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**Place-Based Simulation Modelling:**

**Agent-Based Modelling and Virtual Environments**

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## Background: The Motivation for Agent-Based Modelling in Criminology

Since the earliest geographical explorations of criminal phenomena, scientists have gradually come to the realisation that crime occurrences can often be best explained by analysis at local scales. For example, the works of Guerry (1831) and Quetelet (1842) – which are often credited as being the first spatial studies of crime – analysed data that had been aggregated to regions approximately similar to U.S. States. The next major seminal work on spatial crime patterns was borne out of the Chicago School in the twentieth century (e.g. Shaw and McKay, 1942) and increased the spatial resolution of analysis to the census tract (an American administrative area that is designed to contain approximately 4,000 individual inhabitants). With the availability of higher-quality spatial data, as well as improvements in the computing infrastructure available to researchers (particularly with respect to spatial analysis and mapping), more recent empirical spatial criminology work can operate at even higher resolutions. The 'crime at places' literature (e.g. Eck and Weisburd, 1995; Weisburd and Amram, 2014) regularly highlights the importance of analysing crime at the street segment or at even finer scales. For example, it has been found that as much as half of all criminal activity can be accounted for by as few as 5% of all street segments (Andresen et al., 2016).

These empirical realisations – that crime patterns vary substantially at micro places – are well grounded in the core environmental criminology theories of: routine activity theory (Cohen and Felson, 1979); the geometric theory of crime (Brantingham and Brantingham, 1981, 1993); and the rational choice perspective (Clarke and Cornish, 1985). Note do editor: could link to the encyclopaedia chapters that cover these theories here Each theory focusses on the *individual-level* nature of crime, the behaviour and motivations of individual people and the importance of the immediate surroundings. For example, routine activities theory stipulates that a crime is possible when an offender and a potential victim meet at the same time and place in the absence of a capable guardian. Hence to properly understand or model this dynamic it is necessary to capture these individual factors. The geometric theory of crime suggests that individuals build up an awareness of their surroundings as they undertake their routine activities, and it is where these areas overlap with crime opportunities that crimes are most likely to occur. These awareness spaces will typically be unique for each individual so, again, to capture this dynamic it is necessary to account for individual heterogeneity. Finally, the rational choice perspective suggests that the decision to commit a crime is partially a cost-benefit analysis of the risks and rewards. Again, to properly understand or model this decision it is important to capture the motivations, awareness, rationality, immediate surroundings, etc., of the individual.

In summary, advances in both empirical and theoretical work point to the importance of modelling *individuals* in the crime system and including a highly disaggregate representation of space (i.e. 'micro-places'). Unfortunately one of the most common methods for modelling crime, regression, is somewhat poorly suited capturing these dynamics. As with most traditional modelling approaches, regression models represent the underlying system through mathematical aggregations. The resulting models are therefore well suited to systems that behave in a *linear* fashion (e.g. where a change in model input leads to a predictable change in the model output) and where low-level heterogeneity is not important (i.e. we can assume that everyone in a particular group of people will behave in the same way). However, as alluded to earlier, the crime system does not necessarily meet these assumptions. To really understand the dynamics of crime patterns, and to be able to properly represent the underlying theories, it is necessary to represent the behaviour of the individual system components (i.e. people) directly. For this reason, many scientists from a variety of different disciplines are turning to individual-level modelling techniques such as agent-based modelling.

**Keywords:** agent-based modelling, crime simulation, travel to crime, virtual environment, NetLogo, virtual laboratory.

## An Introduction to Agent-Based Modelling (ABM)

### Historical Context

Crime occurrences are the result of individual behaviour patterns (e.g. by offenders, victims, guardians, or others). Understanding the causes and consequences of different behaviours and their relationship with crime has taxed criminologists, as well as scientists in related disciplines, since their inception. Unfortunately, the 'traditional' means of modelling social systems, where heterogeneous components are distilled down into homogeneous units, make it virtually impossible to draw any meaningful conclusions about their inner workings or micro dynamics (Batty, 2008), particularly at fine geographical scales.

Agent-based modelling (ABM) is a methodology that reverses the traditional, aggregate, modelling paradigm. It is an interdisciplinary field that has emerged from the study of chaos, complex adaptive systems and computers / computational modelling (Macal and North, 2010; Cioffi-Revilla, 2014). Although the first agent-based model is often credited to the ground-breaking work of Thomas Schelling in the 1960s (Schelling, 1969) – who was later awarded the Nobel Memorial Prize in Economic Sciences, with Robert Aumann, for his work on conflict theory and social simulations (Cioffi-Revilla, 2014) – the field did not begin its rapid rise in popularity until the late 1980s / early 1990s.

Agent-based models (ABMs) evolved from a similar class of computational model called a *cellular automata*. Although both methods centre on simulating the behaviour of individual units ('cells' or 'agents'), agent-based models encompass greater qualitative and quantitative features than their relatively simple cellular automata counterparts. These features – which include individual autonomy, goal-directed behaviour, mobility, and greater environmental complexity (Cioffi-Revilla, 2014) – allow ABMs to be effective at representing complex and self-organising systems (Heath et al., 2009) whose behaviour is driven by individual actors and their interactions. This approach to modelling has been shown to be much more effective at simulating complex systems – where the overall system behaviour is dependent on the interactions between individual units – than traditional aggregate approaches (Schelling, 1969; Epstein and Axtell, 1996; Batty, 2012). ABM of social systems, such as the 'crime system', is one of the most rapidly growing class of computational models (Cioffi-Revilla, 2014).

The popularity of field began to rise exponentially as personal computing (both in terms of hardware and software) removed the historical computational limits on the capabilities of social simulations (Gilbert and Doran, 1994; Gilbert and Conte, 1995). A wealth of diverse models began to emerge; one of the most important being *Sugarscape* (Epstein and Axtell, 1996). *Sugarscape* exemplified the 'generative' approach to modelling social systems (broadly termed Generative Social Science), whereby social phenomena are not pre-imagined but rather *emerge* from the behaviour of the individual agents. This ability of ABMs to 'grow' (Epstein and Axtell, 1996) social phenomena is particularly relevant for modelling spatial crime. It allows the researcher to design a model according to their theoretical understanding of the dynamics of the system (for example by designing agents who respond in a manner that is consistent with criminology theory). They can then run the model to see whether these fundamental rules lead to model outcomes that are comparable to real world observations. In other words, are the theoretical mechanisms able to produce a model that is sufficiently similar to the observed real world outcome? By using ABM as a scientific instrument, it is possible to assess the "generative sufficiency" (Birks et al., 2012) of theory.

#### *What is an agent-based model?*

Despite the volume and diversity of ABMs that have been produced, there is surprisingly no definition that universally describes them. However, many authors are in broad agreement about the major features that ABMs should exhibit (Epstein, 1999; Bonabeau, 2002; Wooldridge, 2009; Crooks et al., 2008; Macal and North, 2010; Crooks and Heppenstall, 2012). These include:

- **Autonomy**. Agents act independently, free from a central controller. They can control their own state and make independent decisions.
- **Heterogeneity**. Agents are not usually identical, neither in their behaviour nor their state. Groups of similar agents might be formed through interactions, but these groups are not pre-determined.
- **Interactions**. Agents can interact with each other, exchange information, and influence each other's behaviour.
- **Environment**. The model contains a space that allows agents to interact. This is not necessarily a geographical space, for example the agents might interact over a network.
- **Reactivity**. Agents can sense their environment and respond to changes.
- **Bounded rationality**. Although agents tend to act rationally to some degree, they should not have full knowledge of the world and hence their rationality is bounded. This allows them to make mistakes.

Although there is a broad agreement that ABMs will include *some* of the components listed above, the application area and research questions ultimately determine the overall form and function of the agents. For example, in their model of street-level drug markets, Dray et al. (2008) used a variety of different agents (drug users, dealers and wholesalers, police constables and outreach workers) who all utilised different behaviours, but the heterogeneity within these groups was limited (e.g. all drug users behaved according to the same set of rules). Similarly in the burglary model published by Malleson et al. (2013), although agents were able to interact with their environment by committing burglary, the agents themselves did not interact. Both of these models are clearly agent-based, even though they do not fully account for every feature listed above.

