Using an Agent-Based Crime Simulation to Predict the Effects of Urban Regeneration on Individual Household Burglary Risk

Nick Malleson, Alison Heppenstall, Linda See, Andrew Evans

This is a draft of a paper published in Environment & Planning B. The full reference is:

Malleson, N., A. Heppenstall, L. See, A. Evans (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*.

doi:10.1068/b38057 http://www.envplan.com/abstract.cgi?id=b38057

Using an Agent-Based Crime Simulation to Predict the Effects of Urban Regeneration on Individual Household Burglary Risk

Abstract

Making realistic predictions about the occurrence of crime is a challenging research area. City-wide crime patterns depend on the behaviour and interactions of a huge number of people (including victims, offenders, passers-by etc.) as well as a multitude of environmental factors. Modern criminology theory has highlighted the individual-level nature of crime – whereby overall crime rates emerge from individual crimes that are committed by individual people in individual places – but traditional modelling methodologies struggle to capture the complex dynamics of the system. The decision whether or not to commit a burglary, for example, is based on a person's unique behavioural circumstances and the immediate surrounding environment.

To address these problems, individual-level simulation techniques such as agent-based modelling have begun to spread to the field of criminology. These models simulate the behaviour of individual people and objects directly; virtual "agents" are placed in an environment that allows them to travel through space and time, behaving as they would do in the real world. This paper will outline an advanced agent-based model that can be used to simulate occurrences of residential burglary at an individual-level. The behaviour within the model closely represents criminology theory and uses real-world data from the city of Leeds, UK, as an input. The paper demonstrates the use of the model to predict the effects of a real urban regeneration scheme on the local population of households.

Key words: Crime simulation, burglary, agent-based modelling, offender behaviour

1 INTRODUCTION

The analysis and prediction of crime continues to be a difficult task because the crime *system*[*] is so complex. City-wide crime patterns depend on the behaviour and interactions of a huge number of individuals (including victims, offenders, passers-by etc.) as well as numerous environmental influences. Opportunity theories in environmental criminology (Cohen and Felson, 1979; Brantingham and Brantingham, 1981b; Clarke and Cornish, 1985) highlight the individual-level nature of crime, wherby overall crime rates emerge from individual crimes that are committed by individual people in specific locations. With residential burglary, for example, The ‘individuals’ involved include the burglar(s) who commit the crime, other people in the vicinity of the crime and the property which is burgled; all embedded within the greater urban environment surrounding the event.

An accurate model of crime will be able to account for all of these factors and simulate them directly at the level of the individual (Brantingham and Brantingham, 1993). However, most crime modelling research utilises models that cannot capture the complex dynamics of crime (Eck and Liu, 2008) – i.e. simulating the interactions between offenders, victims/guardians and the environment. To address these problems, individual-level simulation techniques such as agent-based modelling have begun to emerge in the field of criminology. These models simulate the behaviour of individual people and objects by placing virtual “agents” in an environment that allows them to travel and behave as they would do in the real world.

This paper will outline an agent-based model (ABM) to simulate occurrences of residential burglary at an individual-level. The behaviour within the model closely represents criminology theory and uses real data from the city of Leeds. In the next section the relevant theories are discussed and Section 3 then outlines the model in detail. The study area and the data required as model inputs are outlined in Section 4, while Section 5 describes the real-world scenario to which the model is applied. The results and their implications for local crime reduction practices are discussed in Section 6, followed by conclusions.

2 CRIMINOLOGY THEORIES AND CRIME MODELLING

A crime event is the product of a number of coinciding factors such as the motivations and behaviour of the criminal, the influence of the physical surroundings and the behaviour of the victim. Although this makes the crime system extremely complex, occurrences of crime are not random and a large body of literature has evolved to explain some of the patterns underlying criminal occurrences. This study will draw upon these research findings to create a model that closely reflects current theoretical and empirical understanding of the burglary system.

---

[*] Here the *crime system* is defined as the set of components (e.g. the environment, victims, offenders, policy makers etc.) whose behaviours and interactions lead to the emergence of city-wide crime patterns.

2.1 Environmental Criminology and the Geography of Crime

Since the pioneering work of Quetelet (1831) and Glyde (1856) in identifying the spatial patterning of crime occurrences, researchers have been progressively moving towards using smaller units of analysis. However, modern environmental criminology theories and recent empirical research (Bowers et al., 2003; Weisburd et al., 2004; Groff et al., 2009; Andresen and Malleson, 2011) suggest that even the smallest areal units of analysis (such as census output areas of less than 1000 people) hide important intra-area crime patterns. For example, it has been found that burglars choose individual homes based on their individual characteristics (Rengert and Wasilchick, 1985), which challenges assumptions of community or neighbourhood heterogeneity with respect to burglary risk. To address this, a trend of studying the *micro places* in which crime occurs has begun (e.g. Eck, 1995).

The relationship between crime and its location is complex, which is expressed by Brantingham and Brantingham (1993) through the concept of an "environmental backcloth" that is so detailed as to have an "uncountable" number of elements. The backcloth includes physical features such as street networks, buildings and land-use types (Brantingham and Brantingham, 2008) and social elements that affect how residents or passers-by respond to a (potential) crime event.

The first published environmental criminology theory (Andresen, 2010), *routine activity theory*, was developed by Cohen and Felson (1979) and states that a target, an offender and the absence of a capable guardian[*] must be present for a crime to occur. The convergence of these elements in the same space and time depends on peoples' routine daily activities. For example, burglary occurrences generally correspond to times that houses are empty, e.g. while parents travel to school in the mornings and afternoons (Rengert and Wasilchick, 1985; Cromwell and Olson, 2005) or when students are attending university classes (Robinson and Robinson, 1997).

A related theory that expands Hägerstrand's (1970) time-geography concepts is the *geometric theory of crime* (Brantingham and Brantingham, 1981a; 1993). The theory considers how the routes used to travel around a city influence knowledge of the environment, behaviour, and the spatio-temporal locations in which offenders are likely to commit crime. For example, burglars do not search for targets at random but look for targets near important "nodes", e.g. friends' houses and leisure/work places (Brantingham and Brantingham, 1993). Therefore, it is important to consider an individual's awareness of their urban environment; they are likely to commit a crime where awareness overlaps with appropriate opportunities (as illustrated by Figure 1).

[*] Routine activity theory was later adapted to include the concepts of a "place" for the crime to occur, a "manager" of the place and a "handler" who watches over the offender (Felson, 2008).

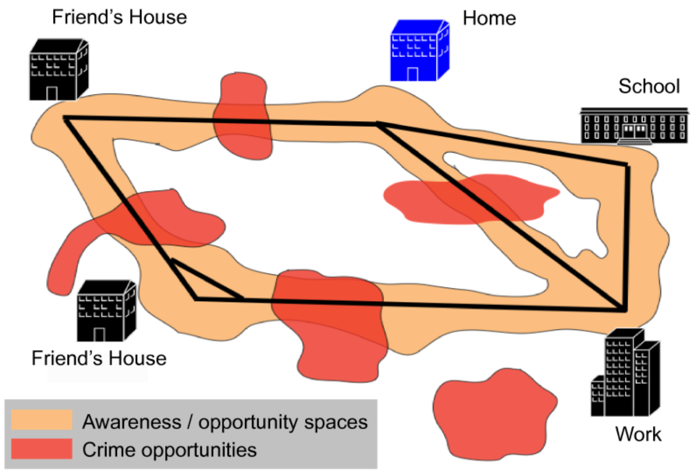

Figure 1: Nodes, paths, edges and activity/opportunity spaces in the geometric theory of crime, adapted from Brantingham and Brantingham (1993).

Finally, the *rational choice perspective* (Clarke and Cornish, 1985) suggests that offenders' thoughts can be modelled as a formal decision, weighing up potential rewards or benefits of a successful crime with the potential risks or costs if apprehended. In this manner, a crime will only be committed if it is *perceived* as profitable. Although it has been shown that this is rarely the case and instead offenders tend to focus on the rewards and underestimate or even neglect the risks – Vito et al. (2007) provide examples from the literature documenting interviews with offenders which support this view – rational choice theory still has value in criminology because there is evidence of rationality in choice of area to burgle or the specific targets to approach.

These three theories largely agree on the mechanisms that lead to the spatio-temporal patterns of crime. Importantly, each theory emphasises the individual-level nature of crime occurrences; crimes are the result of the behaviour of individual people and framed in complex, highly varying, environments. This theoretical conclusion has important implications for the choice of modelling methodology for crime analysis, as discussed below.

2.2 Traditional Methods of Modelling Crime

Crime analysis in a "traditional" sense – following the work of Guerry (1831) and Quetelet (1842) – uses aggregate crime rates or counts as the dependent variable in, for example, a regression equation (Brantingham and Brantingham, 1998; Groff, 2007a). The statistical methods used are numerous and constantly changing, but they share many similarities. Typically, there is one dependent variable of interest (i.e. crime rates) and model accuracy is usually determined through goodness-of-fit statistics such as the mean absolute error, root mean squared error, or a regression line, which is fit to the data; R^2 is then calculated to determine the amount of variance explained. A review has been undertaken by Kongmuang (2006). However, statistical models also have drawbacks including:

- **System complexity**. Although linear models are "computationally convenient" (Eck and Liu, 2008), they cannot capture the dynamics of complex systems. For example, statistical models generally utilise simple functional relationships and fail to capture the effect of the historical path of individuals and its effect on their behaviour. ABMs on the other hand, can represent complex real world interactions including personal histories.
- **The importance of "place"**. Although the use of disaggregate data is becoming more common with the growth of 'crime at place' research (Weisburd et al. 2009) – recent studies have analysed crime at the household (Tseloni, 2006) and street (Johnson and Bowers, 2009) levels – many techniques still use spatially aggregated data and therefore struggle to account for the micro-effects that may result in a significant variation in crimes on a street by street basis (Andresen and Malleson, 2011).
- **Spatial realism**. Euclidean distance is often used which does not take road networks or impassable barriers (e.g. major roads or rivers) into account. These will influence where people travel, their internal awareness spaces, and where they are likely to commit crime.

