UNDERSTANDING A BURGLARS TARGET SELECTION PROCESS THROUGH THE ADAPTATION OF AN AGENT-BASED BURGLARY MODEL USING RECENT QUALITATIVE RESEARCH

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Abstract

The amount of burglary in England and Wales has increased in the past year, reinforcing the importance of implementing preventative policing measures to combat such crimes. This project modifies an agent-based burglary simulation model to improve its performance at predicting spatial patterns of crime. Several updated models were created by implementing research findings from a recent qualitative study of burglar target selection methods. Each model created was compared against both the original models results and real burglary data, with three areas of potential improvement being identified. The model's hotspot prediction capability was assessed using kernel density analysis, the level of clustering exhibited was tested through the calculation of L Function values and the distance of the journey to crime was measured and analysed.

Results showed that each model created was able to improve upon some aspect of the initial model, however none could consistently return more accurate burglary patterns across all methods of analysis. However, the report finds evidence that the accuracy of the model's predictive capability may be improved through the implementation of agent morality, opportunistic behaviour and interpersonal motivation. The accurate implementation of these ideas are identified as key areas for future research to assess whether they do in fact impact the spatial pattern of burglary.

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1. Introduction

A perpetrator commits the act of burglary when they *"enter any building or part of a building as a trespasser and, having done so, steal or attempt to steal anything"* (Office for National Statistics, 2017b). Domestic burglaries (those targeting residential properties) account for 205,869 burglaries, or around 50% of those committed in England and Wales (Office for National Statistics, 2017a); a figure that is up 3% from the previous year. This slight increase comes at the end of a steady downward trend in burglary rates that began in the mid-1990s when the crime was seen to be at its peak (Office for National Statistics, 2017b).

The fact that burglary rates are still able to increase shows that there remains room for improvement in the development of policing strategies designed to combat burglary. One way that these techniques are created is by using *predictive policing*, a method that allows the police to use data to anticipate the spatiotemporal location of crime and prevent it from occurring (Pearsall, 2010). Rather than reacting to a crime once it has already happened, predictive policing allows policy makers to generate preventative strategies to actively limit the opportunity for crime. These strategies can be tested beforehand using simulated environments to assess how their implementation might affect crime rates in the real world, with a common method of simulation being the use of an agent-based model (ABM).

This project seeks to make improvements upon an existing ABM (Malleson, 2010) to improve its predictive power of real burglary data, doing so through the integration of findings from a recent qualitative study into an offender's target selection process (Addis, 2017). It aims to improve upon three main areas of the model: its ability to predict burglary hotspots, the level of result clustering it exhibits and its ability to predict the distance of journey to crime. It is hoped that by improving these areas, the model will be better equipped to be used for predictive purposes to lower burglary rates.

1.1. Aims & Objectives

Aim

To study the effects of implementing recent burglary research into an existing agent-based model to better model spatial crime patterns.

Objectives

- Complete a thorough literature review into the factors surrounding burglary target selection.
- Review initial ABM and rerun final solution for later comparison.
- Review recent qualitative research and select findings that can be added to extend the model.
- Implement extra functionality into the model to alter agent behaviour.
- Collate results and perform visual and statistical analysis to assess whether additions have improved the performance of the model.
- Discuss results and draw conclusions for further research.

2. Literature Review

The Brantinghams (1981) describe every crime as having four dimensions: legal, victim, offender and spatial. The spatial dimension is where the other three elements come together for a crime to happen. Studies show that the locations of burglary offences cluster in space, leading to certain areas being at higher risk than others (Johnson & Bowers, 2004a). This clustering is down to *aggregate criminal spatial behaviour* in which independent criminals react in a similar manner to the prevalence of opportunity for crime (Brantingham & Brantingham, 1984). As opportunity is spread unequally over the spatial dimension (Ratcliffe, 2002), clusters will appear within areas with more suitable targets for offending.

The study of how crime events are affected by their spatial environment is known as *environmental criminology* (Bottoms & Wiles, 2002) and this forms an important area of research in *predictive policing*. By studying where and why these crime clusters appear, police forces can better position resources to attempt to decrease burglary levels in at-risk areas, with literature describing a considerable amount of research in the field (Addis, 2013; Jones & Fielding, 2011). However, simply mapping crime locations in itself is not enough to be able to generate meaningful responses, it must be supplemented with strong knowledge of the relevant background criminological theories (Chainey & Ratcliffe, 2005).

2.1. Criminological Theories

It is widely accepted that the movements, actions and decisions made by a burglar in the lead up to a crime are governed by several criminological principles. While they alone cannot completely explain the full reasoning behind every offence due to the inherently complex nature of human behaviour, they can fundamentally explain the spatial pattern of burglary.

2.1.1. Routine Activity Theory

The first theory is the Routine Activity Theory (Cohen & Felson, 1979) which seeks to explain the component factors that are required for an offence to occur. The theory states that a crime can only happen when a motivated offender encounters a suitable target while free from the supervision of a capable guardian (Felson, 2008).

While applicable to many types of crime, it is an important method for explaining the conditions required for a burglary to take place. In this case, a motivated offender is one that would need to burgle to satisfy a personal need, for example to obtain wealth to fuel a drug habit. A suitable target would be one that fits the offender's template of how an appropriate target should look, based on their own skills and past burglary experiences (Brantingham & Brantingham, 1978). However, the offender must first escape a capable guardian such as a parent or authority figure before they would consider offending due to the knowledge that a guardian would hold them accountable for their actions. However, it is important in this case to note the contextual verb; for a burglary to occur the offender must be *motivated*, the target *suitable* and the guardian *capable*. If an offender is not motivated, for example by not currently requiring wealth, then an offence will not occur. Similarly, a target may not be suitable to a particular offender by not meeting their required standards for burglary, for example by being too visible to neighbours or in an unsuitable community. Guardians may also be incapable, thereby not discouraging the offender from their actions, an example being CCTV cameras which have been found to be an ineffective deterrent to a drunken offender (Chainey & Ratcliffe, 2005).

Since its proposal, the Routine Activity Theory has been adapted multiple times to further explain the cause of crime. Extensions have been made to the idea of guardians who, rather than being their own separate entity, instead act as overseers for the other elements of the model (Eck, 2003). The updated theory suggests that a crime occurs at the coming together of a motivated offender and a suitable target in an appropriate place, and that capable guardians for all three elements must be absent (Felson, 1995).

2.1.2. Crime Pattern Theory

While Routine Activity Theory describes the factors that cause a crime to occur, it alone is not enough to determine why a crime occurs in a particular place. Therefore, research analysing the spatial pattern of burglary requires a further theory as its foundation. That theory is the Brantinghams' Crime Pattern Theory (Brantingham & Brantingham, 1993) which seeks to explain why a particular criminal chooses to offend in a specific set of locations rather than their crimes being spread randomly across the spatial landscape.

The basic theory suggests that the houses selected as targets by a burglar are chosen due to their proximity to locations that the offender frequents (*activity nodes*) or the routes they use to travel between them (*paths*) (Brantingham & Brantingham, 2008). From these, burglars build up an *activity space* of the areas that they visit while performing both criminal and innocent actions (Brantingham & Brantingham, 1981). Through building this activity space, the offender can consciously or unconsciously gain awareness of the areas around them. This may include making mental notes of the characteristics of certain communities they pass through, noting dwellings with advantageous properties that may be suitable for burglary or simply having a feeling of 'fitting in' to an area that can be important when searching for a target (Rengert & Wasilchick, 1985). This observation builds up a criminal's *awareness space* which holds knowledge that they will use to determine targets during the burglary process. This awareness space is dynamic and can decay, with areas around formerly used nodes and paths fading from a criminal's memory over time (Bernasco, 2010).

Although it is known that burglars often lead chaotic and unstable lives (Jacobson, et al., 2003), there remains several common nodes that act as bases for criminal behaviour, the strongest of which is the offender's place of residence. The Brantinghams suggest that risk of burglary is high around an offender's home due to the time, money and effort expended to travel larger distances when similar opportunities can be found closer by (Brantingham & Brantingham, 1981). This is an example of the *principle of least effort* (Zipf, 1949) and can go towards explaining why the distances of journeys to burglary are so low. Furthermore, places of work may also provide important nodes in an offender's awareness space, although this is heavily dependent on the offender, with many being unemployed (Wiles & Costello, 2000). Similarly, social areas such as pubs and restaurants may be nodes if visited, but this depends on whether the criminal has enough wealth to visit these areas.

2.1.3. Optimal Forager Theory

The Crime Pattern Theory shows how an offender can build up a knowledge map of potential targets around places they frequent. However, this fails to explain the behaviour of the offender when selecting a house to burgle. Although burglars exhibit a myriad of different methods for target selection, one common technique relates to the Optimal Forager Theory (Krebs & Davies, 1993).

The Optimal Forager Theory was originally developed to describe the movement of animals when searching for food. It states that while foraging, an animal will look to maximise its foraging currency (i.e. energy intake) while working under energy and time constraints (Sinervo, 1997). Animals that are more efficient foragers are more likely to succeed in a survival-of-the-fittest scenario. In this way, Optimal Forager Theory can be utilised to explain a range of behavioural patterns far beyond its original scope, particularly the 'foraging' pattern of burglars searching for a target.

Regarding burglary, the Optimal Forager Theory is modified to state that when searching for a victim, the burglar will seek to maximise profitability of an offence while minimising the effort and risk involved in its execution (Johnson & Bowers, 2004b). This behaviour directly causes a pattern of burglary clustering known as repeat or near-repeat victimisation (Johnson, et al., 2010). This is where, after an initial burglary at an address, the risk of further burglaries increases at that address and those around it for a short period before returning to previous levels. The chance of further burglary increases greatest nearest to the victimised house, particularly at addresses next door, on the same side of the street and with identical layouts (Bowers & Johnson, 2005). From the burgled house, burglary risk decays outwards until it reaches normal levels at a radius of around 300-400 metres. Furthermore, burglary risk decays temporally from the time of the initial offence for a period of up to 6 weeks, after which it returns to normal (Johnson & Bowers, 2004a). The likelihood of repeat victimisation is greatest in deprived areas (Bowers, 1999) due to the financial difficulty for a victim in installing improved security measures to deter a criminal from returning (Tilley, et al., 2011).

The reason for this increase in burglary risk is down to the behaviour of the initial offender. If targeting a property previously burgled (repeat victimisation), the offender will be aware that previously stolen items may have been replaced since, and may also be returning for certain valuable items not taken in the previous crime (Ashton, et al., 1998). If committing a near-repeat crime at a nearby property, the offender can expect a similar potential reward to the previous crime, therefore will be confident of maximising their foraging currency (Johnson & Bowers, 2004b). Furthermore, having already committed a crime in the area, they will have a good local awareness space so will be aware of escape routes and visibility of properties. This, combined with their knowledge of the interior of the property previously targeted, gives the offender an excellent *knowledge base* of the area, decreasing risk of being caught (Johnson & Bowers, 2004a). The theory suggests that they will be likely to return to the area to reoffend, and will continue to do so until they run out of suitable properties or feel that the risk has become too great, at which point they will move to another area and repeat the process (Bernasco, 2009).

2.1.4. Rational Choice Theory

A complementary theory to the previous examples is Clarke & Cornish's Rational Choice Theory (Clarke & Cornish, 1985). It agrees with the Optimal Forager Theory in stating that a criminal makes decisions based on a rational weighing-up of the risks and rewards of committing an offence, and will choose to offend if the perceived benefits of success outweighs the potential punishment of failure. The theory suggests that the decision to offend is the culmination of a long decision-making process in which the offender will, at a particular moment, make a decision based on their readiness to commit the crime and the suitability of an opportunity (Clarke & Cornish, 1985). An offender's readiness is based on a vast number of background factors relating to their personality, upbringing, skills and needs, while their reaction to an opportunity depends on their assessment of the event and the strength of motivating factors.

The obvious counterpoint to the Rational Choice Theory is that it incorrectly assumes that criminals are perfectly rational creatures. The caveat therefore is that the subject is limited by *bounded rationality* (Simon, 1976), which states that all decisions are made with an incomplete base of knowledge. When weighing up the situation, an offender will have difficulty estimating the chance of being caught and the severity of a potential punishment, so cannot make a perfectly rational decision (Cornish & Clarke, 2008). They may also be constrained by an incomplete skill set, a lack of time to complete the offence or a pressing motive such as a drug addiction (Cornish & Clarke, 1987). For these reasons, the offender will have to settle for an imperfect solution, whether it be burgling a house that will not provide a satisfactory reward or getting apprehended while targeting one that was unsuitably risky.

2.2. Burglary Attractors/Deterrents

While an understanding of the background theories that drive criminal behaviour is an important asset for anybody who wishes to study the spatial variation in burglary, such information is still purely theoretical. For effective conclusions to be drawn from spatial analysis, it is important to note how these theories apply in the real world by observing how they influence the real-life factors present in an offender's decision to burgle. The rational offender will consider certain situational attributes when choosing a property to burgle (Maguire & Bennett, 1982).

2.2.1. Accessibility

As burglars can be seen to operate according to the principle of least effort (Zipf, 1949),the ease of access to a property plays a part in their decision-making process. It can be split into two sections; the act of getting to and from a property and the act of getting in and out of it.

A property's proximity to the burglar's current location has been found to be important when they are selecting a target (Bernasco & Luykx, 2003) due to the effects of the Optimal Forager Theory. As they are looking to minimise time and effort, a burglar will generally seek out targets nearby unless the promise of a greater reward convinces them to travel further afield (Hough, 1987). For this reason, proximity to key nodes such as an offenders home (Townsley, et al., 2015), work and social areas (Bernasco & Luykx, 2003) has been found to be a key factor in explaining spatial patterns of burglary.

The attributes of a house will also affect its perceived accessibility. Burglars will tend to prefer detached or semi-detached houses due to the extra choice in entry points (Felson, 2002) and will tend to choose ground floor flats over those higher up for ease of access (Bernasco, 2006). Finally, houses will frequently be chosen based on how many suitable escape routes they provide (Palmer, et al., 2002), with one ethnographic study naming it the most important factor burglars consider when choosing a target (Nee & Taylor, 1988).

2.2.2. Security

One factor a criminal will factor in when assessing a property's suitability is the levels of security it displays. The implementation of physical security features such as locks, lighting and door/window bars acts as a physical barrier between a burglar and the contents of the property. In this way, security acts as a capable guardian for the place of the crime (Barberet & Fisher, 2009) so common sense suggests that high levels of security will act as a deterrent to the searching offender. Some studies find that burglary risk is higher in houses with little or no security, with such properties being seven times more likely to be burgled than those with top-level security (Pease & Gill, 2011). Security measures that are particularly unattractive to burglars are CCTV cameras (Palmer, et al., 2002), dogs (Nee & Taylor, 1988), external lights and door and window locks (Tseloni, et al., 2017). Furthermore, increased security measures have been found to decrease fear of burglary in occupants (Cozens, et al., 2005).

However, literature is divided about the true effectiveness of security measures, with some suggesting that its deterrent effect is limited (Reppetto, 1974; Wright, et al., 1995). Scepticism has been aimed towards target hardening schemes, which are near-unanimously perceived by burglars as being ineffective (Nee & Taylor, 1988), and burglar alarms, which have been found to possibly even increase the risk of burglary at a property (Tseloni, et al., 2017). In certain cases, the presence of security features may have the unintended effect of attracting a burglar due to the belief that there must be *"something to steal"* (Armitage & Joyce, 2016, p. 30), particularly to more experienced, 'professional' style burglars who may have the skills and tools to surmount such systems.

2.2.3. Occupancy

Another factor with complex significance in the decision-making process is whether a property is perceived to be occupied or not. Common sense would again dictate that the presence of an occupant would deter a burglar from attempting to enter a property, and studies have found that in most instances this theory holds true (Budd, 1999). However, this is not always the case, as the importance of an unoccupied target appears to depend largely on the preferences of the burglar, with some burglars interviewed expressing indifference to the matter. Bennett & Wright (1984) found that some criminals are happy to enter an occupied property if the owners are asleep, noting the increased likelihood of valuables being present. Furthermore, Fox & Farrington (2012) classified a small number of burglaries as being motivated by a desire for confrontation, meaning in such cases occupancy is actually sought out. Cases such as these that complicate matters may go towards explaining why the inverse relationship between occupancy and burglary, while still being present, is not as strong as with other factors (Hough, 1987).

Burglars use several methods to assess the level of occupancy in a property before deciding whether to target it. One commonly described method involves knocking on the front door and waiting for an answer, with the criminal making an excuse and moving on if answered (Palmer, et al., 2002). Other criminals check for certain visual clues when scoping a property, such as the presence of vehicles (Mawby 2001).

2.2.4. Visibility

When assessing the viability of a property, a rational burglar will consider their chances of being spotted while entering and leaving. A property that is highly visible from all angles will deter a burglar due to the increased risk involved in getting in and out without being spotted (Shu, 2009). Burglaries are more likely to be unsuccessful when committed on houses that can be easily seen from neighbour’s properties (Johnson & Bowers, 2004a), particularly those in tight-knit communities or those with neighbourhood watch schemes. Similarly, houses that are on busy travel routes may also be avoided due to the likelihood of an offence being witnessed from the street (Jacobs, 1962).

Certain features have found to be particularly important in modifying the visibility of a target. The most extreme example is the presence of large hedges or fences around a property. Their occurrence serves to drastically reduce the natural surveillance of a property and has been found to be one of the largest attractors for burglars (Palmer, et al., 2002). Similarly, the presence of external security lights can alter a property’s visibility, rendering burglars unable to work undetected under cover of darkness (Farrington & Welsh, 2002). Finally, neighbourhood layout can also play a part, with research showing that houses on culs-de-sac provide less suitable targets due to the surveillance that such layouts provide causing a burglar to stick out further (Newman, 1972). However, this effect is reversed if the culs-de-sac are connected with footpaths that provide cover and escape routes for criminals (Armitage & Joyce, 2016).

2.2.5. Community

Another factor a burglar will consider when planning where to offend is the type of area that a potential target is in. Although common sense would state that an offender would target areas of high affluence due to the perceived increase in reward from such areas, this has been found not to be the case (Bernasco, 2006). In fact, the link between community factors and burglary rates is much more complex than that, with both poorer and richer areas being targeted by criminals. The reasoning for this is that burglars tend to come from more disadvantaged or deprived areas (Wright & Decker, 1996) and so may not always be able to travel to the affluent areas that provide the most rewarding opportunities. For this reason, a common crime pattern is that crime figures soar in affluent areas near more deprived areas as this decreases the distance constraints a disadvantaged offender encounters when burgling a more attractive target (Bowers & Hirschfield, 1999).

