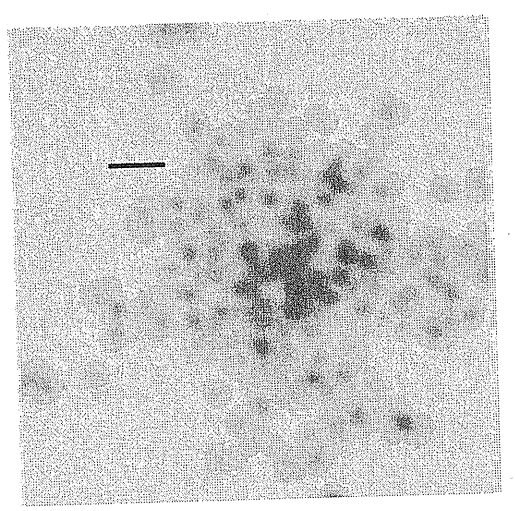
"disc-like" central region of high density crime, a region with a rough exterior contour, a region of isolated crime "crime hotspots" and then finally a dispersed region of isolated crime locations (Figure 9c). The maximum distance of crimes from the origin of movement is approximately 12 times farther than in the simple random walk case. The spatial pattern seen here in the distribution of crime locations has been recognized as a general property random walks under some conditions (Arapaki, Argyrakis, & Bunde, 2004; Larralde, Trunfio, Havlin, Stanley, & Weiss, 1992; Yuste & Acedo, 2000). Despite the apparent regular geometry to the distribution of crimes, note that the abundance of crimes in space is very different between Figure 9a, b, and c. When activity is spread out over a much larger area (e.g., μ = 1.2, Figure 9c) the density of crimes at the origin of movement is much lower compared with the case where movement is concentrated around the origin (e.g., $\mu = 3.0$, Figure 9a).

Figure 9 represents hypothetical crime patterns in an environment assuming that crime opportunities are uniformly distributed in space and that the offender is willing to commit crimes whenever an opportunity is encountered. However, we must also recognize that the interaction between different types of random walks and environmental structure is potentially an important source of spatial pattern generation (e.g., Sole, Bartumeus, & Gamarra, 2005). However, because of the complexities involved in characterizing different types of environmental structure, these issues are beyond the scope of the current paper. It is easier to get a feeling for the impact of local informal social control and surveillance on the spatial patterning of crime. Here we assume that local forms of informal social control will cause

Figure 10. Simulated crime locations for a spatially constrained offender in a continuous 2D environment. (a) Crimes are assumed to occur probabilistically as an increasing function of the distance from the origin of movement. (b) Density of crime locations. The offender was forced to return to the origin after every 100 moves. Movement directions are uniformly distributed and movement distances are from equation (1) with $\mu = 2.0$. Simulation consisted of 10,000 individual moves resulting in 3017 crime locations. Scale bar in (b) is 50 arbitrary units.



(a)



(b)

Figure 11. Simulated crime locations for a spatially constrained offender in a continuous 2D environment. The offender was forced to return to one of two origins after every 100 moves. Return to the lower-left origin occurred 60 per cent of the time. Return to the upper-right origin occurred 40 per cent of the time. Movement directions are uniformly distributed and movement distances are from equation (1) with μ = 2.0. Crimes are assumed to occur at the distal end point of each move. Simulation consisted of 10,000 individual moves. The origins are located at 1000, 1000 and 1106, 1106. Scale bar is 50 arbitrary units.

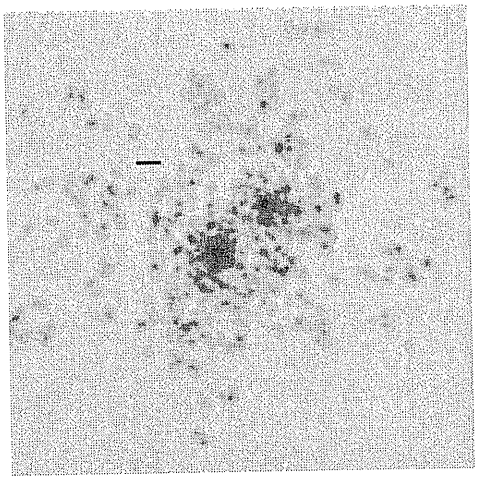
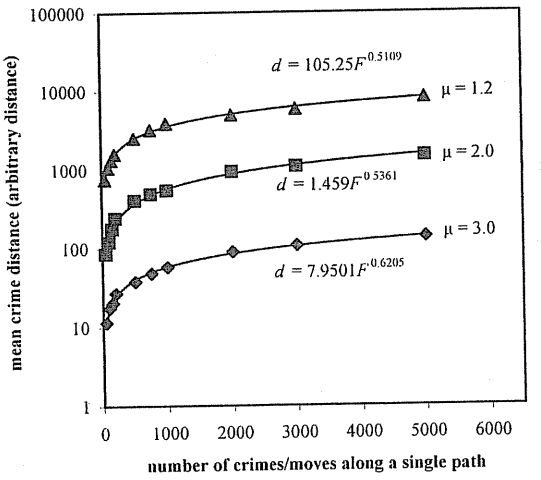


