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Crime Emergence and Simulation Modeling: Modeling Crime Space

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Crime Emergence and Simulation Modeling: Modeling crime space

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Introduction

Criminology is entering a new era of theory development and research. We are increasingly aware that we live in an evolving world; that patterns emerge in the activities of individuals and groups; that the patterns grow in strength and fade; that we learn and forget; that changes are dynamic and reactive to perturbations; and, that people develop cognitive stability after a surge of rapid change and move towards making new actions routine. This awareness of dynamic change interspersed with periods of stability is reflected in theories in all disciplines that make use of dynamic systems concepts. The list includes cognitive science, systems biology, and computational physics among others. Tied closely to theoretical changes in understanding dynamic systems are improvements in research tools, mostly comprising a linking of mathematical and simulation modeling to methods for assessing actual patterns of change and stability. Research tools are themselves evolving very quickly and criminological researchers are becoming more aware of the computational tools available to them that open new ways of exploring and learning about patterns in crime.

This chapter explores several new modeling approaches and research findings, showing how they may be used to explore and enhance theory. There is a special emphasis on Target Choice Selection, focusing on Crime Pattern Theory and the Geometry of Crime (Brantingham and Brantingham, 1978a, 1984, 1991; Brantingham and Brantingham, 1981, 1993a, 2008). This exploration is described through a series of research examples and a case study of the target choice behavior of high repeat offenders. The goal is to explore the emergence of patterns better understood against the urban backcloths for high repeat offenders. Emphasis is in this case study is particularly placed on the *structural* backcloth but will be expanded in future studies to include other backcloth components such as the social, the cultural, the economic, and the derived vernacular architecture that combine with structural components to form neighborhoods.

Emerging patterns of criminal events have different meanings in different contexts. Crime does not depend just on the interaction of an individual who has some given risk tolerance with a potential target and its security attributes. The individual and the potential target must always be understood as placed in time and within a space and its underlying morphology. The dynamically changing structure of the underlying urban morphology helps to shape crime patterns and influences the researchers' ability to see and understand the emergence of hot spots or crime clusters.

As can be seen from this book, this is a rapidly expanding area of research with many interesting conceptual and methodological paths being opened. The authors of this chapter pass to the other chapters the introduction and review of the field in general. Within the page constraints of a chapter we decided to focus on the work developed in and near the Institute for Canadian Urban Research Studies (ICURS). This more limited work should be considered as a small part of a growing theory and research domain.

Background: Simulations

Simulation modeling has several general categories of techniques ranging from the building of objects and testing them in laboratory such as crash testing of cars; to human/computer interaction such as virtual environment studies[i]; to building a rule model grounded in a mathematical model that mirrors both actual actions and the reasons behind those actions.

In criminology interest appears to be strongest in simulation modeling built on rules and mathematics that reflect reasons for actions. These rules-based models are used to assess the logic and consistency of theories or to explore a range of resulting patterns that can emerge from variations in the rules (see Liu and Eck, 2008, for an overview and examples of simulation modeling in criminology). Operational simulation models may be complicated with many sub-parts and rules within the sub-parts. Theoretical models usually stay simple with the ability to modify only a few parts. This type of modeling has value but when successful at the theoretical level, it produces a demand to verify it in the real world and make it a working model.

In either approach the goal is clarity and consistency with theoretical or operational validity. The process of model building forces the model builder to be clear about assumptions, to be clear about relationships of model parts, and, to identify what is and is not included within the model. Models are supportable when past research is included in construction of the rules, but are found to be of high value when they explore new areas of thought. Theory development and modeling are closely tied. Computational biology and computational physics as exemplars are leading to a new field of computational criminology. The merging of criminological theories with the power of computer science and mathematics opens new doors for both theory building and research.

The most common simulation techniques used in criminology are *agent based models* and *cellular automata*. Models that are more mathematical are also used as well, including neural networks, Bayesian networks, game theory, partial differential equations (PDE) and topology. None of these techniques are new in science (see for example Turing, 1936, 1938; von Neuman and Morgenstern, 1944; Forrester, 1969; Euler, 1741) but are part of the contemporary evolution of criminology as theoreticians and researchers explore in a stronger way how activities evolve, change and adapt and how activities are non-recursive or involve feedback loops. The emergence of new patterns can be seen as a result of such feedbacks and changes.

In agent based models classes of individuals (agents) are identified; and rules are developed to control their movement in time and space. The rules, depending on the goal of the model, may identify how characteristics of an agent's risk taking influences offending or how the age of an offender may influence choice of target type. In these models the strength of characteristics may be changed in an experimental way to see alternative results or may be optimized to fit a real pattern of offending. The models are run with variations in conditions to provide some insight into results produced by these changes. The models usually include interactions between agents and interactions between agents and the backcloth upon which they operate. This is a type of modeling that will grow in importance in criminology as the skills for agent based modeling become part of the research methodology canon. In the future, to avoid excessively complicated models, software such as *CoreASM* developed by Uwe Glässer (Farahbod and Glässer, in print, 2010; Farahbod et al., 2007) that can use abstraction and detailed subparts as well as model specific programs and general approaches such as *REPAST* are likely to see much more use.

A second popular technique in current use by criminologists is cellular automata (CA) modeling of a type that began with von Neuman in the 1940's but which has matured in recent decades. These models are sets of rules based on objects within a cell and interaction between these objects and their neighbors in adjacent cells (Dabbaghian et al., 2010). Cellular automata at present typically use rules that apply to all neighbors. This type of modeling can be used for very straight-forward modeling such as the impact of concentrations of drinking establishments on nearby crime patterns. However, when CA models are used geographically, they tend to encourage viewing crime more like disease diffusion. This is like “draping” abstract models over an identified real space. The geographic application of cellular automata models pull towards a complexity on the one hand and towards a relaxation of mathematical assumptions on the other. Innovation in this type of modeling is likely in the near future. For criminological purposes it would be good to continue towards the addition of direction of diffusion, that is, a physics meaning of diffusion whereby diffusion is shaped by the structure in which it occurs.

System Dynamics is another simulation tool used to model flows of objects, people, criminal cases and other defined volumes. Its origin was in understanding decision making and, within criminology, is most often used for modeling the operations of the criminal justice system (Alimadad et al., 2008).

In all modeling approaches, entities or objects are identified and rules covering actions are defined clearly. The process of conversion of rules into equations and computing rules and code requires testing the equations and code for completeness and logical consistency with the stated rules and assumptions. It is important to note that the entities and rules are always based on some theory. Model building for the social sciences imposes strong clarity requirements and thereby helps identify weak areas in the theories, usually producing improvements. The process itself is non-recursive and brings research methods and research into a non-recursive relationship as well.

Background: Theory

The case study presented here is based on *Crime Pattern Theory* (1993a) that itself evolved from an earlier theoretical approaches to *Target Choice Selection* (Brantingham and Brantingham, 1978a) and the *Geometry of Crime* (Brantingham and Brantingham, 1981). The theory builds on the concepts of crime attractors and crime generators (Brantingham and Brantingham, 1995), target choice behavior (Brantingham and Brantingham, 1978a), and the identification of the importance of paths, nodes and edges[ii] (Brantingham and Brantingham, 1993b).

The premise for Crime Pattern Theory is:

> All sciences, social or natural, want understandable theories. In the natural sciences, such as physics or chemistry, theories are developed within a well-defined, closed intellectual environment. The social sciences cannot exist in a closed or limited environment. The concepts in social sciences may never be conceived or viewed, except as a game, without considering how they interact with a highly variable, never static environmental backcloth, that is, an ever-changing set of socio-cultural, economic, legal, structural, and physical surroundings that include, among other things, the activities of individuals, of groups, and of organizations. No firm boundary can be placed around particular elements within a theory that can separate them from the backcloth…. A theory must be flexible, able to explain criminal events against diverse variations in the backcloth, to be of much value, a theory must make it possible to recognize … patterns at many levels of resolution.
>
> (Brantingham and Brantingham 1993a: 265)

Figure 1 provides a brief summary of Crime Pattern Theory. There is a criminal event process that includes triggering events, and some type of search (minimal to extensive) based on an offender's crime/risk template. The template influences the offender's target search; the decision to offend or not. Decisions to commit crimes following identification of targets change, to some degree, the offender's template. The template is formed based on the elements of the backcloth that are part of an offender's activity and an awareness space as shaped by their own and others' routine activities. Both the awareness space and the activity space are changed by both criminal and non-criminal events (Brantingham and Brantingham, 1981:43). There is a recurrent cycle of action, adaptation, repetition of what is perceived as a successful action, more adaptation and change and, sometimes, enhanced focus. The feedback loops are continuous and exist at varying spatial and temporal scales (Brantingham and Brantingham, 1995: 266-273).