In summary, statistical approaches face difficulties with representing the dynamic processes that drive the system under study: that of individual incidents located in a specific time and space involving individual people. This makes it difficult to draw conclusions regarding how the individual behaviour of victims or offenders may be affecting the occurrence and rate of crime. The most natural approach to modelling complex systems is to simulate the individual units directly, allowing them to interact as they would do in reality (Bonabeau, 2002). Agent-based modelling provides the means to achieve this goal through modelling dynamic processes at the micro level; offering a complimentary approach that is better suited to the examination of dynamic systems.. The behaviour of burglars, victims, guardians, etc. can be modelled explicitly, in a rich environment that closely reflects the real world and emphasises the importance of "place" and of an individual's unique circumstances and behavioural traits.

2.3 Agent-Based Crime Modelling

An ABM is a type of computer simulation comprised of autonomous, decision making entities called 'agents'. Each agent is an individual object able to act independently of central control and can therefore represent a virtual 'person'. As the model iterates, each agent has the ability to assess its circumstances and make an informed/educated decision about its future course of action (Bonabeau, 2002). Agents are placed in a virtual environment (which are commonly spatial) in which they can move around and interact with other agents. Through these mechanisms, more realistic human behaviour can be incorporated (Moss and Edmonds, 2005) and models can be used to create systems which mimic real scenarios.

ABMs have been applied to many subject areas but only recently to crime. Nevertheless, the application areas are broad; models include simulations of drug markets (Dray et al., 2008), repeat victimisation (Johnson, 2008; Pitcher and Johnson, 2011) street robbery (Liu et al., 2005; Groff, 2007a, 2007b, 2008) and burglary (Birks et al., 2008; Hayslett-McCall et al., 2008; Malleson et al., 2009). More details can be found in Liu and Eck (2008) and Groff and Mazerolle (2008). In general the model presented here improves upon the existing published examples by:

- **Enhancing the behaviour of the offenders** through a comprehensive cognitive framework (as discussed in Section 3.2) which provides agents with a rich behavioural model. Although Birks et al. (2008) made use of a simpler framework, other research which makes use of more realistic environments – e.g. Groff (2007a,b 2008) and Hayslett-McCall et al. (2008) – have not attempted this. Other models use agents whose behaviour is partly pre-determined, such that agents do not change their behaviour if their circumstances change whilst performing a particular action. Here, an agent can "change their mind" at any time, abandoning a chosen course of action in favour of another if internal or external factors change.
- **Improving the realism of the environment**. Although other models have started to make use of real-world environmental data, the research presented here includes the widest variety of both physical and social environment attributes. In addition, this model incorporates a comprehensive representation of the transport network (including the ability for car, foot and public transport travel) which is absent from other models but important to realistically account for offender awareness and activitiy spaces.

3 MODEL OUTLINE

The model consists of two major parts: the environment and the agents. Section 3.1 will address the environment – indicating how it is able to represent the "environmental backcloth" (Brantingham and Brantingham, 1993) – and Section 3.2 will outline the structure of the virtual agents, illustrating how they have been developed to simulate the behavioural characteristics of real burglars.

3.1 Constructing the Virtual Environment

In an ABM, the *virtual environment* represents that space that the agents inhabit. In this application, the environment is spatial and has two major requirements: it must allow the agents to travel from one place to another using the available transport networks and it must also incorporate the important factors that form the environmental backcloth. To accommodate these requirements, the environment consists of the *transport* layer, which is used by the agents to navigate the environment; the *individual properties* layer, which contains the potential burglary targets (i.e. individual houses); and the *communities* layer, which is used to account for the effects of environmental factors such as community cohesion.

3.1.1 The Individual Properties Layer

It has been shown that the physical form of an area, including natural features and the design of the built environment (Jeffery, 1971; Newman, 1972), has a significant impact on local communities and on crime (Bottoms et al., 1992). Modern 'crime at place' research, in particular, emphasises the importance of including high-resolution data about a local area (see, for example, Armitage, 2011). The individual properties layer encapsulates some of these features by representing the physical attributes of individual houses[*] that might increase or reduce their burglary risk. Establishing the vulnerability of a house is non-trivial, however, as there are a variety of factors that can influence a potential burglar's decision regarding whether or not to burgle. Table 1 lists the variables that have been chosen to express household burglary risk in this research, their empirical justification and the direction of their effect on household vulnerability to burglary. The datasets drawn together for this specific study are discussed in Section 4.

Table 1: Household variables and their theoretical support.

House Variable	Justification for use
Accessibility Refers to building features that directly affect the difficulty of entering the property. In the model, highly accessible buildings are easier for a burglar agent to enter and therefore have a higher burglary risk.	Qualitative research (Cromwell et al. 1991; Wright and Decker, 1996) has found that burglars favour properties that are easy to enter. This can be affected by the number of potential entry points; terraced houses (Felson, 2002) , ground floor corner flats (Robinson and Robinson, 1997) and single-family dwellings (Bernasco and Nieuwbeerta, 2005) have been found have a higher burglary risk. Physical target hardening (i.e. reducing the ease of access to the property) and educating victims have been found to reduce risk in a wide variety of contexts (Weisel, 2002; Hirschfield, 2004; Hamilton-Smith and Kent, 2005; Nicholas et al., 2005; Newton et al., 2008).
Security A measure of the effective physical security of the house. High *security* lowers the burglary risk.	Although closely related to the *accessibility* variable, a separate variable for security is used in this research so that physical building characteristics can be separated from security measures (e.g. burglar alarms).
Visibility A measure of how visible the house is to neighbours and passers-by who can act as suitable guardians and deter a potential burglar. *Visibility* reduces the victimisation risk.	Also known as "surveillability" (Cromwell et al., 1991), a variety of research suggests that properties which are obscured from the view of neighbours and passers-by are more vulnerable (Mayhew, 1984; Brown and Bentley, 1993; Weisel, 2002; Felson, 2002; Cromwell and Olson, 2005).
Traffic volume A measure of the amount of pedestrian or vehicle traffic outside the house; high levels make it	Although similar to the *visibility* variable, a separate variable is used to represent the estimated traffic volume so that the physical attributes that effect household visibility (such as vegetation) can be isolated from the number of people who are likely to pass a

[*] Here, a 'house' refers to a property which can contain one or more separate living areas but is not a block of flats (blocks of flats are excluded at present).

difficult to gain access to a property without being seen and reduces a house's burglary vulnerability.	property. For example, a property might be very visible to passers-by but actually have very little traffic passing it. It is important to note that although a high value for the traffic volume variable reduces household burglary risk; it is possible that houses on busy roads are more likely to be passed by the burglar agents in the first place, which will indirectly increase their risk. Agent-based modelling is an ideal methodology to capture these types of non-trivial and relationships.
Occupancy A measure of occupancy as burglars are less likely to enter properties that are occupied. *Occupancy* reduces a household's burglary risk.	Many qualitative (Cromwell et al., 1991; Brown and Bentley, 1993) and quantitative (Kent et al., 2006) studies have found that most burglars will not intentionally enter a property if it is occupied (Wright and Decker, 1996).

3.1.2 The Communities Layer

Although the physical environment has a significant effect on burglar behaviour, the complexity of the environmental backcloth extends well beyond simple physical factors. It is also important to consider the social factors that surround a crime event. As Bottoms et al. (1992, page 118) comment, "communities, like individuals, can have careers in crime". Therefore to truly capture the dynamics of modern environmental criminology theory, it is necessary to model the individual behaviour of all the people who make up a community and could, in theory, be involved with a crime event. However, it is beyond the scope of this research to model *every* person in a city and hence the communities layer will be used to estimate the behaviour of other people whose presence might deter a potential burglar. Table 2 outlines the variables that make up the layer.

Table 2: Community variables and the justification for their use in a model.

Community Variable	**Justification for use**
Collective Efficacy A measure of how cohesive a community is and how likely the residents are notice and intervene in potential crimes. In the model, houses located in areas with a high collective efficacy will have a lower vulnerability to burglary.	Levels of community cohesion have been citied as important determinants of crime since the 1940s (Shaw and McKay, 1942) through to the 1970s and '80s (Jeffery, 1971; Newman, 1972; Wilson and Kelling, 1982). Recent quantitative research also points to a link between crime and community cohesion (Sampson et al., 1997). In this research, collective efficacy is estimated from *concentrated disadvantage*, *residential stability* and *ethnic heterogeneity* (following Shaw and McKay, 1969; Sampson et al., 1997; Bernasco and

	Luykx, 2003; Browning et al., 2004).
Attractiveness A measure of the abundance of valuable goods within houses in an area. Community attractiveness increases household burglary risk.	Burglar interviews (Cromwell et al., 1991; Wright and Decker, 1996) as well as quantitative research (Wilkström, 1991; Bowers and Hirschfield, 1999; Bernasco and Luykx, 2003; Snook, 2004) suggest that areas with a high socioeconomic status are attractive to burglars*.
Occupancy An estimate of the probability of houses in the community being occupied at a given time. High occupancy is assumed to reduce burglary risk.	Numerous studies (Cromwell et al., 1991; Wright and Decker, 1996; Brown and Bentley, 1993, Kent, 2006) have found that increasing signs of occupancy is a means of reducing burglary risk.
Sociotype A numerical description of the "type" of the community. When agents in the model assess household burglary vulnerability, they consider how similar the area is to that which they live in. If the areas are similar then the houses are more likely to be burgled by that individual agent.	Interviews suggest that a person is less likely to burgle in an area that they feel they stand out in (Wright and Decker 1996). To account for this, the *sociotype* for each community is a vector made up of all the available sociodemographic data and the difference between two communities is the Euclidean distance between the two vectors.

When deciding whether or not to commit a burglary, an agent takes all the household and community variables into account for each individual house they travel past. However, it must be noted that, due to the lack of individual-level household data, in the results discussed later (Sections 5 and 6) the values for the household variables *occupancy* and *attractiveness* are homogeneous for every house in a community. This is because the socioeconomic data that can be used to estimate the variables are released as part of the UK census and are therefore only available at aggregate levels (the UK census Output Areas are used as community boundaries here). Work is currently underway to generate individual-level data that can be used to improve the representation of victims in the model (Malleson and Birkin, 2011).

