Chapter 19
Using Agent-Based Models to Simulate Crime

Nicolas Malleson

Abstract Due to the complexity of human behaviour and the intricacies of the urban environment, it is extremely difficult to understanding and model crime patterns. Nevertheless, a greater understanding of the processes and drivers behind crime is essential for researchers to be able to properly model crime and for policy-makers to be able to predict the potential effects of their interventions. Traditional mathematical models that use spatially aggregated data struggle to capture the low-level dynamics of the crime system – such as an individual person's behaviour – and hence fail to encapsulate the factors that characterise the system and lead to the emergence of city-wide crime rates.

This chapter will outline a realistic agent-based model that can be used to simulate, at the level of individual houses and offenders, occurrences of crime in a real city. In particular, the research focuses on the crime of residential burglary in the city of Leeds, UK. The model is able to predict which places might have a heightened burglary risk as a direct result of a real urban regeneration scheme in the local area.

19.1 Introduction

Understanding the processes and drivers behind crime is an important research area in criminology with major implications for both improving policies and developing effective crime prevention strategies (Brantingham and Brantingham 2004; Groff 2007). Advances in environmental criminology theory (e.g. Cohen and Felson 1979; Clarke and Cornish 1985; Brantingham and Brantingham 1993) have highlighted a shift in the field towards understanding the importance of the social and environmental contexts in which crimes occur, rather than focussing purely the behaviour of offenders.

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Furthermore, the complexity of the crime system – which consists of the dynamic interactions between the individuals involved in each crime event as well as their interactions with others and with their environment – means that individual-level approaches are the most suitable modelling methodologies for simulating the crime system.

This chapter will discuss how agent-based models (ABM's), coupled with realistic geographic environments, can be used to simulate crime. In particular, it will focus on the crime of residential burglary and outline a current agent-based simulation model that can be used to make predictions about future burglary rates in the real world. The model described is based on the city of Leeds, UK.

The chapter is organised as follows. The next section will outline the important drivers of the crime system that must be included in a model followed by a discussion on how crime has been modelled previously. The remainder of the chapter will then discuss a model that can be used to simulate residential burglary and will demonstrate how it can be used to simulate the effects that urban-regeneration can have on burglary.

19.2 Background: Environmental Criminology

Crime is a highly complex phenomenon. An individual crime event is the result of the convergence of a multitude of different factors including the motivations and behaviours of the offender, influences of the physical surroundings, community-wide effects such as community cohesion, the actions of the victim and the behaviour of other people such as the police or passers-by. Associated with this already complex framework are additional factors such as a diverse urban geography and obscure human psychology.

Criminology can help to understand patterns of crime. However, pre-1970 criminology research was largely dominated by studies into victims, the law and offenders (Andresen 2010) and thus omitted a vital element; the *place* in which the crime occurs. It was to this end that the field of "environmental criminology" arose as a discipline to study the *spatial* variations of crime and the underlying reasons for these variations (Johnson et al. 2002). The remainder of this section will discuss examples from environmental criminology research for a crime model. Although the focus is on the crime of residential burglary, many of the factors are relevant for most other types of inquisitive crime.

19.2.1 Physical Factors

Major advancements in criminological theory in the 1970s solidified the link between the physical form of an area and its affect on crime (Jeffery 1971; Newman 1972). With respect to burglary, the important physical factors that determine a house's vulnerability can be classified into three groups as identified by Cromwell et al. (1991).

The first group, *accessibility*, relates to how easy it is to actually enter a property. For example, detached houses and ground-floor flats have been found to be vulnerable because there are more potential entry points (Robinson and Robinson 1997; Felson 2002). The second category of physical factor that might influence burglary is *visibility* and refers to the extent to which a residence can be seen by neighbours and passers-by (Cromwell et al. 1991). Buildings that are less visible are generally easier for offenders to access without being seen by others. Visibility can be affected by objects such as large hedges or other buildings that can obscure the view of the property as well as factors like the distance between the house and its connecting road, levels of street lighting and the amount of passing traffic. Finally, *occupancy* represents whether the residents are at home or not.

19.2.2 The Social Environment

Although physical factors are clearly important determinants of burglary risk, the "environmental backcloth" (Brantingham and Brantingham 1993) extends well beyond these simple physical factors. It is also important to consider the *social* factors that surround a crime event. Unfortunately, whereas the relationship between physical factors and burglary risk is often fairly straightforward, that of the social environment and crime is not. For example, deprived communities often suffer disproportionately high crime rates (Baldwin and Bottoms 1976; Sampson et al. 1997) but the reverse has also been found (Wilkström 1991; Bowers and Hirschfield 1999).

Fortunately, the relationship between other variables is more straightforward. Students, for example, are often a highly victimised group (Tilley et al. 1999; Barberet et al. 2004) as student households are often seen as an easy targets (Deakin et al. 2007) and can contain an abundance of attractive goods. Other demographic factors that can increase burglary risk include the age of residents, the tenure type (e.g. publicly rented compared to privately owned) and the number children/young people in the area (Tilley et al. 1999).

Another factor that is not necessarily related to socioeconomic status, but can have a strong impact on crime rates, is community cohesion. It is hypothesised that if a community looses the ability to police itself then crime is the "natural response" by individuals. This process can occur when an area contains a transient population as people do not stay in area long enough for make friends and develop a feeling of "community" and ownership over the area. The importance of community cohesion is evidenced by the seminal theories it has provoked (e.g. Shaw and McKay 1942; Jeffery 1971; Newman 1972; Wilson and Kelling 1982) and by the large body of empirical research that supports it (Hope 1984; Brown and Bentley 1993; Wright and Decker 1996; Sampson et al. 1997; Kawachi et al. 1999).

In summary, this section has illustrated that the relationship between crime and the surrounding environment is complex. In order to model the system, it must be determined if a high crime rate is due to the types of housing in the area, the houses' physical properties, the number of and behaviour of potential burglars, the amount of community cohesion or for other reasons that have yet to be identified. However, using the appropriate methodology it is nevertheless possible to account for all these features in a crime model as the following section will discuss.

19.3 Modelling Crime

19.3.1 The Geography of Crime

Since the first pioneering work on the geography of crime in the nineteenth century (Quetelet 1831; Glyde 1856), crime research has moved to smaller and smaller units of analysis. However, with the exception of a small number of "crime at place" studies (e.g. Eck 1995; Weisburd et al. 2009a, b), most research still uses aggregated [AU1] data and there has been very little work into what the most appropriate unit of analysis should be (Weisburd et al. 2009a, b). Modern environmental criminology theories (e.g. Cohen and Felson 1979; Brantingham and Brantingham 1981; Clarke and Cornish 1985) suggest that an individual crime depends on the behaviour of *individual* people or objects and should thus be analysed at the level of the individual (Weisburd et al. 2004). This is extremely relevant with the crime of burglary because burglars choose *individual* homes based on their *individual* characteristics (Rengert and Wasilchick 1985). Models that uses aggregate-level crime or demographic data will therefore suffer, to a greater or lesser extent, from the ecological fallacy (Robinson 1950). Indeed, recent crime research has shown that individual- or street-level events exhibit considerable spatial variation which would be hidden if analysed at even the smallest administrative boundaries (Bowers et al. 2003; Weisburd et al. 2004; Groff et al. 2009; Andresen and Malleson 2010).