[-- Insert Figure 1 **--]**

People who commit crimes are like all people. We learn; we forget; we develop mental templates that shape what we see and what we look for. We develop routines for our daily lives, but non-routine activities occur and modifications are made. Crimes lead to repetition, but always subject to change; actions shape crime templates that in turn shape action; patterns emerge. This is non-linear but frequently moves towards regularity (Brantingham and Brantingham, 1995). Learning a “good time” and a “good place” for a crime is as natural as learning a good route to commute to work or developing a normal routine for shopping or finding friends to meet for an evening out. Patterns are recognizable when seen against the backcloth.

Simulations, tied with this understanding of the routine, provide a tool for exploring the impact of the urban backcloth. It is possible to explore how changes to the backcloth influence crime decisions and how crime decisions change the backcloth. Models provide the computationally intensive tools for exploring spatial-temporal patterns and, through clear definition of rules, provide a way to see how similar processes may produce very different results as the conditions change. Models in computational criminology open the door to bringing research tools into line with theoretical advances that explore dynamic and changing environments.

Geometry of Crime

Notes on the Geometry of Crime (1981) was a theoretical article written before the advent of current computational powers. It was, however, theoretically tied to the importance of understanding the complex interactions between people and places with a special emphasis on how past knowledge and past social networks influence decisions and activities over time and how activities, including criminal activities, are influenced by the attractors, generators and pathways of everyday life. It fit within a tradition in psychology, geography and parts of sociology that looked for improved understanding of people as agents and how the patterns of their activities follow discernable, dynamic, continuously changing rules and how patterns emerge. While no equations were included in the original article, it was conceptually based on a type of mathematics called *topology*. At the time of the writing of that article, topology was just entering applied mathematics and criminology (Brantingham and Brantingham, 1975; Brantingham and Brantingham, 1978b). It is well established in the natural sciences now and is beginning to enter criminology research. Note that this is a type of mathematics that is understood by some as being Venn Diagrams with unions, intersections and adjacency. Those concepts are part of topology but only form a small component of the total field.

Today social science is opening a new door to research in which social theories are merging with theories and applications in computer science, applied mathematics and complex systems. It is a play with a word in the title of this book but new ways of advancing crime research are *emerging.* It is an interesting time.

The Geometry of Crime presents ideas in a standard mathematical way where the concepts are first introduced without conditions and then additional concepts are added incrementally. In the briefest of summaries of the ideas in Geometry of Crime, individuals form routine daily activities with nodal or stopping points and regular (but modifiable) routes between the activity nodes. Each person may develop his or her own pattern of daily activity, but in the aggregate, regular patterns emerge, with some very high common activity areas and some less active areas forming across the urban backcloth. Routes vary in intensity too. As is well known, these individual and aggregate patterns are influenced by personal socio-economic and demographic attributes (see for example Chapin, 1974; Gould and White, 1974; Felson, 2010) and by the underlying backcloth of the area. Individuals develop activity and awareness spaces, pass these on to others and, by their actions, create modifications to the backcloth. The modifications may be major to minor in the aggregate such as creating the push for more or fewer entertainment areas, more or fewer restaurants, growth or decline in a city and even changes in the vernacular architecture of places within a city.

It is argued within the Geometry of Crime that individuals have varying motivation to commit crimes and that motivation is linked to experiences in daily living. A first crime for some could be almost accidental. A repeat offender tends to return to areas of prior successful crimes and develops a modifiable crime template (Brantingham and Brantingham, 1978), but one that has within it classes of preferences and rules (in a cognitive psychology sense) for deciding where and whether to commit offences. The time in the daily (or annual) life cycle, knowledge of the dynamic surrounds, and expectations all influence choices. Suitable target choice categories are developed (and change), but not all actual potential targets will be identified or addressed. The most likely *actual* targets will be located within the offender's normal daily awareness space. Ideas developed by Chapin (1974) on human activity patterns still hold true today.

The non-recursive nature of the process of offending is such that there may be persistence in a concentration of offending; there may be a diffusion of offending when neighborhood edges become porous or permeable (See Brantingham and Brantingham, 1975, 1978b, for an early attempt at defining natural neighborhoods with edges of varying levels of permeability. See Frank et al., 2010b; Kinney et al., 2008 and Brantingham et al., 2008a, for more recent work in this area of topology).

An example of the topology of crime as described in the Geometry of Crime is shown in Figure 2. The same rules influencing offender decision-making can produce varied patterns of offending in a Euclidean space. Offenders frequently choose targets near important activity nodes[iii] and along travel routes between the nodes. The same exact rules for target choice are used in each of the four parts of Figure 2. In 2 (a), there is one individual with a home location and a frequent route to a commercial centre of activity.

[-- Insert Figure 2**--]**

For this diagram it is assumed that suitable targets are uniformly distributed along the routine pathway and that there is a random distribution of crimes around the activity nodes and around the route. Figure 2 (b) shows what the pattern would look like for this individual when the activity node location is on the main connector road. Figure 2 (c) has *both* nodes (home and commercial centre) on the main road, producing what is clearly a linear cluster. In the final part of the Figure, 2 (d), the home and commercial nodes are adjacent or overlapping. The associated crime, without any change in the decision or event rules, becomes a string, a single cluster or what many would identify as a hot spot depending on node positions on the road network.

What is shown in Figure 2 is very much like the twisting and stretching of a balloon (Brantingham and Brantingham, 1981: Figure 1.12). The implicit awareness space is identical in a homological sense in all four parts of the figure. Part (a) has the nodes stretched the furthest apart. In part (d) the path or route connecting the two nodes has disappeared at this scale. But the rule stays unchanged.

An overlay of suitable targets could be added (see Brantingham and Brantingham, 1981:37-43). For example, consider an individual with a preference for an attractive commercial node. Now, using the same target choice rule but an alteration in location of attractive targets, the rule produces one cluster of crime, but a cluster that moves. As important, understanding crime patterns (and the value of distance measures) requires consideration of why distance traveled varies between individuals.

Geometry of Crime presents alternative views for individuals, small networks of offenders and aggregate crime. Implicit in Geometry of Crime is a dynamic urban backcloth.

Beyond Geometry of Crime

There is much new theoretical work and research consistent with and supportive of the Crime Pattern Theory and its component parts. Reviewing this growing theory and research domain is beyond the scope of the chapter. The other chapters in this book provide a good overview as well as details of some of these developments. The focus of this chapter is, instead, on complementary and augmenting work being undertaken at the Institute for Canadian Urban Research Studies (ICURS) at Simon Fraser University.

We would suggest that criminological researchers continue to follow research from other fields, ranging from environmental psychology to urban planning, that provides information about how people form awareness spaces and how these are modified. It is worth reading the works of several baseline theoreticians from other disciplines who developed ideas that remain relevant in helping identify emerging patterns. These, in our view, include: Kevin Lynch, Reginald Golledge, William Michelson, and Egon Brunswick. Their ideas about how people learn and use space and place complement criminological theories and research that address emerging and persistent crime and offending patterns.

ICURS theory-based research explores both the criminal event and the persons involved in it. This is done using Royal Canadian Mounted Police (RCMP) “E” Division data for British Columbia and an archive of calls for police service for the City of Vancouver. This is possible under a Memoranda of Understanding (MOU) between ICURS and the Vancouver Police Department and a research MOU between ICURS, the Ministry of Public Safety and Solicitor General (PSSG) and the RCMP "E" Division.

The PSSG/RCMP MOU has made it possible to build large databases and explore, in computationally intensive ways, detailed but anonymized data where individuals are linked to criminal events (among many defined relationships with the criminal event: as victims, as witnesses, and as offenders). It is possible to analyze co-offending and repeat offending patterns. It is possible to analyze the extent to which individuals shift between offender and victim status over time and space. Offender target choice data is joined with detailed, geographically situated socio-economic information and with specific urban form data including streets and land uses. It is possible with this data set to begin to build models of the dynamic urban backcloth and the repeating patterns of individuals acting on and in that backcloth.