* It is important to note that although some studies suggest that areas with a high socioeconomic status are more attractive to burglars, it is often the case that deprived areas exhibit the highest burglary rates because they house larger numbers of offenders who do not travel far. Here this contradiction is addressed through the use of distance decay whereby the attractiveness of a distant neighbourhood is weighed against its distance from the burglar agent (see Section 3.2).

3.1.3 The Transport Layer

As mentioned previously, crime models often use Euclidean distance to represent space. This precludes the incorporation of features such as roads and the public transport network that shape a person's awareness of their environment. Therefore the model outlined here includes a realistic transport network consisting of roads (to be driven or walked), bus routes and train lines. Also, the speed of an agent varies by type of transport available such that car drivers on major roads can travel more quickly than those on minor roads. This is important because it is possible that a journey is a *shorter distance* on minor roads, but has a *quicker time* on major roads and hence the person's awareness space may be restricted to the major road route. Public transport routes (buses and trains) are included in a similar manner to walking/driving routes, with the exception that the network must be joined and left at specific stops. For example, Figure 2 depicts the patterns produced by a single virtual burglar when they do and do not have access to public transport.

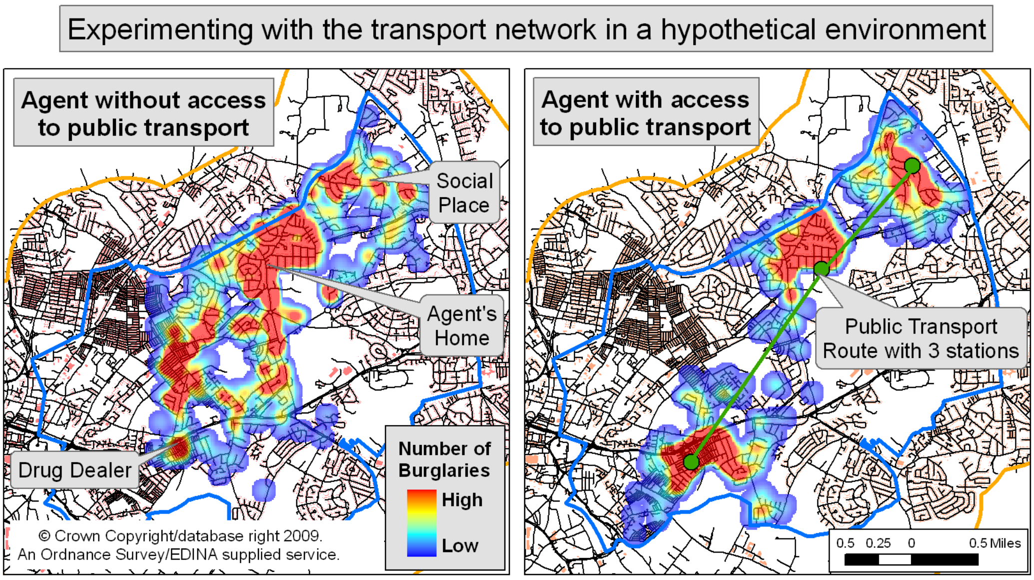

Figure 2: Illustrating the effects of a virtual public transport network on burglary locations in a hypothetical environment (using real GIS road data).

3.2 Building Realistic Agents

Accounting for the "soft factors" exhibited by humans – such as seemingly irrational behaviours and complex psychology (Bonabeau, 2002) – can be problematic, particularly because they must be defined explicitly in models which work at the micro-level (O'Sullivan and Haklay, 2000). Fortunately there are published cognitive frameworks to assist with simulating human behaviour in a computer model. In this application the PECS framework is used, whereby agents have a number of *motives* that vary in strength; at any point in time the strongest motive is the one that drives an agent's behaviour.

The first decision to make is which motives to include. Research suggests that it is common for a burglar to become aware of a burglary target by passing one on a routine activity and so it must be decided which behaviours are used to make up a burglar's daily routine activities. Two common drivers for burglary are the need to support a drug addiction (Scarr, 1973; Cromwell et al., 1991; Hearnden and Magill, 2003) and to socialise (Scarr, 1973; Wright and Decker, 1996, 2005). Three obvious choices for motives are therefore:

1. *Drugs* – the level of substances in an agent's system; this will be higher in the periods following drug use and decline over time. If required, agents can purchase drugs from dealers.

2. *Social* – a measure of the amount of socialising an agent has done; as with *drugs* this will deteriorate over time and costs money. An agent can spend time socialising in specified places (i.e. bars or friends' houses).

3. *Sleep* – a measure of how in need of sleep an agent is. Agents can seek sleep at home when they require it. The sleep motive is a means of normalising the agent's behaviour, without it they would have no need to ever travel home. Also, the need to sleep is generally stronger at night which helps to enforce more realistic temporal behaviour on the agents (Malleson et al., 2010).

Although reducing the entire range of human behaviour into these three drivers is a vast simplification, these variables are sufficient for creating simple daily burglar behaviour. The simple structure nevertheless represents an improvement in terms of behavioural realism over existing agent-based crime models (e.g. Groff, 2007a; Birks et al., 2008; Hayslett-McCall et al., 2008; Malleson et al., 2009). Also, because the PECS framework is modular it is easy to add or remove different types of behaviour as appropriate and the future potential for improved behaviour is broad.

Agents start the simulation at home with low motivation levels (i.e. they are satisfied and are not motivated to perform an action). Over time, their motivation levels increase and they become motivated to perform an action (*sleep*, *take drugs* or *socialise*). The simulation is configured so that on a *typical* day, an agent must sleep for eight hours, socialise for two hours and purchase drugs once. To purchase drugs or to socialise requires money which must be sought through burglary. At present the income gained from a single burglary is constant and sufficient to allow the agent to purchase drugs and socialise once. Hence, on average, an agent will burgle once per day. However, the probability of committing a burglary depends on the suitability of the houses that the agent passes and how highly motivated they are at the time, so they will have days where no burglary takes place. Over time they become more desperate as motives increase regardless, hence there will be other days when multiple burglaries take place. In this sense the agents are truly autonomous; the amount of time they spend performing different activities depends entirely on their own behaviour with no central control.

The model currently runs for a fixed number of time steps, during which period the criminals will commit crimes. The number of model iterations per simulated day is configurable but one iteration equates to one minute of simulated time here (e.g. there are 60*24=1440 iterations per day). Each model is run for 30 simulated days (43,200 iterations) which is sufficient time for the resulting crime patterns to become stable – running the model for longer does not influence the results. Although the number of crimes that an agent will commit is not fixed, it will be similar for different agents and across different simulations because the rate at which the agents' desires increase is constant. Future work will look at giving offenders more individual drivers.

Agents do not have global knowledge of all the houses and communities in the environment; they are only 'aware' of those that they have passed whilst travelling. At the start of the simulation, agents will travel to social locations or drug dealers – they begin the simulation with sufficient wealth for this – so their initial awareness space consists of the buildings and communities that they pass on the way to these places. As the simulation continues their social locations can change (this will be discussed in Section 5.1) and hence their awareness space expands. Also, burglary involves some searching which can also increase the areas covered by awareness spaces.

The process of burglary is broken down into three parts (Figure 3) and the first decision is where to start the search. To decide this, an agent considers every community that they are aware of and calculates the probability, P, of travelling to a community, c, from their current location in community, a, as follows:

$$P_a \propto \frac{1}{dist(c,a)} + attract(h,a) + socialDiff(h,a) + prevSucc(a) \tag{1}$$

where, h is the home area of the agent (the community in which they live), *dist(c,a)* represents the distance to the target community from the agent's current location, *attract(h,a)* is the affluence of the target community relative to where the agent lives (attractiveness is greater if the agent lives in a more deprived area) and *prevSucc(a)* is a measure of how successful they have been at burgling in community a in the past. The *socialDiff(h,a)* term represents the demographic difference between the agent's home neighbourhood (h) and a, (the difference in their *sociotypes*). This is the Euclidean distance between all the demographic variables that make up the two sociotypes; in this manner agents are more confident at burgling areas that are similar, socially, to where they live. It is possible that one or all of the terms in equation (1) can be 0, so the model is purposely additive – if one value is zero it should not rule out the possiblility of looking for a target in community c, just make it less likely. The community with the largest value for P is chosen by the agent as the place for them to start their search.

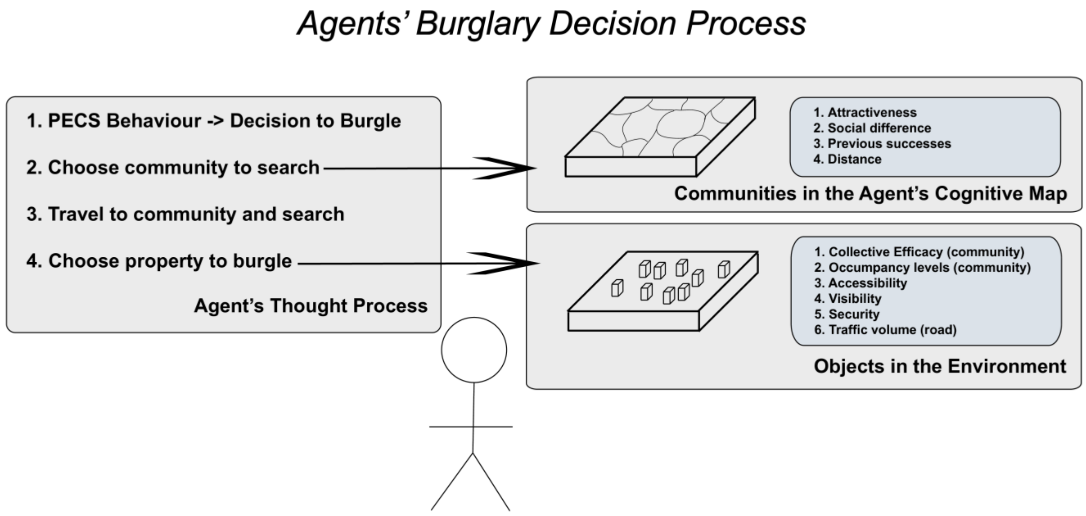

Figure 3: The environmental variables that dictate where an agent will start to search for a burglary target and whether or not they decide to burgle the individual houses that they pass.