*The Structure of an Agent-Based Model*

At the most basic level, an agent-based model consists of individual *agents*, and means of allowing agents to *interact*. Typically this consists of some spatial environment in which agents can move around, but does not necessarily need to include geography (the 'space' could be a social network for example). Individual agents are equipped with behavioural rules (discussed in more detail below) that determine how they should behave under a set of given circumstances. Importantly, these behavioural rules can be founded on widely accepted theories. The rules themselves can vary substantially in complexity. Thomas Schelling's famous model of segregation (Schelling, 1969) used agents whose behaviour was determined entirely by a simple count of the number of nearby agents, whereas more recent examples from the field of environmental criminology include advanced behavioural models that represent the main features of contemporary behavioural theories (e.g. Groff, 2007b; Birks et al., 2012; Malleson et al., 2010, 2013).

The process of executing an agent-based model, as depicted in Figure 1, is as follows:

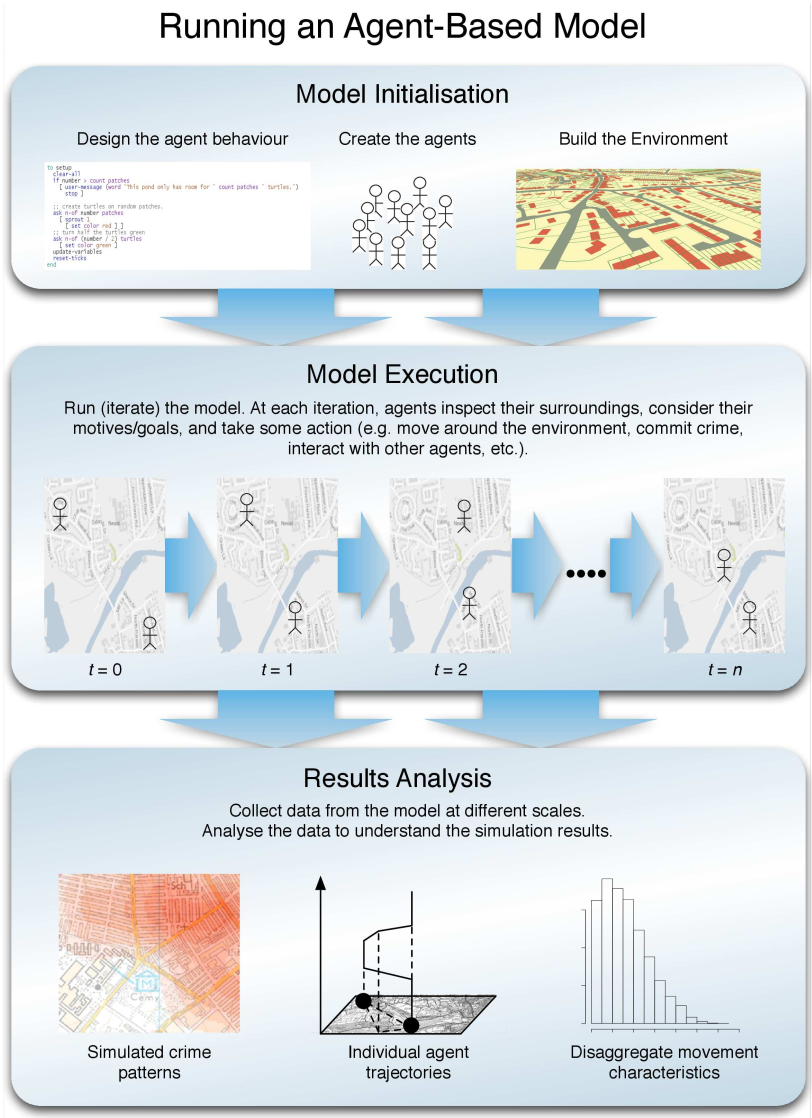



Figure 1: The process of initialising, running, and analysing an agent-based model.

1. To begin with, the model is initialised. This involves creating the individual agents and situating them within a virtual environment. For modelling spatial crime this environment will typically contain the features that are necessary to allow the agents to behave in a suitable manner, e.g. some combination of buildings, nodes/anchor points, transport networks, etc.

2. Time in agent-based models is usually represented as a series of discrete steps called *iterations*. Each time the model iterates, every agent is able to assess its surroundings, make some decisions, and perform some action. Therefore executing the model involves iterating it until some predetermined condition has been reached. These conditions could include a certain number of crimes having been committed, a certain amount of time having passed, or once the model has reached equilibrium. The video available at

https://www.youtube.com/watch?v=5ySbS075MyA

presents a visualisation of a running agent-based model. This example visualises a model published by Malleson et al. (2010, 2013) and will be discussed in greater detail below.

3. Once the model has finished running, the results can be analysed. This is usually a much more complicated process than that of analysing results from traditional statistical models. This is because ABMs can produce a huge amount of information about the different elements of the system. For example: the model might report the times and locations of crime events for

aggregate analysis; it might report the detailed movement traces of all agents for an analysis of how the agents move around the space; or it might report statistics such as the average journey to crime curve, rates of repeat victimisation, etc.

It is important to note that a huge volume of work has emerged regarding the means of designing, building, and analysing agent-based models. This short entry cannot touch on most of these important developments. For a generic introduction to building reliable agent-based models, the interested reader could refer to Railsback and Grimm (2012) or Gilbert and Troitzsch (2005) for a broader introduction to social simulation.

Representing Agent Behaviour

One of the most important (if not *the* most important) aspects of an agent-based model is the behaviour of the agents. Ultimately the results of the model fundamentally depend on the behaviours of the agents, so it is vital that the rules are appropriate. The rules themselves depend heavily on the research question – in some circumstances very simple agents will be appropriate, whereas under other circumstances it might be necessary to implement a higher degree of complexity in decision making. Human behaviour is extremely diverse, which poses problems for researchers who need to define formal mathematical rules to emulate cognitive processes. Individuals can possess complex and diverse personality traits, wildly different past experiences, varying levels of knowledge, and complicated emotions that can give rise to behaviour that can seem irrational at best and entirely random at worst. Attempting to simulate any aspect of this cognitive mess might seem entirely foolish. Fortunately, however, it is not necessary to simulate the entire spectrum of human behaviour. Indeed it would probably be foolish to attempt to. Instead, the research questions can be used to define precisely which aspects of human behaviour are important to model, and to what level of detail. For example, the offender agents in the model implemented by Hayslett-McCall et al. (2008) only have the behaviours that are important in defining the key research area that the authors are exploring: that of the journey to residential burglary. The decision to burgle is affected by features such as *motivation* (i.e. how motivated an individual might be to commit a burglary), *desireability* (i.e. the extent to which an agent perceives a target as desirable) and the degree of *guardianship*. It is not necessary to over-complicate the model with further behavioural complexity, as this would not contribute to a better understanding of the underlying question (Elffers and van Baal, 2008). Indeed, by thoroughly reviewing the relevant theoretical literature and empirical results, the behaviour of the agents can be designed to explicitly represent the factors that are deemed to be important. Interestingly, if the model fails to represent the underlying system properly then it might be because the underlying theoretical explanations themselves are at fault (a point that we will return to later).

For models with relatively simple behaviours, simple rules are often sufficient to determine how an agent should behave in a given situation. For example, the following threshold-based rules, adapted from Kennedy (2012), illustrate how an agent who has a certain level of hunger might decide whether to concentrate on finding food or on doing something else:

```
IF hunger IS ABOVE hunger_threshold THEN search_for_food
OTHERWISE do_something_else
```

One of the most interesting aspects of ABM is that even simple rules such as the one above can lead to unexpected model outcomes. Often it is the *interactions* between the agents that are important, not purely the behaviours themselves. That said, models of spatial crime will typically include more advanced features than the simple threshold-based rules outlined above. Fortunately, a number of *cognitive frameworks* exist that reduce the difficulty of implementing relatively advanced behavioural models. Probably the most commonly used architecture is "Beliefs-Desires-Intentions" (BDI: Bratman et al., 1988) where *beliefs* represent the agent's internal knowledge of the world (i.e. its memory); *desires* represent all the goals that the agent is trying to achieve; and *intentions* represent the most important goals that the agent chooses to achieve first. Although the BDI architecture has been widely used, it has also suffered some criticism due mainly to its reliance on practical reasoning. No action is performed without some form of deliberation (Balzer, 2000) but people rarely meet the requirements of such rational models (Axelrod, 1997).