Burglars also tend to target certain communities due to their desire to offend in similar area to their home. Partly this is down to a need to remain inconspicuous while searching for a target to avoid any unwanted attention from residents (Rengert & Wasilchick, 1985). For this reason, areas with less cohesive populations are often at greater risk of burglary as the burglar is deemed less likely to stand out amongst a more fractured community (Markowitz, et al., 2001). A further advantage to seeking out similarity in a target community is that familiar surroundings provide an offender with a stronger knowledge base of an area from which to base decisions (Herbert & Hyde, 1985). Due to this, findings show that the area an offender comes from is the most likely area they will target (Wiles & Costello, 2000), with over two thirds occurring in a location near to an offender's home (Farrington & Lambert, 1994). This is especially the case when they have lived in an area for longer, giving further weight to the Brantinghams' theory that the home is a key node in an offender's awareness space (Bernasco, 2010).

If a burglar does decide to travel outside their own community to offend, they still may not choose to travel to an affluent area, as other socioeconomic pull factors have also been found to attract burglars. Studies have found that one of the most desirable factors is the presence of students (Malleson, 2010). This attraction is again partly caused by the lack of cohesion in student areas, as the large transient population brings instability to the community and allows burglars to blend in (Kenyon, 1997). Furthermore, students are notoriously careless about security, with many failing to utilise even basic security measures such as locking doors (Barberet, et al., 2003), removing the capable guardian for the property. Finally, the mobile student populations often own the latest expensive portable electronic devices such as laptops and smart phones; items that are immensely attractive to burglars due to their portability, concealability and simplicity to sell on (Barberet & Fisher, 2009).

2.3. The Journey to Crime

Another important aspect of an offender's target selection process is the journey that they take when searching for an appropriate opportunity. It is on this journey that an offender will observe the situational clues of properties they pass and compare them to their expected template of a suitable target to decide whether to break in or not (Brantingham & Brantingham, 1978). Therefore, an understanding of the movement of a burglar around their environment gives a good indication of where they will choose to offend.

With the assumption that the journey to crime begins at their home, studies have found that the distance travelled to most burglaries is very short (Herbert & Hyde, 1985). Results differ slightly due to differences in study area layout and offender demographics, but most find that the average journey is around 1.68 miles (Snook, 2004) or 1.88 miles (Costello & Wiles, 2001). However, a burglar will increase the length of their journey for more rewarding opportunities, with the level of reward for a burglary increasing with the distance of the journey to it (Snook, 2004). This again proves that Zipf's Least Effort Principle holds for burglars (1949) as they will attempt to minimise effort expenditure unless the rewards otherwise outweigh it. However, a caveat to this theory is that burglars will generally tend to travel a small distance away from their home before contemplating offending due to the perceived risk of being recognised by a neighbour (Brantingham & Brantingham, 1993).

Several factors affect the distance an offender is willing to travel to burgle, one of which is how limited they are in their mobility. A study in Sheffield showed that over a 30-year period, the distance the average burglar travelled to offend increased with their potential access to a vehicle (Wiles & Costello, 2000). Similarly, burglars who claimed to travel to targets on foot were found to undertake shorter journeys than those who did so in vehicles (Snook, 2004). As well as taking less effort to travel to targets further away, the use of a vehicle provides a quicker escape route than on foot and allows the theft of larger items from the scene, reasons which often lead to vehicles being stolen at the scene of the burglary for escaping in (Donkin & Wellsmith, 2006).

Other important factors relate to the demographic of the offender. The age of the perpetrator may play a part, with some studies finding that younger offenders stay closer to home when offending (Baldwin & Bottoms, 1976). The reasoning for this relates again to their access to vehicular transport, as well as their smaller awareness space to offend in and the stricter control of capable guardians such as parents (Snook, 2004).

The types of burglar movement can broadly be split into two categories: searching behaviour and opportunistic behaviour. Criminals who display *"instrumentally rational"* (Wiles & Costello, 2000, p. 3) behaviour make a conscious choice to offend before reaching the scene of the crime, often travelling to a known area to begin searching for a suitable target. Within this class of burglar, Canter & Larkin (1993) propose two subtypes of movement. A commuter burglar will travel outside their home area to another suitable community before beginning their search in that area, while a marauder burglar will use their home as a central base and begin searching from there.

In contrast, *"affectually rational"* (Wiles & Costello, 2000, p. 3) criminals act on opportunity, committing a crime only when a chance situation presents itself to the burglar, such as passing an unoccupied property with a window left open. An opportunity of this type may present itself during an offender's criminal or non-criminal activities (Brantingham & Brantingham, 1993) so this burglar may be more difficult to predict.

Literature is divided as to the prevalence of each trait amongst burglars. Wiles & Costello argue that opportunism is the main method of target selection, with 70% of burglars *"not primarily driven by plans to offend"* (Wiles & Costello, 2000, p. 43). On the other hand, Nee & Taylor categorised 76% of burglars as *"searchers"* (Nee & Taylor, 1988, p. 108) who actively hunted for an appropriate target. However, it is likely that most burglars exhibit signs of both traits depending on the situation.

2.4. Agent-Based Modelling

In recent years, a new method of analysis has been used with increasing frequency to study the spatial distribution of burglary: the agent-based model (ABM). An ABM is a simulation environment in which individual micro-level agents are left to interact with their environment and each other to produce macro-level outputs (Holland, 1992). Each agent in the model takes in inputs from its surroundings which are then processed according to their internal rule set to generate an output; in this way, an ABM can be seen as a form of automata (Crooks & Heppenstall, 2012). This causes ABM's to be an extremely powerful computational tool, as even small populations of agents with simple internal rulesets can model complex scenarios that may otherwise be difficult to predict (Bonabeau, 2002). To run an agent based model, the population is set up to include a set of relevant agents which is then left to interact for a set period of time before the output results are observed (Axtell, 2000).

An agent in an ABM needs to exhibit several behavioural traits. It must be *autonomous*, meaning that it can freely move and interact without the input of a central controller such as a human (Castelfranchi, 1995). It must be *heterogeneous*, i.e. can be programmed to have individualistic tendencies that are not present elsewhere in the population (Crooks & Heppenstall, 2012). Agents must also exhibit *interactivity* in that they need to communicate information to and from their surroundings (Genesereth & Ketchpel, 1994). Finally, they must be *reactive* to respond to the information they receive to produce relevant results (Woolridge & Jennings, 1995).

An advantage of using an agent-based model for spatial crime analysis is that they can capture large-scale results that would be otherwise impossible to detect just by looking at an agent's individual implementation (Bonabeau, 2002). By observing the big-picture results generated, the complex interactions can be visualised in a simple manner for more effective use in developing crime prevention techniques. A individual characteristic that is otherwise hard to observe is the effects of bounded rationality, which can be programmed into an agent to account for human imperfection and therefore spatial variation in outputs (Crooks & Heppenstall, 2012).

Another benefit of using an ABM for this purpose is that their structure allows for the generation of complex modelling environments of real-world social theories that may otherwise be inappropriate for purely mathematical solutions to handle (Axelrod, 1997). This social aspect of crime means that any solution requires the abstraction of human interaction to produce relevant results. ABM's can allow for the implementation of this concept through the programming of human behavioural frameworks such as BDI (Beliefs, Desires, Intentions) and

PECS (Physical, Emotional, Cognitive, Social) into agents to model human behaviour (Kennedy, 2012). However, this benefit of ABM is also its main drawback, as the more accurate the human behaviour implemented, the more complicated and computationally expensive the model becomes, meaning a trade-off is required for the model to remain useful (Malleson, 2012).

A recent example of an ABM being used for crime simulation is the burglary model created by Malleson (2010). This highly complex model creates burglar agents within a study area and allows them to interact with a dynamic environment to model the location of burglaries in the region. The system uses the Repast Simphony modelling platform (Repast, 2017) to allow for the integration of GIS into the model. Through this, the agents can operate in a simulation of a real-world environment to allow for more powerful prediction of real crime and to more accurately observe how theoretical changes to the environment can affect spatial burglary patterns.

The environment of the model is split into two layers. The individual layer of the model contains features such as houses and roads within the study area. Each property has several pieces of information linked to it, particularly the attractor/deterrent factors for a potential burglar. The factors chosen for the model are a property's accessibility, occupancy, visibility, security, attractiveness and traffic volume; the method of calculation for each value can be found in Malleson (2010). Additionally, the environment contains a community layer containing each of the Output Areas that make up the study area. Each OA in this layer contains a set of demographic variables taken from the Output Area Classification (Vickers, et al., 2010) along with a community efficacy value indicating the level of cohesion in the area. The values in both layers of the model are used by the burglar agents to decide where to offend.

Each agent in the model is randomly assigned a home property along with a workplace (if the agent is able to work), drug dealer and social locations. Through visiting these key nodes, the agent builds up an awareness space that can be drawn upon when burgling. The agents exhibit behaviour adapted from the PECS framework. They each seek to satisfy the basic needs of sleeping and generating wealth, with wealth being used to socialize and purchase drugs. The fulfilment of each need is done through a specific set of actions attached that the burglar must complete, with the action of burglary being performed when an agent is unable to generate wealth through other means.

When the decision to burgle is taken, a three-stage process occurs. The agent decides where in their awareness space to begin their search based on current proximity, attractiveness of the area difference in OAC sociotype from the agent's home area and the previous amount of success they have had burgling in the area. The agent then begins the search by travelling to the chosen area and exploring it in a radial pattern. Finally, the agent assesses properties that they pass during their search and assess their suitability based on the characteristics of the property, as defined by the individual layer, and the strength of their current guiding motive; offending once a suitable target has been found.

3. Methodology

To achieve the aim set out by this project, the model created by Malleson (2010) was chosen for adaptation using up-to-date research. For this purpose, the research conducted by Addis (2017) was selected as the chosen study, findings from which were to be implemented within the model. For his research, Addis conducted interviews with incarcerated burglars in the HMP Leeds prison, with particular focus on establishing the modus operandi and target selection process of the offender.

The focus of Addis's research allowed it to be particularly appropriate for use within the current project as the accuracy of Malleson's work depended largely on the translation of offender behaviour and decision-making into the model. Therefore, the responses of the real offenders could be directly tested within the ABM to find key factors in the burglary process that may have been overlooked. An extra benefit of choosing this research to base the project upon is that the burglars interviewed were offenders from the West Yorkshire area, the same study area used in the initial model. Therefore, the insights obtained are likely be more relevant than any from offenders in a different area or country.

The methodology involved creating new instances of the model based on the original version created by Malleson (Model 1); however, each version was modified to include a new finding from Addis's research not previously implemented. Two main results sets were returned from each model. The first is a collection of offenders, containing the locations of each agent's home, work, social and drug dealer property. The second is a point pattern of burglary locations, along with information on the offender that committed the crime and the community and property factors that influenced the burglar's decision at that time.

Each model was run for a total of 43200 iterations as this was found in the initial research to be the optimum length of time for the model to reach equilibrium (Malleson, 2010, p. 152). Furthermore, the runs were repeated 10 times with the output being the concatenation of every set of results. This was done to take a good average of each models results so that any anomalous runs would not drastically affect the outcome.

3.1. Data

The data sets used during the undertaking of this project are the same as those used in Malleson's original agent-based model. Primarily, this was due to the difficulty in obtaining updated burglary offender datasets for comparative purposes. The initial intention was to use a dataset provided by the West Yorkshire Police Force containing contemporary offender data, including each criminal's known addresses and the locations of any burglaries attributed to them. By using this dataset, it was hoped that the accuracy of Malleson's model in predicting burglary locations and journey-to-crime distances could be assessed when run with a newer dataset. However, it proved impossible to obtain the required dataset within the timeframe set for the project, therefore a compromise was decided to make use of Malleson's original aggregated offender data as the basis of comparison. While this allows comparability to the results generated in Malleson's project, it is accepted that any useful results generated by this project should be checked for validity with an up-to-date dataset as further research.

3.1.1. EASEL Area

The study area used for the project is the EASEL (East and South-East Leeds) regeneration area in Leeds, West Yorkshire [Figure 3.1]. The EASEL scheme was a regeneration program aimed at creating new sustainable communities in a deprived area of Leeds to narrow the gap between it and the rest of the city (Leeds City Council, 2005). One of the aims of the regeneration was to increase the cohesion in the community to positively impact levels of relevant crimes such as burglary.

Since the initial research was conducted, the EASEL scheme has been withdrawn due to private sector cuts (Leeds City Council, 2010); however, due to the continued prevalence of crime and deprivation in the area, it remains a useful area to model. Furthermore, while Malleson's research assessed how the regeneration scheme would affect potential future crime rates, this project seeks to improve upon the implementation of that model in more general terms. Therefore, the use of an outdated scheme as an example study area does not invalidate the results.

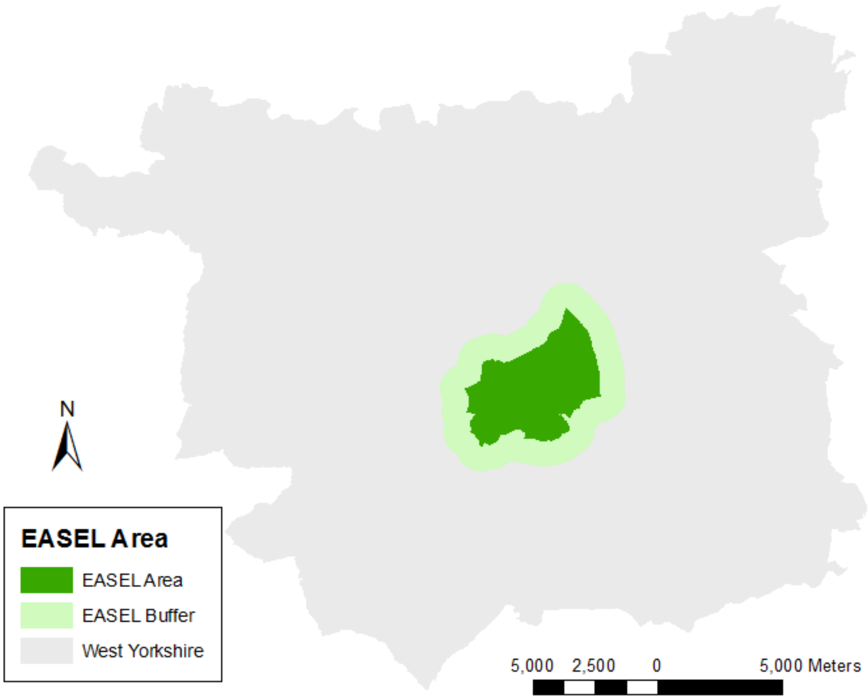


Figure 3.1: EASEL study area within West Yorkshire.

The study area covers approximately 1700 hectares and contains around 79000 people living in 36500 households (Leeds City Council, 2006). Furthermore, it contains the neighbourhoods of Burmantofts, Richmond Hill, Gipton, Harehills and Seacroft which have been designated areas of particular concern with regards burglary levels (Gilert, 2013). Building and road data for the area [Figure 3.2] were obtained from the Ordnance Survey MasterMap facility (Ordnance Survey, 2017) and were prepared as part of Malleson's original project to categorise each for use within the GIS element of the model. Burglars and burglaries were also generated in a 1km buffer around the EASEL area. This was done to avoid boundary issues when processing density surface results and to allow for burglars of reasonable proximity to the study area to offend within it, however any burglaries occurring in the buffer were discarded from final results sets.

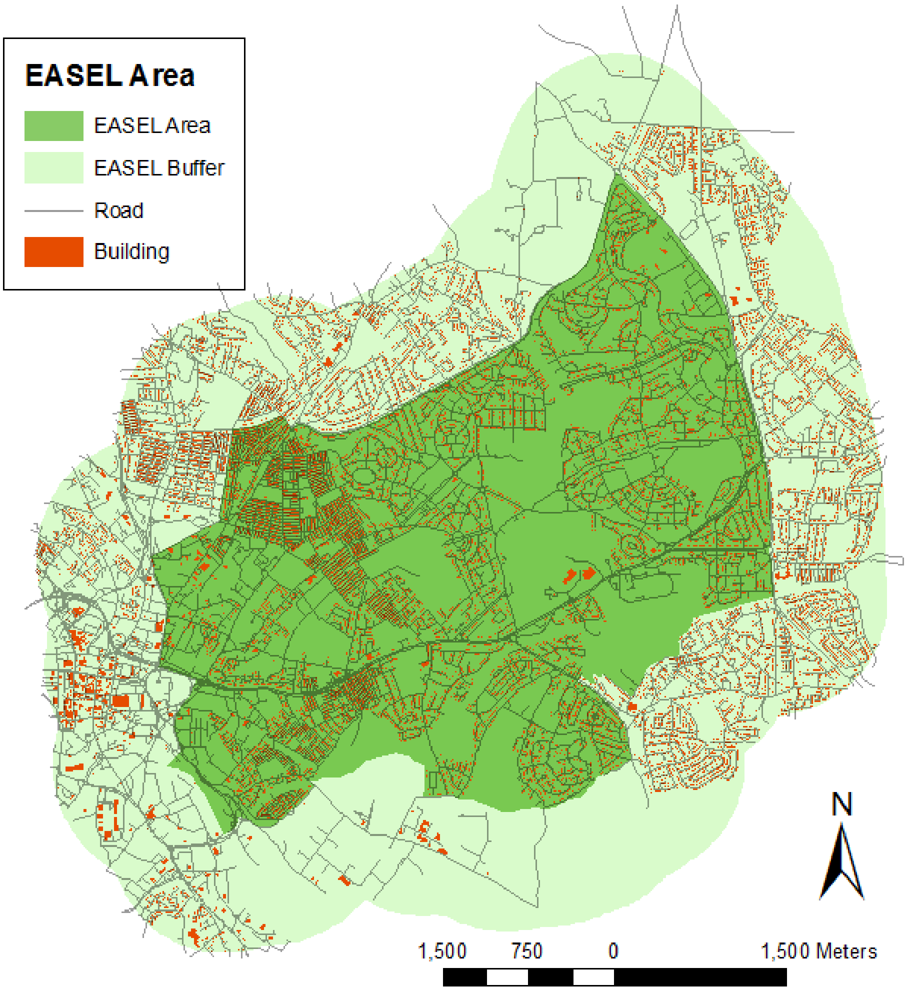


Figure 3.2: Closer view of EASEL area showing building and road layers.

3.1.2. Communities Layer

The other environment layer in the model is the communities layer that contains data about the characteristics of the area that each house is within. Furthermore, the layer contains information used to generate agents in appropriate locations, which it does using data on the aggregated locations of home addresses of burglars in the nominal dataset. The communities layer is again the same one used in Malleson's research as it contains the required aggregated crime data. The layer consists of the 489 Output Areas that make up the study area and buffer.

The first portion of the layer contains a set of 41 variables that describe the attributes of the population in each of the relevant Output Areas, along with the community efficacy values that can be generated from them. The variables are taken from the Output Area Classification (OAC) developed by Vickers et al. (2010) and contain information on the demographics, employment, households and socioeconomic factors of an area. The variables can then be used to apportion an area into one of seven supergroups [Figure 3.3] and further into groups and sub-groups, each containing communities that are similar in nature.