ICURS researchers are undertaking a series complimentary research programs focused on understanding people, movement, targets and decisions. These research programs use some new algorithms but are not dictated by any one approach to data analysis. The research is non-recursive and abductive (Peirce, 1903, as cited in Turrisi, 1997). We believe that with growth in computational criminology we have theory and research techniques drawing closer together and that we will be able to see how different research approaches may be addressing different views of the same complex issue.

Directionality in Offending

Awareness spaces are limited and have an orientation. Rengert (1989) was explicit about directionality being a component to journey to crime. We have undertaken some research that looks at the directionality of offending. The basic form of Crime Pattern Theory argues that people develop routines, including routine travel pathways to some major activity nodes. Crimes are more likely to occur along these routes or at these activity nodes. While there is always variation from the routine, under the theory it is more likely that the paths or routes will have a cardinal direction while traveling towards an end goal. That is, with the end goal of reaching a city center that lies to the north, people tend to chose paths and turnings that keep their orientation towards that end goal. Crimes are expected to occur around the start point and the end node, and along the route or path between them. Frank and colleagues (Frank and Brantingham, 2009a, 2009b, 2009c, 2009d; Frank et al., 2010a) find strong support for the directional pull of a dominant regional shopping center/city center in shaping where offenders commit their offences. The directional offending vectors of most individual offenders point toward the dominant node, providing strong aggregate patterns. When there are multiple shopping centers (but no dominant one) within a community their directional pull on different offenders is varied and aggregate patterns can appear chaotic.

In a set of related studies, Frank and Brantingham (2009c, 2009d) find that while low repeat offenders tend to exhibit a single major directionality vector, high repeat offenders may exhibit multiple narrow directional vectors in traveling to their crime sites. Using RCMP “E” Division data for the Province of British Columbia, they found that 80% of the high repeat offenders’ crimes are captured in two radial angles of under 25° each, that is, they have clear directional preferences in seeking targets but have more than one orienting destination node. Frank and Brantingham (2009d) also found that the most prolific offenders exhibit an increase in the number of rays of narrow angles that capture the majority of crimes. This increase is more than expected for the increase in the number of crimes observed and suggests that the most prolific offenders have expanded awareness spaces (Brantingham and Brantingham, 1981).

Work proceeds on improving concepts of directionality and algorithms for measuring directional beyond circular statistics. In particular it is important to consider that most routes followed are bidirectional, and that paths develop between most activity nodes. All loops can be to and from nodes and a home location. Some may be loops along the same route between activity nodes, some may be unidirectional loops. All of these offer a challenge to researchers who must identify destination attractors as well as routes. Initial research is strong in finding identifiable directions towards activity nodes and likely possibility that what appear to be scattered crime may make it possible to identify the major non-criminal activity locations of repeat offenders.

In a complementary research theme, we are exploring the impact of specific land uses and major roadways on patterns of criminal events. This research has emphasized the prominent role that the built environment plays in determining the spatial patterning of crime and disorder events within the urban environment (Kinney et al., 2008; Wuschke, 2008). The pull of major roads and common activity nodes has been found to be considerable within several Metropolitan Vancouver suburbs. At a broad scale, commercial and recreational land uses, and major roadways are associated with a disproportionate amount of criminal events. When investigating these patterns at a more detailed level, it is clear that specific types of land use have stronger influences on the spatial distribution of criminal events. Within the broad category of commercial land uses, we find shopping centres and bars to be associated with higher levels of calls for service, as compared to other types of commercial land use. While residential land use has significantly fewer calls for service per unit, low-rise apartment buildings are associated with more calls per unit than other residential sub-types (Wuschke et al., 2009). At the micro-scale, *specific* bars, shopping malls and apartment blocks report disproportionate rates of calls for service, while other bars, shops and apartments remain relatively free from criminal events (Kinney et al., 2008). Commercial concentrations and major arteries within the built environment are expected to be significant parts of the structural backcloth that shapes crime patterns.

Our Institute is also engaged in building and using simulation models in conjunction with researchers in other universities and in other departments at Simon Fraser University. Two are worth special notice. One was the development of an agent based simulation called *Mastermind* (Brantingham et al., 2008b; Glässer et al., 2007; Brantingham et al., 2005) that makes it possible to explore how agents find their way on road networks and commit crimes when they encounter suitable targets; and how, by intersecting in time and space, they form social networks.

Mastermind has been used with both hypothetical and actual road networks to explore how awareness spaces might be formed. Homes, targets and attractor nodes are placed randomly in Mastermind, but rules on movement can be varied. Movement rules explored to date include: random movement; Dykstra shortest path; and random meandering from the shortest path for a short period of time. The results are revealing. The shape of the road network matters, as does the location of activity nodes. Perhaps, most interesting, random movement away from a Dykstra path appears promising as a model for real offender movement. Limited ($\pm\,\varepsilon$ with maximum values) meandering around a Dykstra shortest path appears to reflect the exploration of surrounding areas to a distance similar to what might be expected in neighborhoods with permeable borders or for people who live within a neighborhood. Totally random and Dykstra's shortest path movement rules show limitations.

In a second related study, Nicolas Malleson from the University of Leeds has undertaken research that directly addresses agent based modeling of burglary (Malleson, 2010; Andresen and Malleson, 2010; Malleson et al., 2010; Malleson et al., 2009; Malleson and Brantingham, 2009). His model simulates agents in a realistic virtual environment who use daily travel behavior patterns. The model has forecasting capabilities to identify high-risk houses. Malleson also has an agent-based model on the formation of new travel paths as activity nodes change.

While each of the studies described above had different short-term research goals and used different tools, the underlying theme has similarities: how and why do people move around differently? What are the aggregate patterns of crime that may be associated to home, routes and major activity nodes? Do offenders reflect wayfinding and directionality in their crime locations? Overall, how can we understand crime patterns better by understanding the structural backcloth of an urban area and associated activity and awareness spaces?

Model and Case Study: Repeat offenders

The model and a test case study described below build on “Beyond the Geometry of Crime” by exploring first a hypothetical and then an actual spatial pattern of repeat offending. A model of repeat offending based on a hypothetical street, home and attractor node structure was built through simulation. This hypothetical model was then compared to the actual pattern for persons who were charged or chargeable for at least 15 crimes in a specific British Columbia city during a four year time period between 2002 and 2006. Results for both the model and the test case are presented below.

The basic model is derived from *Beyond Geometry of Crime*. Activity nodes are placed within the test space. A hypothetical route connecting these nodes using a main road and up to two auxiliary roads is also identified. Within the model, activity nodes and main roads may be randomly placed in the test space. An awareness space is created around these activity spaces using a buffer. The initial model reported here has two major activity nodes and a bi-directional route between these nodes. Expansions of this model will involve development of rules for different buffer sizes under different conditions, a more complex route between the activity nodes, a variable buffer-size based on distance and road-segment and the computational calculation of optimal size when compared to actual data.

The model testing and case study follows four steps: 1) Development of an abstract model for testing of awareness space strength; 2) experimental simulation of repeat offending for classes of nodal points consistent with Figure 2; 3) comparison of repeat offending with random distribution of crime locations; 4) review of repeat offender cases and classification into spatial patterns defined under Figure 2, that is, patterns associated with movement to and away from activity nodes and on or near main roads.

The union of buffer areas around the nodes and the routes forms the awareness space. Crimes are expected to have a higher probability of occurring within the awareness space. Estimated crime locations were chosen randomly from the awareness space. Minimum distances are calculated for all crime locations, both locations under the model and the random crime, from the set of distances to all the nodes and routes connecting the nodes.

The model can be further described according to the following equations:

$$AS = G(v, e)$$

Where AS is the Activity Space and G is the associated Graph connecting the nodes, v, and the roads, e [iv]. This is shown in Figure 3, with there being 6 nodes connected by 5 edges.

[-- Insert Figure 3**--]**

An awareness space AW is constructed by placing a buffer zone, *B,* of a fixed radius around graph G, illustrated in Figure 4.

$$AW = B\left(G(v, e)\right)$$

[-- Insert Figure 4**--]**

Crimes, denoted by c, are expected to be located within buffer *B*, given some perturbations ($\pm\varepsilon$), as shown in Figure 5. Note that in Figure 5, although the majority of the crimes fall into the buffer zone, there are perturbations to the model, unexpected journeys outside of *B*, and some crime locations end up outside *B*.