A less widely used architecture is "Physical conditions, Emotional states, Cognitive capabilities and Social status" (PECS: Schmidt, 2000). Schmidt proposes that it is possible to model the entire range of human behaviour by accounting for those four factors. PECS has been put forward as an improvement over BDI because it does not assume rational decision making and is not restricted to the relatively restrictive factors of beliefs, desires and intentions (Schmidt, 2000). Instead, PECS individuals are imbued with a number of competing *motives* (such as "clean the house", "eat food", "raise children", "sleep" etc). Each motive has an associated strength, that changes depending on the circumstances of the agent, and whereby the strongest motive ultimately drives the agent's behaviour. The factors that can influence a motive strength include the agent's internal state (an agent with a low energy level might feel hungry) as well as other external factors (e.g. an agent who smells cooking food might become hungry even if they do not have low energy levels, or might choose to eat simply because it is a time of day at which they would normally eat). Personal preferences can also come into play, where some people feel a need more strongly than others even though their internal state variable levels are the same. Using PECS, extremely complex motives that require considerable deliberation can be included as well as more instinctive reactions that require only minimal rational decision making (such as pulling a hand away from a burning object).

In criminological studies that use agent-based modelling, the approach to defining agent behaviour is diverse. Although there has been some limited use of PECS (see Malleson et al. 2010, 2013) in most studies (e.g. Birks et al. 2012, 2013; Dray et al. 2008; Groff 2007a,b; Hayslett-McCall, 2008) no explicit behavioural framework is used. Instead bespoke rules are created as needed, in a similar manner to those of the threshold-based approach discussed above. These include rules that trade off the possible gains of committing a crime with the risks, procedures that allow agents to construct a memory of the places that they have visitted, and algorithms that determine how they should navigate the environment. For example, the probability of an agent offending at a given location and time in the model published by Birks et al. (2012) is the product of their motivation, the attractiveness of the potential target, and the offender's awareness of the target:

$$p\ (\text{offend}) = p\ (\text{motivated}) \times p\ (\text{attractive}) \times p\ (\text{aware})$$

**Representing Space in Agent-Based Models**

In the study of place-based crime, the design of the virtual environment is, obviously, extremely important. The way that the environment is represented in a model and the features that are included will determine the types of patterns that the model is able to create. Geographical Information Systems (GIS) are an invaluable tool for the study of spatial crime patterns (Chainey and Ratcliffe, 2005), and the incorporation of GIS with ABMs is an important step towards allowing models to more accurately represent the spatial context that the crime system is embedded in. That said, an accurate spatial environment is not a pre-requisite for a place-based crime model, and some authors go as far as to say that accurate spatial representations detract from the core aims of an agent-based crime model because the additional complication that they bring makes it more difficult to understand the underlying behavioural rules and interactions that drive crime patterns (Elffers and van Baal, 2008). As noted by Axelrod (1997), if the goal of a simulation is to better understand the underlying dynamics, then it is the fundamental model assumptions that are important, not the accuracy of the surrounding environment. Therefore the following discussion will provide an introduction to the two main mechanisms by which space is included in agent-based crime models. It will draw on two specific examples, one using an abstract environment (Birks et al., 2012) and another using a more realistic, GIS-inspired environment (Malleson et al., 2013).

### 3.1 *Abstract Representations of Space*

One of the advantages of ABM is that it is extremely well suited to exploring how the interactions and behaviours of individual people can lead to the emergence of interesting phenomena, such as crime occurrences. In many circumstances, a highly-detailed representation of the world is not a necessary part of the model. It might be sufficient to provide a relatively simple, *abstract* space within which agents are able to move around and interact with each other.

Arguably the most famous example of an agent-based model with an abstract environment is Thomas Schelling's model of residential segregation (Schelling, 1969). The model concisely demonstrates how individual choices made by agents lead to the emergence of unexpected macro-level patterns. In Schelling's model there are two types of agents, here represented by blue and red counters, as illustrated in Figure 2. Each agent is autonomous and contains a desire to live in a neighbourhood (defined by its 8 surrounding cells), that has a percentage of neighbours who are of the same type. In the example illustrated by Figure 2, this preference is set to 50% – i.e. to be 'content', an agent must live in a place where at least half of the surrounding agents are of the same type as itself. Time in the model is represented by the variable $t$. When the model is initialised ($t$=0), the agents are randomly distributed across the space. At each iteration of the model, each agent examines its neighbours and determines whether or not there are a sufficient number who are of the same type. If this number is less than 50% then its preferences are not met and the agent moves to any of the unoccupied cells. As the model iterates ($t$=1, $t$=2, and so on) the agents move around until they reach a point that they are all satisfied and none choose to move ($t$=$n$). The most interesting outcome of the model is that segregation emerges even when agents have relatively low preferences for similar neighbours. In the example illustrated here, agents are content for nearly half of their neighbours to be of a different type, and yet the model results in extremely segregated neighbourhoods. Therefore, although the environment is a long way from realistically representing the real world, by observing how the behaviours and interactions of agents across space play out, it is possible to draw hypotheses about real patterns of segregation; namely that segregation might occur even when people have low preferences for people of a similar type. There is evidence that such mild tastes and preferences for certain neighbourhood types can lead to the emergence of real-world segregation (Benenson et al., 2002), so even this simple model might be reliably representing particular facets of human behaviour.

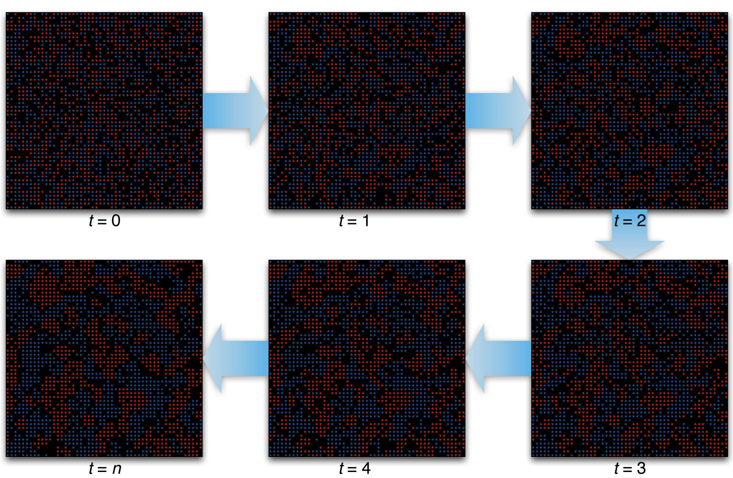



Figure 2: An example of the results of Schelling's segregation model with *similar preference* set to 50%. Model generated using NetLogo software (https://ccl.northwestern.edu/netlogo/).

[inline]Note to Editor: here I could include a box with instructions about how to download and run this model. It is cross-platform and freely available. Is that appropriate?

The use of abstract environments, such as that illustrated above, is common in agent-based crime models – for example Dray et al. (2008) explore drug market dynamics in Melbourne and Liu et al. (2005) design a model of street robbery in the city of Cincinatti – but this section will discuss one model in particular: that of Birks et al. (2012). This model is chosen because it exemplifies the *exploratory* approach to ABM by directly testing the "generative sufficiency" of various environmental criminology theories in an abstract agent-based model. In other words, it answers the question: are the underlying theories sufficient to produce a system that echoes the dynamics of the real crime system? If the answer is 'yes', then there can be greater confidence in the applicability/reliability of the theories, if 'no' then there is evidence that they might need refinement.

The Birks et al. (2012) model attempts to simulate residential burglary and consists of a virtual environment that contains navigational nodes (a proxy for a transport network) and potential targets (houses). Every time the model is executed, the environment is randomly re-generated. This minimises the environment-specific impacts on the results (Birks et al., 2012). The model contains one type of agent: potential offenders. The behaviour of the agents has been designed so that they are consistent with three fundamental environmental criminology theories. These rules dictate how they move and encounter targets (*routine activities*), choose to offend (*rational choice*), and learn about their environment (*crime pattern theory*). Importantly, each of these behaviours can be deactivated, so that the agents no longer behave in line with the specification for a particular theory. If the results of the model no longer share the characteristics of real-world burglary patterns, then the model has provided some evidence that the theories are a necessary part of the offender behaviour and thus reliable. On the other hand, if a theory is deactivated and the results are still plausible, then perhaps the theory is not an important aspect of the underlying behaviour of the burglars.

To quantify the reliability of the model results (i.e. to determine how similar the results are to real burglary patterns) the authors compare three characteristics of real and simulated burglary data:

1. Degree of *spatial clustering* using the Nearest Neighbour Index;
2. Distribution of *repeat victimisation* using the Gini coefficient;
3. *Journey to crime distances* using the journey to crime curve.

A model that accurately captures the dynamics of the real burglary system will produce data that share similar characteristics (as defined by the three statistics above) with real world burglary data. Ultimately the authors find that although each theory improves the accuracy of the model, *rational choice* has a lower influence than *routine activities* or *crime pattern theory*. Therefore although the model environment does not represent a real place, and the results could not directly be used to inform crime prevention strategies, the use of an abstract environment reduces the additional complexity afforded by a complicated (realistic) spatial environment and allowed the authors to concentrate entirely on the *theoretical mechanisms*.