That said, the majority of crime models to date employ regression techniques and look for relationships using aggregate data. For a review of commonly used approaches the reader is directed to Kongmuang (2006) but, in general, the central drawback is that statistical models fail to address the importance of the individual: individual people, incidents, locations and times.

Following this, ABM appears to be the most appropriate methodology for modelling crime and the following section will explore the use of ABM for crime analysis in more detail.

19.3.2 Agent-Based Crime Modelling

19.3.2.1 Advantages and Disadvantages

An obvious advantage with ABM is its ability to capture emergent phenomena. Environmental criminology research tells us that the geographical patterning of crime rates is an emergent phenomenon, resulting from the interactions between individual people and objects in space. Only "bottom-up" approaches truly capture this phenomenon.

Closely related to it ability to reproduce emergent phenomena is the ability of ABM to create a *natural description* of the system under observation (Bonabeau 2002). There are many systems, particularly in the social sciences, that cannot be sensibly modelled using mathematical equations (Axtell 2000; O'Sullivan 2004; Moss and Edmonds 2005). Because, with an agent-based model, rules are specified directly for each individual unit there is no need to try to coax a higher-level model into performing as if it were modelling individuals directly. Therefore, by using ABM the "natural variety" of cities becomes part of the model, rather than smoothed out by aggregate methods (Brantingham and Brantingham 2004).

Of course there are some disadvantages to using agent-based modelling for crime analysis. Crime systems are highly dependent on human characteristics such as seemingly irrational behaviour and complex psychology. However, formally defining these characteristics in a computer model is extremely difficult and can lead to reduced behavioural complexity (O'Sullivan and Haklay 2000). If the behavioural complexity of the agents is adequate, then computation power can become a problem as each decision made by each agent becomes more computationally expensive.

19.3.2.2 Incorporating Geography

To gain a better understanding of the spatial nature of crime, geographic information systems (GIS) are routinely used to analyse crime data sets (Hirschfield et al. 2001) and are becoming an increasingly important tool for crime analysts (Chainey and Smith 2006; Weir and Bangs 2007) and recently they are also being used for another purpose; agent-based crime modelling.

In order to make predictive analyses (i.e. predicting future crime rates in a real city or neighbourhood) it is essential that the environment is a realistic representation of the physical area under study. Therefore the coupling of agent-based models with GIS is essential. This is not such a daunting task as it once was as many toolkits are now available to support researchers in this activity such as Repast Simphony (North et al. 2005a, b) and Agent Analyst (The Redlands Institute 2009).

However, a researcher must be aware that incorporating a GIS with an ABM can result in an *overly-complex* model that is as difficult to understand as the underlying system itself. Too much complexity can detract from our understanding of the dynamics that are at the heart of the system (Elffers and van Baal 2008). As Axelrod (1997) notes, if the goal of a simulation is to more fully understand the underlying dynamics then it is the fundamental model assumptions which are important, not the accuracy of the surrounding environment.

19.3.2.3 Existing Agent-Based Crime Models

Following the remarks made by eminent environmental criminologists (such as Brantingham and Brantingham 1993), researchers are starting to realise the benefits of ABM for studying crime. Initial models, (e.g. Gunderson and Brown 2000; [AU2] Winoto 2003; Melo et al. 2005; Malleson et al. 2009a, b) were relatively simple and did not necessarily incorporate realistic urban environments. They were typically used to explore theory or determine how changing variables such as offender motivation or police behaviour impacted on offending rates. More recently, advanced models have begun to emerge that can explore crime rates in real cities and can be used to make real-world predictions. For example: Dray et al. (2008) used ABM to explore drug market dynamics in Melbourne; Liu et al. (2005) present an agent-based/cellular-automata model of street robbery in the city of Cincinatti; Birks et al. (2008) and Hayslett-McCall et al. (2008) have independently developed agent-based burglary simulations; and Groff and Mazerolle (2008) have developed an urban simulation for street robbery with a realistic vector road network. It is not possible to discuss these models in more detail here. For more information about current agent-based crime modelling applications the reader is directed to the recent book entitled "*Artificial Crime Analysis Systems: Using Computer Simulations and Geographic Information Systems*" (Liu and Eck 2008) or a special issue of the Journal of Experimental Criminology entitled "*Simulated Experiments in Criminology and Criminal Justice*" (Groff and Mazerolle 2008).

19.4 A Simulation of Burglary

Having suggested that ABM is the most appropriate methodology for modelling crime, this section will strengthen the case for ABM by outlining, in detail, an advanced burglary simulation. Then Sect. 19.5 will show how the model can be used to predict crime patterns after an urban regeneration scheme. For more information about any aspects of the model, the interested reader is directed to Malleson (2010).

19.4.1 The Virtual Environment

The virtual environment is the space that the agents inhabit and, in a crime model, must incorporate many of the factors that form the "environmental backcloth" (Brantingham and Brantingham 1993). Along with a road and public transport networks that the agents can use to navigate the city, the environment must include individual buildings – to act as homes for the agents and as potential burglary targets – and community-wide factors such as deprivation and community cohesion.

19.4.1.1 The Community Layer

In Sect. 19.2 it was noted that people other than the offender can have an affect on crime by acting as victims or guardians. This is particularly relevant to burglary because an offender is unlikely to attempt to burgle if they are aware that the house in occupied or if they are being observed by passers-by. In an ABM, people are represented as agents. This approach demonstrated success when it was included in a burglary model that operated on an abstract environment (Malleson et al. 2009a, b). However, creating a simulation of every person in a *real city* is an immense undertaking. Instead, the behaviour of people other than offenders can be simulated through a *community* layer in the virtual environment. In this manner, factors that would otherwise originate directly from agent behaviour can be estimated for each community based on the socio-demographic information about that community. For example, houses in student communities are likely to be vacant at different times (e.g. in the evenings) than communities who predominantly house families with small children. Rather than simulating individual household behaviour, it is possible to *estimate* occupancy rates for the whole community based on demographic data.

UK data for the layer can be extracted from the 2001 UK census (Rees et al. 2002b) and also from deprivation data published by the UK government such as the Index of Multiple Deprivation (Noble et al. 2004).[1] These data can then be spatially referenced through the use of administrative boundary data available through the UKBORDERS service (EDiNA 2010). It was noted in Sect. 19.3 that the use of administratively-defined areal boundaries can pose serious problems to research because the boundaries are not designed to be homogeneous. To mediate these problems in this research, individual-level data will be used wherever possible (houses and roads, for example, are represented as individual geographic objects).