[-- Insert Figure 5**--]**

For each crime location, a distance, $D°$, can be calculated as follows:

$$D° = \min\{min_{i=0}^{|v|}(d(c, v_i), min_{i=0}^{|e|}\, d(c, e_i))\}$$

where $D°$ is the minimum of all distances to all edges and vertices within the graph, d is the Euclidean distance from crime location c to vertex v_i or edge e_i.

It should be noted that this model did not include a temporal sequence in the analysis for two reasons. Unlike Journey to Crime literature it is not assumed that offenders always start at a home location and that distances should be measured from that point. It is argued that individuals frequently commit crimes from other prior points of relative stationary activity, that is, another primary activity node or some short-term activity node (Wiles and Costello, 2000). As well, our data only includes offenders and their offences which are known to the police. Clearance rates suggest that high repeat offenders with 15+ known crimes have committed many other offences. The time between actual crimes is uncertain.

Experimental simulation:

The model, as described above, was implemented and the theory simulated. The simulation was run 100 times under the abstract model with a fixed buffer distance of one unit, where, as comparison, the entire route was of length 20 units. As shown in Figure 2, spatial patterns under exactly the same decision rules will appear quite different as the nodes move towards main roads and closer together along main roads.

Figure 6 provides a visual representation of the results and the largest dispersion of points (Figure 6a). The dispersion decreases as the distance between activity nodes decrease (Figure 6b-c), and eventually overlap to cluster into what would be called a hot spot (Figure 6d). At one level a visual pattern emerges. At another level of abstract relationships, the pattern is near but only discernable through analysis. The actual patterns in all parts of Figure 6 are homeomorphic or equivalent. Models may be in an abstract space, but analysis of actual crime data is enhanced through consideration of the backcloth.

[-- Insert Figure 6**--]**

[-- Insert Figure 7**--]**

A straightforward measure, the mean and standard deviation of the distances from the road network, was used to test the power of the model for distinguishing between model generated data (Figure 6) and random data (Figure 7).

Comparison with random patterns:

The radius of the buffer zone B is relatively small compared to the entire length of the road-segment. This was found to be true when investigating actual crime patterns (Wuschke, 2008), and hence was built into the model. As can be seen in Table 1: Distance of crimes in the awareness space from roads or activity nodes, when the crimes are clustered within the buffer zone, the mean distance does not change significantly as the two attractors get closer to each other (Figure 6a-c), but significantly decreases when the two attractors are immediately in each other's neighbourhood (Figure 6d). With the two attractors in immediate proximity, there is a significantly reduced journey to crime, with a clustering of crimes near the attractors and home node alike. The reduced journey is shown in the significantly smaller mean distance.

[-- Insert Table 1: Distance of crimes in the awareness space from roads or activity nodes**--]**

Comparing the model to the patterns generated by the uniformly distributed crime locations (Figure 7), the pattern is completely different. As the attractors get closer to each other, and eventually end up in the same neighbourhood, the mean distance to each crime location increases from 3.6 to 9.4 units. Whereas the standard deviations were similar in the buffer zone approach, they increased significantly as the two attractors approached each other. This clearly indicated that the amount of travelling the offender has to do to get to the crime locations would increase as their awareness space decreased. Turned around, the number of crimes located within the awareness space decreased from 4 to only 2 as the two attractors shifted closer. This is not consistent with theory, as it would be expected that as the two attractors move closer, that area becomes more familiar to the offender, resulting in an increase in criminal occurrences in the local area immediately surrounding the nodes. The model (see Figure 6d) captures this expected relationship.

[-- Insert Table 2: Distance of crimes uniformly distributed from roads or activity nodes**--]**

To illustrate the effect of the buffer zone depicted in Figure 6, it helps to add more crime locations. Although Figure 8 shows far too many crime locations for this pattern to be realistic for a single real offender, it can be thought of as the pattern for many offenders living in one neighbourhood, travelling across a city to another neighbourhood (perhaps containing a large attractor, such as a regional mall). Here, the pattern of offenses can clearly be seen. Notice that some crime locations, although red (indicating they're associated to the buffer-zone model) are further than other crime locations in blue (associated to the uniform distribution of crimes). This is a by-product of the $\pm\,\varepsilon$ term of the model, whereby some of the offenders temporarily leave their awareness space to commit a crime just outside of it.

[-- Insert Figure 8**--]**

Review of repeat offender patterns:

This case study looks at patterns that are recognizable with an understanding of the urban backcloth. Pattern recognition is an important research question. Figures 9 and 10 provide a bit more information about advances in pattern recognition. The focus in this chapter is point patterns and directional vectors, not raster imaging. It is suggested that the reader review advances in identifying boundaries and edges in raster images and consider how these tools may be translated into analogous tools for point and vector data. TOPO© uses point/area data to identify neighborhood boundaries and their potential permeability

(Brantingham et al., 2008b, Frank et al., 2010b). This is an analysis algorithm that is similar in many ways to finding a distinction line between black-grey-white.

Figure 9 presents an image of the traditional distinction between random, regular and clustered. We are adding an example of an advancement in cluster analysis (Ester, 2009 - Figure 9: **d**) that statistically identifies clustering across a broad range of shapes.

[-- Insert Figure 9: **--]**

The statistical techniques will continue to improve and, as is shown in the second clustered image, we are beginning to be able to add more constraints on the definition of *clustered*. It is, however, important to be able to place the pattern into context. Figure 10 presents an example.

[-- Insert Figure 10: Crime **--]**

In this figure there are several point patterns illustrating crime locations. In 10(a) the points are random and the major street network is also random. There is the appearance of early stages of the emergence of a clustering on streets within a central triangle and a potential linear cluster along a main road. In 10(b) there are two clearly defined clusters that are dependent on the clustering of roads. Under *Beyond Geometry of Crime*, there would be an assumption (to be explored in operational crime analysis and management) that there are no suitable targets along the main road connecting the two clusters, but people committing crimes could easily travel between the two clusters. Figure 10(c) introduces a river to separate the two clusters. Under these backcloth conditions the pattern shown is likely to be the result of offenders staying on one side of the river, a very different pattern than in 10(b). Figure 10(d) has a road network that is a grid. Here, there are clear clusters and, given this road network, questions should be asked about the attractiveness of the two areas for crime, considering additional dimensions of the urban backcloth. As well, contemporary mobility is different from that of the Shaw and McKay Chicago School period and the crime cluster is likely to be produced by potential offenders who may or may not live near the crime cluster. The distribution of home locations of offenders becomes of particular interest.

When moving from theoretical patterns to actual crime data, interesting patterns emerge. In this case study, all repeat offenders having fifteen or more charged or chargeable offences were selected from the RCMP crime event records (2002-2006) for one British Columbian city. The population of the city and immediate surrounding areas, as reported in the 2006 Canadian Census, falls into the 50,000-100,000 range. Eighteen prolific repeat offenders were identified from within the study area, including seventeen males and one female repeat offender. Figure 11 displays the home nodes, attractor nodes, and event locations of a subset of the repeat offenders included in this study. In order to maintain data anonymity, only major routes have been displayed on these figures. Further, some environmental landmarks have been shifted and edited to prevent the identification of individuals in this study. However, all spatial relationships between key activity nodes and routes have been maintained in order to ensure the accurate representation of the activity spaces of each individual. It is important to note that the scale of each sub-figure is unique to the individual offender and his or her awareness space - while some offenders operate across a small spatial scale, covering a larger geographic area (as with Figures 2(a) and 11(a)), others offend largely within close proximity to their home location and activity nodes (as with Figures 2(d) and 11(d)).

When applying the theoretical and simulation models to actual data, several differences become apparent. Most notably, the majority of repeat offenders reported more than one home node over the four year time span of this study - on average, each offender reported three different home addresses within this timeframe (median = 3, mode = 2). Adding further complexity, several activity nodes are often apparent, typically associated with shopping centers or commercial zones. In spite of this complexity, the general patterns and trends described in Figure 2 (above) hold true for the majority of repeat offenders within this study area.