*Accurate Spatial Environments*

The Schelling (1969) and Birks et al. (2012) models demonstrates how ABM can be a valuable tool for exploring how behavioural theories might play out in the real world. Their spatial representations are a long way removed from the real world, but are able to represent the *characteristics* that are necessary to situate the behavioural theories. Although the results from models such as these add to our broad understanding about the underlying mechanisms that drive a system, they have limited *direct* practical value. Of course a better understanding of broad offending behaviour can inform crime reduction policy, but such models cannot assist planners with understanding how crime patterns *in specific streets or neighbourhoods* might vary with changes in policy or changes to the physical/social landscape in an area. To do this, agent-based models require a spatial environment that more realistically represents the real world. Models that fall under this category are often termed *predictive*; they are used to make predictions about the current or future state of a real system.

As with *explanatory* crime models, predictive models are also popular. For example: Hayslett-McCall et al. (2008) have an developed agent-based burglary simulation situated in the city of Dallas, Texas; Elizabeth Groff developed a number of street robbery simulations that are situated in Seattle (Groff, 2007b, 2007a; Groff and Mazerolle, 2008a; Groff, 2008); and Park and Buckley (2015) have developed a residential burglary simulation in a three-dimensional geographical environment. Whilst any of these could be used as examples in the following discussion, the focus will be on a burglary model produced by the lead author and colleagues (Malleson et al., 2010; Malleson, 2012; Malleson et al., 2013). This model is described in some detail in order to illustrate the ways that high-resolution spatial data coupled with advanced behavioural frameworks can be used to represent the crime system in a high degree of detail and to potentially influence policy at a local level.

The aim of the burglary simulation was to create a model that was able to reliably represent part of a real UK city, configure the model so that it reflected real spatio-temporal residential burglary patterns, and then alter the virtual environment to forecast the impacts of real local authority plans on the spatial distribution of burglary. For these reasons the virtual environment needed to include all of the *important* features of the "environmental backcloth" (Brantingham and Brantingham, 1993). In this case, the environment included the following:

- A **transport network** of roads to be walked or driven along. Transport networks are important in a geographic crime model because they restrict the agents' movements to certain paths and influence how they navigate the city and ultimately where they can go. The Ordnance Survey Integrated Transport Network (ITN) MasterMap layer was used. The ITN consists of line objects that represent all the different types of roads, including alleyways, motorways, pedestrianised areas, etc. Using these data it was also possible to vary the speed that agents travel around the environment based on the transportation available to them; agents with cars were able to travel quickly along major roads but more slowly along minor, residential streets. Such travel behaviour is an important way for the agents as they build up a cognitive awareness of their surroundings (discussed below).
- **Individual buildings** that act as the targets for burglary, the residences of the offender agents, and the locations of 'social places' (places where agents might go to socialise) and 'drug dealers' (locations that can be used to purchase drugs). Here, Ordnance Survey MasterMap data were used to represent the physical environment to a high degree of detail. Figure 3 illustrates some of the physical objects that are available. These data were used to create buildings with a realistic spatial footprint and to estimate factors such as *accessibility* (a measure if how easy it is to gain entry to the house) and *visibility* (the level of visibility of the house to neighbours and passers-by).
- **Communities** to represent the social factors that might influence a burglary decision. One of the influences of the community type will be to determine whether a property is likely to be occupied at a given time, and who might be present on the street (i.e. a measure of guardianship). Different groups of people exhibit very different routine activities, such that houses in an area predominantly habited by university students will have very different occupancy patterns to those that are predominantly habited by families with small children (for example). In the model, data from sources such as the UK Census and other administrative data (such as the Index of Multiple Deprivation) were used to estimate these factors. Another important aspect that can be accounted for in the communities layer is that of *community cohesion*. There is a body of evidence that suggests that residents in cohesive communities are more likely reduce the attractiveness of properties in the area (Sampson et al., 1997) and therefore variables were created to represent: *concentrated disadvantage*; *residential stability*; and *ethnic heterogeneity*.

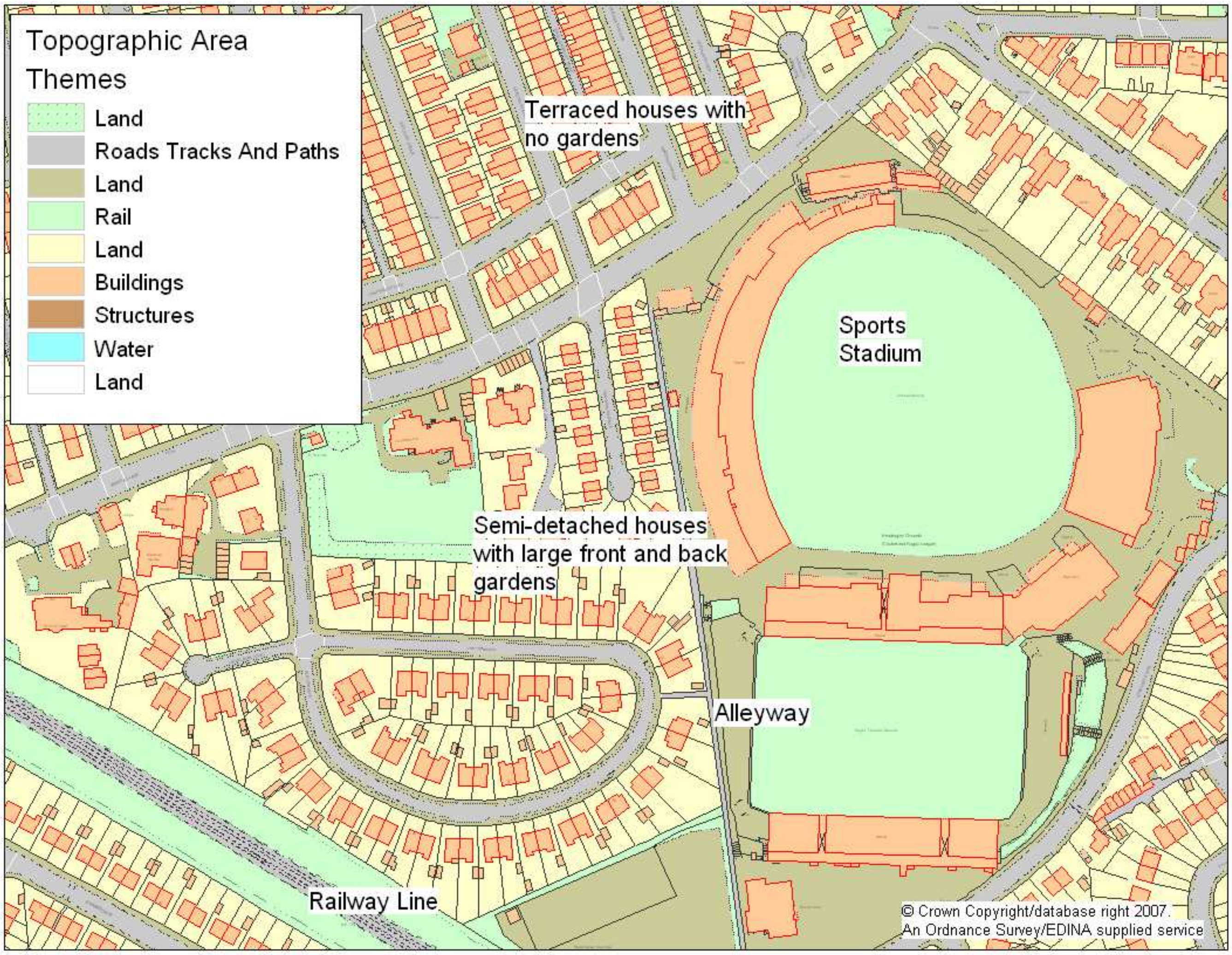



Figure 3: An example of the Ordnance Survey MasterMap Topography layer. Taken from Malleson (2010).

As a demonstration of the effectiveness of agent-based crime models with realistic transport networks, Figure 4 illustrates the difference that a public transport route can have on simulated burglary patterns. A single agents exists who can be allowed to use a simple public transport network or not. When the agent has access to public transport they use the service to travel between their home, their drug dealer and a place that they visit to socialise. Due to the differing awareness spaces created by different public transport methods, the locations of burglaries are much more heavily clustered when the agent uses public transport. This is because they are less aware of the overall simulation area because they have not explored it as they would do if there were no public transport availability. This seemingly simple result is significant because it demonstrates how an agent-based model can cleanly account for criminology theory such as crime pattern theory and routine activities theory.