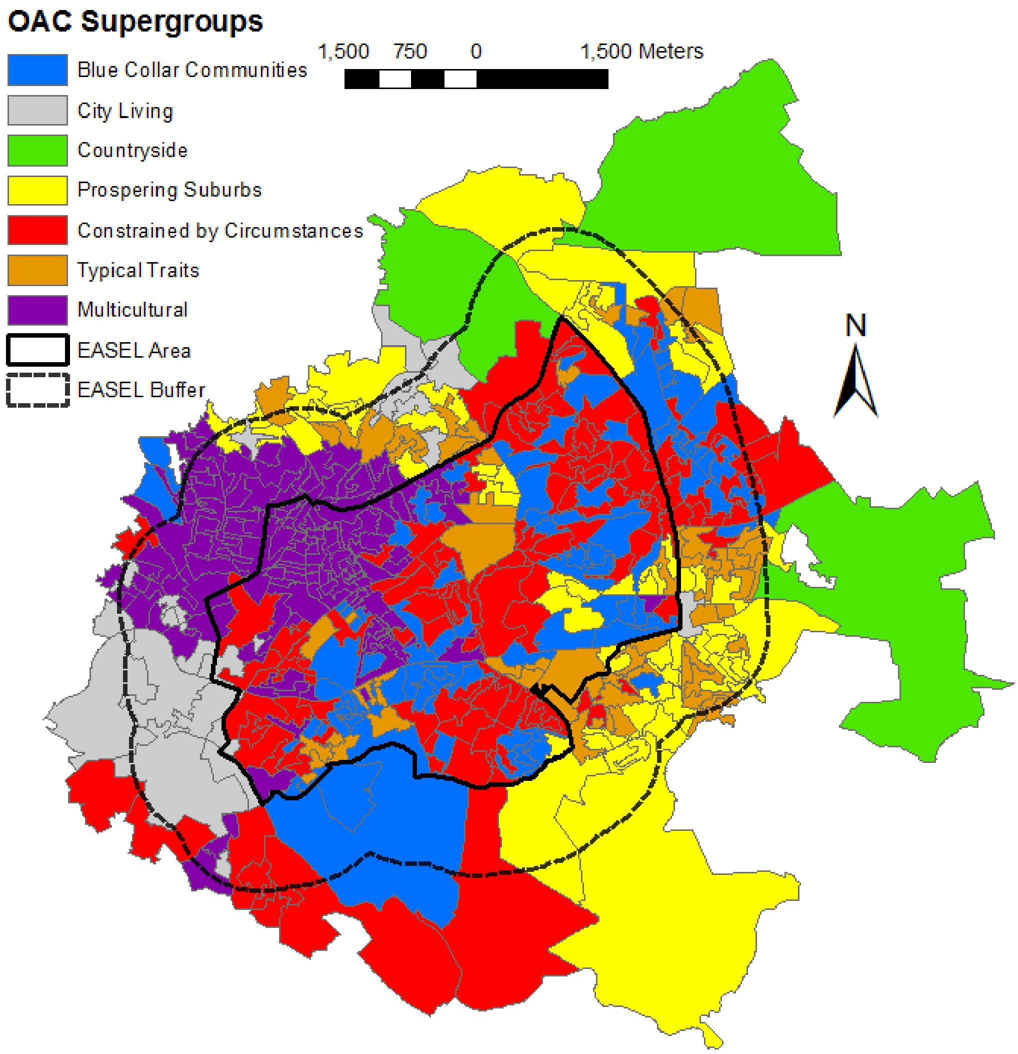


Figure 3.4: Output Area Classification supergroup for each OA in the study area.

As well as the OAC, the communities layer also contains the information on offender locations that the model uses to apportion agents around the study area. This information was generated from the dataset used by Malleson, provided by Safer Leeds. It contains the postcode location of all nominals linked to a burglary between the dates of 1st April 2003 and 31st March 2004, aggregated up to Output Area level [Figure 3.4]. In total, the layer defines 105 burglars to be created in 69 different OA's, with the model randomly assigning each agent a dwelling within the correct community during initialisation. By aggregating the home addresses of real-life offenders rather than randomly selecting houses across the study area, the crime patterns generated should better fit real occurrences of crime, particularly as literature suggests the home to be the key node of an offender's awareness space (Brantingham & Brantingham, 1981).

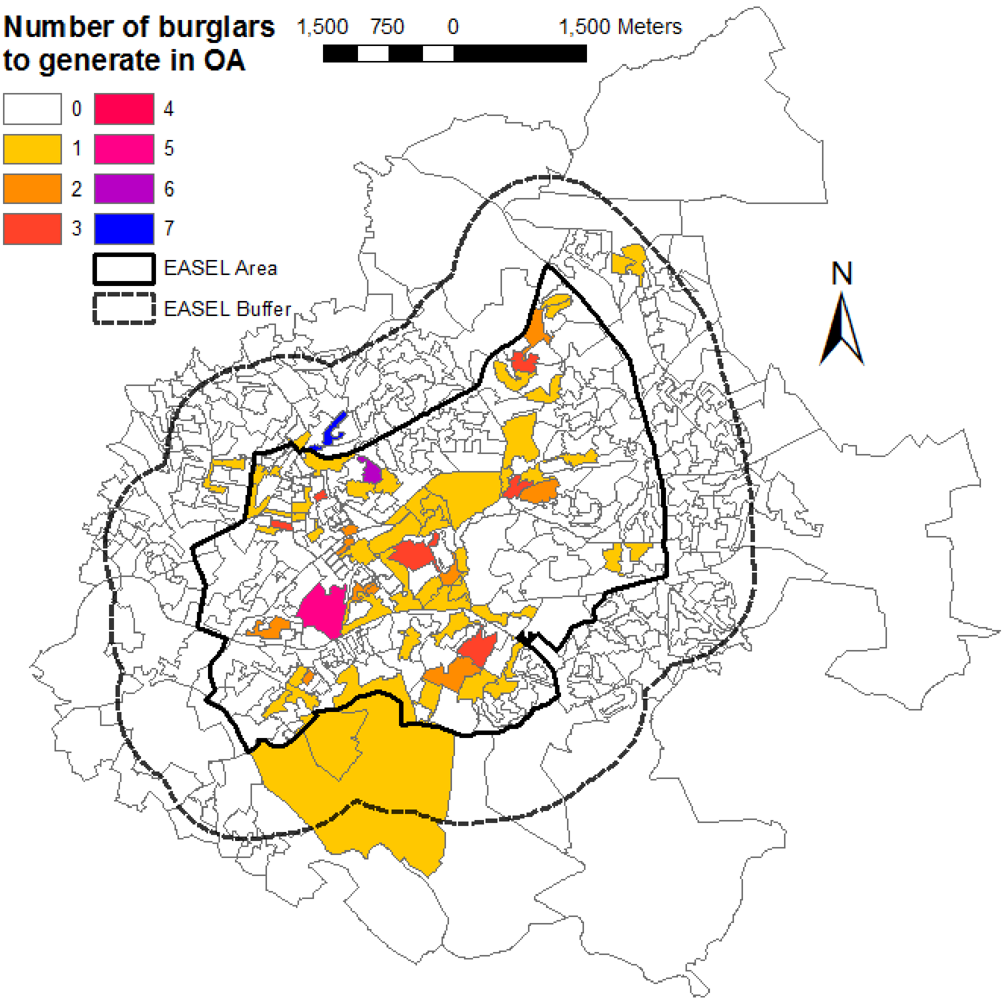


Figure 3.5: Aggregated offender location data in the communities layer.

3.1.3. Burglary Data

As well as the nominal location data, Safer Leeds also provided a dataset containing the location of all the burglaries that occurred in the study area, along with information about the nominals that were linked to the crime. In total, it contained the locations of 4983 burglaries in the EASEL area between 1st April 2003 and 31st March 2004 [Figure 3.5], though did not contain information on those that took place within the buffer. Furthermore, through linkage with the nominal dataset, it was possible to give an approximate distance for the journey to each crime for comparison purposes [Table 3.1].

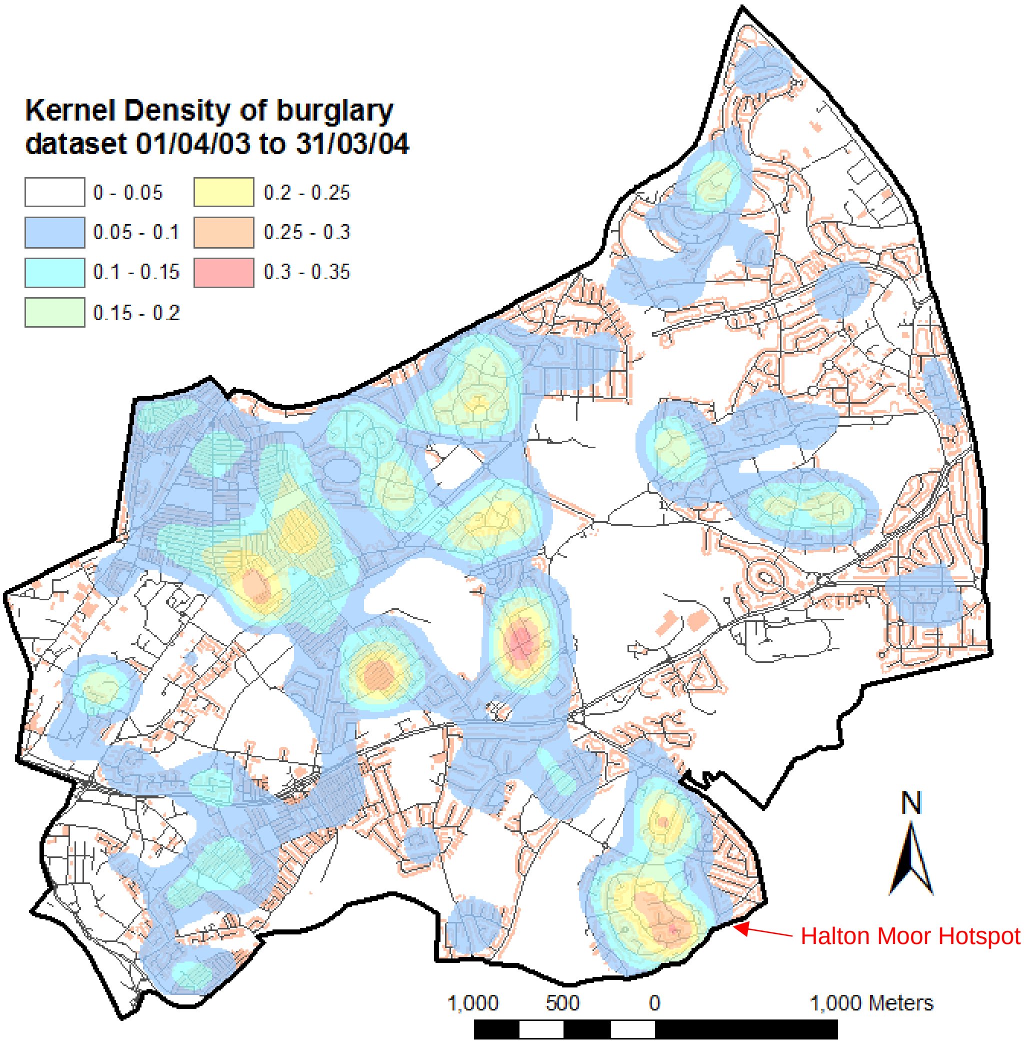


Figure 3.6: Burglary rates in study area 2003-2004 showing spatial clustering of burglaries. Highlighted is the unexplained Halton Moor hotspot (Malleson, 2010, p. 193).

Table 3.1: Distance of journey to crime for the real-life dataset.

Model	Mean distance of journey to crime (m)	Standard Deviation (3sf)
Expected	862	833

3.2. Models

3.2.1. Model 1: Validation

The first model to be run was the final solution created by Malleson in Section 7.4 of his research (Malleson, 2010, p. 201). This model was rerun to provide a base of comparison from which improvements could be assessed, with subsequent models using this version as a platform to build upon. The success of any models created could be determined by comparing the results from it against the results from this initial model when being assessed against the expected burglary dataset. The parameters of this model were determined through the trial-and-error process of calibration upon data from the period of 1st April 2001 to 31st March 2002 as undertaken in Malleson's research (Malleson, 2010, p. 184).

3.2.2. Model 2: South Asian

An interesting finding from the interviews conducted by Addis related to the attractiveness of South Asian communities as targets for burglary (Addis, 2017, p. 165), a phenomenon attributed to several factors. Primarily, houses that contained families of South Asian origin were thought to have large amounts of expensive jewellery inside that could be easily stolen during an offence. Cultural traditions amongst these ethnic groups mean that often a woman's wealth is tied up in high quality gold jewellery as opposed to cash or other assets (Lawrence, 2003). This provides an attractive target to a potential burglar, particularly in times when the price of gold is high which has been found to increase rates of burglary in such communities (Braakmann, et al., 2017). This could go towards explaining the offender's perception that the South Asian population *"don't believe in banks"* (Addis, 2017, p. 165) and instead tie their assets up in more accessible ways. Furthermore, Participant 21 refers to being able to resell stolen goods back to those within the Asian community. This is likely referring to the stolen jewellery and other valuables that are a symbol of status within the community so can be easily resold to others in the area.

Aside from the prevalence of jewellery, another attractive feature of South Asian communities identified was their frequent attendance of religious services. Participant 21 (incorrectly) identified Sunday as the main day of prayer for Muslim communities, stating that this was an attractive time to burgle a property due to the increased likelihood that the house would be unoccupied. Studies have found that around 59% of Muslims in Britain visit a religious service once a week, compared with around 8% of Anglican Christians (Christian Today, 2005), meaning there should be greater opportunity to enter an unoccupied property during this time of worship.

Malleson's research used the *% Indian, Pakistani, Bangladeshi* variable from the OAC [Figure 3.6] in several statistical models and found it to be the fourth highest correlating demographic factor with burglary of an area (Malleson, 2010, p. 72). However, it was theorised there that this was due to South Asian communities being conterminous with areas of high deprivation, therefore being vulnerable for the same reason deprived areas are. Furthermore, the prevalence of these ethnicities was factored into the calculations for ethnic heterogeneity to calculate community efficacy values, however they are not used anywhere in the initial model as a factor of attractiveness, making their inclusion worthwhile.

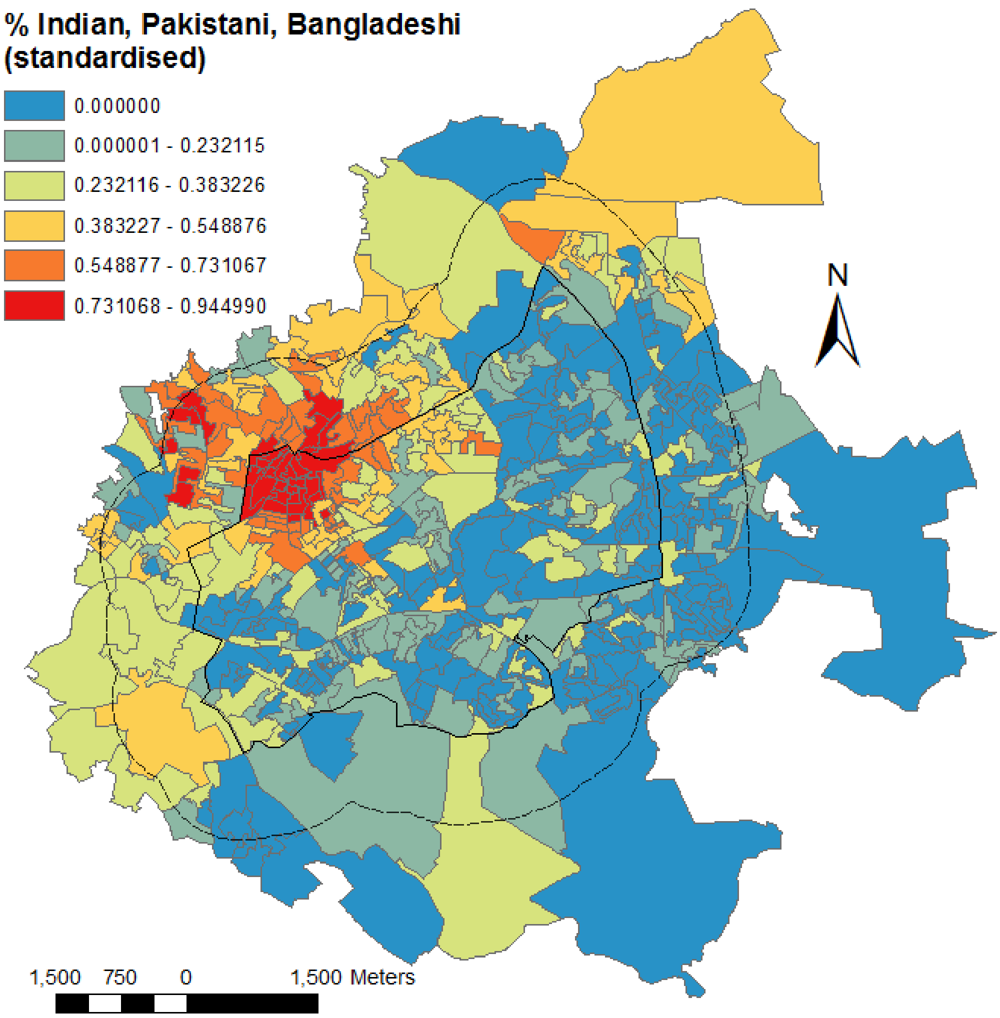


Figure 3.7: % Indian, Pakistani or Bangladeshi in each OA of the study area (standardised).

To implement these findings in the model, the equation for the calculation of a community's attractiveness had to be modified. The equation normally considers four standardised variables: % of students, average rooms per house, % of houses with more than one car and % of people with higher education qualifications. The attractiveness is then calculated as the mean of the four values. By adding a fifth value of the % of people who identify as Indian, Pakistani or Bangladeshi, the model could be updated so that a burglar takes this into consideration when choosing an area to burgle.

3.2.3. Model 3: No Children

A further deterring factor identified by burglars is the presence of children at a property, the reasoning for this is hypothesised to be twofold. Firstly, a property that contains children is likely perceived by a criminal to have more chance of being occupied at any point of the day (Cohen & Felson, 1979). This is down to the mother or another guardian being present to look after any children in the household, particularly younger ones who may not yet be in school (Hakim, et al., 2000). The occupancy of a household in the model is already affected by guardian roles, as the number of economically active people looking after a family is a component variable in the calculation.

On top of children's effect on occupancy, Addis's research also brings up another deterrent factor not present in the literature; the consequence of morality. Several burglars interviewed were keen to stress that they would avoid burgling properties that had clear evidence of children living inside on ethical grounds, with one participant attributing this to a desire to *"do the right thing"* (Addis, 2017, p. 168). Participant 8 claimed to take particular care not to target such properties around Christmas due to the guilt of taking presents from children; a decision that goes against literature findings of Christmas to be *"the burglars' party"* (Sorensen, 2004) where burglary rates are highest.