An obvious requirement of the community layer is a measure of *occupancy*. In this simulation, occupancy is calculated at different times of day based on the proportions of the following demographic variables: *students*; *working part time*; *economically inactive looking after family*; *unemployed*. These four variables were chosen because they are able to represent common employment patterns. Another important relationship noted in Sect. 19.2 was that *community cohesion* has a large influence on crime; residents in cohesive communities are more likely to be mindful their own and their neighbours' property. For this model, community cohesion is calculated from three variables that have been identified in the literature (Shaw and McKay 1969; Sampson et al. 1997; Bernasco and Luykx 2003; Browning et al. 2004) as important: *concentrated disadvantage*; *residential stability*; *ethnic heterogeneity*. With the exception of concentrated disadvantage which is obtained directly from the Index of Multiple Deprivation, all other variables can be established from the UK census.

In a similar manner to community cohesion, research has shown that potential burglars feel more comfortable in areas that are similar to their own because they do not feel that they will "stand out" (Wright and Decker 1996). This concept can be formalised through the creation of a *sociotype* which is a vector containing values for all the available census and deprivation data for each area. Therefore, the similarity between a target community and a burglar's home community can be calculated as the Euclidean distance between the two sociotypes.

[1] Census data is published through CASWEB (Mimas 2010), For more information about the census see Rees et al. (2002a, 2002b)

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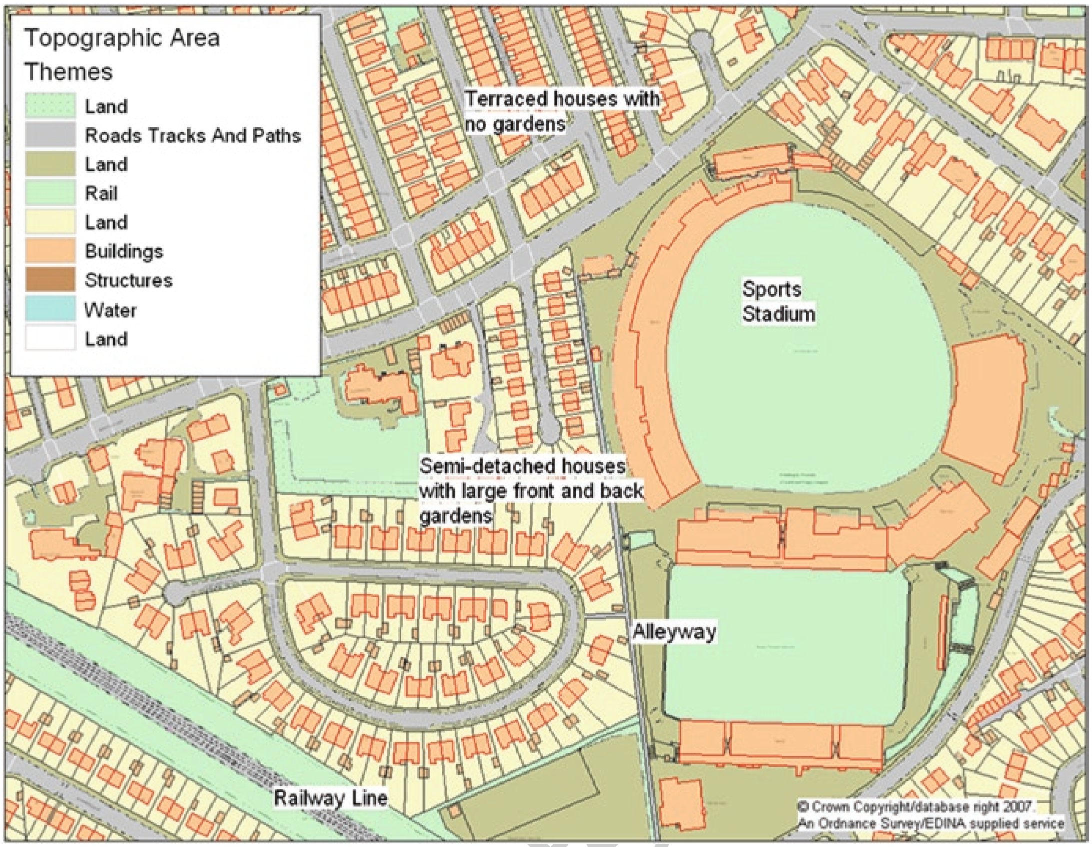

Fig. 19.1 An example of the OS MasterMap Topography layer which shows how different types of houses can be distinguished and the types of geographic objects that *could* be included in a crime model (Taken from Malleson (2010))

The final community-level variable, *attractiveness*, incorporates a measure of the affluence of the target community and therefore the potential available returns from burglary. Ideally this would be calculated individually for each property but in the absence of individual-level affluence data a community-wide variable must be used, based on census data. Evidence suggests that the following census variables provide good affluence measures: *percentage of full time students*; *mean number of rooms per household*; *percentage of houses with more than two cars*; and *percentage of people with higher education qualifications* (Bernasco and Luykx 2003; Kongmuang 2006).

19.4.1.2 The Buildings Layer

For the burglary simulation discussed here, Ordnance Survey MasterMap data (Ordnance Survey 2009) was used to represent the virtual environment in a highly detailed way. The product contains a number of different "layers" which can, separately, be used to represent the network of roads as well as other features such as buildings, rivers, parks etc. Figure 19.1 illustrates the Topography layer which is [AU3] used in the model to create residential houses. Some cleaning and filtering processes

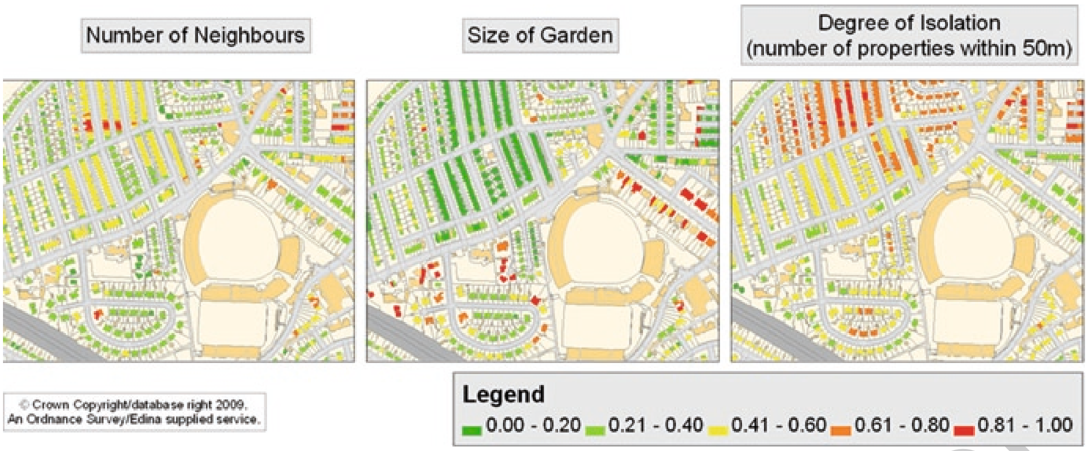

Fig. 19.2 Number of adjacent neighbours, size of garden and the number of neighbours within 50 m. All normalised to the range 0–1 (Taken from Malleson (2010))

were required to extract *houses* from the set of all buildings (which includes structures such as cinemas, shopping centres, garages etc.) but otherwise the data is ready for input.