The second stage in the burglary process involves travelling to the chosen area and searching. This approach treats burglars as “optimal foragers” (Johnson and Bowers, 2004; Bernasco and Nieuwbeerta, 2005). Research has shown that burglars exhibit discernible search patterns (Johnson and Bowers, 2004; Brantingham and Tita, 2006) and in this model the burglars’ search pattern is similar to the “tear-drop” identified by Rengert (1996). The burglar searches on the way to their chosen community; then once they reach the area they search in a “bulls-eye” expanding circle so that the overall pattern looks like a teardrop connecting the agent’s starting position and the location that marks the start of the bulls-eye search. If an agent has not found a target within a certain amount of time, the burglary process is repeated; the agent chooses a new start location, travels there and begins the search again.

Throughout the entire burglary process, the agents observe each house that they pass and determine whether or not each one is suitable for burglary. The variables that influence suitability are illustrated in Figure 3 and the overall suitability, *S*, of each house, *i*, is simply the sum of the relevant household and community variables:

$$S_i = CE_i + TrafficVolume_i + Occupancy_i + Accessibility_i + Visibility_i + Security_i \quad (2)$$

where CE_i is the collective efficacy of the community that the house is located in. All variables are normalised to the range 0 – 1 and, with the exception of occupancy, are unique for each house. Rather than attempting to simulate the daily habits of all people in the city as well as just the burglars, occupancy is estimated from community demographics. Four groups were identified as having different occupancy patterns to ‘normal’ employees (whose houses are assumed to be empty between 9am and 5pm): *students*, *unemployed*, *part-time workers* and *families*. The proportions of these groups in an area have the following effects on occupancy: students increase occupancy during the day but decrease it at night when they are socialising (Robinson and Robinson, 1997); unemployed increased occupancy during the day; part time workers have slightly increased occupancy during the day (but less than unemployed) and; families have decreased occupancy around school opening and closing times but increased occupancy at other times in the day.

When deciding whether or not to commit a burglary, the suitability of each house is compared to the strength of the motive that is driving the agent. As the strength of the motive overtakes the suitability of the house, the agent commits a burglary. Therefore a “desperate” agent is more likely to burgle a house that has a low suitability level; a decision they might not have made if their motive had not been so strong.

4 DATA AND THE STUDY AREA

The model can be applied to any region for which appropriate data is available (e.g. Vancouver: Malleson and Brantingham, 2009) and in this paper the experiments apply to an area of approximately 1700 hectares in the city of Leeds, UK. The study area (Figure 4) is situated in the large, ongoing urban regeneration scheme called EASEL (East and South-East Leeds). EASEL contains some of the most deprived neighbourhoods in the country and, therefore, Leeds City Council has instigated an ambitious urban renewal scheme (EASEL Team, 2007). Among other things, the scheme will build hundreds of new houses to attract new tenants and construct new roads, transport links and employment opportunities. As Beavon et al. (1994) note: “cities create the backdrop for crime through their control of roads, commercial development, housing, building costs and transportation networks” which makes EASEL an ideal candidate for crime forecasting using this model. Although the scheme is still underway at the time of writing, future work will be able to re-evaluate simulation results. Table 3 outlines the data required by the model for the Leeds simulation, all of which is available for England and most for the entire country so could be used to simulate any UK urban area.

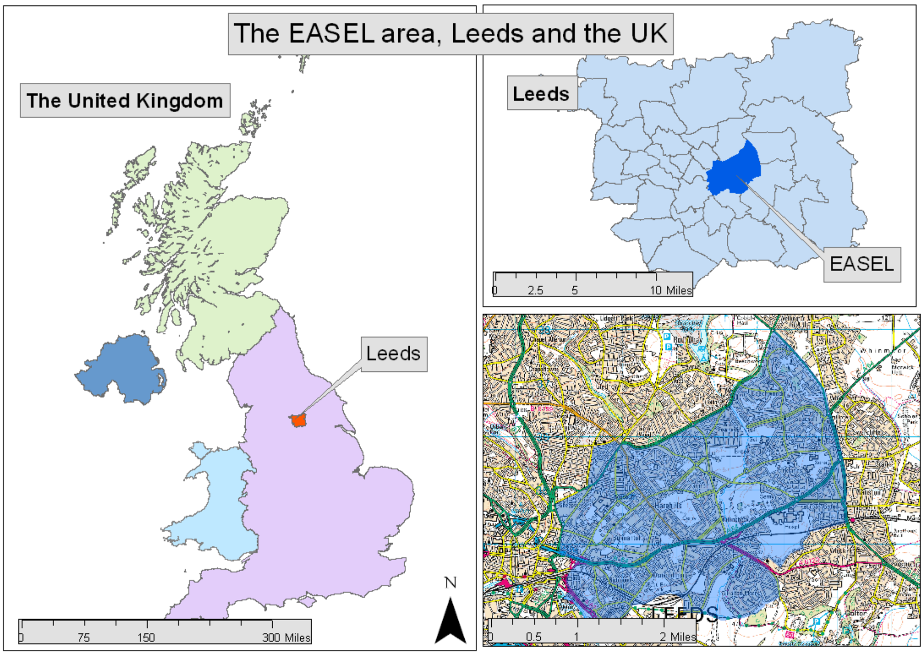

Figure 4: Leeds, UK, and the EASEL area.

Table 3: Data required by the model and sources for the Leeds simulation. For extensive details regarding how the layers were derived from real data see Malleson (2010).

Required data	Source and description
Community-level Data	
Socio-deomographic data	Data required to build a representation of communities: • 2001 UK census (Rees et al., 2002) • The Output Area Classification (Vickers and Rees, 2006, 2007)
Deprivation data	Specific deprivation data used to estimate community cohesion: • The Index of Multiple Deprivation (Noble et al., 2004)
Areal boundaries	Geographic data for community boundaries:

	• Census Output Area (OA) boundaries
Household-level Data	
Buildings	The location and types of buildings (e.g. house, shop, etc): • Ordnance Survey (OS) MasterMap Topographic Area layer (Ordnance Survey, 2009) • OS MasterMap Address Point data (Ordnance Survey, 2009)
Transport Network Data	
Road network	The road network: • OS MasterMap Integrated Transport Network (ITN) layer (Ordnance Survey, 2009)

In addition, crime data are required for the locations of drug dealers and to provide the number of expected burglaries for validation of the simulations. The data consist of all crimes recorded by the police in the Leeds area for the period 1st April 2000 to 31st March 2001 (chosen to coincide with the 2001 UK census). There are a number of implications for using this type of data in research as not all crime is reported to the police in the first place – even if it is reported, the crime might not necessarily be *recorded* by the police – and human error in address recording might mean that some crime data are not geocoded properly. Fortunately, burglary often has high reporting rates – the British Crime Survey suggests 69% in 2010/11 (Chaplin et al. 2011) – and the data were cleaned extensively by the police before use so these problems are limited.

5 THE SIMULATION SCENARIO AND MODEL CALIBRATION

5.1 Model Setup

To limit boundary effects the simulation area extends for 1km beyond the EASEL boundary (see Figure 5), but any crimes committed outside this area are disregarded. Drug dealer locations were established directly from the crime data by creating a virtual dealer address for every point in the data set where a drug dealing-related crime had been recorded. Social locations were set to buildings classified as "restaurants and cafes" and "public houses and bars". Future work will improve the definition of a social locations, including the possibility of inter-agent socialising (i.e. visiting friends' houses). The starting locations and number of offender agents were also determined directly from the crime data, creating a point for every known burglar in the offender data for the period 2001 – 2002. This results in 273 burglar agents in an area of approximately 30,000 households. Because offender addresses are only available at the postcode level, each address in the model is actually a house chosen at random within the postcode area. Future work will attempt to capture these populations more accurately.