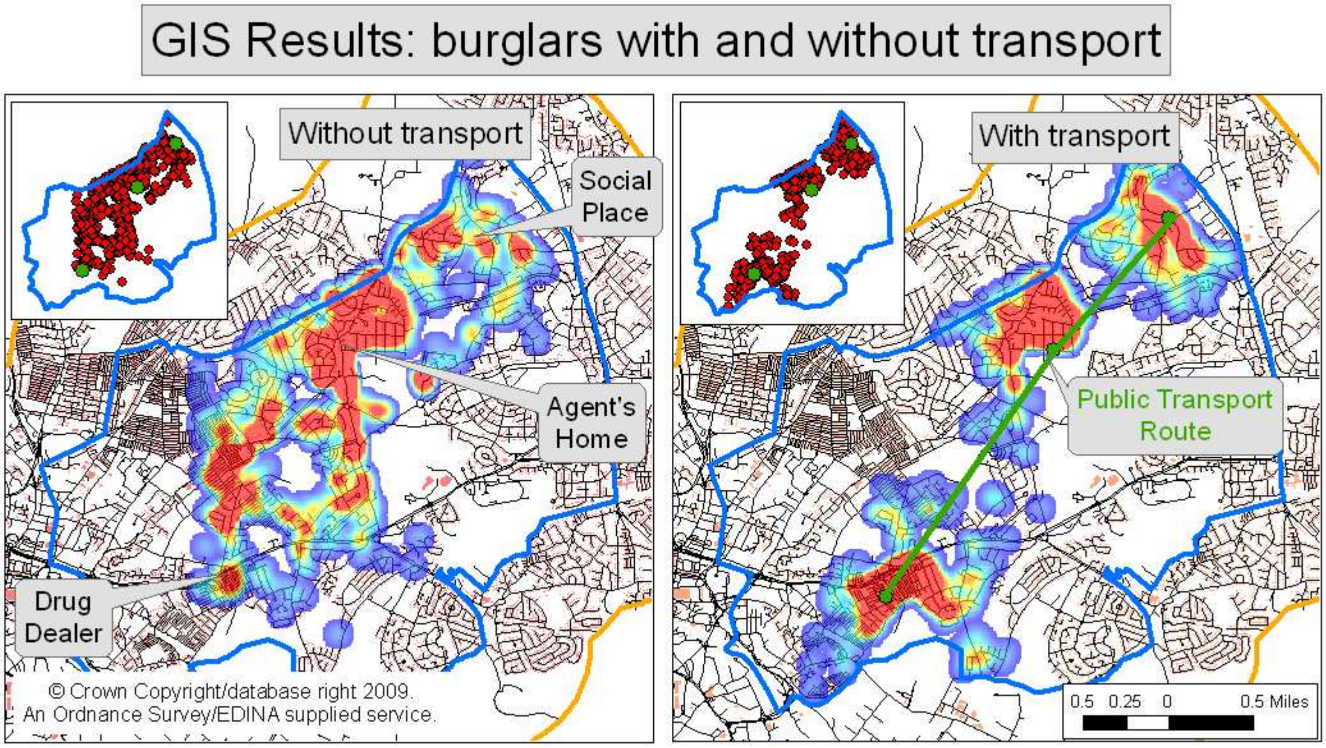



Figure 4: An example of the impact of public transport on the hypothetical burglary patterns caused by a single burglar agent. Red and yellow areas highlight the places with the most burglaries. When the agent has access to public transport, their routine activities are more limited to the streets surrounding transport stops and therefore – because they first attempt to target houses that they are aware of – their burglaries are clustered around the points at which they enter or leave the transport system. When they do not use public transport, they tend to build up a greater awareness of the environment and their burglary locations are more spread out.

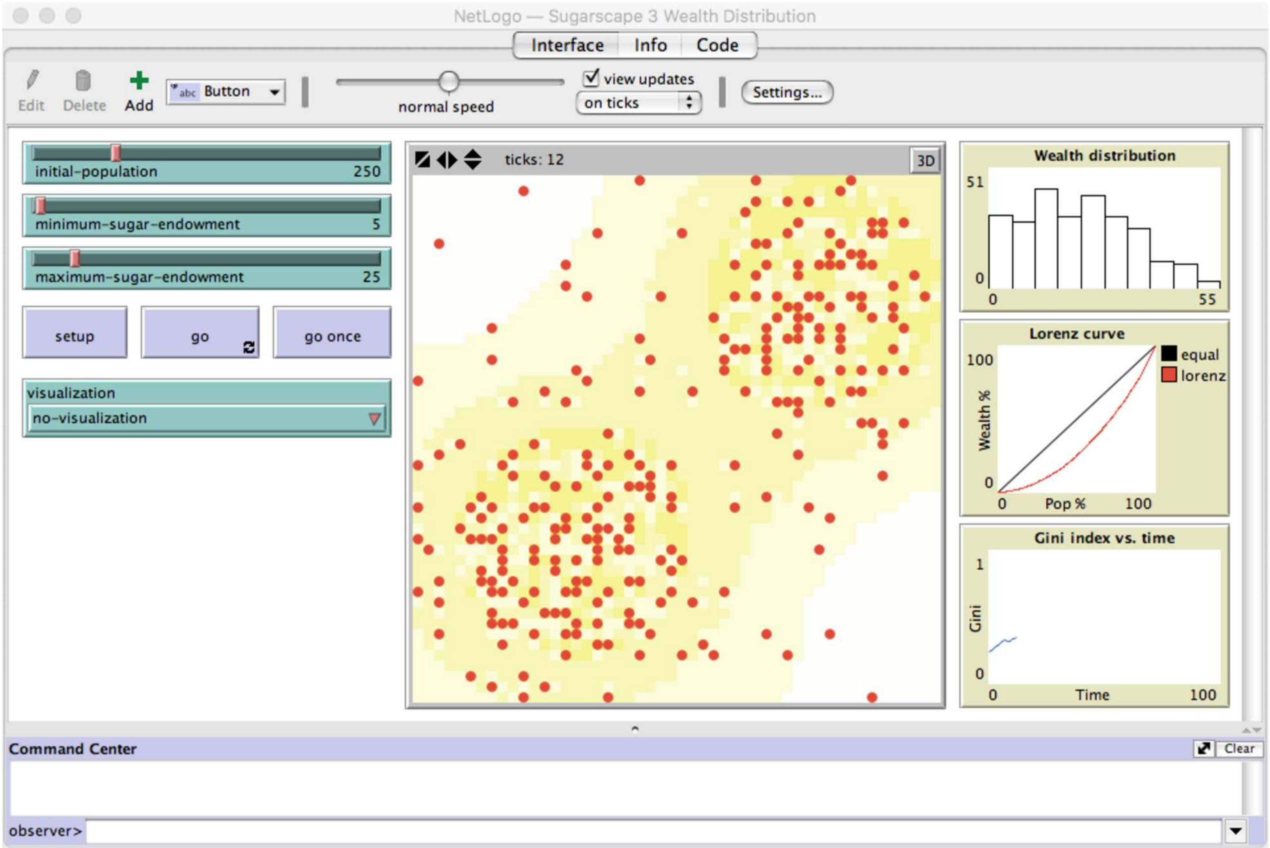
As with other agent-based crime models such as that of Birks et al. (2012), offender agents in the Malleson et al. (2013) model have been imbued with behavioural rules that replicate environmental criminology theories. It is important, however, to include an appropriate level of complexity – too simple and the agents might be unable to represent behaviour to an appropriate degree of realism, too complex and the model becomes no easier to understand than they real system that it is based on. Theory suggests that it is important for burglar agents perform realistic daily activities in order to build up an accurate picture of the virtual environment (an "awareness space") from which they subsequently choose burglary targets (Cohen and Felson, 1979; Brantingham and Brantingham, 1981, 1993). Therefore behaviours are required that support these typical routines. In the model outlined here, the PECS behavioural framework was used to control the agents. Each agent had three different motivations, and the strength of these changed depending on the circumstances of the agent. The three motives for the agents were: *drug use* (a common motivation for burglary in the study area at the time); *sleep* (everyone needs to sleep, and this motive has the effect of pulling agents back to their homes thus creating more realistic awareness spaces); and *socialising* (agents have a need to socialise occasionally). Clearly this is a vast simplification of the rich variety of needs that affect a real person but they are sufficient to create realistic daily behaviour and to represent the theoretical requirements.