[-- Insert Figure 11: Nodes, major routes and criminal events for select repeat offenders in study area, mapped according to crime topology.**--]**

Figure 11(a) shows two distinct home nodes and one key attractor node. All three nodes are located off of major routes. Likewise, all three nodes have several criminal events in near proximity. The remaining criminal events are clustered largely on the major routes which link each of these activity nodes. Figure 11(b) reflects the home node located off of a major route, but three key activity nodes located directly on main roads. In this case, offences are largely clustered along the major routes that link home and activity nodes. Figure 11(c) includes the additional movement of the home nodes towards main transportation routes. With three separate home locations and four separate activity nodes, all offences are linearly clustered on main routes linking these activity spaces. Figure 11(d) shows home and attractor nodes clustering in the same local neighbourhood. Here, criminal events are grouped within this same limited geographic area. Notice the increase in scale from Figure 11(a) to 11(d) - as the activity nodes move first closer to the major activity routes, then closer to each other, the awareness space may reduce in geographic area.

All of the repeat offenders identified in this study were classified into one of the four categories shown in Figure 11, or identified as falling into an alternate pattern of offending. Results from this classification are displayed in Table 3. Overall, 83.3 percent of repeat offenders in this study can be classified into one of these four categories. Within this classification system, Category A contains the highest percentage of repeat offenders from this study area (38.8%). Further, a majority of offenders (61.1%) can be classified into either Category A or Category B, having distinct clusters of crime around home nodes, activity nodes, and extended pathways connecting the two locations. These classifications have included a variety of offence types, with each category containing offenders associated with a range of personal and property crimes of varying seriousness. Subsequent case studies will make further distinction between crime type and will consider varying land use and socio-economic conditions associated with the urban neighbourhoods.

[-- Insert Table 3: Classification of Repeat Offenders--]

The backcloth matters. The examples here are consistent with the same simple rule: repeat offenders are attracted towards suitable targets in their normal awareness space. The only key difference between repeat offender crime patterning is the location of the nodes and likely routes for travel. It should be noted that modeling that follows up on these patterns should reflect the evolution of high repeat offenders' awareness spaces over time. In Crime Pattern Theory and the Geometry of Crime, an initial target or victim may be truly opportunistic, but with success, an area (fixed or mobile depending on the type of victim) can form as an attractor on its own or at least produce an expansion in the offender's awareness space (Brantingham and Brantingham, 1981:46).

Conclusions

We are entering into a new period of advancement in theory and research with an understanding of the importance of feedback loops or non-recursive patterns. The growing power of computationally intensive research makes much of this advancement possible. However, we should never lose sight of the ideas of Piaget (1956), Brunswik (1952), Lynch (1960), Golledge (King and Golledge, 1978), Bunge (1962) and Michelson (1977). Before the advent of high levels of computational power these scholars pointed out how people act within their environments or how the environment impacts on human actions. We would like the reader to consider the importance of the urban backcloth and the dynamic, but comprehensible nature of what surrounds us. We are part of the surrounds and should not lose sight of this as new theories and new forms of research develops.

This particular case study of high repeat offenders follows an abductive approach to research that consciously attends the continuous feedback loop between research and theory. Both the abstract model and the detailed histories of repeat offenders indicate the importance of the structural backcloth, but provide insight into both the importance of the unusual and the importance of abstraction.

The high repeat offenders in this research city leave traces of their attraction to high activity nodes such as home and shopping centres, but they are almost exclusively frequent residence movers. With one exception, they appear to move from one address to another once or twice a year. Over the time span of this case study they have no single home address. Figure 10.4 in *Notes on the Geometry of Crime* is an abstract generalization. It applies as a single, temporally stable model for the activity space of most offenders, but must be reformed many times over the course of a criminal career for high repeat offenders. They have many home nodes and many associated work sites, shopping sites and entertainment areas. Their awareness and activity spaces change over time with their residential moves.

In considering the criminal activity spaces of these high repeat offenders, the importance of major roads is apparent. The highways and major arteries seem to dominate their crime patterns. Our current data do not include the offender's mode of transit, but the distances involved are large enough that walking is unlikely to be the means by which most of them to reach their crime sites (specifically, those classified into Categories A and B, in Figure 11 and Table 3).

We will develop additional distance algorithms and awareness space algorithms, but it seems that:

1. Research on distance to crime sites from a major activity node (with Journey to Crime research this is usually the identified home) should consider the number of nodes that could be called homes. Awareness spaces grow from activity spaces, but for repeat offenders evolving awareness spaces feedback and influence future activities. Moving from one home location to another does not necessarily mean that the awareness space around the prior home location fades immediately. A large variation in distance measures may be traces of residential mobility as well as activity levels based on current residential locations.

2. The value of Euclidean distance metrics appears to depend on what is being measured and how the pattern of connection by major roads is addressed. The distance to a major road from both the offender's start point and the intended destination node appears to be an important determinant of that offender's crime pattern.

3. Most importantly, an emergent crime pattern grounded on assumptions about activity spaces and awareness spaces is made much more visible by attention to a city's structural backcloth and the dynamics of its change over time.

The models need to maintain simple, clear rules but allow for variation in the number of activity nodes as well as major roads and multiple shopping locations when there are multiple home locations.

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Table 1: Distance of crimes in the awareness space from roads or activity nodes

Model	Mean Distance	Standard Deviation
Both attractors off main road	0.53974773	0.067881945
One attractor off main road	0.540575228	0.072386986
Both attractors on main road	0.525975803	0.065843532
Both attractors in the same neighbourhood	0.331083279	0.056398839

Table 2: Distance of crimes uniformly distributed from roads or activity nodes

Uniform Distribution	Mean Distance	Standard Deviation
Both attractors off main road	3.58139559	0.381300879
One attractor off main road	4.807426714	0.553986595
Both attractors on main road	6.483122654	0.828113233
Both attractors in the same neighbourhood	9.365986044	0.833335175

Table 3: Classification of Repeat Offenders

Repeat Offenders	Clustering Classification				
	A	B	C	D	OTHER
Count	7	4	2	2	3
%	38.8	22.2	11.1	11.1	16.7