Along with the variables that represent household attractiveness and occupancy – which are modelled at the level of the community because insufficient individual-level data are available – Sect. 19.2 identified the following factors as important determinants of household burglary risk:

- **Accessibility** – how easy it is to gain entry to the house (e.g. the number of windows or doors);
- **Visibility** – the level of visibility of the house to neighbours and passers-by;
- **Security** – effective physical security e.g. dogs or burglar alarms;

Parameter values for *accessibility* and *visibility* can be calculated directly through an analysis of the geographic household boundary data. Visibility can be calculated by using a GIS to compute both the size of the garden that surrounds each property and the number of other properties within a given buffer distance. Using similar geographic methods, the accessibility of the house can be estimated by determining if the house is detached, semi-detached or terraced by counting the number of adjacent buildings to the house. Figure 19.2 presents values for these variables normalised into the range 0–1. Although the geographical techniques are coarse and there are some errors (for example some terraced houses towards the north of the map have a larger number of neighbours than should be expected) they are able to broadly distinguish between the different physical house attributes that will influence burglary.

With regards to household *security*, there is unfortunately limited national or local data that can be used to estimate individual household security precautions. Generally, therefore, this value is set to be the same for every house so does not influence household burglary risk.

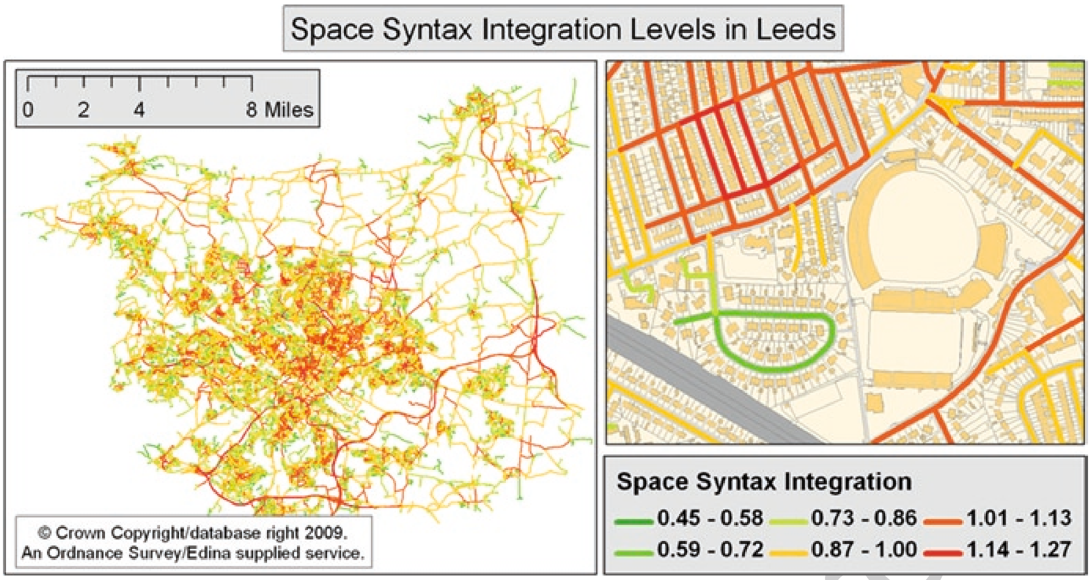

Fig. 19.3 Space syntax integration values for the entire city and a local area

19.4.1.3 The Transport Network

Transport networks are required in a geographic crime model because they restrict the agents' movements to certain paths and affect where and how the agents navigate the city. To include virtual roads, the Integrated Transport Network (ITN) MasterMap layer can be used. The ITN layer consists of line objects that represent all the different types of roads, including alleyways, motorways, pedestrianised areas etc. Using these data it is also possible to vary the speed that agents travel around the environment based on the transportation available to them.

Through an analysis of the roads data, it is possible to estimate the traffic volume on each road and this can affect the burglary risk associated with the houses on the road. Although most evidence suggests that houses which are situated on busy roads have a heightened burglary risk because they are more likely to be known by potential burglars (Brantingham and Brantingham 1993; Beavon et al. 1994), it is also possible that houses on busy roads are *less* of a risk at certain times of day because gaining undetected access can be more difficult.

Estimating traffic volume can be accomplished by using theories from the "space syntax" research area and analysing the *connectivity* of the road network.[2] Roads that are the most "integrated" (i.e. the most highly connected) have been found to correlate with large amounts of pedestrian and vehicle traffic and have been used in other crime studies (van Nes 2006). Figure 19.3 illustrates the integration values for all Leeds roads.

[2] For more information about space syntax techniques, refer to Hiller and Hanson (1984), Bafna (2003) or Park (2005).

19.4.2 The Burglar Agents

In the social sciences, agent-based models often use agents to represent people and this poses a substantial challenge: how should complex human psychology be included in a computer model? This section will address this issue and discuss how the burglar agents have been constructed for the burglary simulation.

19.4.2.1 Modelling Human Behaviour

Including human behavioural characteristics in agents – such as seemingly irrational behaviour and complex psychology (Bonabeau 2002) – can be a very difficult task to accomplish. However, agent cognitive architectures exist that can simplify the process of building a cognitively-realistic human agent. The most commonly used architecture is "Beliefs-Desires-Intentions" where *beliefs* represent the agent's internal knowledge of the world (i.e. its memory); *desires* represent all the goals which the agent is trying to achieve; and *intentions* represent the most important goals which the agent chooses to achieve first. Although the BDI architecture has been widely used (Rao and Georgeff 1995; Müller 1998; Taylor et al. 2004; Brantingham et al. 2005a, b), 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 rational choice models (Axelrod 1997).

A less widely used architecture is "PECS" (Schmidt 2000; Urban 2000) which stands for "Physical conditions, Emotional states, Cognitive capabilities and Social status". The authors of the architecture propose that it is possible to model the entire range of human behaviour by modelling those four factors. PECS is seen as an improvement over BDI because it does not assume rational decision making and is not restricted to the factors of beliefs, desires and intentions (Schmidt 2000). Instead, an agent has a number of competing *motives* (such as "clean the house", "eat food", "raise children", "sleep" etc.) of which the strongest ultimately drives the agent's current behaviour. Motives depend on the agent's internal state (an agent with a low energy level might feel hungry) as well as other external factors (an agent who smells cooking food might become hungry even if they do not have low energy levels). 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. For more information about the framework and how it has been used in an abstract crime model see Malleson et al. (2009a, b).