Another important agent component is the *cognitive map*. As an agent navigates the virtual environment, they keep a record of the houses (and the communities that the houses are situated in) as they pass them. This allows two important characteristics of the burglary system to be included. Firstly, the agents' cognitive maps will be more detailed around their homes and the places they visit on a regular basis (as illustrated in Figure 4). Therefore these areas are more at risk of burglary simply because an agent is aware of the opportunities that they present. Secondly, the ‘near repeat hypothesis’ (Johnson et al., 2007) suggests that following a burglary, the victim and their neighbours have a heightened burglary risk for a short time. As agents in the model remember where they have been, it is possible to increase the likelihood that they revisit recently victimised properties.

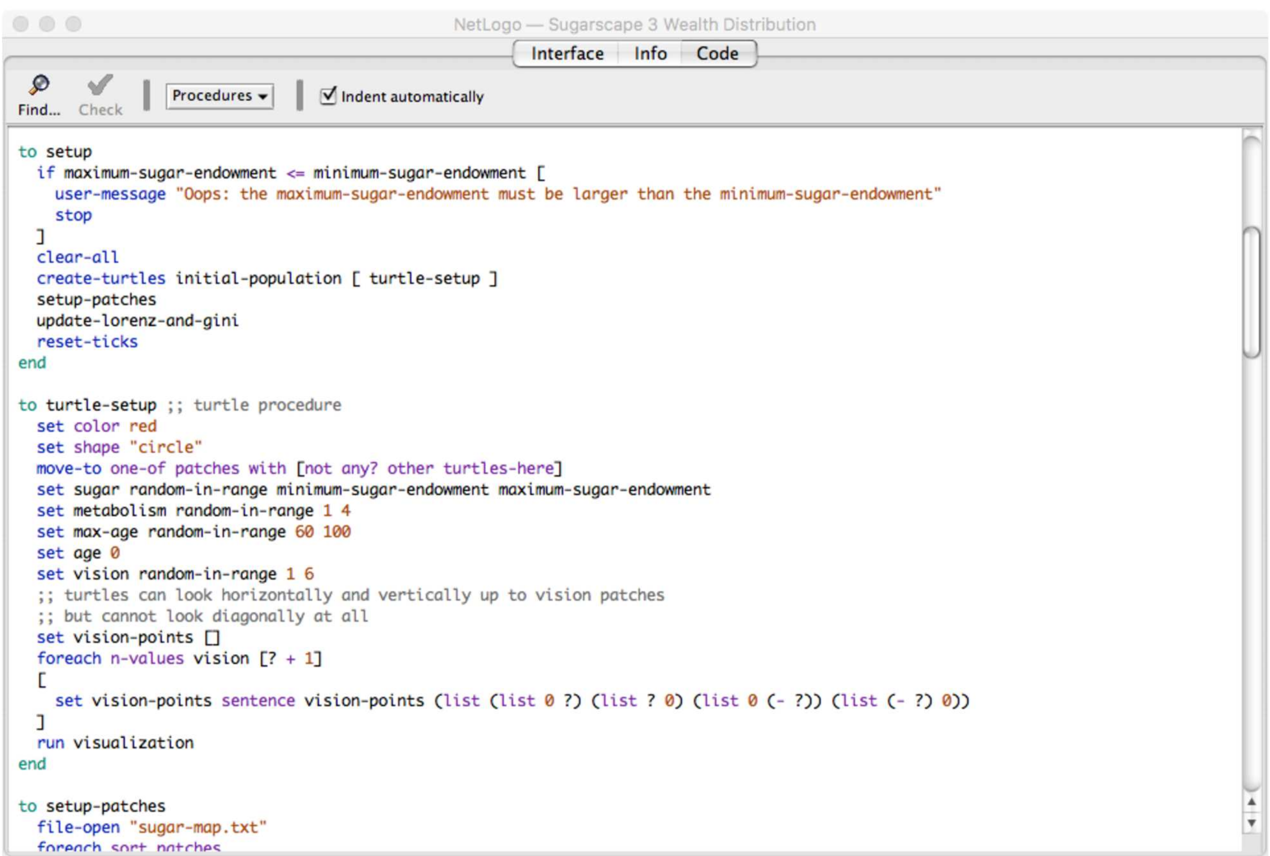
To run the model, all agents start at home. Over time, their motivations increase in size to the point that they will need to take some action to satisfy them. If the agents want to purchase drugs or to socialise, they will first need to commit a burglary in order to generate wealth. To do this, the agents consider all of the neighbourhoods that they are familiar with in their cognitive map, and visit the one that they think will be the most likely to offer a burglary target. Once they arrive in the neighbourhood, the search the area by examining the individual houses looking for one that is sufficiently attractive. If they do not find one after searching the neighbourhood for a predetermined time, then the agent visits another neighbourhood and repeats the search. This process is repeated until a target is found and they can then continue to satisfy the original goal that has made burglary necessary. The burglary process attempts to reflect literature on, for exmaple “optimal foragers” (Johnson, 2004), and known search patterns (Rengert, 1996).

The model was applied to examine the consequences of an urban regeneration scheme. Interestingly it found that, after regeneration, a relatively small number of houses near to the site of the regeneration were at a greater risk than their neighbours due to their location on a main road that was regularly used by the burglar agents to navigate the area. Without modelling the heterogeneous routine activities and awareness spaces of the agents it would not have been possible to begin to forecast potential policy impacts at such a local scale. A second interesting result was that the model significantly under-predicted the number of burglaries that occurred in one particular neighbourhood. On discussing this result with policing partners, it became clear that in that neighbourhood in particular, burglary was often motivated by social factors (such as bullying or intimidation of the victims) rather than monetary factors. Therefore the fundamental model assumptions (that burglary was primarily financially motivated) did not hold to the same degree across the whole city. This model ‘failure’ highlighted the places were the underlying theories did not play out to the same degree in the real world. Overall, although the additional geographical complexity afforded to models such as that outlined here makes them less amenable to testing theories, the realistic representation of the surrounding geography makes them potentially valuable as a tool for forecasting the impacts of new policies on a local area.

**Tools for Implementing Agent-Based Models**




(a) The NetLogo Interface Tab




(b) The NetLogo Code Tab

Figure 5: The NetLogo Interface tab (a) and the Code tab (b).

One of the greatest hurdles that has traditionally prevented the widespread use of ABM is technical. Historically, models have needed to be programmed from scratch. Not only does this prohibit their development from people who cannot write computer code, it also requires some considerable amount of time even for those who can code. Fortunately, in recent years several agent-based modelling toolkits have been developed. Some of these reduce the burden on individuals who write their own models using computer code, and others offer graphical interfaces that allow models to be created without having to write any computer code at all. Whilst it is impossible to discuss all relevant libraries here (there are hundreds of them), three commonly used open source libraries will be briefly outlined with a view to educating the reader about the most relevant for their application. For a fuller introduction, the interested reader can refer to the documentation for the particular toolkit (all are well documented) or to the recent review by Kravari and Bassiliades (2015).

[inline]Note to editor: I can include links to each of these toolkits, let me know if that would be appropriate. They're not difficult to find with simple web searches though

Probably the most well known ABM toolkit, and one that is regularly used in agent-based crime modelling (e.g. Birks et al., 2008, 2012, 2013) is **NetLogo**. The two main elements to the NetLogo program, as depicted in Figure 5, are the 'Interface' tab and the 'Code' tab. The Interface supports graphical elements that can be used to control the simulation or to report results (e.g. sliders, buttons, switches, graphs, etc.). The 'Code' tab is used to define the model logic; i.e. how the model should run and how the agents should behave. Although NetLogo does require the use of some computer coding, its language is based on the Logo language which was originally developed to help children to learn to code. This means it is a reasonably easy language to learn when compared to other, more advanced computer languages.

Another very popular toolkit is **Repast** (the Recursive Porous Agent Simulation Toolkit). Like NetLogo, Repast provides useful model components, such as functions to create graphs, take videos, schedule events, etc. It also has extensive functions to read and write spatial data and to create geographically-realistic worlds. Repast was used to create the Malleson et al. (2013) model discussed earlier. Models in Repast can either be created using the Java programming language, a language that is similar to Logo called 'ReLogo', or though point-and-click state charts (no programming). North et al. (2013) provide a good review and summary of Repast's current capabilities.

Finally, **MASON** (the Multi Agent Simulation Of Neighbourhoods) is a less well known library that uses the Java programming language. As with other toolkits, its core functionality includes dynamic charting (e.g. with histograms, line graphs, etc.), model visualisation, and data input/output. The GeoMASON extension allows developers to include geographically-realistic space in their model. An example of such a model is illustrated in Figure 6. Although the requirement to first learn Java is a hurdle for some model developers, the toolkit is efficient and contains extensive analysis and modelling features.