The two relevant variables from the OAC were the % of population aged 0-4 and % of population aged 5-14 [Figure 3.7]. Malleson's research found both variables to both be very mildly negatively correlated with burglary rates, indicating that as the number of children increases in an area, burglary rates fall slightly. This fits with research that finds that house with children present suffer 16% less burglary than those without (Tseloni, et al., 2004). However, these new findings linking morality to household attractiveness were yet to be implemented in the model, therefore could be added in Scenario 3.

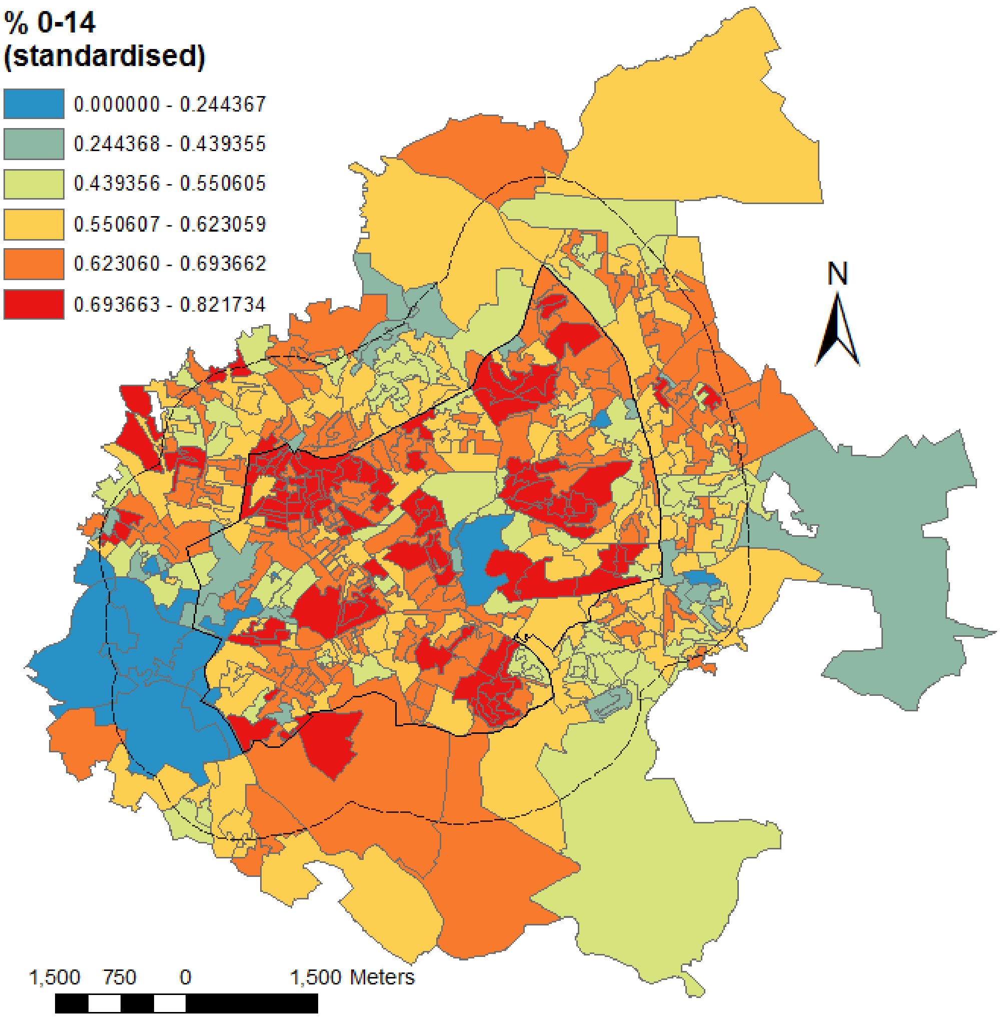


Figure 3.8: % 0-14 for each OA in the study area (taken from the mean value of % 0-4 and % 5-14, standardised).

Similar to Model 2, the attractiveness calculations of the model could again be updated to add in the relevant age-related variables. However, this time both the *% 0-4* and *% 5-14* variables were required, therefore the value being added to the calculation was the mean of both values. Furthermore, as the relation between children prevalence and burglary rates were negative, the value had to be reversed so that more children would be unattractive to a burglar. The attractiveness of an area could then be calculated from the mean of this value and the four others from the initial model.

3.2.4. Model 4: Low Security / Occupancy

A more general observation inferred from Addis's research involves the importance of the different attractors and generators that burglars look for when visually assessing a potential target property. The initial version of the burglary model set identical weightings for accessibility, visibility, security and occupancy; this research however hypothesises that burglars may not deem these factors equal. While accessibility and visibility seem to be universally seen as important, the same cannot be said for security and occupancy.

Despite Malleson's findings that increasing the security weighting of the model generates better fitting results (Malleson, 2010, p. 197), the new research corroborates previous literature that security may not always be seen as a deterrent by a burglar. Several participants argued that the type of security measure present played a big part in determining the attractiveness of a property, with basic security alarms being singled out as a poor deterrent (Addis, 2017, p. 181). Similarly, the presence of complex security features could be seen as attractive to a burglar who could see it as a challenge or protecting something of great value (Addis, 2017, p. 178), and may not pose a threat to a more well-equipped offender who could have the tools to circumvent such a system. 22% of the study group also mentioned the prevalence of opportunistic burglary where security measures were bypassed entirely by entering properties through open windows or doors (Addis, 2017, p. 177).

Feedback was similar regarding the occupancy of a property, with an unoccupied house generally being seen as a preference but not necessarily essential (Addis, 2017, p. 193). Several offenders described how they would use stealthy tactics to move about an occupied home without being caught, with some even enjoying the *"buzz"* of such a risky operation (Addis, 2017, p. 183). Furthermore, one participant claimed to prefer the property to be occupied due to the increased likelihood of valuables being present (Addis, 2017, p. 183).

For these reasons, it was decided to create another scenario of the model with lower weightings given to the security and occupancy of a property to compensate for those burglars who may not be deterred by these factors. A new burglar type was created based Validation model agent; however, this burglar gave a weight of 0.25 to the two factors rather than the 0.5 weighting given previously.

3.2.5. Model 5: No Elderly

Another deterrent factor identified by the research participants was the presence of elderly people in a home, with 61% of those questioned claiming this would cause them to avoid burgling a property (Addis, 2017, p. 166). The major reason given for this was the perception that an elderly victim would be most vulnerable to a burglary, a belief that has been backed up with scientific study (O'Neill, et al., 1989). While several participants identified the physical risks of targeting an older victim, such as the possibility that the offence *"could give [the victim a] heart attack"* (Addis, 2017, p. 167), they failed to consider the further psychological (O'Neill, et al., 1989) and economic (Cook, et al., 1978) impacts that burglaries have been found to particularly have on older victims.

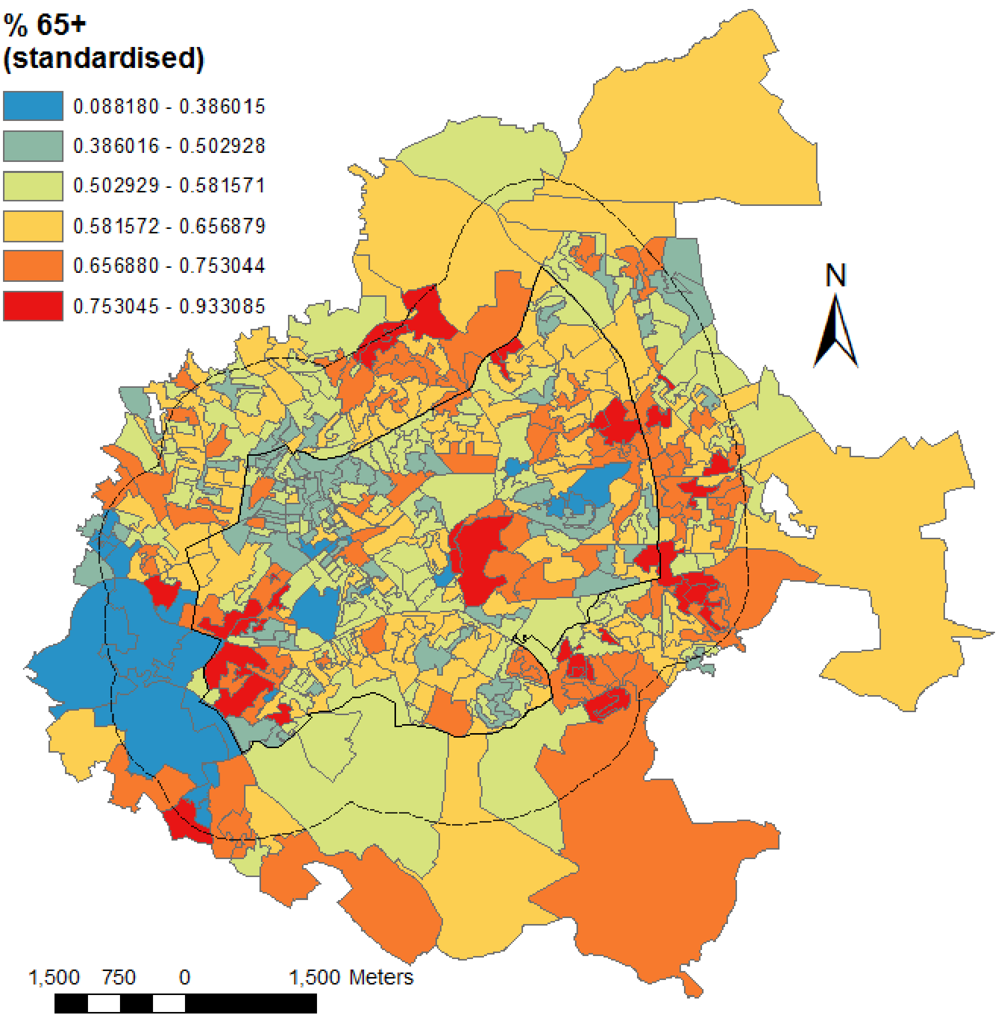


Figure 3.9: % 65+ in each OA of the study area (standardised).

Other reasons identified include a burglar's moral reasoning that an elderly resident has earned their respect through a lifetime of work, therefore does not deserve to be burgled (Addis, 2017, p. 167). Factors relating to occupancy were also discussed, as the perception is that elderly residents are more likely to be home throughout the day, therefore burgling their property poses more risk of confrontation (Cook & Cook, 1976).

The relevant OAC variable to be tested is the % of the population that are aged 65 and over [Figure 3.8], which is expected to have an inverse relationship with burglary rates. This is a finding corroborated by Malleson's research which found it to be the sixth highest negatively correlating factor (Malleson, 2010, p. 72), although this was hypothesised to be related to its lower prevalence in inner-city areas rather than it being a deterring factor in its own right. Studies such as those conducted in the USA by Cook & Cook (1976) also explore this link, finding the 65+ age bracket to be the least likely to experience burglary.

Similar to Models 2 and 3, the OAC variable is added as a fifth factor in the model's attractiveness calculations to determine each areas initial pull for an offender, with the variable first being reversed due to high prevalence being a deterrent.

3.2.6. Model 6: Burglar Types

One area of functionality that was introduced but never explored in Malleson's initial research was the possibility of generating different types of burglar with different attributes in the same model. Up to now, the model has only been initialised with one type of burglar at a time, however in reality there exists a wide range of criminals with broadly different modus operandi (Fox & Farrington, 2012; Vaughn, et al., 2008). By implementing multiple different types, it is possible to assess how each type of behaviour affect the accuracy of the model. Addis's research identified five broad types of offender, which will be detailed below. Each typology modified some of the weightings for the factors that affected a burglar agent's target selection process to better fit the modus operandi of that criminal. Unfortunately, little literature exists on how each type of burglar perceives the importance of the various factors, therefore judgement had to be used when setting the weightings, the values of which were set using trial-and-error.

3.2.6.1. Professional

A significant body of literature refers to a particularly skilled type of burglar that can be thought of as a *'professional'*. The professional burglar can be identified by their use of sophisticated operating techniques such as the use of tools to bypass security devices and disguises or confidence tricks to blend in to surroundings (Addis, 2017, p. 55). Goods taken are often of higher value than with other typologies and homes targeted are usually unoccupied to leave no witnesses and no evidence (Fox & Farrington, 2012). Offences are frequently planned over a longer period, with targets possibly visited over several days or weeks to assess occupancy patterns and vulnerabilities (Nee & Taylor, 1988). The number of burglars seen to be skilled enough to fit this category is low (Davidson, 1981), although this is likely highly underrepresented due to the decreased likelihood that the burglar will be caught or linked back to a crime (Hough, 1987).

As well as setting the weights for each of the target selection factors [Table 3.2], the drug addiction mechanism was also modified for this agent. It is assumed that a professional burglar would be less likely to be operating to feed a drug addiction. Therefore, the professional burglar has a level of drug addiction that is set randomly during implementation with each professional agent having a 50% chance of being mildly addicted to drugs. This contrasts with the previous models in which it remained the same for each agent.

Table 3.3: Modified variable weights for the Professional burglar.

Variable	Effect	Weight in Model	Reason
Community Factors			
Attractiveness	High	2	Seeks higher value rewards
Distance to Area	Low	0.2	More willing to travel for greater profits
Property Factors			
Community Efficacy	Low	0.2	Able to blend in to community to avoid suspicion
Security	Low	0.1	Uses tools and skills to bypass security systems

3.2.6.2. Interpersonal

A less common type of burglar are those that commit crime for interpersonal reasons, a motive that goes against the current assumption made by literature (and the initial model) that all burglary is motivated by a desire for money. Interpersonal burglary is motivated by two main factors. The first is the burglars desire for confrontation with a resident of a property, with burglaries in this category often being caused by a dispute between parties (Fox & Farrington, 2012) or as a method of intimidation on the part of the offender such as in the case of the Halton Moor hotspot (Malleson, 2010, p. 193). The other motivation for interpersonal burglary is for sexual purposes, with offenders entering a property to commit sexual assault or voyeuristic acts (Vaughn, et al., 2008).

The implementation for this type was more complicated than with others due to the different motivation for burglary. Therefore, a new motive had to be specified in the model that remained independent from an agent's wealth, replacing the drug addiction motive for this agent. It handles a burglars need to commit an interpersonal burglary and can only be satisfied by offending, with the need to do so constantly depleting at a randomly generated rate. Furthermore, a new method of victim selection had to be defined that reverses the influence of property occupancy so that an offender targets properties that are occupied wherever possible. The weights for each factor can be seen in Table 3.3.

Table 3.5: Modified variable weights for the Interpersonal burglar.

Variable	Effect	Weight in Model	Reason
Community Factors			
Attractiveness	Low	0.25	Motivated by interpersonal reasons not monetary gain
Previous Success	High	0.75	Often burgles people known to them due to dispute
Property Factors			
Occupancy	High	10 (reversed)	Wants to target property where the tenant is home
Traffic Volume	High	0.75	Doesn't want to be seen from street
Visibility	High	0.75	Wants to avoid being seen by neighbours when entering property

3.2.6.3. Opportunistic

Another behavioural trait not previously implemented in the model is burglary as a reaction to opportunity rather than as the endpoint to a specific searching process. The defining feature of this type of burglary is the lack of forced entry into a property, instead taking advantage of an insecurity such as an open window or door (Addis, 2017, p. 177). While this opportunity may come about when searching for a specific target to attack it can also be presented to the criminal during their day to day activities, therefore requiring little or no planning or foresight from the offender (Farrington & Lambert, 1994). The offence therefore will require little skill or specialist equipment, and will likely leave no evidence (Fox & Farrington, 2012).

Although this burglar takes advantage of opportunities that they may pass, this behaviour was difficult to implement properly in the model without data on how often a property may be left insecure. Therefore, it was decided that opportunism should be faked through manipulation of factor weightings alone [Table 3.4].

Table 3.7: Modified variable weights for the Opportunistic burglar.

Variable	Effect	Weight in Model	Reason
Community Factors			
Attractiveness	High	1	Will only act upon a suitably rewarding opportunity
Property Factors			
Accessibility	High	2	Seeks property that is easy to get into
Community Efficacy	High	0.75	Wants to avoid attracting suspicion, especially if opportunity presents itself in daylight
Occupancy	High	1	Doesn't want confrontation: will only attack property left insecure when the owner has left
Security	Low	0.1	Not deterred by security measures as will enter through open door/window
Traffic Volume	High	2	Does not want to be seen from street, especially in daytime
Visibility	High	1	Wants to avoid detection by neighbours, especially in daytime

3.2.6.4. Disorganised Amateur

A large proportion of burglaries are found to have been committed by inexperienced *'amateur'* offenders who tend to burgle items with less value than older, more experienced offenders (Snook, 2004). While sharing similarities with the opportunistic class in that they target insecure properties when the chance presents itself, this class do so due to a lack of skill and an inability to operate another way. Disorganised Amateurs tend to travel shorter distances to offend, likely due to their limited access to transport and smaller awareness space (Townsley, et al., 2015). While often motivated by money, this type is also more likely to offend out of boredom or due to the influence of other people (Hearnden & Magill, 2004). While currently exhibiting a lack of skill and sophistication due to their age, this burglar will often begin to display signs of other typologies as they grow older and gain experience (Fox & Farrington, 2012).

The assumption with this type of burglar is that they are likely too young to have fully developed a drug addiction that needs funding through criminal actions. Therefore, the implementation defines a 25% chance that a generated agent will be mildly addicted to drugs. Aside from this, the only other code altered regards the weightings of the search factors [Table 3.5].

Table 3.9: Modified variable weights for the Disorganised Amateur burglar.

Variable	Effect	Weight in Model	Reason
Community Factors			
Attractiveness	High	1	Will only act upon a suitably rewarding opportunity
Distance to Area	High	3	Will look to avoid travelling far due to lack of transport and awareness
Previous Success	High	2	Will want to stay in comfort zone and not risk attacking a new property where possible
Property Factors			
Accessibility	High	0.75	Seeks property that is easy to get into
Community Efficacy	High	0.75	Lacks the sophistication to blend into surroundings without acting suspiciously
Occupancy	High	2	Seeks to avoid confrontation as does not know how to handle it
Security	High	5	Does not have the skills or tools to bypass complex security
Traffic Volume	High	1	Does not want to be seen from street
Visibility	High	1	Wants to avoid detection by neighbours

3.2.6.5. Disorganised Chaotic

A further type of disorganised burglar, this type lacks sophistication not through inexperience but through diminished capability due to substance addiction, homelessness or mental illness (Vaughn, et al., 2008). This typology will likely offend more indiscriminately and at a quicker rate due to their desire to accumulate cash at any means necessary (Malleson, 2010). Burglaries of this type are often messy affairs with little care taken and evidence left behind including proof of forced entry (Fox & Farrington, 2012). This class is the most likely to be motivated by a need to obtain drugs, one of the most common desires for burglars (Hearnden & Magill, 2004).