Figure 1: Feedback in Crime Pattern Theory

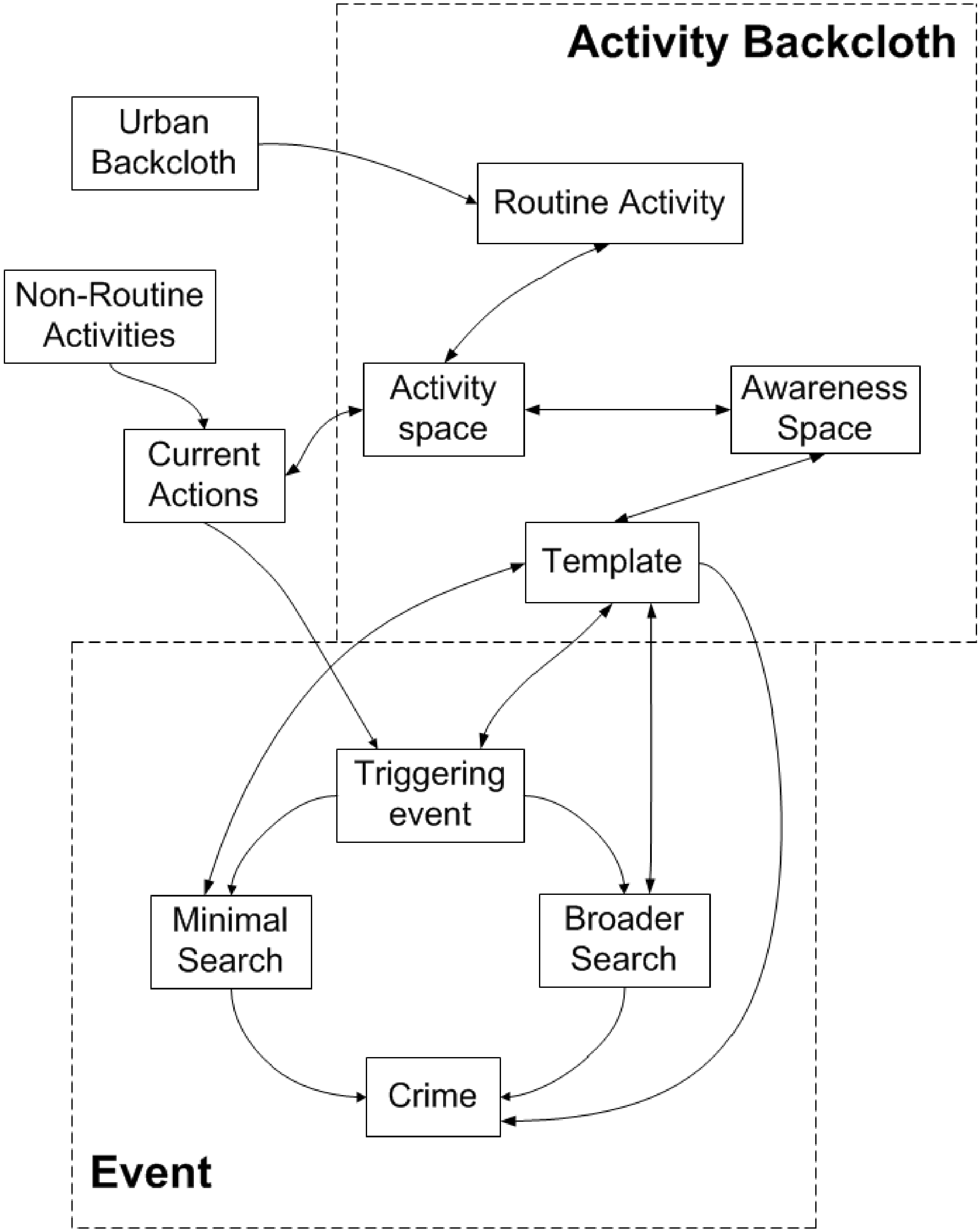


Figure 2: Topology of crime

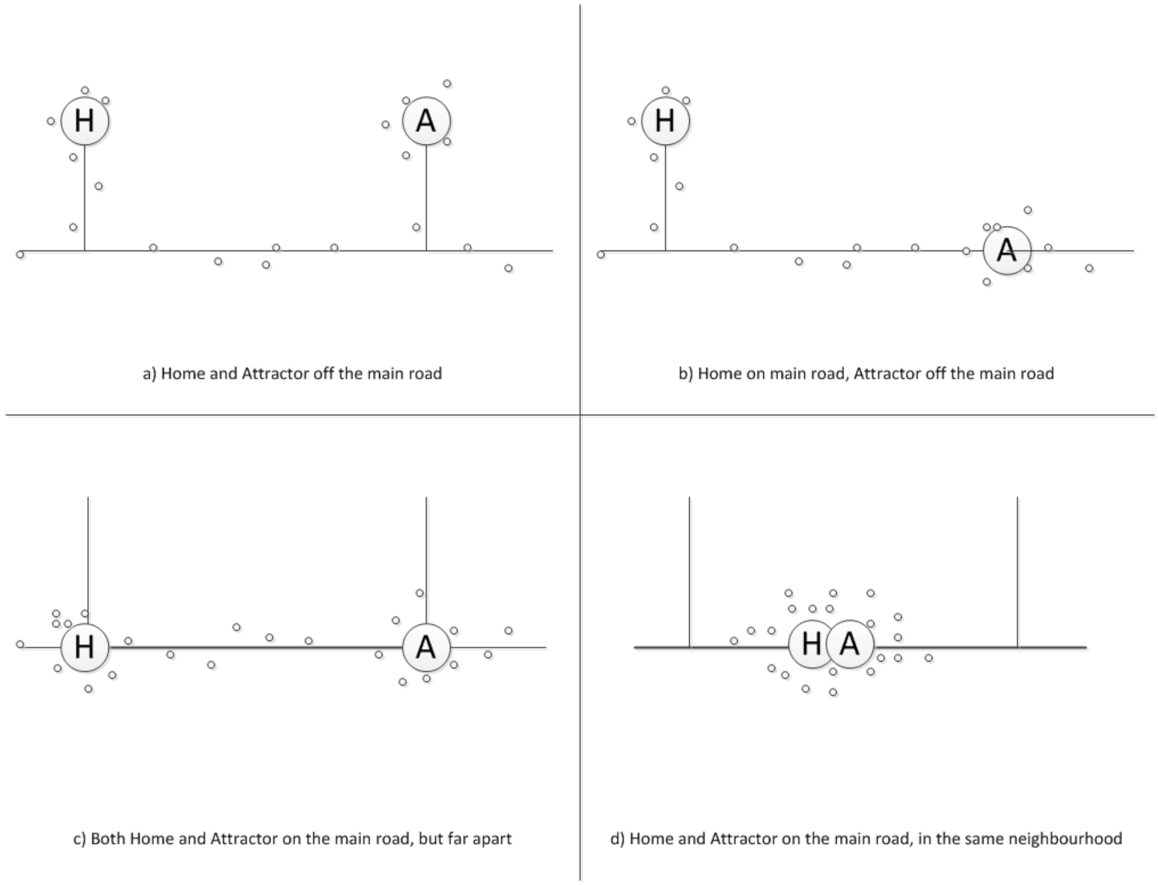


Figure 3: Nodes and edges

Figure 4: Activity space buffer around nodes and edges

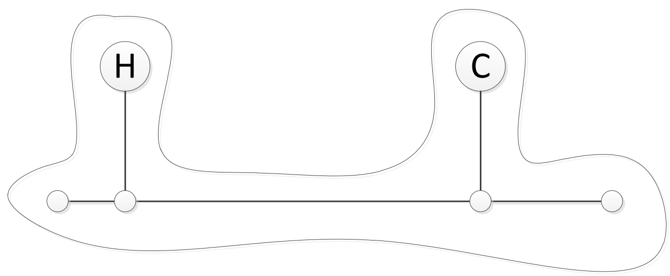


Figure 5: Crimes placed within and around activity space buffer

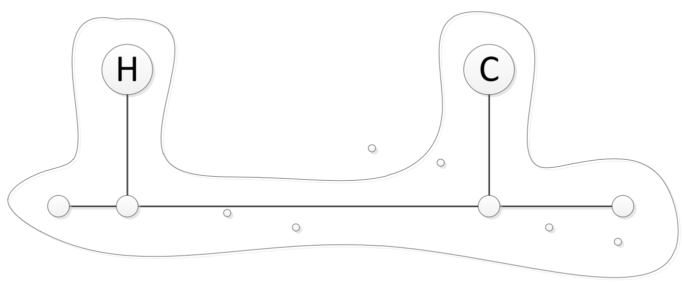


Figure 6: Random distribution of crimes along awareness space

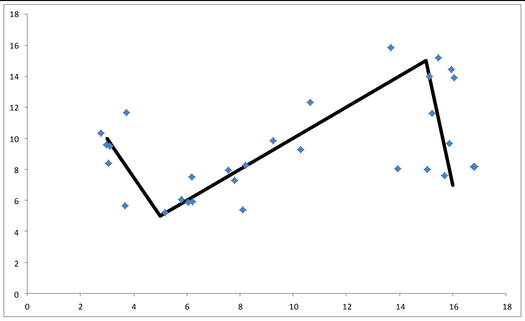
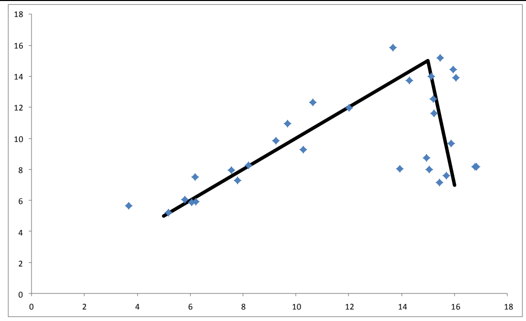
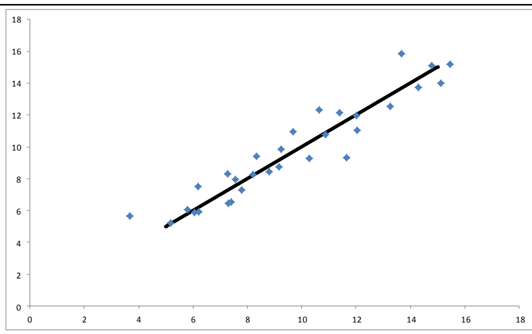
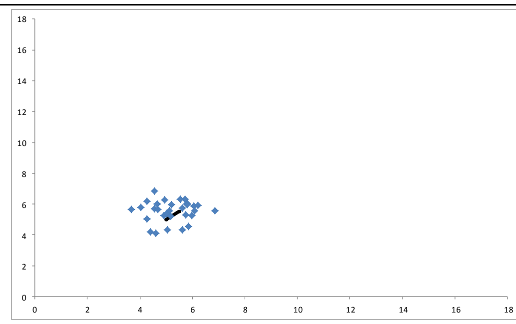
	
a) Crime distribution with 3 road-segments	b) Crime distribution with one of the activity nodes on a major road
	
c) Both activity nodes are on the same road-segment	d) Both activity nodes are very close to each other

Figure 7: Uniform random distribution of crimes in the entire space. Crimes falling into the awareness space are highlighted in red.