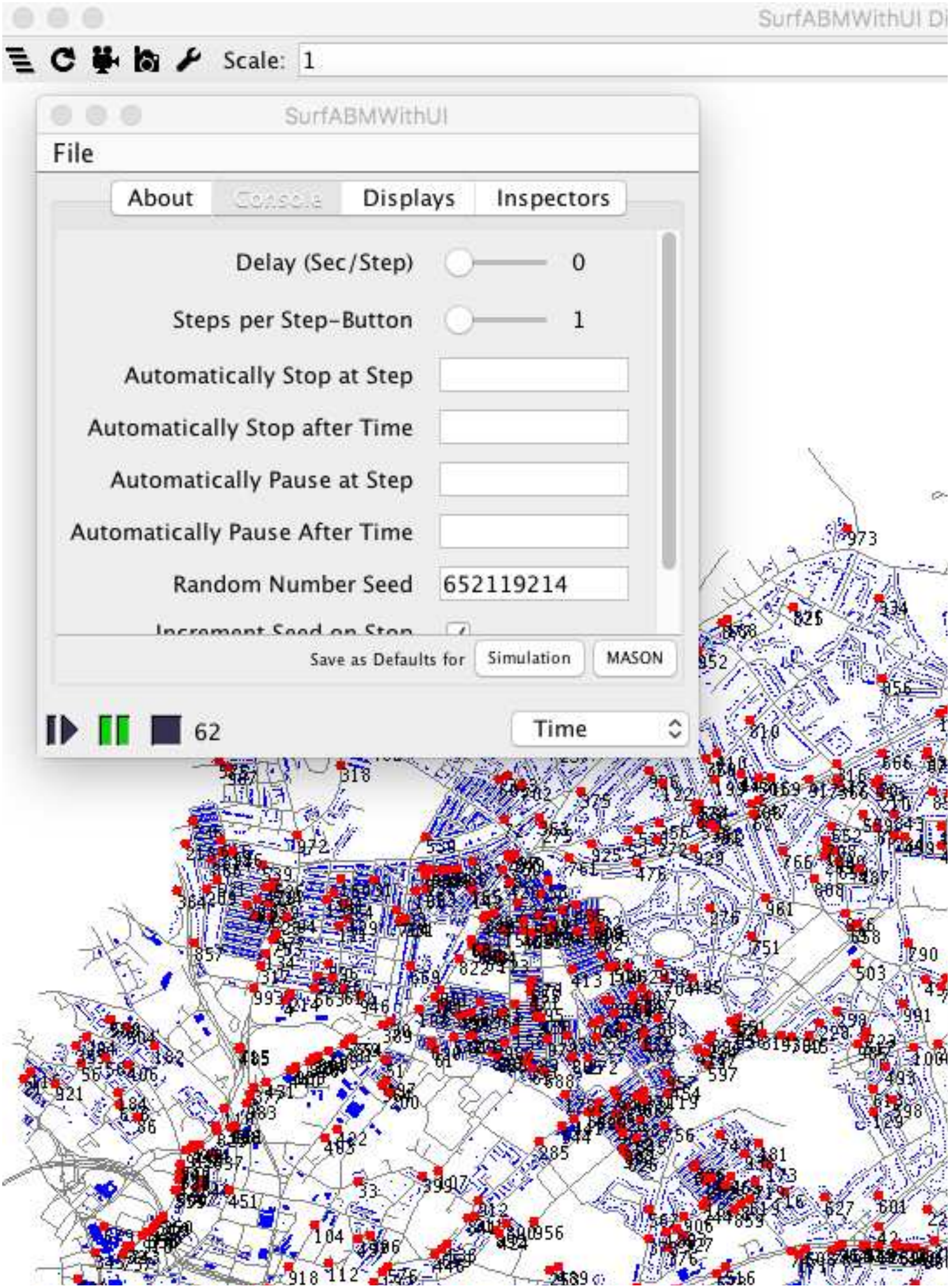

SurfABMWithUI
Scale: 1
File
About
Console
Displays
Inspectors
Delay (Sec/Step) 0
Steps per Step-Button 1
Automatically Stop at Step
Automatically Stop after Time
Automatically Pause at Step
Automatically Pause After Time
Random Number Seed 652119214
Increment Seed on Stop
Save as Defaults for
Simulation
MASON
62
Time

Figure 6: A spatial model under development using the MASON toolkit.

## A Critique of ABM for modelling spatial crime

Thus far, agent-based modelling has been presented as a powerful methodological tool for exploring spatial crime patterns and for better understanding crime theories. There are, of course, difficulties that have yet to be overcome by the community of modellers. The following will summarise some of the benefits of the use of ABM for modelling spatial crime before discussing the major difficulties.

### *Appeal of ABM*

The central difference between ABM and more traditional, aggregate methods, is that ABM simulates the behaviour of the *individual components* whose activities ultimately define the behaviour of the overall system. In effect, this approach to modelling systems allows models to capture certain system behaviours that are very difficult to represent with aggregate methods that disregard the importance of individual heterogeneity and interactions. A prime example here is '**emergence**':

> "A phenomenon is emergent when it can only be described and characterised using terms and measurements that are inappropriate or impossible to apply to the component units" (Gilbert, 2004)

In this sense, the 'crime system' is emergent. No one individual plans how crimes should be committed across a time and place; the overall distribution of crime is an emergent outcome from the behaviours and interactions of countless individual entities (victims, offenders, guardians, etc.). Crime patterns *emerge* from these lower-level interactions. This 'bottom-up' view of modelling systems is also an excellent means of capturing the core theoretical concepts that underpin environmental criminology. Crime theories predominantly focus on the behaviour of *individual people*, not aggregate, homogeneous groups, so ABM presents a clean and clear way of exploring the ways that theoretical assumptions play out.

Another advantage to ABM, that is closely related to its ability to model emergent phenomena, is its ability to allow modellers to create a **natural description** of the system under study (Bonabeau, 2002). There are many systems, particularly in the social sciences, that cannot be sensibly modelled using mathematical equations (Moss and Edmonds, 2005). In an agent-based model, the rules that drive the behaviour of the system are specified directly for each individual (exactly as they are prescribed by theory) so it is not necessary to try to coax an aggregate model into performing as if it were modelling individuals directly. In ABM the 'natural variety' of cities becomes part of the model, rather than being smoothed out through aggregation (Brantingham and Brantingham, 2004; Batty, 2005). Also, the ability to implement theories directly helps to create a **bridge betweeen verbal theories and mathematical models**. Natural language can be ambiguous whereas computer code is precise. Therefore in order to implement a theory in an agent-based model, the theory must be sufficiently rigorously specified in order to convert its natural language description into precise computer code. In effect, ABM can promote the "rigorous specification of theory" (Birks et al., 2012).

### *Difficulties*

Of course there are some disadvantages to the use of ABM for modelling social systems, and spatial crime in particular. An advantage with ABM is that it is possible to account directly for 'human' traits such as complex psychology and seemingly irrational behaviour (Bonabeau, 2002). However, formally defining these 'soft' characteristics in a computer model is actually extremely difficult. As these factors must be defined explicitly in an agent-based model, there can be a **tendency towards minimal behavioural complexity** (O'Sullivan and Haklay, 2000). The task of adequately defining behaviour is further aggravated by difficulties in gathering appropriate data to understand complex, dynamic societies (Gilbert, 2004) (a point that will be revisited shortly).

Theories will rarely stipulate *precisely* how someone will behave under given conditions. Instead, they specify the likely behaviours that might take place. This probabilism can be accounted for in ABMs by applying probabilities to particular behaviours. For example, the decision to burgle a house might be specified as a probability that is calculated from factors such as the affluence of the house, taking into account the presence of security measures, the presence of guardians, and an agent's own internal needs/drivers. If the probability is low, the agent will be less likely to commit the burglary, but it is still a possible outcome. Therefore in one model run the agent might choose not to commit the burglary, but in another they might take the opposite decision. This makes the outcomes from a single model run unreliable – they could be the result of pure chance – so models must be executed a number of times to create robust results (Axelrod, 1997). Birks et al. (2012), for example, ran each configuration of their model 500 times. Whilst this is not a necessarily a problem in its own right, it means that models can become extremely **computationally expensive**. ABMs are usually computationally expensive anyway, especially those that involve difficult spatial operations (such as finding the number of buildings surrounding an agent), and having to run a single configuration hundreds of times can make it impossible to obtain robust results.