Figure 12. Relationship between the mean crime distance from the origin of movement and the number of crimes along a movement path before returning to the origin. Relationship is shown for three different values of the Lévy exponent μ. Note the log-linear scaling.



self-censorship of behavior such that an offender will avoid committing crimes too close to home, except when the opportunity for reward far outweigh the potential risks of being caught (but see Kocsis, Rayw.Cooksey, Irwin, & Allen, 2002). Figure 10a shows an hypothetical distribution for the probability that an offender will victimize an encountered crime opportunity as a function of the distance from the origin of movement, assumed to be a routine activity node such as a residence. Close to home, the victimization probability is very low (but still non-zero) and such opportunities will be victimized only rarely. The distribution increases logarithmically with increasing distance from the offender's residence such that far away from the residence crime opportunities are taken with near certainty when they are encountered. Figure 10b shows the results of combining the properties of offender movement modeled as Lévy flights with this self-censoring close to the offender's residence (origin of movement). As in the uncensored cases, there is a general tendency for the density of crimes to be higher closer to the simulated offender's residence, but the overall distribution is much patchier or discrete. In contrast to the previous simulations where the distribution of crimes around the central place covered a large, continuous area, here we have discrete hotspots that are individually smaller and clearly delineated by sharp breaks in levels of crime. Discrete crime hotspots are formed closer to offender's residence and they therefore comprise a greater proportion of the total crime pattern. The origin of movement might be buffered by an area of no crime, consistent with both observation and theory (Brantingham & Brantingham, 1984).

Interestingly, the root causes for discrete hotspot formation are different depending upon distance from the offender's residence. Close to the origin of movement, the offender's decision to self-censor due to local social control and surveillance is the primary reason for the formation of small, discrete hotspots. Far away from the origin of movement, hotspots are generated by constraints on movement; many fewer forays are made out far from the origin and therefore clustering of crime events is entirely the product of these rare stochastic events (see Larralde et al., 1992; Yuste & Acedo, 2000).

DISCUSSION

The simulations presented herein are meant to stimulate thinking about how fundamental features of the ways in which offenders move about their environments in search of suitable targets might be responsible for the generation of crime patterns. Borrowing from foraging theory, we proposed a model of offender movement which uses very limited number of assumptions about how individuals choose: (1) movement directions; (2) movement distances; and (3) when to return to an origin such as a residence location. Furthermore, we have concentrated primarily on the properties of movement distances modeled using the Lévy distribution (equation (1)). Despite the simplicity of the model it is clear that very simple behavioral routines are sufficient to generate a tremendous degree of complexity in hypothetical crime patterns. This observation is in keeping with general perspectives developed in the study of a wide range of complex systems (Camazine, 2001; Hubbell, 2001; Sole & Bascompte, 2006; Turchin, 2003). In particular, we have shown that offender movement strategies that are dominated by single short distance moves (i.e., Brownian Motion) and are directionally unbiased should lead to crime patterns that are concentrated close to the origin of movement, dense and well-bounded; that is there is a relatively sharp edge between areas of high and low crime concentrations (see Figure 9a). If movement routines occasionally include longer distance moves, then an irregular boundary comes to characterize crimes committed farther away from the origin of movement and isolated crime hotspots may also form at even grater distances (see Figures 9b and c). How such general patterns are impacted by differences in the distribution of criminal opportunities in an environment, biases in movement directions or other constraints remains to be investigated. We did briefly explore how self-censoring of criminal activities as a function of proximity to one's residence impacts crime pattern formation with the observation that it tends to enhance the complexity of crime patterns close to home. We anticipate that other constraints will have similarly dramatic impacts. For example, street network structure clearly has a significant impact on empirical crime patterns. Large streets tend to generate more crime simply by virtue of the greater volume of traffic that flows along them (Beavon, Brantingham, & Brantingham, 1994; Cohen, 1980). Similarly, aspects of the environment that serve as crime attractors such as bars or high schools are likely to bias movement in ways that impact crime patterns (Brantingham & Brantingham, 1995; Roncek & Maier, 1991). It seems to us, however, that these are features that should be added once we understand fully the dynamics of the to the baseline models presented here.