In the model, the behaviour of this typology was simulated entirely through the drugs motive, with this being used as a proxy for all factors that cause the chaotic behaviour exhibited. The level of drug addiction was therefore randomly set to a higher value than normal so that the desire to burgle would occur more frequently and become stronger in a shorter time. The factor weightings could then be applied, with the majority of property factors being set to lower values to reflect this burglar's indifference to finding an ideal target [Table 3.6].

Table 3.11: Modified variable weights for the Disorganised Chaotic burglar.

Variable	Effect	Weight in Model	Reason
Community Factors			
Distance to Area	High	1	Likely will not have access to a vehicle, also will want to burgle somewhere close to quickly obtain drug fix
Social Difference	High	1	Will not want to stand out amongst a community
Property Factors			
Accessibility	Low	0.25	Will not be picky about entering a property; will often force entry
Community Efficacy	Low	0.25	Will not care about how cohesive a community is
Occupancy	High	2	Wants to avoid confrontation at all costs
Traffic Volume	Low	0.25	Wants to burgle at all costs so will not care about being seen from street
Visibility	Low	0.25	Wants to burgle at all costs regardless of neighbourhood surveillance

To remain consistent with the previous models, Model 6 was required to generate the 105 burglars in the locations specified by the communities layer. However, the dataset used was not rich enough to define a typology exhibited by each of the real-life nominals, therefore the only fair method was to randomly assign agents of each type to Output Areas to make up the study size. However, this posed a further problem as the number of burglaries in reality that could be attributed to each typology would not be equal, therefore generating an equal amount of each burglar type in the final model would not be appropriate. Further complicating matters was the differing rate at which each type of agent offends within the model, with Disorganised Chaotic criminals burgling more frequently than Interpersonal burglars for example.

To combat this, it was decided to use real-life study findings to determine how many of each burglar type to generate. Unfortunately, it was not possible to find literature stating the percentage of burglars that fit into each type, likely because a burglar will often change their modus operandi depending on the situation (Bennell & Jones, 2005). However, the work of Fox & Farrington (2012) was able to categorise a sample of burglaries into four distinct types that neatly matched those used in this model, producing figures as to the percentage of crimes that fit each category. Calculations could then be performed to assess how many burglars of each type would be required in the final model to generate that percentage of burglaries for each typology.

The results of these calculations can be seen in Table 3.7, which also shows that the percentage of burglaries in the final output closely match the desired target figures. With the amount of each agent decided, they could then be randomly assigned to Output Areas to make the total sample population of 105 burglars [Figure 3.9]. Further work could assess the demographics of burglars that fit each typology and assign them to an Output Area that best suits them, however this is outside the scope of the current project.

Table 3.13: Target and actual percentages of burglaries attributed to each typology in the model, along with the number of burglars required to do so.

Burglar Typology	% of real crimes fitting this category (Fox & Farrington, 2012)	Number of burglars required in final model to achieve this figure	% of model output crimes attributed to this category
Professional	27%	30	26.51%
Interpersonal	12%	16	12.16%
Opportunistic	48%	17	23.78%
Disorganised Amateur		34	24.26%
Disorganised Chaotic	14%	9	13.30%

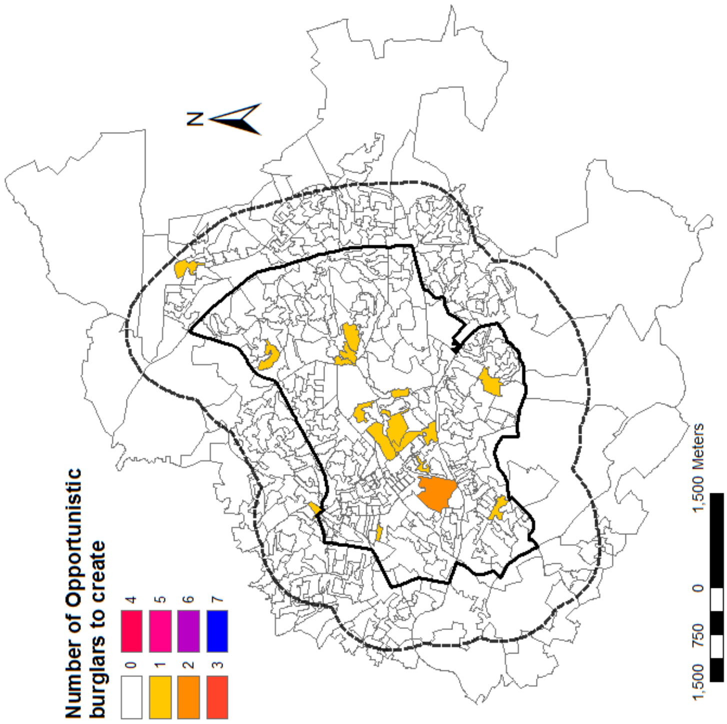
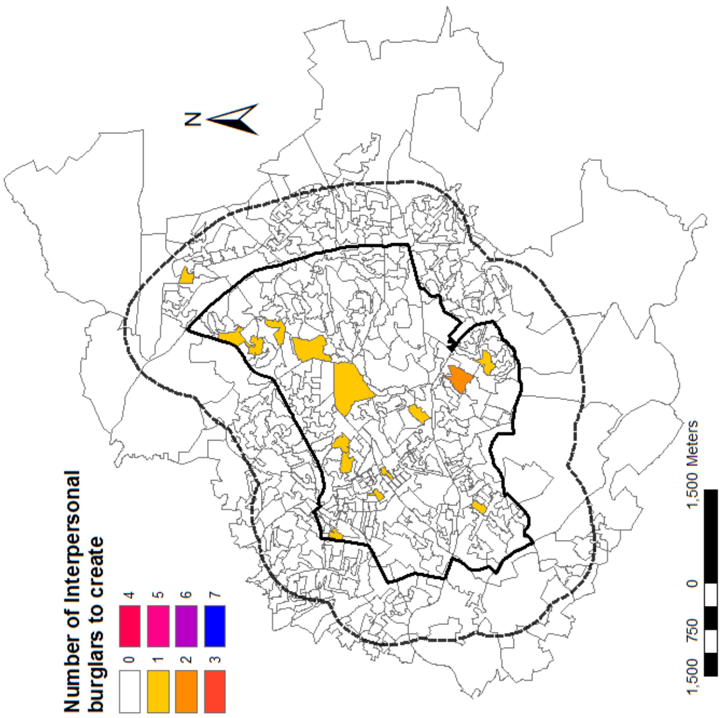
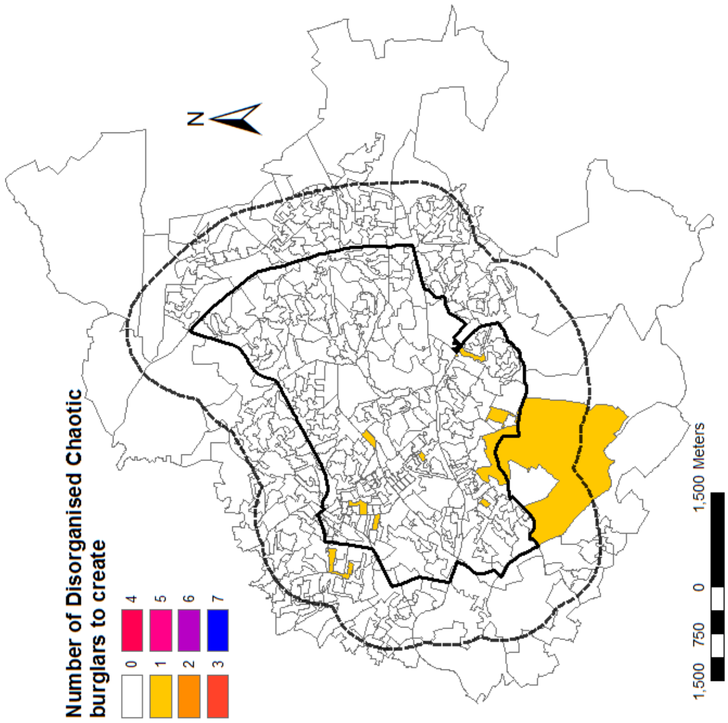
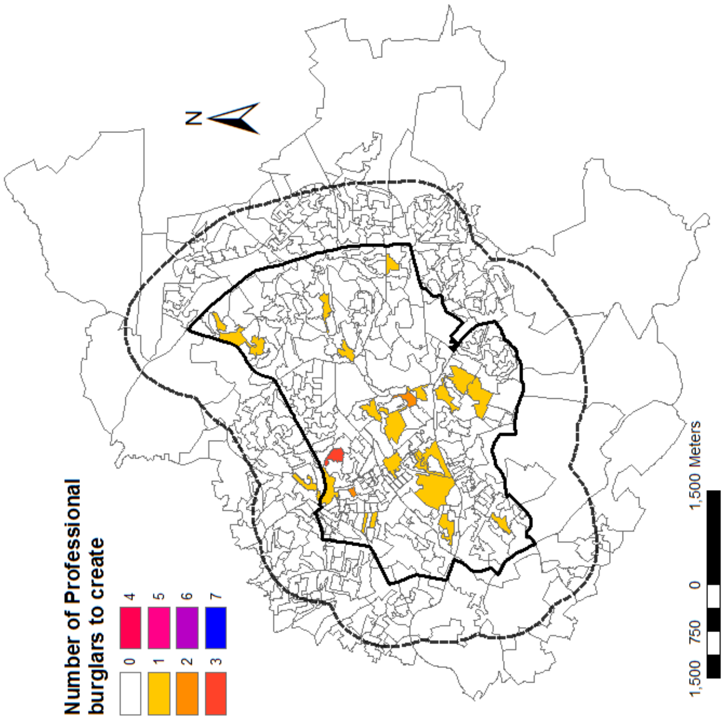
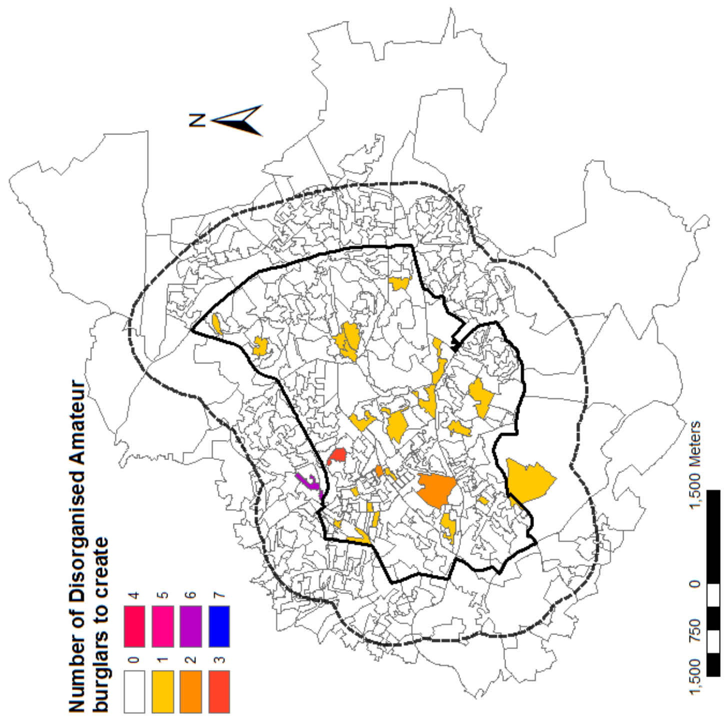


Figure 3.10: Output Areas to generate each type of burglar within, based off the real burglary location data in the communities layer. Each burglar is randomly assigned a home address from one of the houses within that OA.









4. Results & Discussion

The aim of the project is to improve on Malleson's initial model, therefore three areas of comparison were decided upon. The first is the model's ability to predict crime hotspots which can be judged through the method of *kernel density analysis*. The second is the level of clustering that the results set exhibits, measurable by calculating the models *L-Function*. Finally, the results of the distance of journey to crime can be analysed from each model to assess which correctly predicts the proximity of burglaries to the offender's home address.

Each model results set was compared to the results from the expected burglary data set provided by Safer Leeds, with better models returning outcomes closer to the real data set. As Model 1 is the culmination of Malleson's research, any Models that improve upon the results returned by this model can be deemed an improvement. Therefore, the results of all subsequent models were assessed against the performance of Model 1.

4.1. Prediction of Hotspots

Literature suggests that burglaries cluster in space (Johnson & Bowers, 2004a), therefore an important aspect of the model's predictive power is how well it generates these burglary hotspots. To assess this, the results from each model can be displayed using Kernel Density analysis (ESRI, 2017a) which calculates the density of burglaries within a radius around each point in the results dataset. The algorithm was initialised to search in a radius of 250m around each burglary and output the results to a raster grid with a cell size of $10m^2$. Each map was standardised so that density values could be compared independent of the number of crimes that went into the final dataset, as some models caused burglaries to happen more frequently than others. Finally, the maps were modified to be on the same thematic range so that visual comparison could be performed. The expected burglary map for comparison can be seen in Figure 4.1, with the maps for Models 1-6 in Figure 4.2.

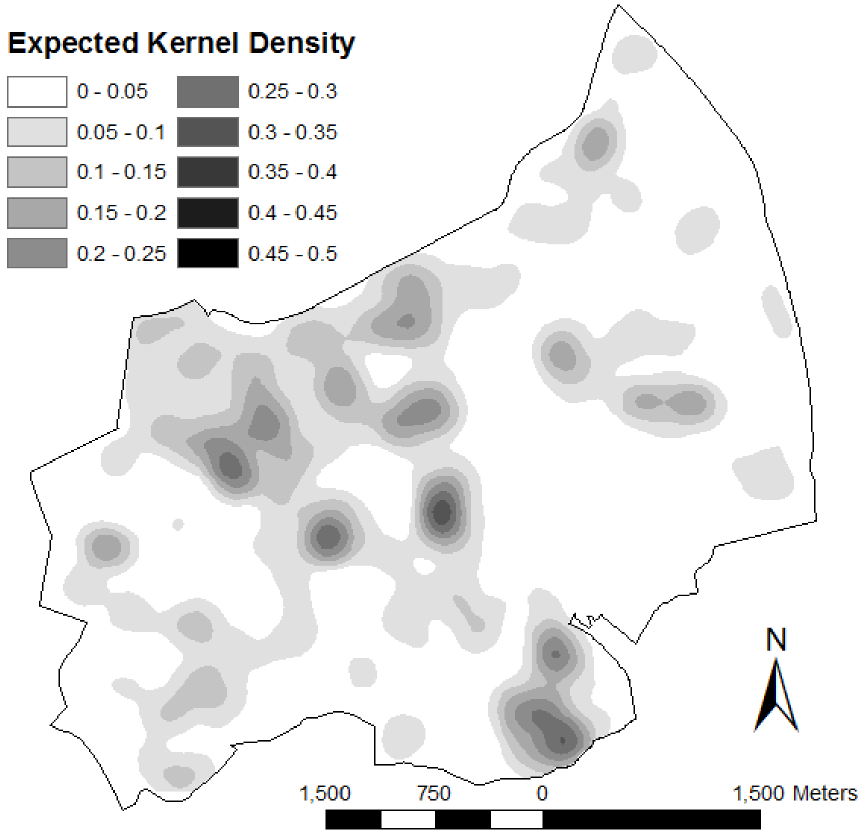


Figure 4.11: Kernel Density for the expected burglary dataset.

From visual analysis alone it is clear that several of the models have generated largely similar hotspot locations, particularly models 1, 2, 3 and 5. This is likely due to the latter three models being heavily based on the first, with only minor changes being made to the attractiveness calculation for each. As this factor is used to calculate the likelihood than an agent will visit a

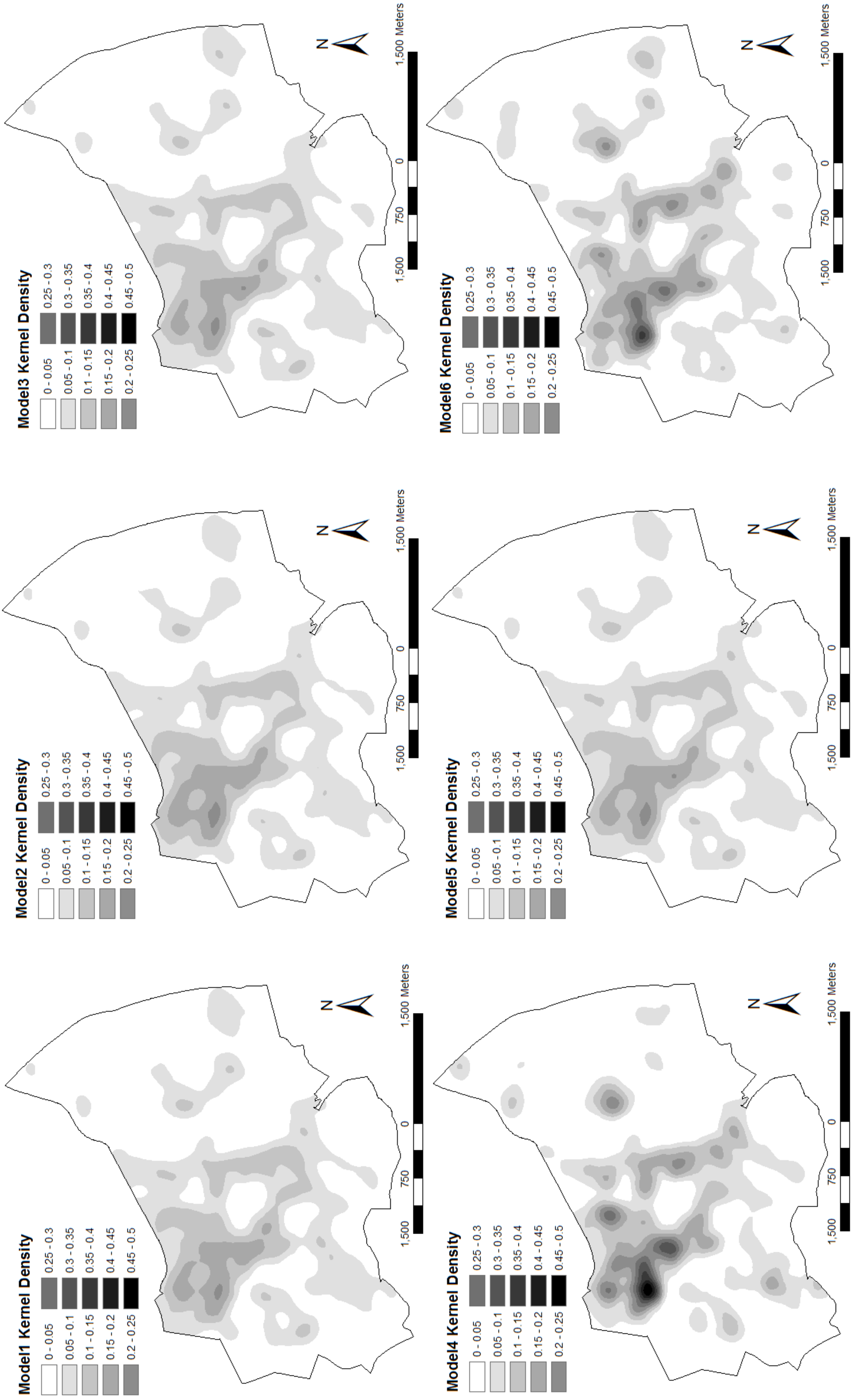


Figure 4.12: Kernel Density for Models 1-6 placed on the same thematic range. Clustering of burglaries is greatest at areas of higher Kernel Density.

certain community to offend, the changes to a community's attractiveness caused by this added factor is clearly not great enough to have a large impact on the output of the model.