The ability to create a *natural description* of a system that ABM offers can have a potential drawback: it becomes very easy to **over-complicate** a model. As Birks et al. (2012) put it:

> "while ABM offers considerable flexibility, the limitless directions a model can progress in dictate that researchers must exercise considerable self-control in selecting what should and should not be included in any model."

A model that is overly-complicated might be no easier to understand than the system that it is trying to simulate in the first place. Therefore the model designer needs to identify the most important aspects of the system that should be included in a model and exclude all else. Identifying these 'important' aspects is not necessarily a simple task, especially if the theoretical explanations that underpin the system behaviours are poorly specified or not well understood.

Where theories are poorly specified, it is often possible to use empirical results or secondary data to parameterise a model. However, because ABM operates at the level of the individual it can often be very difficult to obtain reliable, accurate, high-resolution **data on individual behaviour**. It is possible to simulate extremely complex behaviours using ABM, but if there are no individual-level data with which to validate the model then it is difficult to have confidence in the results. In effect, the advantages of high model complexity and flexibility are tempered by the difficulty of finding suitable values for model parameters based on empirical evidence. For example, in the Malleson et al. (2013) model, agents were able to socialise and visit drug dealers. However, there is very limited empirical evidence for where individual agents might go to undertake these activities and the best that can be done instead is to estimate based on theory and whatever aggregate empirical evidence is available. The proliferation of new **'big data'** sources might offer some answers here. For example, individuals are publishing data about themselves through sources such as social media on an unprecedented scale. There is some potential to utilise these sources to better understand individual behaviour and to calibrate models. For a recent discussion, see Heppenstall et al. (2016). Obviously this approach has serious ethical implications which are discussed briefly below.

Finally, there are also difficulties that relate to the implementation of an agent-based model. This relates to the fact that relatively small pieces of computer code can form integral parts of hundred, thousands, or even millions of agents. It is therefore possible that small errors in the logic of the code can have huge effects on the outcome of the model. This is further compounded when attempting to ensure that work is repeatable because when programmers implement models, they unavoidably include many assumptions which are not documented (O'Sullivan and Haklay, 2000) – although more recently, efforts are being made to overcome this last point through the development of protocols such as *ODD* (Grimm et al., 2006, 2010) and with model repositories such as OpenABM (www.openabm.org/).

Ethical Implications

There are undoubtedly complicated ethical implications associated with the use of ABM to simulate criminal phenomena. The most obvious implication arrises from the question: "if an agent-based model is good enough, can it tell me where someone will commit their next crime?". In other words, if an agent-based model is sufficiently realistic, and the agents represent *real people*, could it be possible to predict if/where/when they will commit crime? There has already been some (albeit limited) interest in this possibility in the media (e.g. Arthur, 2010). Whilst agent-based crime models are a long way from such a level of accuracy, it is important for modellers to clearly set the limits to what they deem as ethically acceptable. Interestingly, there are no established ethical frameworks that modellers can draw on explicitly for agent-based modelling work, although there are attempts to begin creating some (Evans, 2012). Although standard data protection legislation will limit academic research in some countries (such the UK) that utilises individual-level data *and* has policy implications, there are often clauses that permit research with police data. Instead, it is down to the modellers to make it clear that some areas of work, even if they were possible, would be highly ethically dubious. Broadly, university research ethics committees are probably well suited to evaluating these risks.

These ethical risks are also becoming particularly pertinent in the 'age of big data'. Sources that are typically used to derive information about individuals (such as mobile phone use, social media activity, loyalty card use, etc.) are possibly predicated on relatively weak consent. Although many people will agree to the terms and conditions when they use a service, it is not clear that they have read the documentation, let alone understood it. Similarly, if the biasses in the data are not properly understood and accounted for, models run the risk of being wrong at best, and at worst exacerbating existing biassed. For example, there is evidence that PredPol, the well known predictive policing algorithm used by a number of forces across the United States, inadvertently exacerbates existing biasses in police data (Lum and Isaac, 2016). Fortunately the methodologies that underpin PredPol are publicly available, but many others are closed, commercial secrets. It is imperative that agent-based crime models are open source so that the assumptions can be clearly understood and there can be no confusion about what the results show, the context in which they were created, and the limits to their applicability.

## Conclusion

Crime occurrences are the result of the interactions between individual people with their own unique motivations, behaviours, cognition, etc., and are located in a geographical environment that can act to inhibit or even catalyse crimes. Agent-based modelling is an approach to modelling systems that focusses on the individual components that ultimately drive the overall behaviour of the system. In an agent-based model, virtual 'agents' are created who typically represent people. In the context of crime modelling, these are often 'offenders', 'victims', 'guardians', etc. These agents are placed in a virtual environment that can reflect the real world to a greater or lesser extent as necessitated by the research question. Such environments range from the abstract (i.e. a flat, regular, grid-like space) to geographically realistic (i.e. with roads, buildings, etc.). The choice of environment is dependent on the underlying research question. The agents themselves have behavioural rules that determine the actions that they should take in a given situation, and as a model executes the agents are able to observe their surroundings, make decisions, and perform actions. In this manner, a model can re-create the system under study by modelling the actions of the individuals from the *bottom-up*, rather than tying to construct aggregate equations to represent the system from the *top-down*.

Whilst not widespread, the application of ABM is growing and shows great promise as a means of both exploring criminology theory and for answering empirical questions, particularly when geography and the surrounding environmental context are important. There are complicated ethical implications that must be considered, but if conducted carefully there is no reason that such models cannot continue to be a useful tool for criminologists and practitioners.

**Further Reading**

This entry has necessarily ignored a large number of important methodological aspects associated with agent-based modelling. For the reader who would like to learn more about ABM in general, there are a number of excellent text books and shorter articles that are available. These include:

- Gilbert, G. N. and Troitzsch, K. G. (2005). *Simulation for the social scientist*. Open University Press, Maidenhead, England; New York, NY
- Macal, C. M. and North, M. J. (2010). Tutorial on agent-based modelling and simulation. *Journal of Simulation*, 4(3):151–162
- Railsback, S. F. and Grimm, V. (2012). *Agent-Based and Individual-Based Modeling: A Practical Introduction*. Princeton University Press, Princeton
- Wilensky, U. and Rand, W. (2015). *An Introduction to Agent-Based Modeling: Modeling Natural, Social, and Engineered Complex Systems with NETLogo*. MIT Press, Cambridge, Massachusetts
- Macal, C. M. (2016). Everything you need to know about agent-based modelling and simulation. *Journal of Simulation*, 10(2):144–156

There is also a comprehensive book that covers a large and diverse number of geographical agent-based applications:

- Heppenstall, A. J., Crooks, A. T., See, L. M., and Batty, M., editors (2012). *Agent-Based Models of Geographical Systems*. Springer

Whilst the uptake of agent-based modelling in criminology is not broad, there are some particularly important contributions. These include:

- A collection of chapters discussing specific models as well as some broader aspects around the use of ABM to study crime: Liu, L. and Eck, J. (2008). *Artificial Crime Analysis Systems: Using Computer Simulations and Geographic Information Systems*. Information Science Reference, Hershey, PA
- A special issue of the *Journal of Experimental Criminology* entitled "Simulated Experiments in Criminology and Criminal Justice" (Groff and Mazerolle, 2008b)

The two models discussed in detail in this entry were:

- Birks, D., Townsley, M., and Stewart, A. (2012). Generative Explanations of Crime: Using Simulation to Test Criminological Theory. *Criminology*, 50(1):221–254
- Malleson, N., Heppenstall, A., See, L., and Evans, A. (2013). Using an Agent-Based Crime Simulation to Predict the Effects of Urban Regeneration on Individual Household Burglary Risk. *Environment and Planning B: Planning and Design*, 40(3):405–426

Modelling human behaviour is one of the most important, and most difficult, aspect to building agent-based models. For information about how to build complex behaviour into agents using cognitive frameworks, the reader might refer to:

- Kennedy, W. G. (2012). Modelling Human Behaviour in Agent-Based Models. In Heppenstall, A. J., Crooks, A. T., See, L. M., and Batty, M., editors, *Agent-Based Models of Geographical Systems*, pages 167–179. Springer Netherlands
- Balke, T. and Gilbert, N. (2014). How Do Agents Make Decisions? A Survey. *Journal of Artificial Societies and Social Simulation*, 17(4):13

## Links to Digital Material

- The NetLogo website lists a large number of agent-based models that can be run either by downloading the software, or directly in the web browser.

http://ccl.northwestern.edu/netlogo/models/

- Repast and Mason can be found the following urls respectively:
    - https://repast.github.io/
    - http://cs.gmu.edu/~eclab/projects/mason/

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