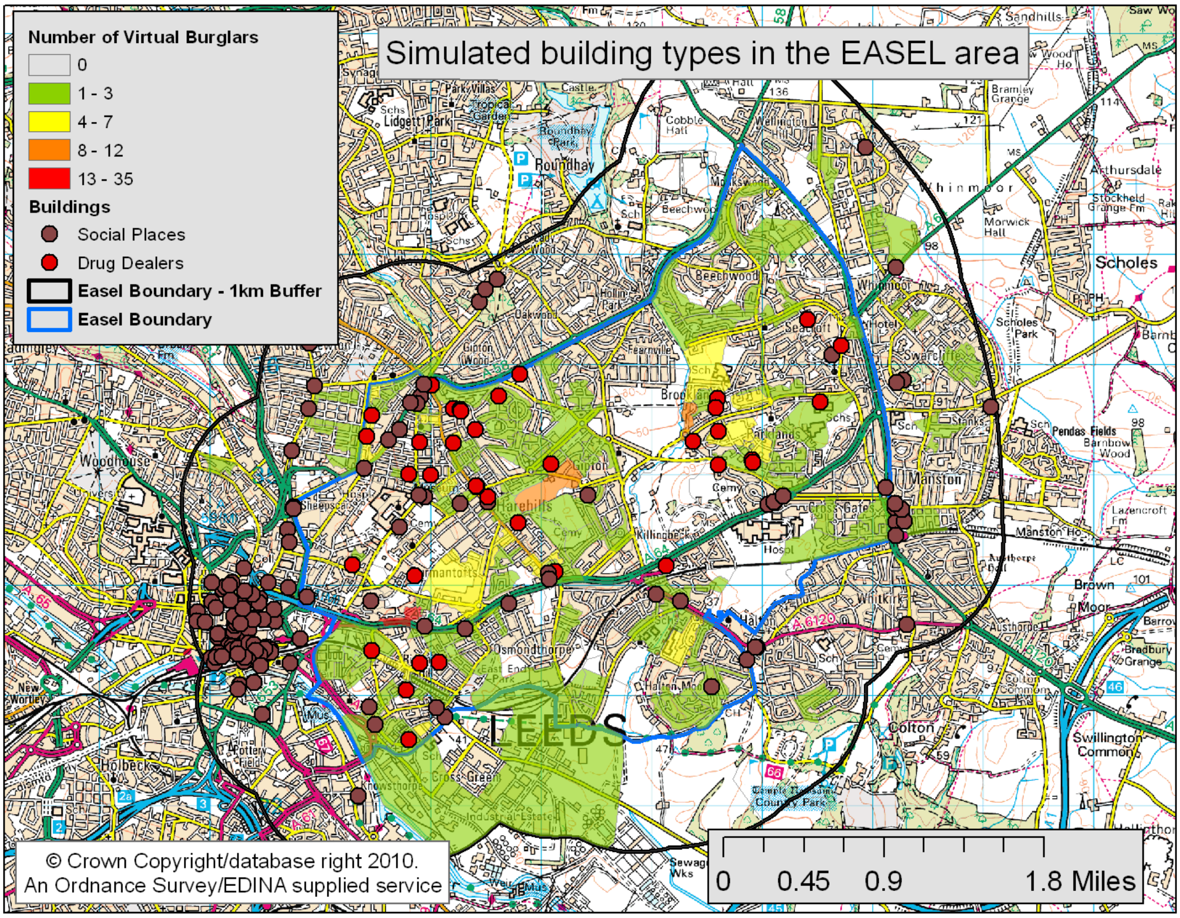

Figure 5: The locations of different building types, established from crime, census and land-use data. (Note that to preserve anonymity, drug dealer points on the map have been perturbed).

It is also necessary to decide *where* an agent chooses to travel if they need to visit a drug dealer or to socialise. This is one of the most difficult features to estimate as there is very limited data which can assist with the assumptions. An agent is assigned a drug dealer at random and always uses the same one. It is likely that in reality a person builds a preference for certain dealers but often travels to different addresses depending on the abundance of supply; an avenue for future research. With regards to social locations it is possible that any agent can visit any social location, but they are *more likely* to visit one that is in a community of a similar type to their own. Again this is likely to be too simplistic but can be investigated further. Section 7 will discuss the implications of having to make such broad assumptions in the context of the agent-based methodology.

5.2 Evaluating the Model

The use of complex models, such as that described here, can actually *detract* from our understanding of the theories that drive them if their processes and dynamics are not fully understood (Elffers and van Baal, 2008). To alleviate these problems, the model was thoroughly verified in a variety of different types of envionment and tested against real data. The expected (real crime data) and simulated datasets (after calibration), along with the differences between are compared in Figure 6. The model generally shows an improvement over a regression model (Malleson, 2010, page 200) and is deemed acceptable for predictive modelling. Of course any policy recommendations must be made with care as there is always a degree of error to the simulation result, which is discussed further in Section 7.

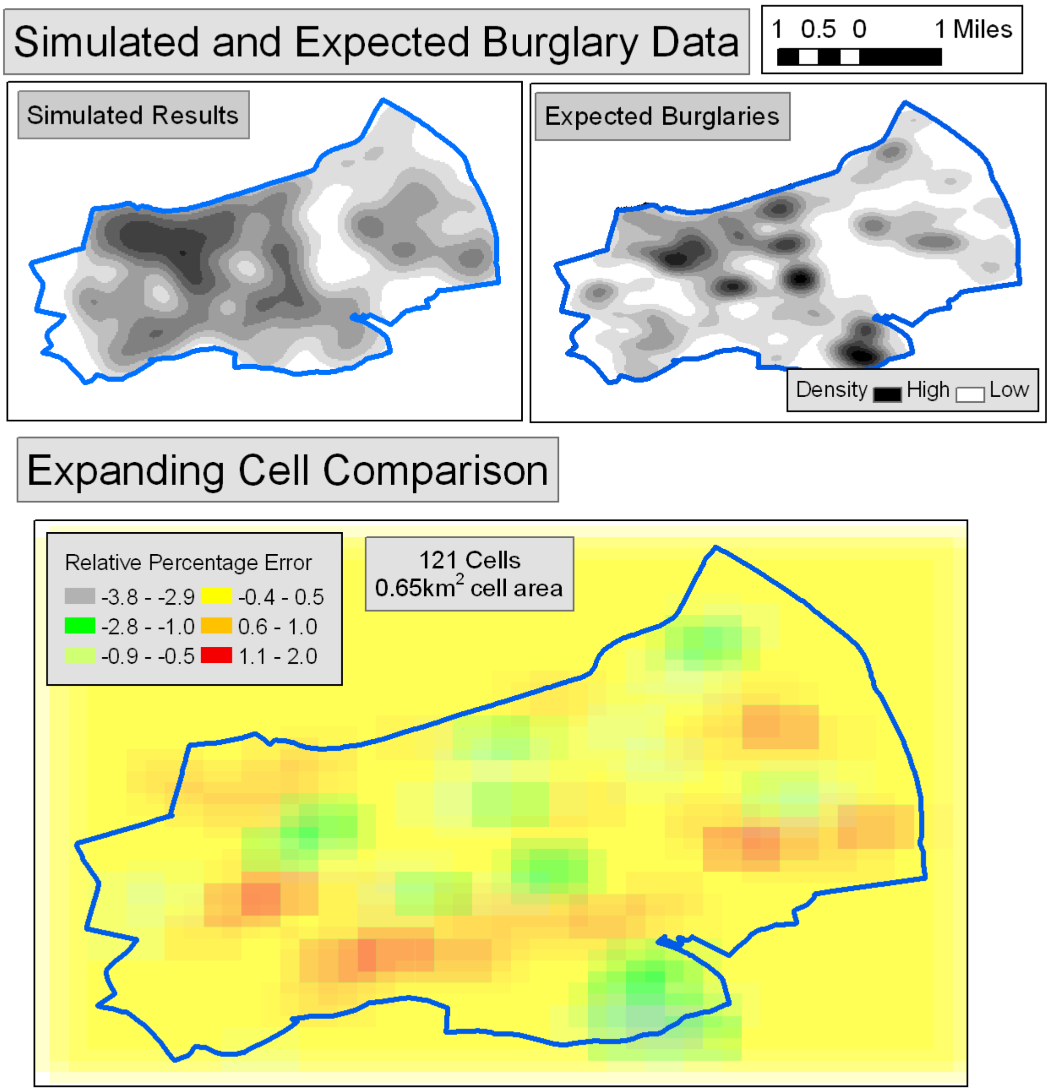

Figure 6: Comparing simulated results (after calibration) to real burglary data. In the expanding cell comparison, square grids are overlaid and the difference between the two point datasets in each cell calculated. This reduces the effects of the Modifiable Areal Unit Problem (MAUP: Openshaw, 1984) and creates a fuzzy spatial error estimate.

5.3 Experimental Scenario

Work was heavily underway on two particular sites in the greater EASEL area during this research, which were therefore chosen for the simulation scenario. Houses in the areas have been demolished and are being replaced with new buildings and new road layouts. The model was used to create an estimate of the effects of the regeneration project on future burglary rates by creating a new virtual urban environment based on housing architectural plans provided by the developers. The scenario here is 'optimistic'; it assumes that the aims of the regeneration scheme – to attract a variety of people and create a cohesive community (EASEL Team, 2007) – will be successful. With hindsight these optimistic assumptions might prove false, but the purpose of this research is to predict the changing patterns of residential burglary under assumptions provided by policy makers. Therefore, the virtual environment was changed to match the areas under development as follows:

- Buildings and roads will be constructed in the virtual environment to reflect the planned layout (based on real development plans).
- The communities in the development areas were set to an average 'typical traits' group to reflect the influx of a variety of people;
- To reflect the planned cohesive new communities, the *collective efficacy* environmental variable was increased to 1.0 (highest possible value) to create highly cohesive virtual communities which reduces suitability of all houses in the community to burglars (see equation 2);
- Building security was set to a high value (1.0) to reflect the high security of all new buildings;

6 RESULTS

This section will discuss the outcomes of the regeneration simulation by comparing the results of the simulation before and after the regeneration environment changes. Because the simulation is probabilistic, the results described are actually the total of 50 individual simulations. Total crime is not predicted but instead the model runs can be used to reflect on the location of crimes and the development of new hotspots under urban regeneration.

Figure 7 maps the outcome of a comparison of crime patterns before and after the regeneration of sites A and B. In the areas of the regeneration sites, it appears that crime has generally decreased. This is expected because the environmental changes (increased household security and community collective efficacy) mean that houses in these areas are more difficult to burgle. The most interesting finding from Figure 7 is that there are a small number of houses that suffer a large increase in burglary as a direct result of the regeneration. The effect is highly localised which is unusual because it might be expected that any crime displacement would be more evenly distributed into the surrounding area (e.g. Malleson et al., 2009).

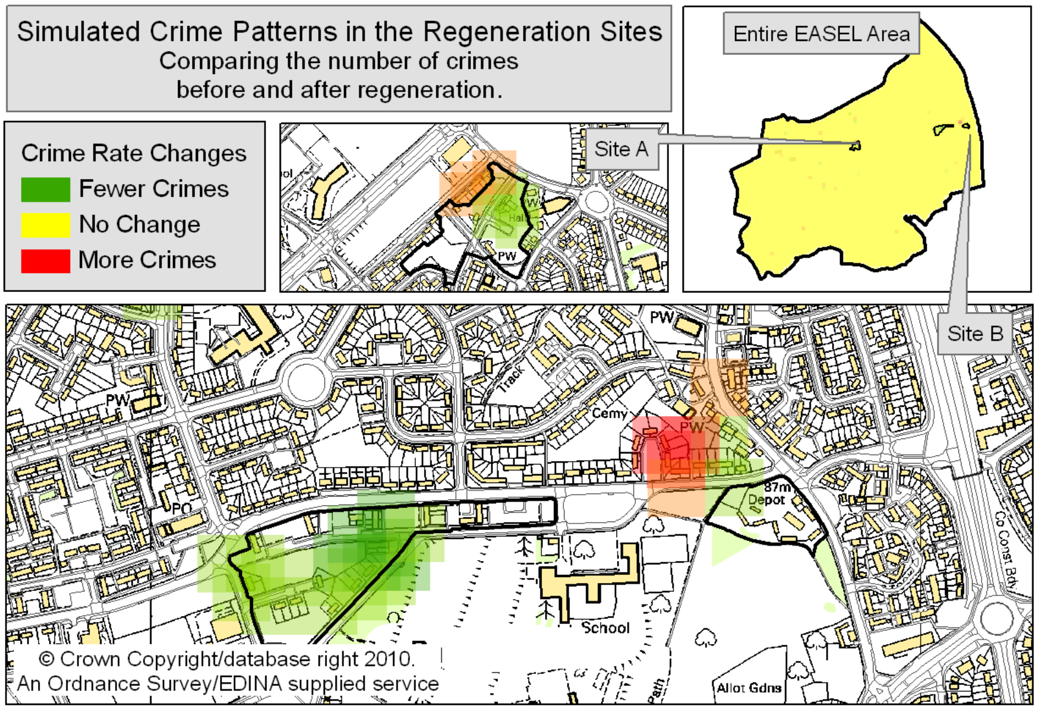

Figure 7: Individual houses that were found to be susceptible to burglary. The areas that are demarked by black lines indicate the exact extents of sites A and B (which are where the new EASEL houses are being constructed).