It is impossible to quantify via observation alone whether any of the scenarios predicted hotspots better than the initial model. Therefore, further maps were created showing the difference in kernel density across the surface of the study area between each model and the expected burglary dataset. By calculating the difference in value at each point, it was possible to observe where each model under and over-represents the clustering of burglaries. The results can be seen in Figure 4.3, with positive results (blue) meaning burglary clustering has been overrepresented at that point and negative results (red) meaning it has been underrepresented.

Again, the results show similarity between most of the models. However, this method also highlights the fact that Model 4 (and to a lesser extent, Model 6) have predicted a large cluster of burglaries in the Harehills neighbourhood to the north west of the study area. Upon closer inspection of the burglaries in this area, it becomes apparent that this is due to the lowered importance of security in these models, with the average security value of burgled houses in the area being 1.827 as opposed to the 0.879 for those in the rest of the study area. It is hypothesised that this is due to the area being the most densely populated region in the EASEL area, therefore when a burglary occurs it increases the security for a larger number of houses in the vicinity than if it had occurred in a sparser region. As the agents are less deterred by this than in other models, the hotspot is created.

What is also clear to see from this method is that none of the models have been able to accurately predict the Halton Moor hotspot in the far south of the study area, an inaccuracy identified by Malleson as an area of weakness in the model (Malleson, 2010, p. 193). The fact that it has not been identified by any of the new models indicates that it is likely caused by burglars motivated by means other than money, rather than it being due to the initial model missing off a key demographic targeted by burglars.

The other major benefit of creating Kernel Density Difference maps is that they can be compared statistically to obtain quantitative results as to each model's similarity with the expected results. A model that perfectly predicted the location and strength of hotspots would have a surface value of zero at every point, therefore the standard deviation from zero of each map can be used to assess the accuracy of that model. The results of this can be seen in Table 4.1, with higher standard deviation indicating a worse performing model and vice versa.

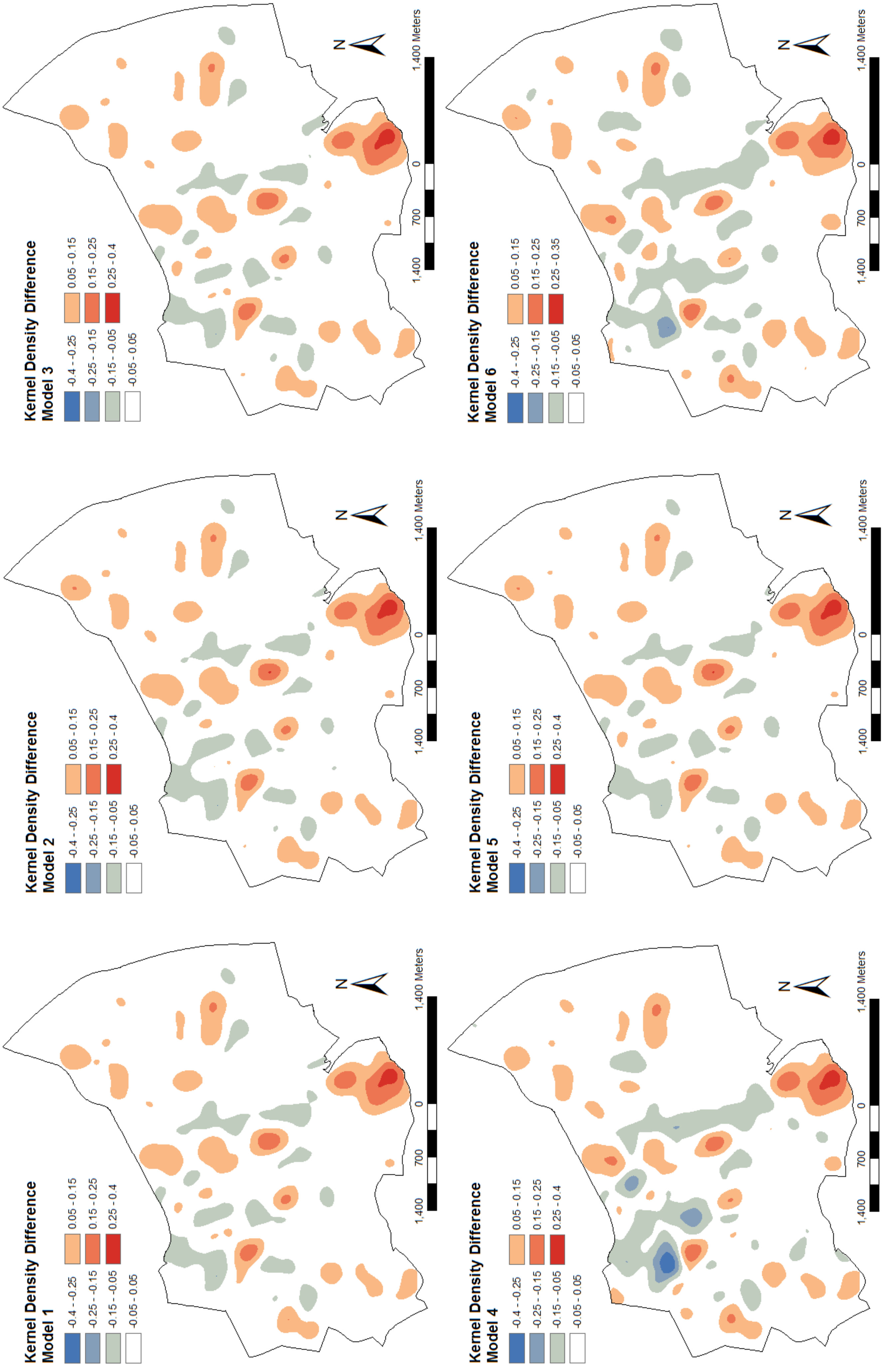


Figure 4.13: Difference in Kernel Density between each model and the expected burglary dataset. Areas in red underrepresent burglary while areas in blue over-represent it.

Table 4.15: Standard deviation of each model's Kernel Density from the expected burglary dataset

Model	Standard Deviation (4sf)	Difference from Model 1
1	0.04924	N/A
2	0.04957	-0.00033
3	0.04918	0.00006
4	0.05887	-0.00963
5	0.04888	0.00036
6	0.05447	-0.00523

From these results, only Model 5 (No Elderly) has made a noticeable improvement on the Validation model, returning Kernel Density results that are closer to those exhibited by the real-life data. As the inclusion of deterrence by elderly residents has improved the fit of the model, it is possible that this is a factor that is taken into consideration by burglars in the study area when searching for a target property. Interestingly, the only other model to have made any improvement was Model 5 which factored in the presence of children, although this improvement was much smaller and could possibly have been caused by fluctuations in the model rather than the variable being tested. Both deterrent groups were highlighted during interview as being avoided on moral grounds, therefore the fact that both improve the model may indicate the importance of morality within a burglar's target selection.

Another interesting result is that Model 4 (Low Occupancy/Security) performed poorest out of all the models at predicting hotspots, likely disproving the hypothesis about burglars being less deterred by occupancy and complex security. This theory was rooted in anecdotal evidence from the literature that burglars are willing to enter occupied properties and can use tools to bypass expensive security systems. This result potentially provides evidence therefore that an offender may, during interview, attempt to misrepresent past actions to make themselves appear in a more positive manner (Addis, 2017, p. 89).

Model 6 (Burglar Types) also performed poorly, however the reasoning for this can be better assessed by splitting the results up by type of burglar [Figure 4.4 & Table 4.2]. Individually, each burglar type performed worse than the Validation method which is to be expected when not using a general burglar agent. However, Model 6 still provides some interesting results. Most notably, the Interpersonal burglar, while performing the worst at accurately predicting expected burglaries, creates highly concentrated hotspots in areas common to no other model. This provides strong evidence that the Halton moor hotspot, which has so far been unable to be modelled through any other means, was created by this type of burglar. Malleson (2010, p. 193) finds anecdotal evidence that the hotspot was caused by burglary being used as a form

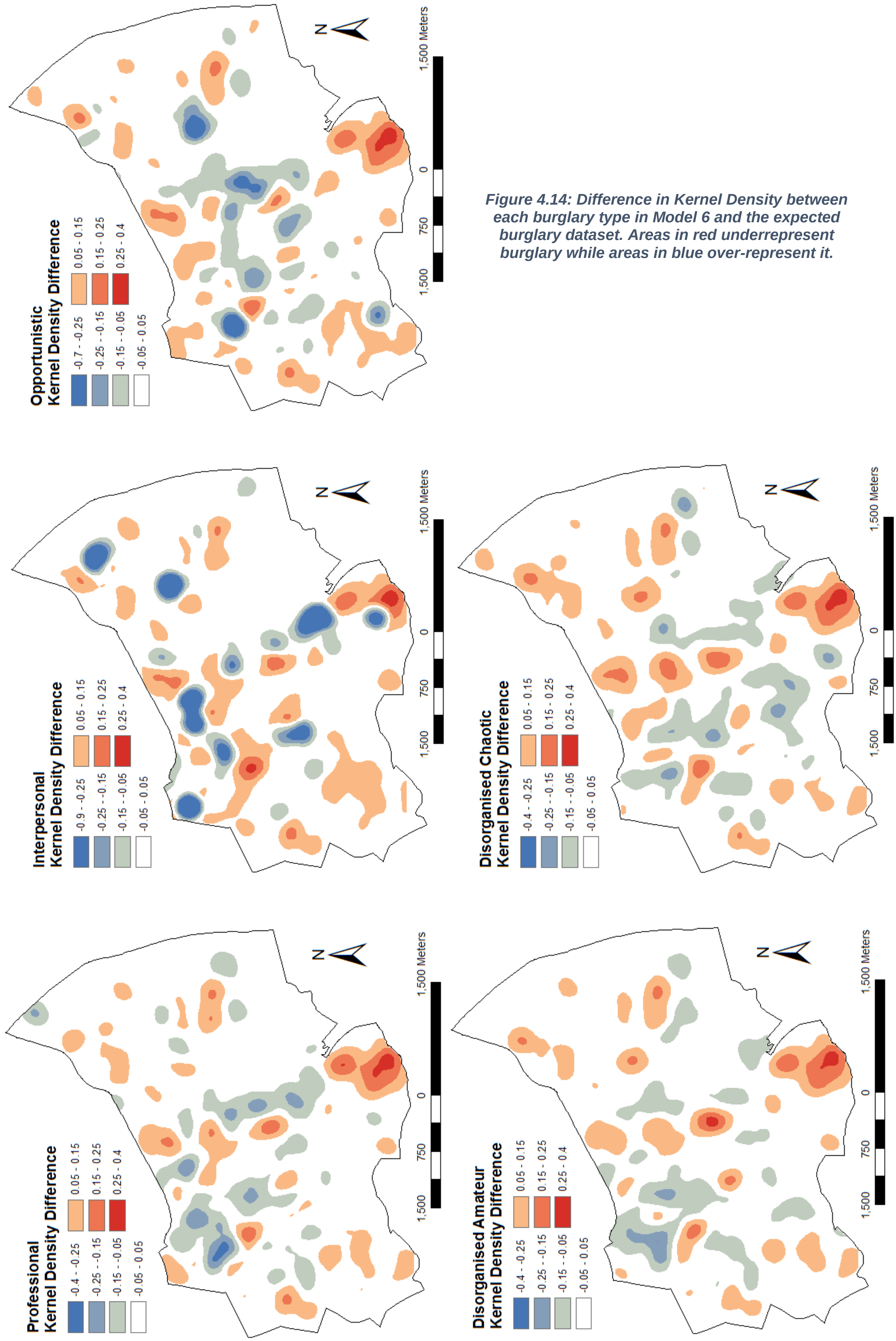


Figure 4.14: Difference in Kernel Density between each burglary type in Model 6 and the expected burglary dataset. Areas in red underrepresent burglary while areas in blue over-represent it.

of intimidation and these results likely confirms this theory. This highlights an area of difficulty for the creator of a predictive burglary ABM as it is extremely difficult to create a model that accurately predicts the location of crime of this kind.

Table 4.17: Standard deviation of each burglar type's Kernel Density in Model 6 from the expected burglary dataset.

Model	Standard Deviation (4sf)	Difference from Model 1
1	0.04924	N/A
6	0.05447	-0.00523
Professional	0.06321	-0.01397
Interpersonal	0.10190	-0.05266
Opportunistic	0.07340	-0.02416
Disorganised Amateur	0.05874	-0.00950
Disorganised Chaotic	0.06213	-0.01289

Aside from the Interpersonal typology, the next worst performance came from the Opportunistic agents. This is an interesting result as it goes against a large body of literature stating that this is a behaviour type exhibited by certain burglars. However, the poor accuracy of this type was again likely the result of difficulties in translating real-life behaviour to the actions of an agent. The occurrence of a suitable opportunity in this manner largely depends on a chance encounter with a temporarily insecure property, therefore without data on the times that each property has an unguarded entry point this behaviour cannot be accurately modelled. The prevalence of opportunistic behaviour in real criminals likely explains much of the variability between the expected burglary dataset and each of the models created.

4.2. Level of Clustering

As well as performing density-based analysis, it is also possible to analyse the resultant point patterns by comparing the distances between burglaries in the results set. While there are several possible techniques for this, the most suitable in this case is Ripley's K Function. Ripley's K is a statistical technique to determine how clustered or dispersed a point pattern is within a defined study area. For each point in the results set, the number of other points within a distance *d* are calculated, this is the number of neighbours that the point has at that distance. The K value for that distance is then defined as the mean number of neighbours for each point divided by the total point density of the overall study area. The calculation can then be repeated for different distance values to determine how clustered the results set is at each distance scale (Dixon, 2002).

To better analyse the results of Ripley's K, a transformation can be performed called the L Function. This modifies the resulting values to set them relative to zero, where zero represents a point pattern exhibiting perfect spatial randomness. Any results greater than zero indicates that the point pattern is more clustered than random while a negative result shows that the features are more dispersed (O'Sullivan & Unwin, 2014). The L Function therefore determines whether the average point has greater or fewer neighbours than would be expected based on the concentration of points across the whole study area.

To generate values for the level of clustering in each model's results set, a script was used from the ArcGIS Spatial Statistics toolbox (ESRI, 2017b). The script calculates the K Value for a dataset and automatically applies the L Function transformation. The parameters of the script were set so that clustering is first determined at the 100m level before incrementing by 100m with each subsequent calculation. This is continued until the 2000m scale for a total of 20 resultant values.

The results for each model are displayed in Figure 4.5, with the expected dataset and a randomly generated point pattern included for comparison. The first item to note is that the technique breaks after approximately the 1300m interval, this is due to the location of burglaries being limited by the size of the study area. Therefore, any results after this point can be deemed irrelevant.

Again, models 2, 3 and 5 produce similar outputs as the Validation model, while models 4 and 6 significantly worsen the level of clustering in the model. At the lowest scales measured (100-200m), the expected dataset is slightly more clustered than the initial model would predict, indicating that the model fails to accurately predict the level of repeat and near-repeat victimisation. This could be an area of potential improvement within the model, as burglars should be more willing to reoffend in an area than they currently are. However, the level of clustering at this distance range is slightly improved in Model 2 (South Asian), potentially due to the targeting of concentrated South Asian communities around the Harehills neighbourhood.

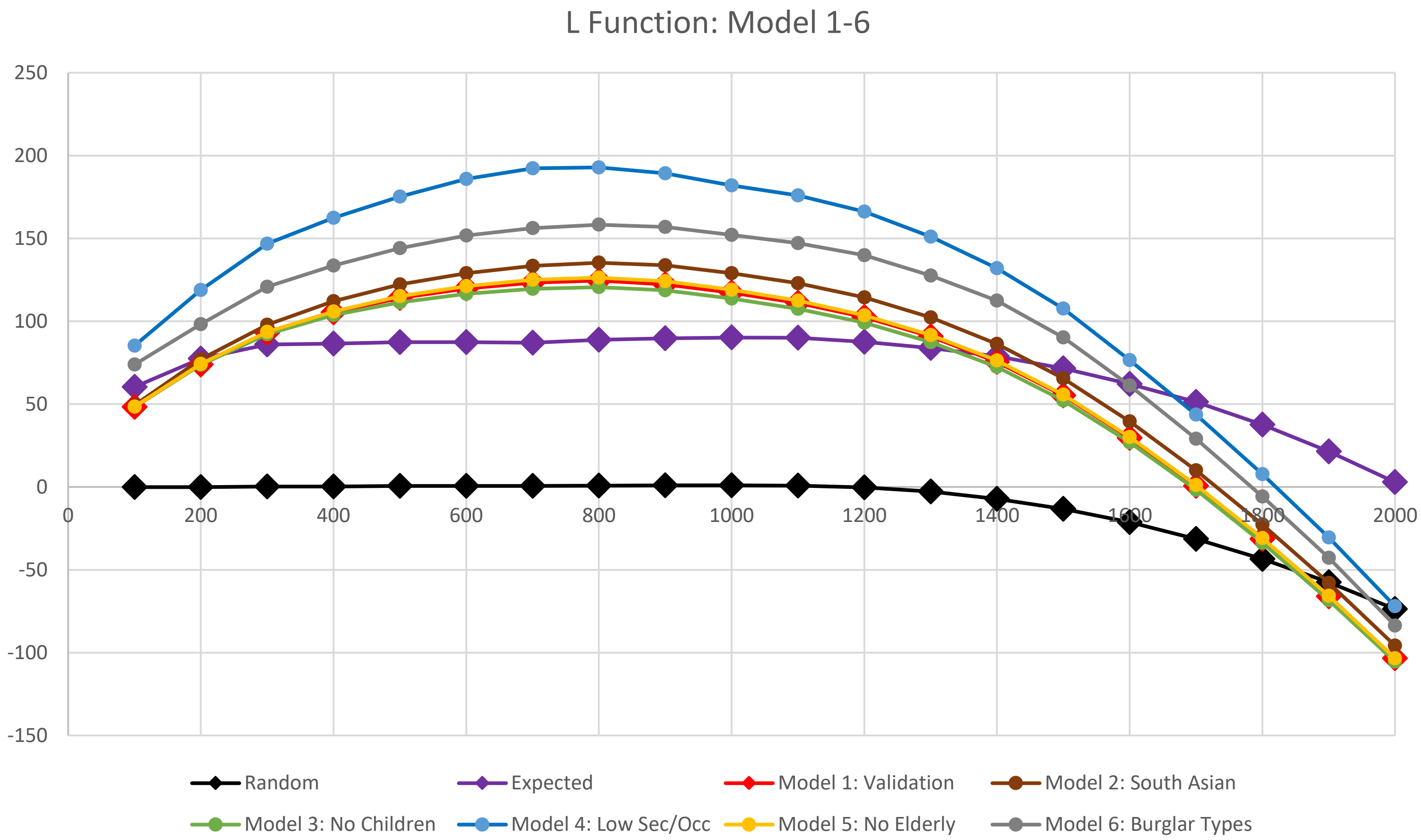


Figure 4.15: Graph showing the L Function results for each model and the expected dataset. Values greater than zero indicate clustering at that distance while values less than zero indicate dispersion.