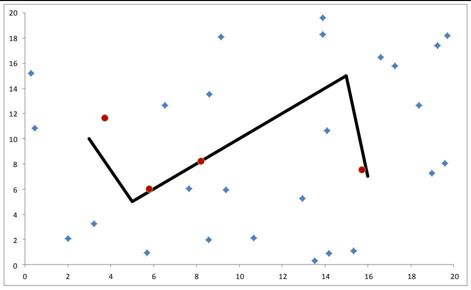
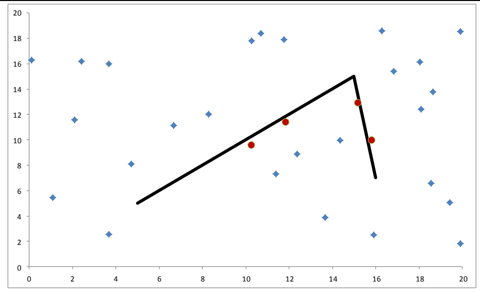
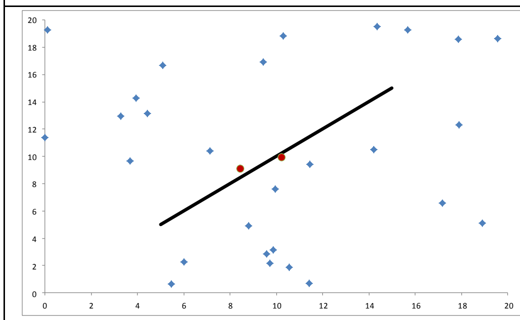
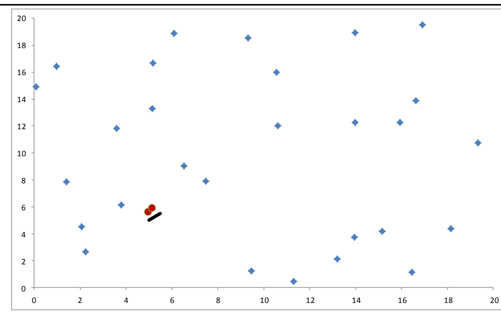
	
a) Crime distribution with 3 road-segments	b) Crime distribution with one of the activity nodes on a major road
	
c) Both activity nodes are on the same road-segment	d) Both activity nodes are very close to each other

Figure 8: An extreme example of the simulation, where all crimes by all offenders overlap. The crimes which fall into the awareness space are shown in red.

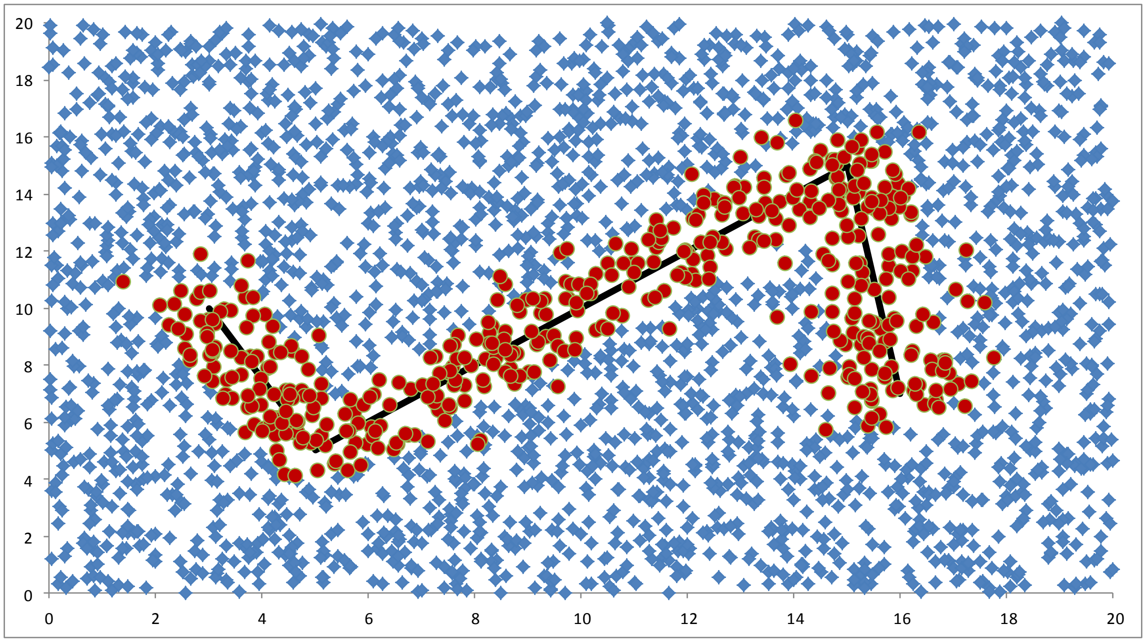


Figure 9: Crime pattern distributions: random, uniform, and two forms of clustered patterns