19.4.2.2 The Burglar Agents

The first decision to be made regarding the agents' behaviour is what internal state variables should be used as these, ultimately, dictate the range of possible motives this figure will be printed in b/w

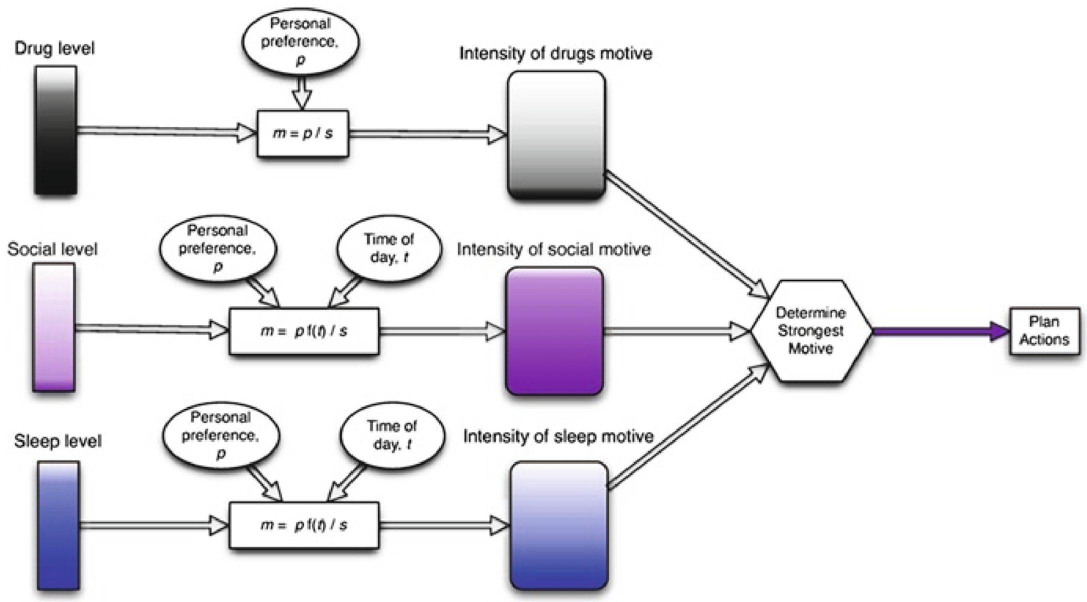

Fig. 19.4 How state variables, *s*, personal preferences, *p* and external factors (e.g. the time of day, *t*) are used in intensity functions to determine the strongest motive. In this example, the agent's *social* level is very low (the agent has not socialised in some time) and this is the strongest motive. The agent will make a plan that ultimately allows it to socialise (this could include burgling to make money first) (Taken from Malleson (2010))

and behaviours. From the crime literature, it is apparent that a common motivation for burglary is the need to sustain a drug addiction or to maintain "high living" (i.e. socialising). Therefore, drug taking and socialising should be included as well as the ability to sleep when necessary.[3] With these behaviours in mind, the following state variables are sufficient:

- *Drugs* – the level of drugs in an agent's system. An agent's motivation to take drugs is based on the level of drugs in their system and a *personal preference* for drugs (i.e. how heavily they are addicted).
- *Sleep* – a measure of the amount of sleep an agent has had. The need for sleep is stronger at night than during the day.
- *Social* – a measure of how much the agent has socialised, felt more strongly during the day.

Levels of these internal state variables decrease over time and, as they decrease, the agents will be more strongly motivated to increase them. Figure 19.4 illustrates how state variable levels are combined with personal preferences and external factors (the time of day in this case) to determine the strongest motive which will drive an agent's behaviour. Although sleep can simply be sought at home, taking drugs and socialising require money which can only be gained through burglary.

Another important agent component is the *cognitive map*. As an agent moves around the environment, they remember all the houses and communities they have

[3] Legitimate employment (whether full-time or temporary) is also common and has been included in the model, but is not a feature that is used in the later case studies.

passed and also where they commit any burglaries. 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 (e.g. drug dealers and social locations in this case). Secondly, it has been found that following a burglary, the victim and their neighbours have a substantially heightened burglary risk for a short time (Townsely et al. 2003; Johnson 2007) because the burglar is likely to re-visit the area.

19.4.2.3 The Process of Burglary

The process of actually committing a burglary in the model is broken into three distinct parts:

1. Deciding where to start looking for victims;
2. Searching for a victim;
3. Deciding upon a suitable target.

From the crime literature, some authors have suggested that burglars act as "optimal foragers" (Johnson and Bowers 2004; Bernasco and Nieuwbeerta 2005). Their decision regarding where to burgle is based on an analysis of potential rewards against risks. In this model the agents work in the same way and consider each area that they are aware off taking into account the distance to the area, its attractiveness, its similarity to the agent's home area and the number of previous successes they have had there. The area which is seen as the most appropriate to that burglar at that particular time is the one they travel to in order to start their search.

Research has shown that burglars do not search randomly for burglary targets, they exhibit identifiable search patterns (Johnson and Bowers 2004; Brantingham and Tita 2006). To reflect findings from the literature (e.g. Rengert 1996), in this model the agents perform a *bulls-eye* search; moving out from a starting location in increasingly large concentric circles (road network allowing). 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.

As the agents travels to their search location and performs their search, they inspect the houses they pass to determine if they are suitable for burglary. The assessment of suitability is based on the community cohesion and occupancy levels of the area, the traffic volume on the road and the accessibility, visibility and security levels of the individual house. The agent is also more likely to burgle if their motivation is high, i.e. as they become desperate to satisfy a need.

19.4.3 Model Implementation

For the simulation described here, the Repast Simphony tool was used (North et al. 2005a, b, c) which consists of a library of tools that can be used by computer programmers as well as a graphical-user-interface for non-programmers. Importantly, the software includes essential geographic functions that allow for the input/output of GIS data as well complex spatial queries. The simulation is written using the Java programming language and, due to the considerable computational complexity, was adapted to run on a high-performance computer grid provided by the National Grid Service (NGS: Geddes 2006).