Between 200m and the breaking point of the technique at around 1300m, the nominal dataset is less clustered than the initial model would predict. This is likely due to the prevalence of opportunistic burglaries in houses in the real-life data that would otherwise be seen as unsuitable targets, with the model struggling to represent this type of burglary. Furthermore, real-life offenders have greater freedom to travel around the study area than the agents in the model that are limited to satisfying their very basic needs. Therefore, the real burglars would potentially encounter opportunities in more dispersed areas than the model agents who are limited in their travels. Finally, the agents in the model are only given 30 days of simulation time to build up an awareness space to offend within, however the real nominals will have been active in the study area for a lot longer so would have a greater knowledge of the surrounding areas from which to select a target.

Within this middle-distance range, the only model that improves upon the initial result is Model 3 (No Children), presumably again due to the distribution of children within the study area. Areas of high incidence are spread across the region which may be forcing burglars away from areas that may otherwise have been attractive. Most notably, incidence is high in the Harehills region that is highly targeted by agents in other models and lower near the city centre to the west which tends to otherwise be avoided.

Model 4 again performed the worst out of the group, exhibiting clustering far greater than the nominal dataset for the entire usable range of distances. This is again due to the inaccurate generation of dense hotspots in areas where security increases after a spate of burglaries. Furthermore, the burglar typology model performs poorly due to the behaviour of some of the offender types within. The L Function results for each type can be seen in Figure 4.6.

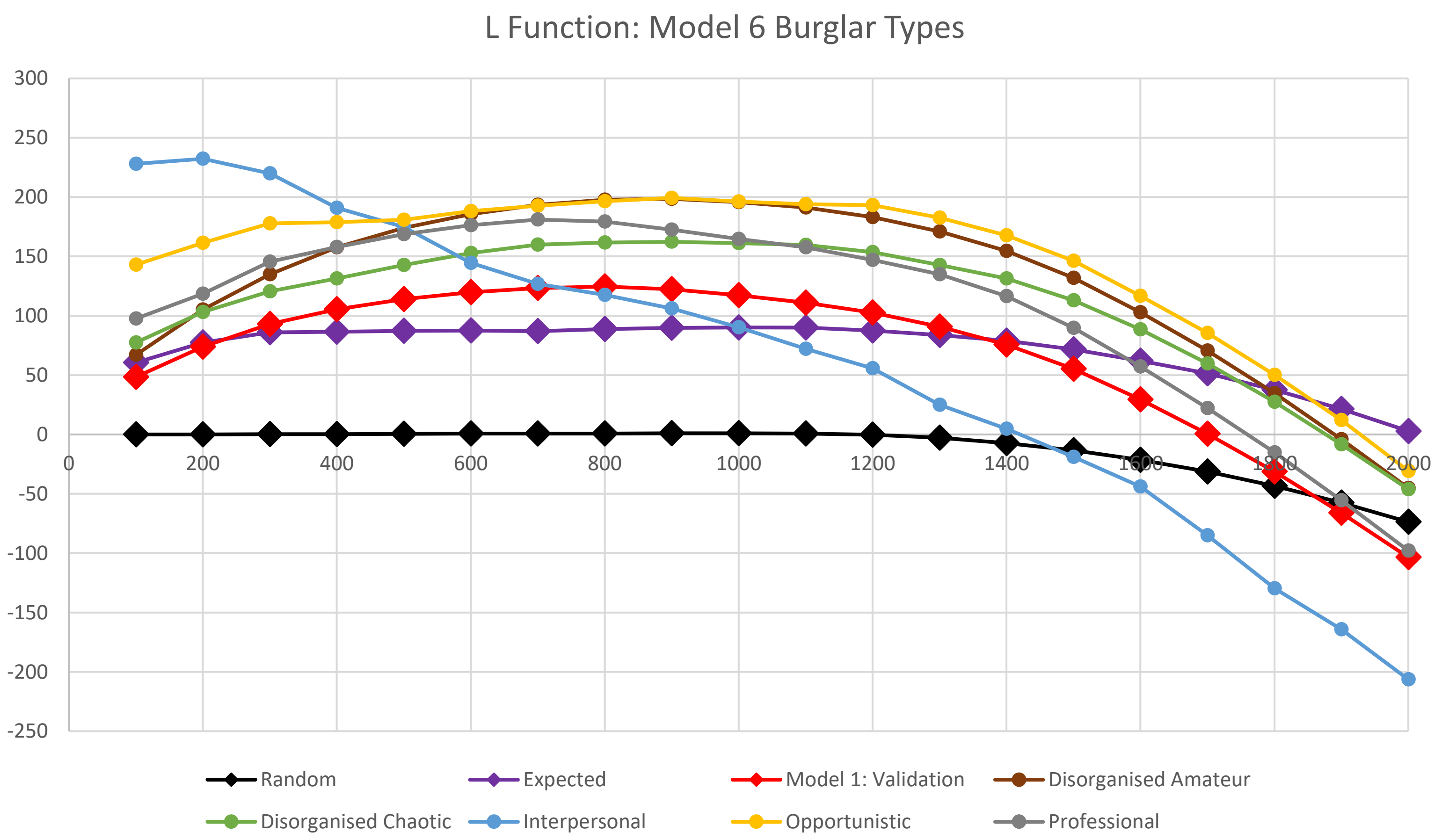


Figure 4.16: Graph showing the L Function results for each burglar type in Model 6 and the expected dataset. Values greater than zero indicate clustering at that distance while values less than zero indicate dispersion.

It is notable that none of the typologies manage to improve upon the level of clustering exhibited by the initial model over the entire range of distances, however some of the types improve clustering at certain levels. In particular, the Disorganised Amateur burglar displays a largely similar level of clustering at the very smallest level of analysis. The reasoning for this is almost certainly down to the increased weighting this agent gives to targeting properties previously burgled and already well known to them. This behaviour can explain why the phenomena of repeat and near-repeat burglaries occur, therefore burglars that act in this manner should be implemented into the model to improve its predictions of clustering at this level. A further avenue for exploration could be to assess whether repeat/near-repeat burglary is most commonly performed by unskilled burglars or whether this result is simply down to favourable weightings for this type.

The graph of the Interpersonal burglar is a further area of interest. Unlike all other models and typologies, the burglaries for this agent cluster greatest at the lowest distance values before rapidly becoming dispersed over greater distances. These results indicate that Interpersonal agents in the model concentrate their offences in very small regions and tend not to offend outside of them. This provides further proof that the Halton Moor hotspot was caused by personal motivation where the focussed spate of burglaries was used to send a message to those in the area.

Again, the Opportunistic burglar returned results that could potentially be anomalous. Theory dictates that the spread of chance opportunity for burglary should be dispersed across the study area as any property has the potential to be left insecure in error. However, the Opportunistic agent generated a burglary pattern that was highly clustered at all distance levels, a result that was unexpected. The cause for this is potentially due to the implementation of the agent, in which the weightings chosen to mimic this burglar’s actions may not have been suitable for simulating the correct behaviour. This again highlights the need to further study implementation of opportunism within the model to better test its effect on burglary clustering.

4.3. Distance to Crime

The final batch of analysis focusses on the distance that a burglar travels to get to the scene of the crime. This is an area of particular interest as it was an aspect of the model that performed poorly in the original research, with the final solution overestimating the average distance of the journey to crime by nearly two-thirds (560m) (Malleson, 2012). Therefore, the original model clearly overlooked certain aspects of a burglar's decision-making process that caused them to offend close to their own home.

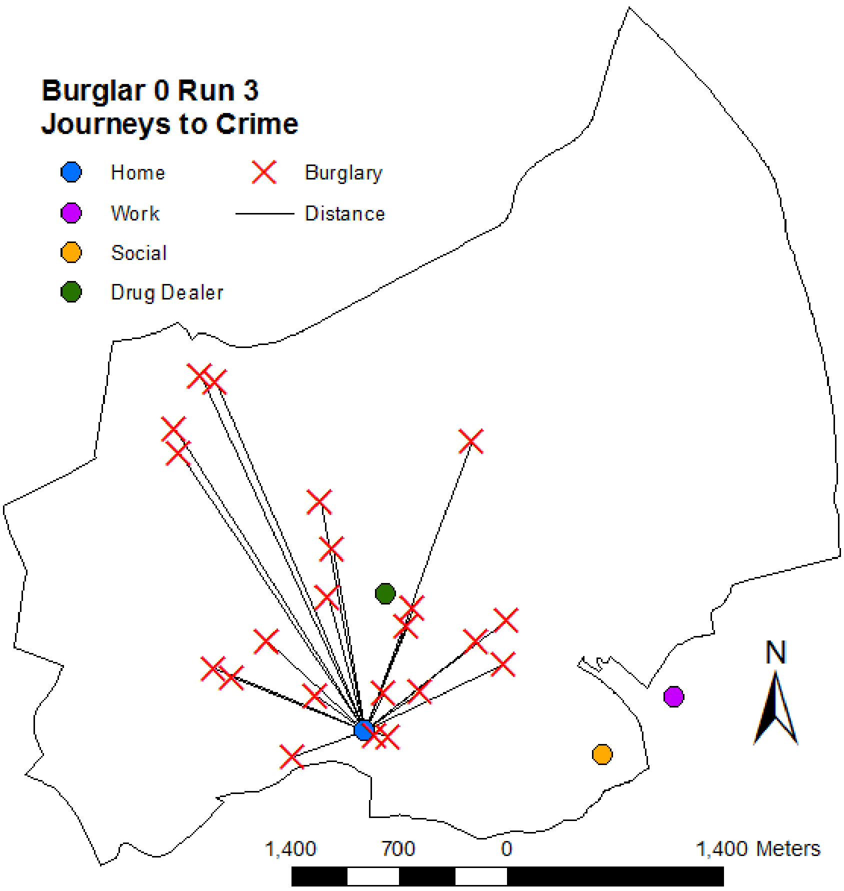


Figure 4.17: Example of the key locations for Burglar 0 in run 3 of Model 1, along with the location of all the burglaries attributed to that agent. Also shown are the lines used to calculate straight-line distance to each offence from the burglar's home.

The methodology used for this task involved calculating the straight-line distance between an agent's home address and the address of the property burgled by that offender. Figure 4.7 shows an example of the distances for one of the agents in Model 1. The distance to crime is calculated using the offender's home location as the initial point, even though the decision to offend may have been taken while the agent was elsewhere in the study area; the reasoning for this choice was twofold. Firstly, the Brantinghams (1981) specify the home as the key node in an offender's awareness space, therefore the majority of crimes should be clustered around this location due to the criminals increased knowledge of the areas around it. Secondly, while it would be trivial to measure distance from the point in the ABM where an offender first decides to burgle, the same cannot be said for the burglars in the expected dataset, therefore the distance from the nominals home address must be used as a compromise.

The distance to crime for each model can be seen in Table 4.3. It is interesting to note that the accuracy of each model at predicting crime distance is inversely proportional to its accuracy at predicting hotspots, with the shorter journeys to crime causing a more inaccurate prediction and vice versa. However, no scientific reasoning for this can be deduced, therefore is likely coincidental. None of the models created can lower the average distance to the value of the nominal dataset, however several make an improvement on the Validation model. Furthermore, all improve upon the Standard Deviation of the target model.

Table 4.19: Average distance of journey to crime for Models 1-6.

Model	Mean Distance to Crime (m)	Standard Deviation (3sf)
Expected	862	833
1	1422	1030
2	1409	1010
3	1424	1020
4	917	876
5	1434	1020
6	1135	984

The model that makes the greatest advancement on both counts is Model 4, meaning that the lowering of weighting for occupancy and security causes the agents to travel a much more realistic distance to offend. A hypothesis for this result is that this model contains agents who are much less selective about the property they target, therefore can find a suitable victim within a shorter distance. While past methods have proved that the changes made to this model significantly worsen its hotspot prediction accuracy, these distance results may indicate that the model is not completely unusable. It is likely that the reason other models overestimate the distance so much is that the agents are too cautious when choosing a property to burgle, whereas Model 4 fails to have this issue. This possibly indicates that the threshold at which a burglar deems a property to be a suitable target is set too high within the model.

The other model that significantly improves the agent's journey distance is Model 6, indicating that certain burglar typologies exhibit behaviour that can improve the journey distance for the model. To assess this, the typologies are again individually assessed, with the results being displayed in Table 4.4. It is important to note that when assessing these results, the random assignment of burglar typologies to Output Areas in the study area should be taken into account. It could be the case that a type of burglar was more frequently assigned home addresses in locations that were more sparsely populated or further away from areas of high opportunity. This could therefore have impacted the distance that the offender would have had to travel to find a suitable property and could skew the results values somewhat. Further work could therefore be done to better assign these burglar types to appropriate areas to obtain more trustworthy results.

Table 4.20: Average distance of journey to crime for each typology in Model 6.

Model	Mean Distance to Crime (m)	Standard Deviation (3sf)
Expected	862	833
1	1422	1030
6	1135	984
Professional	1130	1020
Interpersonal	1201	1180
Opportunistic	933	877
Disorganised Amateur	1411	1080
Disorganised Chaotic	1755	1210

Again, the results show that no burglar type can fully replicate the short distances to crime exhibited by the nominals in the expected data. However, the type that gets closest is the Opportunistic burglar whose average is just 71m farther than expected. This indicates that, despite the problems encountered in accurately implementing this agent behaviour, opportunism plays an important part in shaping the spatial distribution of real-life burglary. Therefore, research should be undertaken to try and overcome the problems in implementing this functionality within the model to better predict burglaries.

A further interesting result is the complex relationship between the average distance value for each typology and the weighting given to 'Distance to Area' during the implementation. While it was intended that a higher weighting would lead to a burglar staying nearer to home, this was found to not be reflected in the results generated. The professional burglar was given a lowered weighting of 0.2 as it was presumed that they would be willing to travel further for greater reward However, the professional burglar travelled the second shortest distance on average, despite not being found to burgle houses with higher attractiveness values. This is likely due to this agent being less deterred by security than others, therefore targeting nearby houses that had been secured after a previous offence rather than travelling further for a better reward.

The Disorganised Amateur burglar also travels greater distances than expected despite this type theoretically having less access to transport and less motivation to make longer journeys. The theory for this unexpected result is that the increased weightings for property factors meant that these agents were unable to find a suitable target, leading them to keep searching for longer and keep moving away from their home.

The biggest anomaly of all related to the Disorganised Chaotic burglar, which was the only type that resulted in poorer distance predictions than the Validation model. This is unexpected as the chaotic burglar is intended to be the least discriminatory about where to offend, therefore should find a suitable target nearer to the start of their search. This result goes against Malleson's theory that the original model overestimated journey distance due to a lack of *"desperate"* burglars who are willing to offend near their own home (Malleson, 2012, p. 16).

5. Conclusion

It is clear from model analysis that the results of the project have been inconclusive, with no single finding from the chosen qualitative research being able to make a significant improvement on the model's ability to predict burglary. Every single further model created during this project was able to improve upon the initial model in at least one aspect of analysis, however none of the models were found to make consistent advancements, highlighting the difficulty in tailoring an agent-based model to a real scenario. The prediction of hotspots was improved when elderly residents and children were added as deterring factors. Similarly, the level of clustering was bettered when South Asian residences were targeted, children were avoided and disorganised amateur offenders were simulated. Finally, the distance of journey to crime was improved when security and occupancy were weighted lower and when opportunistic behaviour was replicated.

5.1. Strengths & Limitations

Overall, the project has been conducted in a professional manner, allowing the results to be valid within a wider context. The choice to use the model as an aid to study the general improvement of spatial burglary prediction means that any conclusions drawn from the research can be applied to predictive policing as a whole rather than only being relevant to this model in this study area. It is therefore hoped that the outcomes from this project can be built upon to better understand the movement of burglars in the wider world.

A further strength of the research relates to the choice to use Addis's qualitative research as the basis of implementation. This work was heavily suited for use in the project due to the strong focus on target selection, as well as the relevance of offender's responses to the chosen study area. The thoroughness of this research allowed for a wide range of behaviour to be modelled and boosted the quality of the results generated.

Finally, the choice to implement different types of burglar within the model involved utilising a powerful section of the model that was not initially used in Malleson's initial research, instead being highlighted as an area of future research. Therefore, the use of this functionality in this project is an important base of research into the future implementation of burglar typologies into the model. The results gained help to illustrate how simple modifications to the modus operandi of offenders can have complex effects on the spatial location of burglary, a finding that would be difficult to observe without the use of an agent-based model.

There were, however, several areas in which the project could have been improved. Predominantly, issues were faced when conducting the methodology of the research, with the abstraction of burglar behaviour into the models being a particular difficulty. The translation of behaviour into the model parameters was hindered by a lack of literature in places, particularly with the implementation of the burglar typologies. Therefore, the weightings of factors had to be determined through guesswork and the location of agents of each type had to be randomly assigned due to a lack of data. This likely led to some of the unexpected findings when analysing the results of these models, therefore further work should be conducted to better refine these implementations before any results can be generated that may impact real-life policing strategies.

Furthermore, the difficulty in obtaining offender data led to the project using the same study area as the original work by Malleson. It is therefore necessary to conduct further work using a different location to ensure that any results generated are not simply a product of using the EASEL area.

5.2. Future Work

Several areas of future work have been previously highlighted in the project, however the most pertinent shall be expanded upon. An interesting finding relates to the influence of morality within offenders, with the elderly and children models indicating that this could play a role in a burglar's target selection process. Therefore, further studies could assess whether the limitations of abstracting human emotions into agents is negatively impacting their ability to simulate crime.

Further work must be conducted into the field of journey distance prediction, as this is still the area in which the model performs worst at. While certain types of behaviour implemented could improve upon this somewhat, more must be done to assess why agents in the model travel greater distances than required to offend.

The primary area of future expansion, however, relates to the implementation of the burglary process as a whole, which the analysis of model results indicated was too restrictive to fully represent all burglary. Much of the variation between model results and expected results is likely due to different types of burglary that have yet to be implemented. Predominantly, the prevalence of opportunistic burglary may explain why real offences are more dispersed than the model predicts. A key area for future work, therefore, involves accurately implementing chance property insecurity into the model to facilitate this behaviour. Furthermore, crimes motivated by means other than money may be the cause of certain hotspots being unable to be modelled previously, therefore a challenging area of research involves finding out how to best implement these actions. Expanding the range of actions that an agent can perform that lead to a burglary event should lead to a better performance by the model in predicting burglary.