The simplicity of the current model brings us to a very important point about the role of simulation (and/or mathematical) modeling in the study of crime. Computer simulation models and especially so-called agent-based models have the advantage that they can be constructed at the scale of observation open to researchers. For example, it is physically possible to go out and observe the behavior of offenders in real environments and then build one's models based directly on these observations. Observation tends to be very rich in detail, however, and there is a real danger that

models designed around observation will become bloated with too many variables. We have opted for the alternative in using the smallest number of variables sufficient to model offender movement. Critics of this work would likely claim that the models are either too simplistic and/or too dependent on stochastic mechanisms to actually be of utility in describing something so complex as crime patterns. For example, it might be argued that the present abstract spatial model, where movement anchored to a single activity node, is very unlike how real offenders move about their urban environments (Brantingham & Brantingham, 1993). However, not only is the simple model developed here is flexible enough to describe crime pattern formation around any location that serves as an origin for movement, including school, work, a friend's home, or a bar, but it also is easily extended to deal with an offender that operate from two or more activity nodes. Figure 11 illustrates a case where a single offender with $\mu = 2$ operates from two different activity nodes, returning after every 100 moves. The offender spends 60% of the time moving out from the lower of the two activity nodes and 40% of his time moving out from the other. It is clear not only that the sizes of the crime zones around each of the origins is approximately proportional to the amount of time spent there, but also that the smaller of the two appears more "disc like" in exterior contour and the larger "rougher" in much mimicking variation of the Lévy exponent μ (see Figure 9). There is also a band of hotspots connecting the areas of highest crime density, reminiscent of a path between activity nodes (Brantingham & Brantingham, 1993).[2] In both cases, it is clear that the distribution of crime locations may display regular spatial properties regardless of the specific location of the origin of movement, or how many activity nodes are involved.

Finally, we contend that the use of simple reductionist models provides a degree of analytical and quantitative tractability that are not available in more "holistic" approaches. While we have concentrated on the basics components of a model of offender movement based on the Lévy distribution and the qualitative crime patterns that this model generates, we also note that there are a number of quantitative measures that could be applied to the analysis of such offender movement systems (see Brantingham, 2006; Viswanathan et al., 1999). For example, there is a very regular relationship between the mean distance at which crimes are committed and both the number of crimes committed over a connected series of moves and the Lévy exponent μ (Figure 12). Simulations using different values of μ generate many unique foraging paths, which in turn generate different numbers of crimes. In general, the mean distance increases as the total number of crimes increases along any one foraging path, but the mean also rises much more rapidly for lower values of μ. In practice, this implies that an offender with more limited movement options (modeled as $\mu \rightarrow 3$) such as a teenager without access to a car will see the mean distance between the teenager's residence and each of the teenager's crimes grow slowly. By contrast, an offender with more diverse movement options (modeled as $\mu \rightarrow 1$) will see the mean grow very quickly (see Brantingham, Brantingham, & Wong, 1991). While further simulation testing and model calibration are clearly warranted, aspects of the relationships between offender movement and crime patterns might be highly predictable.

FUTURE RESEARCH DIRECTIONS

Simulation provides a useful tool for translating empirical observations about offenders and targets or victims made at a microscale into predictions about emergent crime patterns at higher spatio-temporal scales. When conducted alongside more rigorous mathematical analyses, simulations may provide a basis for predicting how and why such patterns emerge. While such methods are may lead to interesting insights about the nature

of crime pattern formation, they deal mostly with what is possible rather than what actually is. We believe that it is necessary to also seek calibration and testing of models following a hypothetico-deductive framework. While it is by no means satisfying to have one's model rejected based on empirical comparisons, this is exactly how a science of crime pattern formation should preceed. The simple models developed here are thus poised to be rejected, if compared directly with empirical crime patterns, because they make a number of very unrealistic assumptions. Our future research on this problem will attempt to do just this. Subsequently, our goal will be to add measured amounts of complexity to the model, examine how this impacts our understanding of crime pattern formation—using both simulation and analytical tools if possible—and then conduct empirical comparisons in an attempt to reject new model predictions. We expect that the most fruitful areas of model development will be in attempting to understand how environmental structure in the form of street networks and distributions of crime opportunities impact crime patterns.

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ADDITIONAL READING

While there are many readings dealing with different aspects of simulation and mathematical modeling, few of these are introductory in nature. As a result, it is often difficult to acquire the conceptual, methodological, and technical skills necessary to build successful models. The additional readings suggested below have been useful to us in explaining the role of modeling in science and in presenting some of the most essential modeling tools.

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ENDNOTES

1 The new location x_j, y_j is given as $x_i + \delta_j \sin \beta_j$ and $y_i + \delta_j \cos \beta_j$ where x_i, y_i is the current location.

2 The path between corridors is much more apparent if the density surface is calculated using a coarser grained kernel