19.4.4 Evaluating the Model – Verification, Calibration and Validation

Evaluating the predictive accuracy of ABMs (see Evans 2011) is a particularly problematic task although one that is extremely important. Not only are the models themselves usually highly complex, but there is often a lack accurate individual-level data against which the model can be evaluated. Following Castle and Crooks (2006), the process of evaluating this model was segregated into three distinct activities: verification, calibration and validation. Verification was accomplished by individually varying each model parameter and establishing its effect on the behaviour of the model. Calibration was manually undertaken based on knowledge of the dynamics of the model and model validity was achieved by testing the extent to which the model is able to represent the system it is attempting to simulate (Casti 1997). [AU4]

19.5 Results of the Burglary Simulation

19.5.1 Scenario Context: EASEL

Parts of the south-east of Leeds, UK, contain some of the most deprived neighbourhoods in the country. To reduce deprivation in these areas, Leeds City Council has instigated an urban renewal scheme which is called EASEL (East and South East Leeds). By creating new houses, transport links, employment opportunities and green spaces, the council hopes to attract residents from outside the area (as well as many from within) to create more stable and less deprived neighbourhoods. Figure 19.5 illustrates where the EASEL boundary lies within Leeds as a whole and also shows how deprived the area is. Only the EASEL area (plus a 1 km buffer) will actually be simulated, i.e. agents within the model cannot move outside of this boundary.

At present, work has begun in two of the EASEL areas referred to here as sites *A* and *B*. The scenario is discussed here is "optimistic"; it assumes that the council's plans succeed and the new communities are both cohesive and the new houses are well designed (secure from burglary). The scenario contains 273 individual offender agents (established through analysis of crime data).

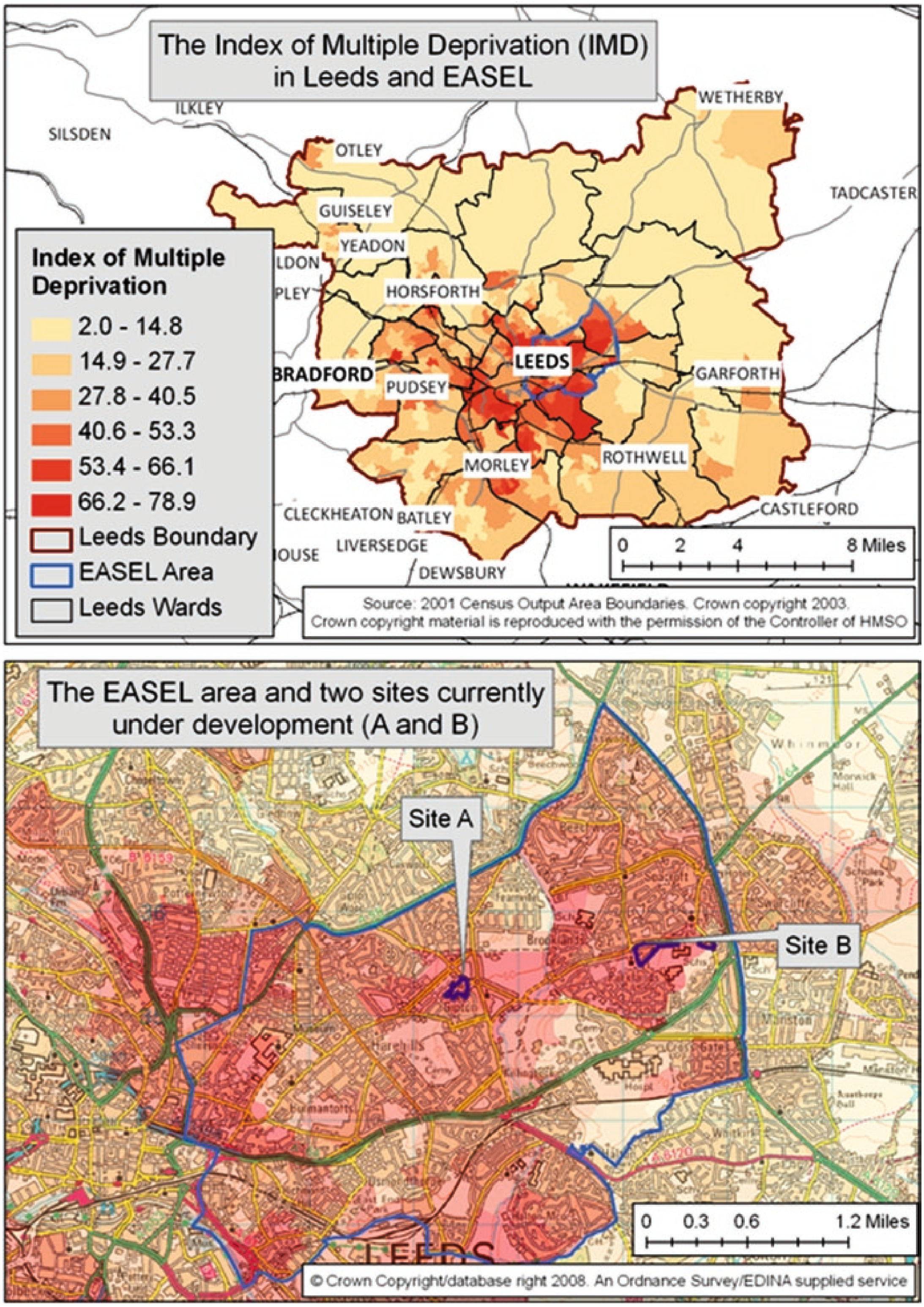

Fig. 19.5 The Index of Multiple Deprivation in Leeds and the EASEL area

19.6 Results

The model was first run *without* any of the proposed EASEL changes to create a benchmark. To ensure that the results were consistent, the simulation was run 50 separate times and the results from all simulations were combined. Having created a benchmark, the levels of security and community cohesion in the affected sites (A and B) were increased to reflect the planned EASEL regeneration changes and the simulation was executed again (50 times).

Figure 19.6 presents the difference in simulated crime rates before and after the proposed EASEL changes. Observing the entire EASEL area (upper-right map) it becomes apparent that, on the whole, the results of the two simulations are very similar. This is to be expected as the simulated environmental changes only cover very small areas. When observing the regeneration areas A and B in more detail, however, it appears that crime rates *within* the areas have fallen. This is not unexpected because the increased security and community cohesion make the houses in the area less attractive burglary targets. However, the orange and red areas surrounding the regeneration zones indicate that there are some houses which show a substantially higher risk of burglary than others. In other words, it appears that crimes are being *displaced* into the surrounding areas. The effect is highly localised which is unusual because it might be expected that burglaries