To explore this result in more detail, the analysis will focus on the area to the north of site B as it suffers the largest relative increase in burglaries. It is clear that there are many houses close to the development site that do not suffer high levels of victimisation after the regeneration and therefore some of the risk might be attributed to the physical attributes of the houses (i.e. their visibility or accessibility). Figure 8(a) shows the difference in the number of burglaries per household before and after the regeneration. Negative (green) numbers illustrate a drop in burglary after regeneneration and positive numbers (red) are indicitative of an increase. There are two houses, in particular, that have a substantially higher burglary count after regeneration. To assess why this might be the case, Figure8(b) illustrates the household burglary risk which is estimated from the mean of the variables that feature in an agent's burglary decision: *accessibility*, *visibility*, *security*, *traffic volume* and *collective efficacy* (note that *occupancy* is not included in this estimate because it changes depending on the time of day). It appears that the highly victimised houses have a risk that is higher than that of their direct neighbours but, as illustrated by the frequency distribution in Figure 8(c), one that is only slightly higher than average. Hence the household parameters do not sufficiently explain why burglary rates should be so much higher in those two houses; there must be other explanations for the burglary increase.

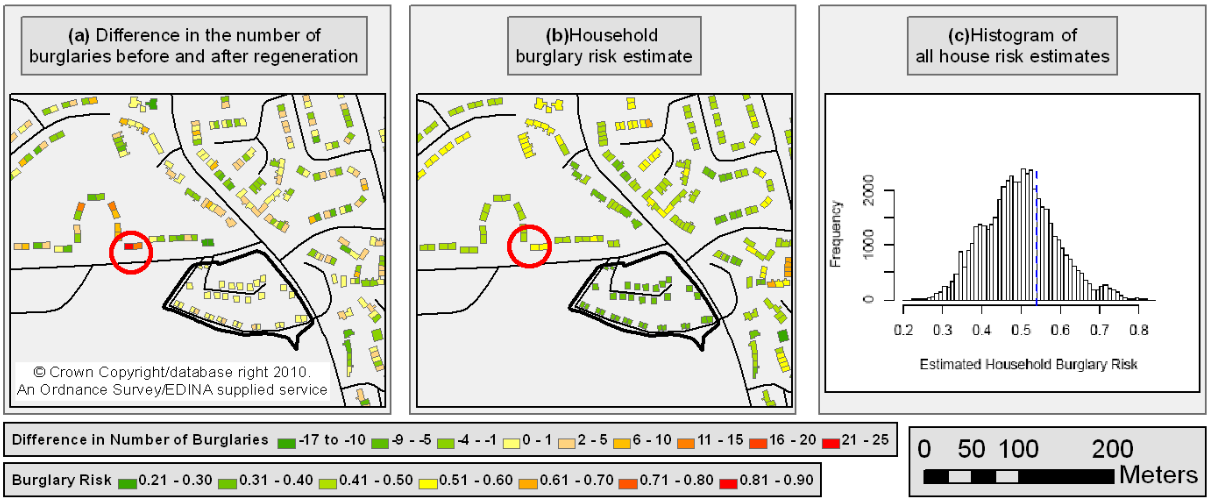

Figure 8: Comparing the difference in burglaries before and after the simulated regeneration to estimated household risk in regeneration site B. The histogram illustrates the risk of the highlighted buildings in relation to all other buildings in the environment. The areas that are demarked by black lines show part of regeneration site B which has had new buildings constructed within it.

A further procedure to assess why certain individual houses have considerably higher burglary rates is to observe the travel patterns of some of the simulated burglars. This makes it possible to determine whether or not the regeneration has changed the behaviour of the burglar agents and, as a consequence, led to an increased number of burglaries in certain houses. In other words, it could be the post-regeneration *urban form* of the area, rather than the attributes of the houses themselves, that increase their risk. To this end, Figure 9 plots, as examples, the movements of two randomly chosen agents who both comitted a burglary in the high-risk houses. For these agents, there were many minor roads in the regeneration area and its surroundings that they did not explore . However, the highly-burgled houses are situated on a main road that runs along the northern boundary of the regeneration area that was regularly used by the agents as part of their routine activities. Furthermore, a close inspection of Figure 9 indicates that the agents passed the houses whilst looking for a burglary target, not necessarily during legitimate travels on some other business (such as travelling to a social location), but within the area known from their routine activities.

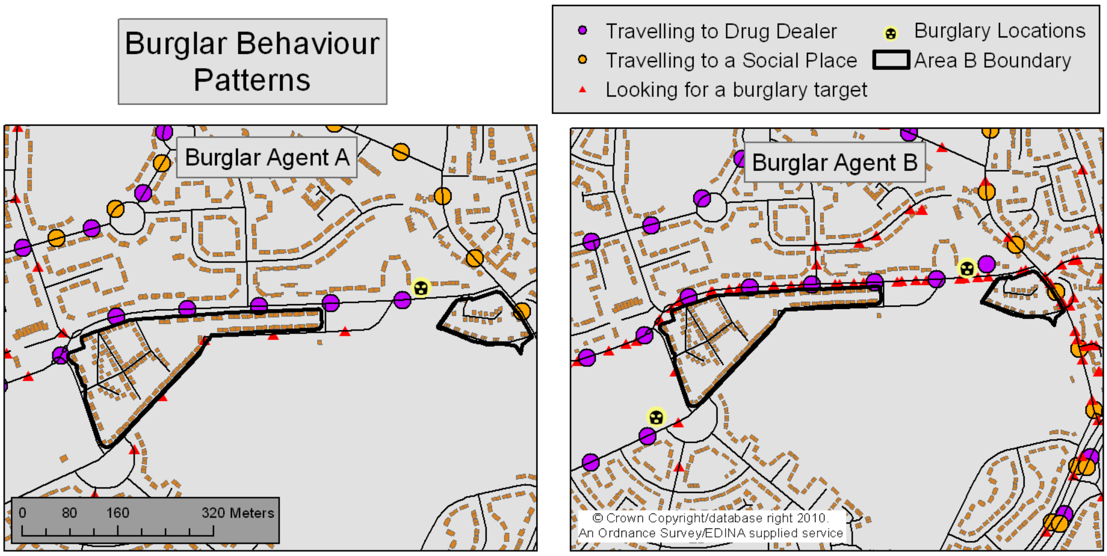

Figure 9: An illustration of the movement patterns of two randomly chosen offenders who both comitted a burglary in one of the two highly victimised houses. Colours indicate the motivation for travelling. Note that time is not displayed, the figure illustrates all journeys made by the agents throughout the simulation.

Therefore it is plausible that the EASEL changes attracted the burglar agents to the area specifically for burglary purposes and the location of the houses on the main road meant that they were certain to be noticed by the agents whereas other houses were not. Hence it is apparent that the houses which had been highly victimised attain part of their risk from their location in space. These findings are strongly supported by the criminology theory. In the cases where the houses do not feature in a burglar's awareness space – because they have not been passed on burglar's routine activities – they have a relatively low burglary risk. Once a burglar becomes aware of the houses near the regeneration area, however, their risk increases. Nevertheless, the theories in isolation could not have predicted which *individual houses* in the regeneration area might be susceptible to burglary. Only when the theories have been implemented in a model that is able to account for the low-level dynamics of the burglary system can specific real-world predictions such as this be made. Although other models could have predicted displacement into the area surrounding a regeneration, identifying individual houses that might suffer the highest risk is a novel accomplishment for a computer model.

7 DISCUSSION AND CONCLUSIONS

This paper has presented a novel burglary simulation operating at the level of the individual (burglar and house) which takes account of the complex individual-level dynamics of the crime system. As with any type of model, there is a degree of error associated with the results. Rather than indicating a failure of the model, however, it is possible that in certain areas the theoretical assumptions upon which the model is based are not applicable. For example, following a discussion with local crime experts (Safer Leeds, 2009), experience suggests that in some neighbourhoods burglars are motivated by non-monetary incentives (i.e. to intimidate residents). However, the burglars in the model are motivated by monetary gains (e.g. to sustain a drug addiction). In this case, therefore, the model was able to demonstrate where common assumptions about burglary fail and thus where crime reduction initiatives that have been successful in other areas might have to be adapted to match this variety in offender motivation.

Although the research is able to explicitly model the behaviour of individual burglars, this also has some drawbacks. For example, assumptions not present in simpler models must be defined explicitly here. It must be decided how much time agents should spend socialising, what they do (and where they go) during the day etc. The advantages of high model complexity and flexibility are tempered by the difficulty of finding suitable values for these parameters based on empirical evidence. This points to the need for further empirical research to investigate who a 'potential burglar' is and what their daily habits are. There is also no mechanism for cooperative burglary by the offenders; each agent works individually. It is likely that, in the real world, there will be some forms of cooperation or at least the dissemination of burglary-related knowledge. Similarly, although the burglary template discussed in Section 3.2 paints a comprehensive picture of the act of burglary, no consideration is given to how an agent converts the stolen goods into money afterwards. This will undoubtedly influence a person's awareness space and will also have consequences for length of time before they need to commit another burglary. All these aspects are recommended as means of improving the model in the future.