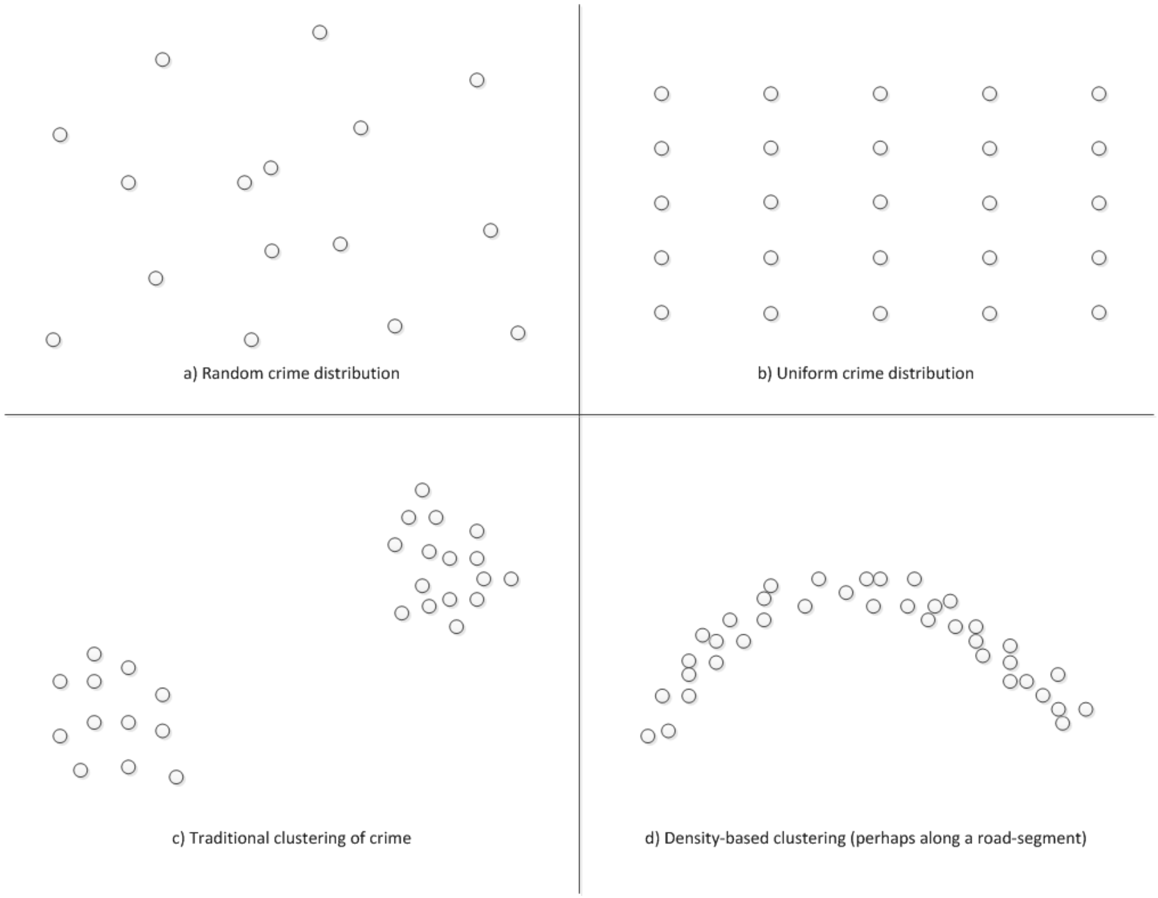


Figure 10: Crime distributions within road networks and built urban environments

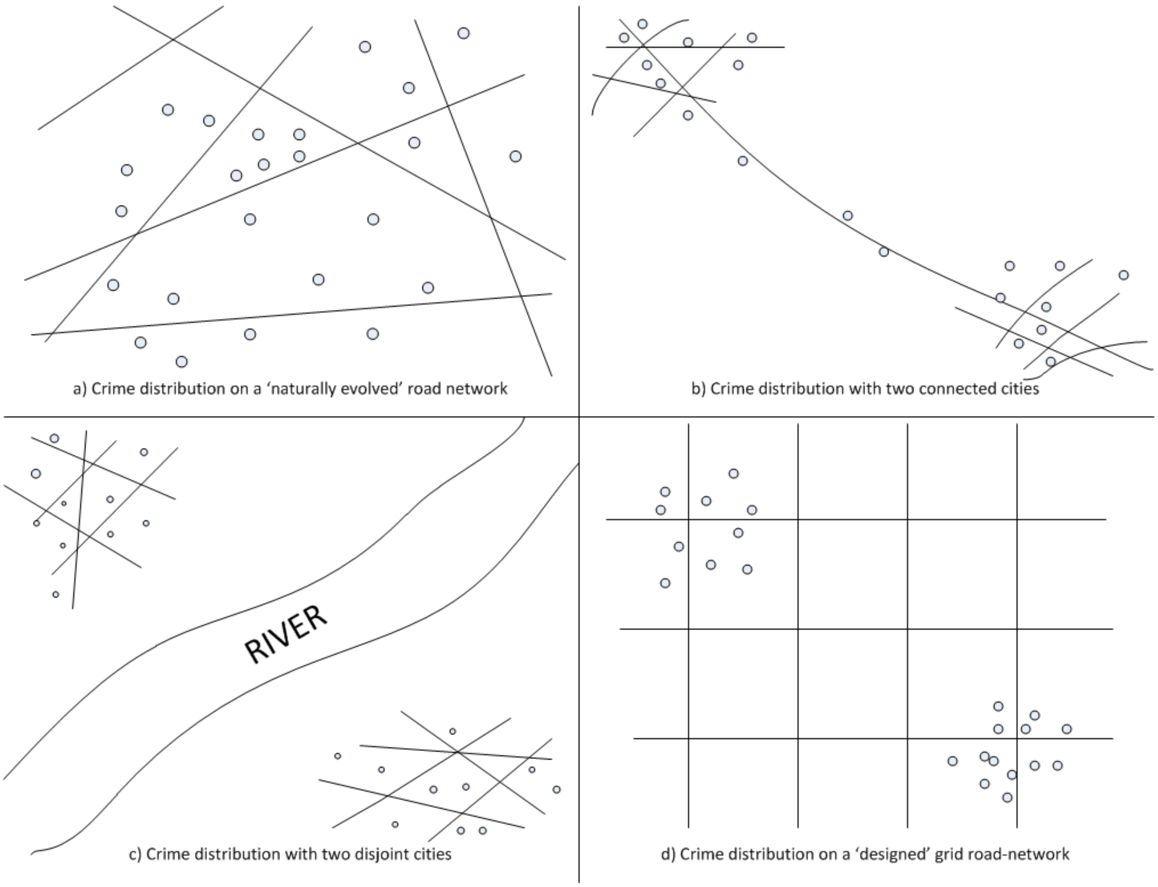
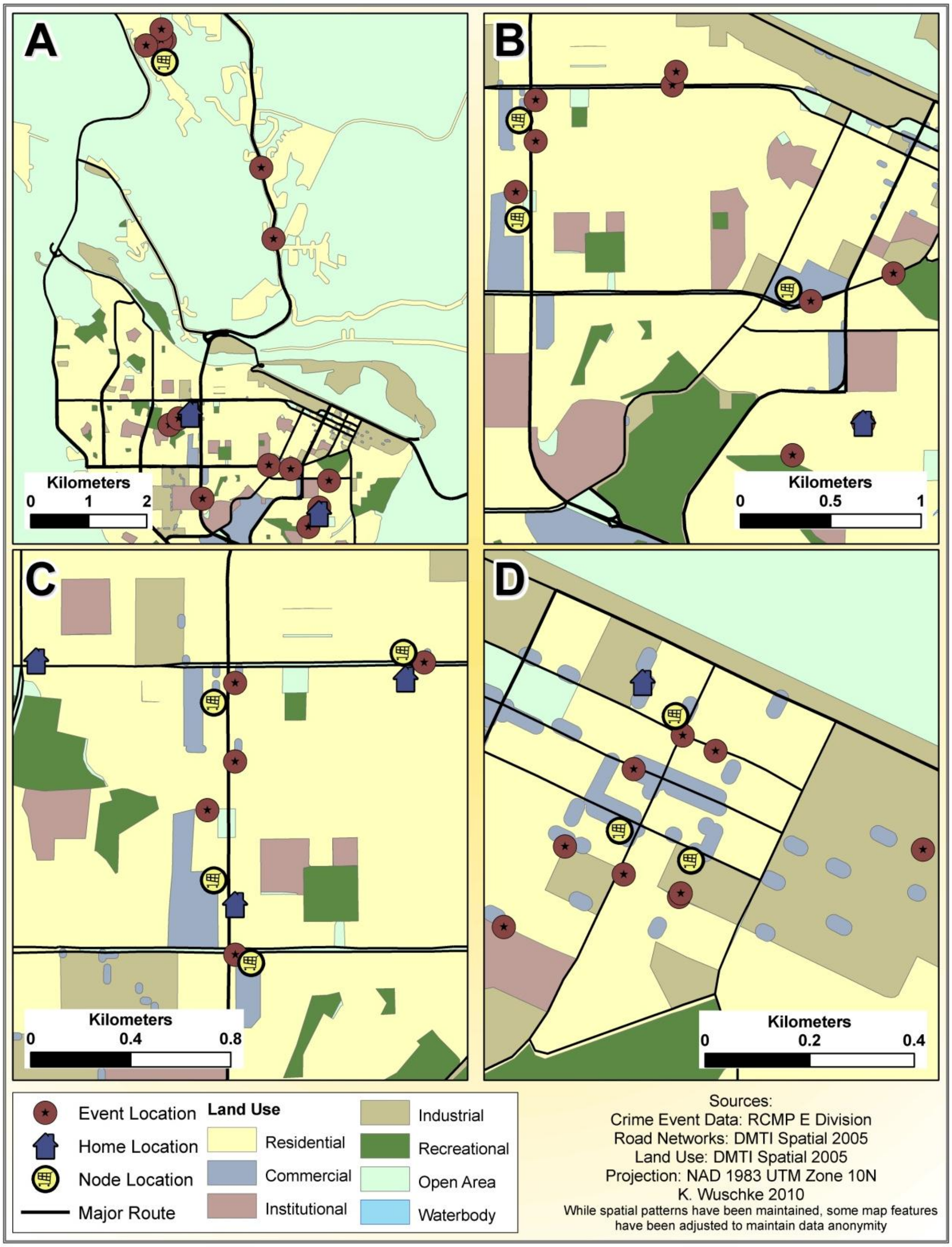


Figure 11: Nodes, major routes and criminal events for select repeat offenders in study area, mapped according to crime topology.



[i] Virtual environment studies in criminology are emerging as a new way to approach decision-making and fear of crime. See Park et al., 2010, for a review of the origins of this type of work and results of several virtual environment simulations.

[ii] The primary publications in this area include Brantingham and Brantingham, 1978a, 1984, 1991; Brantingham and Brantingham, 1981, 1993a, 1993b, 2008; Brantingham and Brantingham, 1995.

[iii] The identification of node types, and the scale used in identifying nodes is an important research and theory issue. These questions will not be covered in this chapter, but the research caution is presented that, while note identification follows an inductive and abductive philosophy of science, care must be taken to ensure that node identification does not become tautological.

[iv] v and e are the usual graph theory notations for vertex and edge. In the language used within this document, they refer to node and road, respectively.