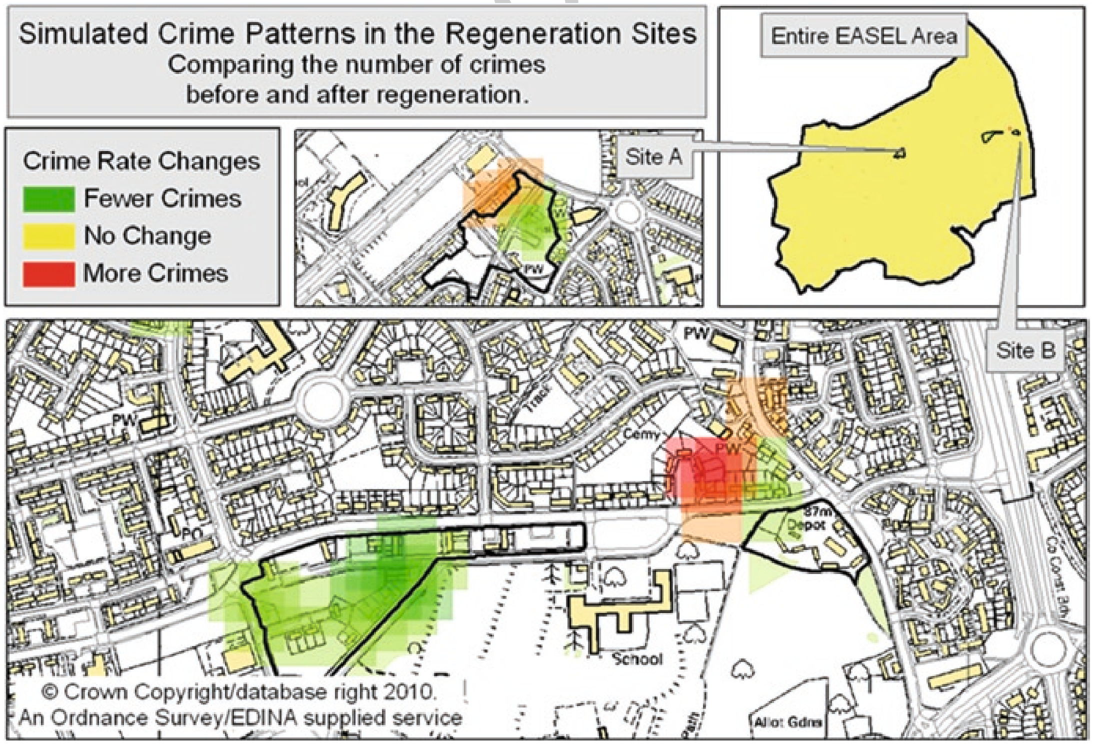

Fig. 19.6 Comparing simulated crime rates before and after regeneration of sites A and B (Adapted from Malleson (2010))

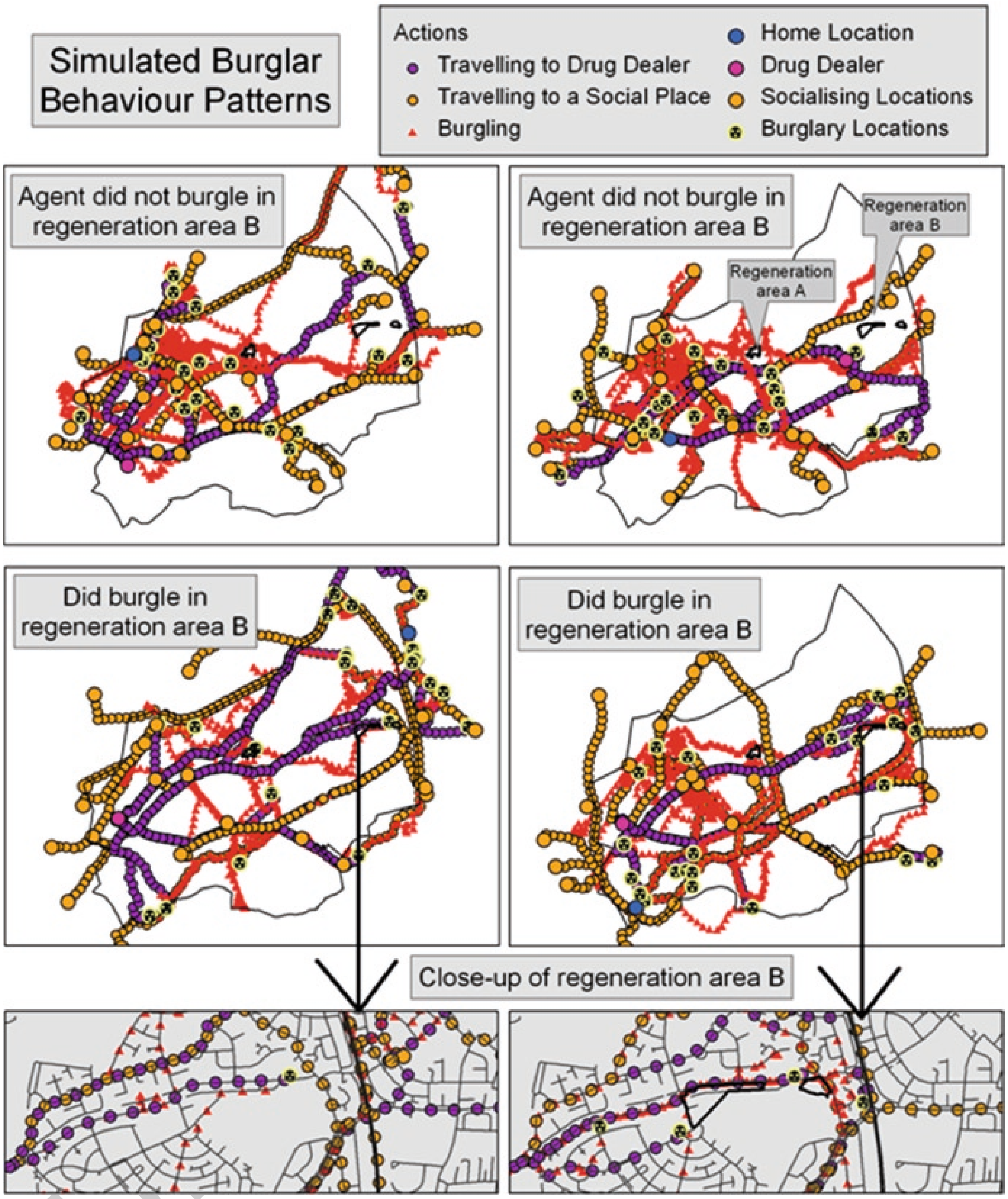

Fig. 19.7 Examples of simulated offender movement patterns in the post-regeneration simulation. Illustrative of the difference between the agents who did and did not burgle in development site B (Adapted from Malleson (2010))

would be more evenly distributed in the surrounding area (for example see Malleson et al. 2009a, b).

The most substantial burglary increases are evident in a small number of houses to the north of the development site B. To explain why these houses in particular suffer a higher crime rate, Fig. 19.7 plots the movements of four agents; two who did not commit crimes in the highly burgled area and two that did. By observing the agents' travel patterns throughout the simulation it is obvious that even the agents who did commit crimes in the highly burgled area still left large parts of site B unexplored. The houses that suffered particularly high burglary rates are situated on a main road that runs along the northern boundary of the development area; a road that was regularly used by burglars. This explains part of their burglary risk; agents did not have to explore the area at length to become aware of them. Also, the houses themselves are slightly more visible and accessible than their non-regenerated neighbours which adds to their risk.