Despite the drawbacks, the model is able to represent the highly complex spatio-temporal dynamics of the crime system through the inclusion of detailed information on individual houses, communities and burglars. The effects of crime reduction initiatives were explored in an area of Leeds, which has obvious relevance to the police and other stakeholders. Such a model could form part of a planning support system for new crime reduction initiatives or urban developments.

References

Andresen, M. A. (2010). The place of environmental criminology within criminological thought. In M. A. Andresen, P. J. Brantingham, and J. Kinney (Eds.), *Classics in Environmental Criminology*. CRC Press.

Andresen, M. A. and N. Malleson (2011). Testing the stability of crime patterns: implications for theory and policy. *Journal of Research in Crime and Delinquency forthcoming 48(1)* 58-82.

Armitage, R., L. Monchuk and R. Michelle (2011). It Looks Good, but What is it Like to Live There? Exploring the Impact of Innovative Housing Design on Crime. *European Journal on Criminal Policy and Research 17*(1), 29-54.

Axelrod, R. (1997). Advancing the art of simulation in the social sciences. In R. Conte, R. Hegselmann, and P. Terna (Eds.), *Simulating Social Phenomena*, pp. 21–40. Berlin: Springer-Verlag.

Baldwin, J. and A. E. Bottoms (1976). *The Urban Criminal: A Study in Sheffield*. London: Tavistock Publications.

Beavon, D. J. K., P. L. Brantingham, and P. J. Brantingham (1994). The influence of street networks on the patterning of property offenses. In R. V. Clarke (Ed.), *Crime Prevention Studies*, Volume 2. New York: Criminal Justice Press.

Bennell, C., B. Snook, P. J. Taylor, S. Corey, and J. Keyton (2007). It's no riddle, choose the middle: The effect of number of crimes and topographical detail on police officer predictions of serial burglarsÕhome locations. *Criminal Justice And Behavior 34*(1), 119–132.

Bernasco, W. and F. Luykx (2003). Effects of attractiveness, opportunity and accessibility to burglars on residential burglary rates of urban neighborhoods. *Criminology 41*(3), 981–1002.

Bernasco, W. and P. Nieuwbeerta (2005). How do residential burglars select target areas? A New Approach to the Analysis of Criminal Location Choice. *British Journal of Criminology 45*(3), 296–315.

Birks, D. J., S. Donkin, and M. Wellsmith (2008). Synthesis over analysis: Towards an ontology for volume crime simulation. In L. Liu and J. Eck (Eds.), *Artificial Crime Analysis Systems: Using Computer Simulations and Geographic Information Systems*, Hershey, PA, pp. 160–192. Information Science Reference.

Bonabeau, E. (2002, May). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences 99*, 7280–7287.

Bottoms, A., A. Claytor, and P. Wiles (1992). Housing markets and residential community crime careers: A case study from Sheffield. In N. Fyfe, D. Evans, and D. Herbert (Eds.), *Crime, Policing and Place – Essays in Environmental Criminology*, Chapter 7, pp. 94–116. London: Routledge.

Bowers, K. and A. Hirschfield (1999). Exploring the link between crime and disadvantage in north-west England: an analysis using geographical information systems. *International Journal of Geographical Information Science 13*(2), 159–184.

Bowers, K., S. Johnson, and A. Hirschfield (2003). *Pushing back the boundaries: new techniques for assessing the impact of burglary schemes.* Home Office Online Report 24/03. London: Home Office.

Brantingham, P. J. and G. Tita (2006). Butterflies, bees and burglars: The behavioral ecology of criminal search strategies. Presentation to the American Society of Criminology (ASC) 31st October – 4th November 2006.

Brantingham, P. L. and P. Brantingham (1981a). Notes of the geometry of crime. In P. Brantingham and P. Brantingham (Eds.), *Environmental Criminology*, pp. 27–54. Prospect Heights, IL: Waveland Press.

Brantingham, P. L. and P. J. Brantingham (1981b). Mobility, notoriety, and crime: A study in the crime patterns of urban nodal points. *Journal of Environmental Systems 11*(1), 89–99.

Brantingham, P. L. and P. Brantingham (1993). Environment, routine, and situation: Toward a pattern theory of crime. In R. Clarke and M. Felson (Eds.), *Routine Activity and Rational Choice*, Volume 5 of *Advances in Criminological Theory*. New Brunswick, NJ: Transaction Publishers.

Brantingham, P. L. and P. J. Brantingham (1998). Mapping crime for analytic purposes: Location quotients, counts, and rates. In D. Weisburd and T. McEwen (Eds.), *Crime Mapping and Crime Prevention*, Volume 8 of *Crime Prevention Studies*, pp. 263–288. Monsey, NY: Criminal Justice Press.

Brantingham, P. L. and P. J. Brantingham (2008). Crime pattern theory. In R. Wortley and L. Mazerolle (Eds.), *Environmental Criminology and Crime Analysis*, Crime Science Series. UK: Willan Publishing.

Bratman, M. E., D. J. Israel, and M. E. Pollack (1988). Plans and resource-bounded practical reasoning. *Computational Intelligence 4*(3), 349–355.

Brown, B. B. and D. L. Bentley (1993). Residential burglars judge risk: The role of territoriality. *Journal of Environmental Psychology 13*, 51–61.

Browning, C. R., S. L. Feinberg, and R. D. Dietz (2004). The paradox of social organization: Networks, collective efficacy, and violent crime in urban neighborhoods. *Social Forces 83*(2), 503–534.

Chaplin, R., J. Flatley, and K. Smith (2011). *Crime in England and Wales 2010/11. Findings from the British Crime Survey and police recorded crime*. London: Home Office.

Clarke, R. V. and D. B. Cornish (1985). Modeling offenders' decisions: a framework for research and policy. *Crime and Justice 6*, 147–185.

Cohen, L. and M. Felson (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review 44*, 588–608.

Cromwell, P. and J. N. Olson (2005). The reasoning burglar: Motives and decision-making strategies. In

P. Cromwell (Ed.), *In Their Own Words: Criminals On Crime (An Anthology)* (4th ed.)., Chapter 5, pp. 42–56. Roxbury Publishing Company.

Cromwell, P. F., J. N. Olson, and D. W. Avary (1991). *Breaking and entering: an ethnographic analysis of burglary*, Volume 8 of *Studies in Crime, Law and Justice*. Newbury Park, London: Sage Publications.

Dray, A., L. Mazerolle, P. Perez, and A. Ritter (2008). Drug law enforcement in an agent-based model: simulating the disruption to street-level drug markets. In L. Liu and J. Eck (Eds.), *Artificial Crime Analysis Systems: Using Computer Simulations and Geographic Information Systems*. IGI Global.

EASEL Team (2007). *East and South East Leeds Area Action Plan*. Leeds, UK: Leeds City Council.

Eck, J. E. (1995). Crime places in crime theory. In J. E. Eck and D. Weisburd (Eds.), *Crime Prevention Studies*, Volume 4. New York: Criminal Justice Press.

Eck, J. E. and L. Liu (2008). Contrasting simulated and empirical experiments in crime prevention. *Journal of Experimental Criminology 4*(3), 195–213.

Elffers, H. and P. van Baal (2008). Realistic spatial backcloth is not that important in agent based simulation: An illustration from simulating perceptual deterrence. In L. Liu and J. Eck (Eds.), *Artificial Crime Analysis Systems: Using Computer Simulations and Geographic Information Systems*, Chapter 2, pp. 19–34. IGI Global.

Felson, M. (2002). *Crime and Everyday Life* (Third ed.). Sage Publications.

Felson, M. (2008). Routine activities approach. In R. Wortley and L. Maxerolle (Eds.), *Environmental Criminology and Crime Analysis*. Devon, UK: Willan Publishing.

Glyde, J. (1856). Localities of crime in suffolk. *Journal of the Statistical Society of London 19*(2), 102–106.

Groff, E. (2007a). Simulation for theory testing and experimentation: An example using routine activity theory and street robbery. *Journal of Quantitative Criminology 23*, 75Ð–103.

Groff, E. (2007b). 'Situating' simulation to model human spatio-temporal interactions: An example using crime events. *Transactions in GIS 11*(4), 507–530.

Groff, E. (2008). Characterizing the spatio-temporal aspects of routine activities and the geographic distribution of street robbery. In *Artificial Crime Analysis Systems: Using Computer Simulations and Geographic Information Systems*, Chapter 12. IGI Global.

Groff, E. and L. Mazerolle (2008). Simulated experiments and their potential role in criminology and criminal justice. *Journal of Experimental Criminology 4*(3), 187–193.

Groff, E., D. Weisburd, and N. A. Morris (2009). Where the action is at places: Examining spatio-temporal patterns of juvenile crime at places using trajectory analysis and GIS. In D. Weisburd, W. Bernasco, and G. Bruinsma (Eds.), *Putting Crime in its Place. Units of Analysis in Geographic Criminology*, Chapter 3, pp. 61 – 86.

Springer.

Guerry, A. M. (1831). *Essai Sur la Statistique Morale de la France*. Paris, FR: Chez Crochard.

Hägerstrand, T. (1970). What about people in regional science? *Papers in Regional Science 24*(1), 6–21.

Hamilton-Smith, N. and A. Kent (2005). The prevention of domestic burglary. In *Handbook of Crime Prevention and Community Safety*. Devon, UK: Willan Publishing.

Hayslett-McCall, K. L., F. Qiu, K. M. Curtin, B. Chastain, J. Schubert, and V. Carver (2008). The simulation of the journey to residential burglary. In *Artificial Crime Analysis Systems: Using Computer Simulations and Geographic Information Systems*, Chapter 14. IGI Global.

Hearnden, I. and C. Magill (2003). *Decision-making by house burglars: offender's perspectives.* Home Office Research Findings 249. London: Home Office.