6. References

Addis, N., 2013. *Exploring the impact and effectiveness of the 'Project Optimal' Burglary Reduction Initiative in Leeds: A Spatio-Temporal Approach.* Liverpool, UK, GISRUK 2013.

Addis, N. J., 2017. *A Mixed Methods Approach to Understanding the Target Selection Criteria of Burglars within Leeds.* Ph.D. Thesis: University of Leeds.

Armitage, R. & Joyce, C., 2016. *Why my house? Exploring offender perspectives on risk and protective factors in residential housing design – an update.* Northamptonshire, UK, Secured by Design Conference.

Ashton, J., Brown, I., Senior, B. & Pease, K., 1998. Repeat victimisation: offenders accounts. *International Journal of Risk, Security and Crime Prevention,* 3(4), pp. 269-279.

Axelrod, R. M., 1997. *The complexity of cooperation: Agent-based models of competition and collaboration.* Princeton, NJ: Princeton University Press.

Axtell, R., 2000. *Why agents?: on the varied motivations for agent computing in the social sciences,* Washington D.C.: Center on Social and Economic Dynamics.

Baldwin, J. & Bottoms, A., 1976. *The urban criminal: A study in Sheffield.* London, UK: Tavistock.

Barberet, R. & Fisher, B. S., 2009. Can security beget insecurity? Security and crime prevention awareness and fear of burglary among university students in the East Midlands. *Security Journal,* 22(1), pp. 3-23.

Barberet, R., Fisher, B. S. & Taylor, H., 2003. *University student safety in the East Midlands,* London, UK: Home Office.

Bennell, C. & Jones, N. J., 2005. Between a ROC and a hard place: A method for linking serial burglaries by modus operandi. *Journal of Investigative Psychology and Offender Profiling,* 2(1), pp. 23-41.

Bennett, T. & Wright, R., 1984. *Burglars on burglary: Prevention and the offender.* Aldershot, UK: Gower.

Bernasco, W., 2006. Co-offending and the choice of target areas in burglary. *Journal of Investigative Psychology and Offender Profiling,* 3(3), pp. 139-155.

Bernasco, W., 2009. Foraging strategies of homo criminalis: Lessons from behavioral ecology. *Crime Patterns and Analysis,* 2(1), pp. 5-16.

Bernasco, W., 2010. A sentimental journey to crime: Effects of residential history on crime location choice. *Criminology,* 48(2), pp. 389-416.

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

Bonabeau, E., 2002. Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences,* 99(suppl 3), pp. 7280-7287.

Bottoms, A. E. & Wiles, P., 2002. Environmental Criminology. In: M. Maguire, R. Morgan & R. Reiner, eds. *The Oxford Handbook of Criminology.* London, UK: Oxford University Press, pp. 620-656.

Bowers, K., 1999. Exploring links between crime and disadvantage in north-west England: An analysis using geographical information systems. *International Journal of Geographical Information Science,* 13(2), pp. 159-184.

Bowers, K. & Hirschfield, A., 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), pp. 159-184.

Bowers, K. J. & Johnson, S. D., 2005. Domestic burglary repeats and space-time clusters: The dimensions of risk. *European Journal of Criminology,* 2(1), pp. 67-92.

Braakmann, N., Chevalier, A. & Wilson, T., 2017. *Asian Gold – Expected Returns to Crime and Thieves Behaviour.* Perth, UK, Scottish Economic Society Conference.

Brantingham, P. J. & Brantingham, P. L., 1978. A theoretical model of crime site selection. In: M. Krohn & R. Akers, eds. *Crime, Law and Sanctions.* Beverly Hills, CA: Sage Publications Inc, pp. 105-118.

Brantingham, P. J. & Brantingham, P. L., 1981. Notes on the geometry of crime. In: P. J. Brantingham & P. L. Brantingham, eds. *Environmental criminology.* Beverly Hills, CA: Sage Publications, pp. 27-54.

Brantingham, P. J. & Brantingham, P. L., 1984. *Patterns in Crime.* New York: Macmillan.

Brantingham, P. J. & Brantingham, P. L., 1993. Environment, routine and situation: Toward a pattern theory of crime. *Advances in criminological theory,* 5(2), pp. 259-294.

Brantingham, P. J. & Brantingham, P. L., 2008. Crime pattern theory. In: R. Wortley & L. Mazerolle, eds. *Environmental Criminology and Crime Analysis.* Devon, UK: Willian Publishing, pp. 78-94.

Budd, T., 1999. *Burglary from Domestic Dwellings: Findings from the British Crime Survey,* London, UK: Home Office.

Canter, D. & Larkin, P., 1993. The environmental range of serial rapists. *Journal of Environmental Psycholog,* 13(1), pp. 63-69.

Carter, R. L. & Hill, K. Q., 1976. The criminal's image of the city and urban crime patterns. *Social Science Quarterly,* 57(3), pp. 597-607.

Castelfranchi, C., 1995. Intelligence Agents: Thories, Architectures, and Languages. In: M. Woolridge & N. R. Jennings, eds. *Guarantees for autonomy in cognitive agent architecture.* Berlin, Germany: Springer-Verlag, pp. 56-70.

Chainey, S. & Ratcliffe, J., 2005. *GIS and crime mapping.* Chichester, UK: John Wiley & Sons.

Christian Today, 2005. *New Study Finds Mosque Goers to Double Church Attendance.* [Online]
Available at:
https://www.christiantoday.com/article/new.study.finds.mosque.goers.to.double.church.attendance/3858.htm
[Accessed 5 August 2017].

Clarke, R. V. & Cornish, D. B., 1985. Modeling offenders' decisions: A framework for research and policy. *Crime and justice,* Volume 6, pp. 147-185.

Cohen, L. E. & Felson, M., 1979. Social change and crime rate trends: A routine activity approach. *American sociological review,* pp. 588-608.

Cook, F. L. & Cook, T. D., 1976. Evaluating the rhetoric of crisis: A case study of criminal victimization of the elderly. *Social Service Review,* 50(4), pp. 632-646.

Cook, F. L., Skogan, W. G., Cook, T. D. & Antunes, G. E., 1978. Criminal victimization of the elderly: The physical and economic consequences. *The Gerontologist,* 18(4), pp. 338-349.

Cornish, D. B. & Clarke, R. V., 1987. Understanding crime displacement: An application of rational choice theory. *Criminology,* 25(4), pp. 933-948.

Cornish, D. B. & Clarke, R. V., 2008. The rational choice perspective. In: R. Wortley & L. Mazerolle, eds. *Environmental criminology and crime analysis.* Devon, UK: Willan Publishing, pp. 21-47.

Costello, A. & Wiles, P., 2001. GIS and the journey to crime: An analysis of patterns in South Yorkshire. In: A. Hirschfield & K. Bowers, eds. *Mapping and analysing crime data: Lessons from research and practice.* London: Taylor and Francis, pp. 27-60.

Cozens, P. M., Saville, G. & Hillier, D., 2005. Crime prevention through environmental design (CPTED): a review and modern bibliography. *Property management,* 23(5), pp. 328-256.

Crooks, A. T. & Heppenstall, A. J., 2012. Introduction to agent-based modelling. In: A. J. Heppenstall, A. T. Crooks, L. M. See & M. Batty, eds. *Agent-based models of geographical systems.* Dordrecht, Netherlands: Springer Science+Business Media, pp. 85-105.

Davidson, R. N., 1981. *Crime and environment.* London, UK: Croom Helm.

Dixon, P. M., 2002. Ripley's K function. In: A. H. El-Shaarawy & W. W. Piegorsch, eds. *Encyclopedia of Environmetrics 3.* Hoboken, NJ: Wiley, pp. 1796-1803.

Donkin, S. & Wellsmith, M., 2006. Cars stolen in burglaries: the Sandwell experience. *Security Journal,* 19(1), pp. 22-32.

Eck, J., 2003. Police problems: The complexity of problem theory, research and evaluation. *Crime prevention studies,* Volume 15, pp. 79-114.

ESRI, 2017a. *How Kernel Density works.* [Online]
Available at: http://pro.arcgis.com/en/pro-app/tool-reference/spatial-analyst/how-kernel-density-works.htm
[Accessed 17 August 2017].

ESRI, 2017b. *How Multi-Distance Spatial Cluster Analysis: Ripley's k-function (Spatial Statistics) works.* [Online]
Available at:
http://resources.esri.com/help/9.3/arcgisdesktop/com/gp_toolref/spatial_statistics_tools/how_multi_distance_spatial_cluster_analysis_colon_ripley_s_k_function_spatial_statistics_works.htm
[Accessed 17 August 2017].

Farrington, D. P. & Lambert, S., 1994. Differences between burglars and violent offenders. *Psychology, Crime and Law,* 1(2), pp. 107-116.

Farrington, D. P. & Welsh, B. C., 2002. *Effects of improved street lighting on crime: a systematic review,* London, UK: Home Office.

Felson, M., 1995. Those who discourage crime. *Crime and place,* Volume 4, pp. 53-66.

Felson, M., 2002. *Crime and Everyday Life.* 3 ed. Thousand Oaks, CA: Sage Publications.

Felson, M., 2008. Routine activity approach. In: R. Wortley & L. Mazerolle, eds. *Environmental criminology and crime analysis.* Devon, UK: Willan Publishing, pp. 70-77.

Fox, B. H. & Farrington, D. P., 2012. Creating burglary profiles using latent class analysis: A new approach to offender profiling. *Criminal Justice and Behavior,* 39(12), pp. 1582-1611.

Genesereth, M. R. & Ketchpel, S. P., 1994. Software agents. *Commun. ACM,* 37(7), pp. 48-53.

Gilert, K., 2013. *Reducing Reported Domestic Burglary in Leeds,* Leeds: Leeds City Council.

Hakim, S., Rengert, G. F. & Shachamurove, Y., 2000. *Knowing your odds: Home burglary and the odds ratio,* University of Pennsylvania: Center for Analytic Research in Economics and the Social Sciences.

Hearnden, I. & Magill, C., 2004. *Decision-making by house burglars: offenders' perspectives,* London, UK: Home Office.

Herbert, D. T. & Hyde, S. W., 1985. Environmental criminology: Testing some area hypotheses. *Transactions of the Institute of British Geographers,* pp. 259-274.

Holland, J. H., 1992. Complex adaptive systems. *Daedalus,* 121(1), pp. 17-30.

Hough, M., 1987. Offenders' choice of target: Findings from victim surveys. *Journal of Quantitative Criminology,* 3(4), pp. 355-369.

Jacobs, J., 1962. *The Death and Life of Great American Cities.* London: Jonathan Cape.

Jacobson, J., Maitland, L. & Hough, M., 2003. *The Reducing Burglary Initiative: investigating burglary,* London, UK: Home Office.

Johnson, S. D. & Bowers, K. J., 2004a. The burglary as clue to the future: The beginnings of prospective hot-spotting. *European Journal of Criminology,* 1(2), pp. 237-255.

Johnson, S. D. & Bowers, K. J., 2004b. The stability of space-time clusters of burglary. *British Journal of Criminology,* 44(1), pp. 55-65.

Johnson, S. D., Bowers, K. J. & Pease, K., 2010. *Predicting Burglary Hotspots.* Cambridge, National Policing Improvement Agency.

Jones, V. & Fielding, M., 2011. *Domestic Burglary Predictive Mapping: Disrupting the Optimal Forager.* Manchester, UK, National Community Safety Conference 2011.

Katz, J., 1988. *Seductions of crime: Moral and sensual attractions in doing evil.* New York: Basic Books.

Kennedy, W. G., 2012. Modelling human behaviour in agent-based models. In: A. J. Heppenstall, A. T. Cooks, L. M. See & M. Batty, eds. *Agent-based models of geographical systems.* Dordrecht, Netherlands: Springer Netherlands, pp. 167-179.

Kenyon, E. L., 1997. Seasonal sub-communities: The impact of student households on residential communities. *British Journal of Sociology,* 48(2), pp. 286-301.

Krebs, J. R. & Davies, N. B., 1993. *An introduction to behavioural ecology.* Oxford, UK: Blackwell Scientific Publications.

Lawrence, C., 2003. *Why is gold different from other assets? An empirical investigation,* London, UK: The World Gold Council.

Leeds City Council, 2005. *EASEL Area Action Plan: Early Issues for consultation.* [Online]
Available at:
http://www.leeds.gov.uk/docs/129%20EASEL%202005%20Early%20Issues%20-%20Main%20Consultation%20Document%20(Full).pdf
[Accessed 5 August 2017].

Leeds City Council, 2006. *East and South East Leeds Area Action Plan: Alternative Options - Looking to the Future.* [Online]
Available at:
http://www.leeds.gov.uk/docs/129%20EASEL%202006%20Alternative%20Options%20-%20Main%20Report.pdf
[Accessed 5 August 2017].

Leeds City Council, 2010. *Notice of Withdrawal of Development Plan Documents.* [Online]
Available at:
http://www.leeds.gov.uk/docs/129%20EASEL%202010%20AAP%20Withdrawal%20Notice.pdf
[Accessed 5 August 2017].

Maguire, M. & Bennett, T., 1982. *Burglary in a dwelling: The offence, the offender, and the victim.* London: Heinemann.

Malleson, N., 2010. *Agent-based modelling of burglary.* Ph.D. Thesis: University of Leeds.

Malleson, N., 2012. Using agent-based models to simulate crime. In: A. J. Heppenstall, A. T. Crooks, L. M. See & M. Batty, eds. *Agent-based models of geographical systems.* Dordrecht, Netherlands: Springer Netherlands, pp. 411-434.

Markowitz, F. E., Bellair, P. E., Liska, A. E. & Liu, J., 2001. Extending social disorganization theory: Modeling the relationships between cohesion, disorder, and fear. *Criminology,* 39(2), pp. 293-319.

Nee, C. & Taylor, M., 1988. Residential burglary in the Republic of Ireland: A situational perspective. *The Howard Journal of Crime and Justice,* 27(2), pp. 105-116.

Newman, O., 1972. *Defensible space.* New York: Macmillan.

Office for National Statistics, 2017a. *Crime in England and Wales: year ending Mar 2017,* Newport, UK: Office for National Statistics.

Office for National Statistics, 2017b. *Overview of burglary and other household theft: England and Wales,* Newport, UK: Ofiice for National Statistics.

O'Neill, D. et al., 1989. Effects of burglary on elderly people. *BMJ: British Medical Journal,* 298(6688), p. 1618.

Ordnance Survey, 2017. *OS MasterMap.* [Online]
Available at: https://www.ordnancesurvey.co.uk/business-and-government/products/mastermap-products.html
[Accessed 5 August 2017].

O'Sullivan, D. & Unwin, D., 2014. *Geographic information analysis.* Hoboken, NJ: Wiley.

Palmer, E. J., Holmes, A. & Hollin, C. R., 2002. Investigating burglars' decisions: factors influencing target choice, method of entry, reasons for offending, repeat victimisation of a property and victim awareness. *Security Journal,* 15(1), pp. 7-18.

Pearsall, B., 2010. Predictive policing: The future of law enforcement. *National Institute of Justice Journal,* 266(1), pp. 16-19.

Pease, K. & Gill, M., 2011. *Home Security and Place Design: Some Evidence and its Policy Implications,* Leicester, UK: Perpetuity Research & Consultancy International.

Rand, A., 1986. Mobility triangles. In: R. M. Figlio, S. Hakin & G. F. Rengert, eds. *Metropolitan crime patterns.* Monsey, NY: Criminal Justice Press, pp. 117-126.

Ratcliffe, J. H., 2002. Aoristic signatures and the spatio-temporal analysis of high volume crime patterns. *Journal of Quantitative Criminology,* 18(1), pp. 22-43.

Rengert, G. & Wasilchick, J., 1985. *Suburban burglary: A time and a place for everything.* Springfield, IL: CC Thomas.

Repast, 2017. *Repast Simphony.* [Online]
Available at: https://repast.github.io/repast_simphony.html
[Accessed 23 August 2017].

Reppetto, T. A., 1974. *Residential Crime.* Cambridge, MA: Ballinger Publishing.

Shaw, K. T. & Gifford, R., 1994. Residents' and burglars' assessment of burglary risk from defensible space cues. *Journal of Environmental Psychology,* 14(3), pp. 177-194.

Shu, C. F., 2009. *Spatial configuration of residential area and vulnerability of burglary.* Stockholm, 7th international space syntax symposium.

Simon, H. A., 1976. From substantive to procedural rationality. In: S. J. Latsis, ed. *Method and Appraisal in Economics.* Cambridge: Cambridge University Press, pp. 129-148.

Sinervo, B., 1997. Optimal Foraging Theory: Constraints and Cognitive Processes. In: *Behavioral Ecology.* s.l.:s.n., pp. 105-130.

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

Sorensen, D. W. M., 2004. *Temporal Patterns of Danish Residential Burglary,* Copenhagen, Denmark: Ministry of Justice.

Tilley, N., Tseloni, A. & Farrell, G., 2011. Income disparities of burglary risk: Security availability during the crime drop. *The British Journal of Criminology,* 51(2), pp. 296-313.

Townsley, M. et al., 2015. Burglar target selection: a cross-national comparison. *Journal of Research in Crime and Delinquency,* 52(1), pp. 3-31.

Tseloni, A. et al., 2017. The effectiveness of burglary security devices. *Security Journal,* 30(2), pp. 646-664.

Tseloni, A., Wittebrood, K., Farrell, G. & Pease, K., 2004. Burglary victimization in England and Wales, the United States and the Netherlands: A cross-national comparative test of routine activities and lifestyle theories. *British Journal of Criminology,* 44(1), pp. 66-91.

Vaughn, M. G., DeLisi, M., Beaver, K. M. & Howard, M. O., 2008. Toward a quantitative typology of burglars: A latent profile analysis of career offenders. *Journal of forensic sciences,* 53(6), pp. 1387-1392.

Vickers, D., Rees, P. & Birkin, M., 2010. *Creating the National Classification of Census Output Areas: Data, Methods and Results,* Working Paper: School of Geography, University of Leeds.

Wiles, P. & Costello, A., 2000. *The 'road to nowhere': the evidence for travelling criminals,* London, UK: Research, Development and Statistics Directorate, Home Office.

Woolridge, M. & Jennings, N. R., 1995. Intelligent agents: Theory and practice. *The knowledge engineering review,* 10(2), pp. 115-152.

Wright, R., Logie, R. H. & Decker, S. H., 1995. Criminal expertise and offender decision making: An experimental study of the target selection process in residential burglary. *Journal of Research in Crime and Delinquency,* 32(1), pp. 39-53.

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

Zipf, G. K., 1949. *Human Behaviour and the Principle of Least Effort: An Introduction to Human Ecology.* Reading, UK: Addison Wesley Press.

7. Appendix

7.1. Full Model Code

A CD containing the full code for the model has been submitted along with this report. Any modifications made from the original model have been highlighted within the code comments.