A close inspection of Fig. 19.7 indicates that the agents passed the houses whilst looking for a burglary target, not during legitimate travels on some other business (such as travelling to a social location). Figure 19.8 illustrates this in more detail. Therefore one can conclude, from this evidence, that the EASEL changes attracted the agents to the area specifically for burglary purposes and the location of some houses on the main road coupled with slightly more physical vulnerability (accessibility and visibility) increased their risk disproportionately to that of their neighbours. Although one might assume that the houses surrounding a regeneration area might experience increased burglary rates (indeed this can be explained by criminology theory), only an individual level model could not have predicted which *individual houses* might be susceptible to burglary above others. Only when crime theories were 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.

In conclusion, it is apparent that the effects of having a slightly higher burglary risk, coupled with their location on a main road, mean that on average particular houses received more burglaries after local regeneration. But only after an examination of the routine activities of the burglar agents as well as an inspection of the individual household characteristics does this become apparent. This result demonstrates the power of agent-based geographic models; here we are able to pinpoint which *individual houses* might suffer a high burglary risk as a direct but unintended consequence of urban regeneration. This also leads to a specific policy implication: the houses identified surrounding site B (as well as some in the site A) should be target hardened.

19.7 Conclusions

This chapter has discussed the use of ABM for analysing and predicting occurrences of crime. In particular, a model that has been used to simulate occurrences of residential burglary was outlined in detail. A brief review of crime research identified a number of key factors that should be included in a model. GIS data was used to create a realistic virtual environment that represents the study area in a high level of detail, including the individual roads that people use to travel around a city and the buildings that they pass on the way. Furthermore, through an analysis of the data it was possible to create estimates of the physical burglary risks associated with every individual house. Agents in the model (the "burglars") were equipped with an

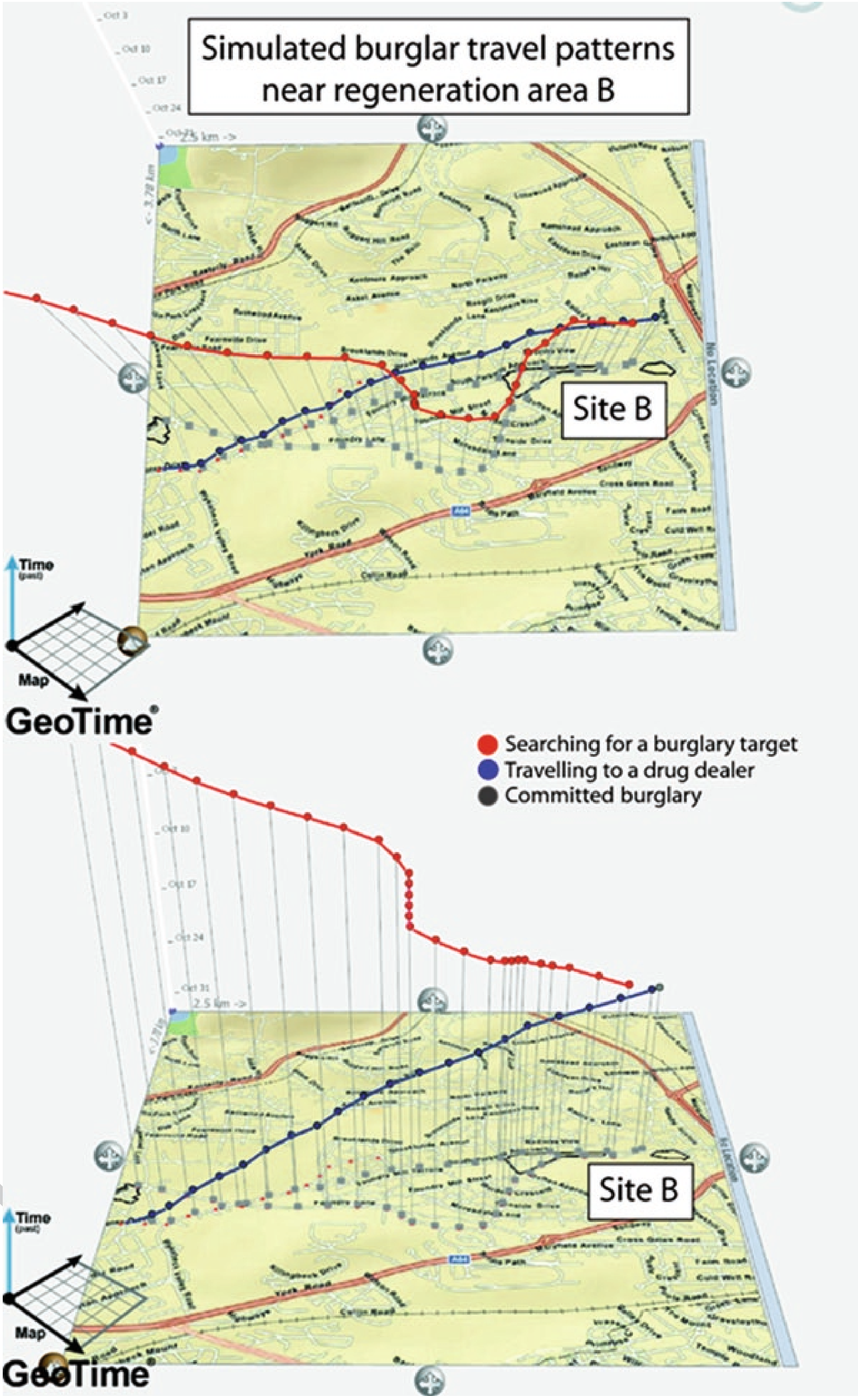

Fig. 19.8 Visualising the journey to and from a burglary close to regeneration area B. The agent travels to the area specifically for burglary. For clarity, both images illustrate the same journey but from different angles (Adapted from Malleson (2010)). GeoTime software used courtesy of Oculus Info Inc. All GeoTime rights reserved

advanced cognitive framework (PECS) and were able to make a comprehensive decision about what action they should take at any given model iteration. As important as the houses and the burglars, "communities" were incorporated into the model through the use of census and deprivation data.

The result is a comprehensive model that can directly account for the interactions and dynamics that drive the underlying system and can be used to make predictive analyses at a high resolution. As an example of the types of experiments that are possible with such a model, it was shown that a small number of houses might be at a higher risk of burglary after a regeneration scheme due to their spatial location and the resulting behaviour of the burglar agents. Although it inevitably has some drawbacks, the agent-based approach is the most appropriate technique for modelling such a system; one that is characterised by individual interactions and contains intelligent organisms that exhibit complex behaviour.

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