Hirschfield, A. (2004). *The impact of the Reducing Burglary Initiative in the north of England*. Home Office Online Report 40/04. London: Home Office.

Jeffery, C. R. (1971). *Crime Prevention Through Environmental Design*. Beverly Hills, CA: Sage Publications.

Johnson, S. (2008). Repeat burglary victimisation: a tale of two theories. *Journal of Experimental Criminology 4*(3), 215-240.

Johnson, S. and K. Bowers (2004). The stability of space-time clusters of burglary. *The British Journal of Criminology 44*, 55–65.

Johnson, S. and K. Bowers (2009). Permeability and Burglary Risk: Are Cul-de-Sacs Safer? *Journal of Quantitative Criminology 26* (1): 89–111

Johnson, S., K. Bowers, and A. Hirschfield (2002). Introduction to the environmental criminology and crime analysis (ECCA) special edition. *Crime Prevention and Community Safety: An International Journal, 4*(1), 7–10.

Kent, J., M. Leitner, and A. Curtis (2006). Evaluating the usefulness of functional distance measures when calibrating journey-to-crime distance decay functions. *Computers, Environment and Urban Systems 30*(2), 181–200.

Kongmuang, C. (2006). *Modelling Crime: A Spatial Microsimulation Approach*. Ph. D. thesis, School of Geography, University of Leeds, Leeds LS2 9JT, UK.

Liu, L. and J. Eck (Eds.) (2008). Artificial Crime Analysis Systems: Using Computer Simulations and Geographic Information Systems. IGI Global.

Liu, L., X. Wang, J. Eck, and J. Liang (2005). Simulating crime events and crime patterns in a RA/CA models. In F. Wang (Ed.), *Geographic Information Systems and Crime Analysis*, pp. 197–213. Reading, PA: Idea Publishing.

Malleson, N. (2010). *Agent-Based Modelling of Burglary*. Ph. D. thesis, School of Geography, University of Leeds, LS6 3DT, UK.

Malleson, N. and P. Brantingham (2009). Prototype burglary simulations for crime reduction and forecasting. *Crime Patterns and Analysis 2*(1).

Malleson, N., A.J. Evans, and T. Jenkins (2009). An agent-based model of burglary. *Environment and Planning B: Planning and Design 36*, 1103–1123.

Malleson, N., A.J. Heppenstall and L. See (2010). Crime reduction through simulation: An agent-based model of burglary. *Computers, Environment and Urban Systems 34*, 236–250

Malleson, N., L.M. See, A.J. Evans, and A.J. Heppenstall (2011). Implementing comprehensive offender behaviour in a realistic agent-based model of burglary. *Simulation: Transactions of the Society of Modeling and Simulation International*. Forthcoming. Available at: http://sim.sagepub.com/content/early/2010/10/20/0037549710384124.abstract

Malleson, N. and M. Birkin (2011). Towards victim-oriented crime modelling in a social science e-infrastructure. *Philosophical Transactions of the Royal Society A.* In press. Abstract available online: https://www.geog.leeds.ac.uk/fileadmin/downloads/school/people/postgrads/n.malleson/ahm_2010_abstract.pdf

Mayhew, P. (1984). Target-hardening: How much of an answer. In R. Clarke and T. Hope (Eds.), *Coping with Burglary*, International Series in Social Welfare, Chapter 3, pp. 29–44. Boston: Kluwer Academic Publishers.

Moss, S. and B. Edmonds (2005). Towards good social science. *Journal of Artificial Societies and Social Simulation 8*(4).

Newman, O. (1972). *Defensible Space*. New York: Macmillan.

Newton, A. D., M. Rogerson, and A. Hirschfield (2008, July). Relating target hardening to burglary risk: Experiences from liverpool. *Papers from the British Criminology Conference 8*, 153–174. Papers from the British Criminology Conference 2008 9? 11 July. Criminological Futures: Controversies, Developments and Debates Hosted by the Applied Criminology Centre, University of Huddersfield.

Nicholas, S., D. Povey, A. Walker, and C. Kershaw (2005). *Crime in England and Wales 2004/2005*. London: Home Office.

Noble, M., G. Wright, C. Dibben, G. Smith, D. McLennan, C. Anttila, H. Barnes, C. Mokhtar, S. Noble, D. Avenell, J. Gardner, I. Covizzi, and M. Lloyd (2004). *The English Indices of Deprivation 2004 (revised)*. London: Office of the Deputy Prime Minister.

North, M., T. Howe, N. Collier, and R. Vos. (2005). The repast simphony development environ-ment. In *Agent 2005 Conference on Generative Social Processes, Models, and Mechanisms*, Argonne National Laboratory, Argonne, IL, USA.

Openshaw, S. (1984) *The modifiable areal unit problem*. Concepts and Techniques in Modern Geography (CATMOG) No. 38. Norwich, Geo Books.

Pitcher, A. and S. Johnson (2011). Exploring Theories of Victimization Using a Mathematical Model of Burglary. *Journal of Research in Crime and Delinquency 48*, 83-109.

Ordnance Survey (2009). Welcome to OS MasterMap. Available online `http://www.ordnancesurvey.co.uk/oswebsite/products/osmastermap` [accessed – Dec 2009].

O'Sullivan, D. and M. Haklay (2000). Agent-based models and individualism: Is the world agent-based? *Environment and Planning A 32*(8), 1409–1425.

Quetelet, A. (1842). A Treatise on Man and the Development of His Faculties. Edinburgh: W. and R. Chambers.

Quetelet, L. A. J. (1831). *Research on the Propensity for Crime at Different Ages*. Cincinnati, OH: Anderson Publishing.

Rees, P., D. Martin, and P. Williamson (Eds.) (2002). *The Census Data System*. John Wiley and Sons.

Rengert, G. (1996). *The Geography of Illegal Drugs*. Boulder, Colorado: Westview Press.

Rengert, G. and J. Wasilchick (1985). *Suburban Burglary: A Time and a Place for Everything*. Springfield, Illinois: Charles Thomas Publishers.

Richards, A. and Gillian M. Sinclair (2009). UK national grid service. In Lizhe Wang, Wei Jie, and Jinjun Chen, editors, *Grid Computing: Infrastructure, Service, and Applications*, chapter 6. CRC Press.

Robinson, M. B. and C. E. Robinson (1997). Environmental characteristics associated with residential burglaries of student apartment complexes. *Environment and Behaviour 29*, 657–675.

Safer Leeds (2009). Safer leeds: Tackling drugs and crimes. Online `http://www.leedsinitiative.org/safer/` [accessed – Oct 2009].

Sampson, R. J., S. W. Raudenbush, and F. Earls (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science 277*, 918–924.

Scarr, H. A. (1973). *Patterns of Burglary*. Washington, DC: U.S. Govenrment Printing Office.

Schmidt, B. (2000). *The Modelling of Human Behaviour*. Erlangen, Germany: SCS Publications.

Schmidt, B. (2002). How to give agents a personality. In *Proceedings of the 3rd Workshop on Agent- Based Simulation, April 7-9*, Passau, Germany.

Shaw, C. R. and H. D. McKay (1942). *Juvenile Delinquency and Urban Areas*. Chicago, IL: The University of Chicago Press.

Shaw, C. R. and H. D. McKay (1969). *Juvenile Delinquency and Urban Areas*. Chicago: The University of Chicago Press.

Snook, B. (2004). Individual differences in distance travelled by serial burglars. *Journal of Investigative Psychology and Offender Profiling 1*, 53–66.

Tseloni, A. (2006). Multilevel modelling of the number of property crimes: household and area effects. *Journal of the Royal Statistical Society A 169,* 205–233.

Urban, C. (2000). PECS: A reference model for the simulation of multi-agent systems. In R. Suleiman, K. G. Troitzsch, and N. Gilbert (Eds.), *Tools and Techniques for Social Science Simulation*, Chapter 6, pp. 83–114. Physica-Verlag.

van Nes, A. (2006). The burglar as a space explorer in his own neighborhood. In U. Mander, C. Brebbia, and E. Tiezzi (Eds.), The Sustainable City IV. Urban regeneration and Sustainability. Wessex, UK: WIT Press.

Vickers, D. and P. Rees (2006). Introducing the national classification of census output areas. *Population Trends 125*, 15–29.

Vickers, D. and P. Rees (2007). Creating the UK national statistics 2001 output area classification. *Journal of the Royal Statistical Society Series A 170*(2), 379–403.

Vito, G.F., Maahs, J.A. and Holmes, R.M. (2007). *Criminology: Theory, Research and Policy*. Sudbury MA: Jones and Bartlett Publishers.

Weisburd, D. V., S. Bushway, C. Lum, and S. ming Y Ang (2004). Trajectories of crime at places: A longitudinal study of street segments in the city of seattle. *Criminology 42*(2), 283–321.

Weisburd, D., G. J. N. Bruinsma, and W. Bernasco (2009). Units of analysis in geographic criminology: Historical development critical issues and open questions. In D. Weisburd, W. Bernasco, and G. Bruinsma (Eds.), *Putting Crime in its Place. Units of Analysis in Geographic Criminology*, Chapter 1, pp. 3 – 31. Springer.

Weisel, D. L. (2002). Burglary of Single-Family Houses, Volume 18 of Problem-Oriented Guides for Police Series. U.S. Department of Justice.

Wiles, P. and A. Costello (2000). *The 'road to nowhere': the evidence for travelling criminals.* Home Office Research Study 207. London: Home Office.

Wilkström, P. (1991). Urban Crime, Criminals and Victims: The Swedish Experience in an Anglo-American Comparative Perspective. New York: Springer-Verlag.

Wilson, J. Q. and G. L. Kelling (1982, March). Broken windows: The police and neighborhood safety. *The Atlantic Monthly 249*(3), 29–38.

Wright, R. T. and S. H. Decker (1996). *Burglars on the Job: Streetlife and Residential Break-ins*. Boston: Northeastern University Press.

Wright, R. T. and S. H. Decker (2005, September). Deciding to commit a burglary. In P. Cromwell (Ed.), *In Their Own Words: Criminals On Crime (An Anthology)* (4th ed.)., Chapter 9, pp. 90–101. Roxbury Publishing

Company.