

# Exploring Crime Generators and Attractors: a Hybrid of Theoretical, Computational and Empirical Approaches

Verity Anne Lindsay Tether

Submitted in accordance with the requirements for the degree of  
Doctor of Philosophy

The University of Leeds  
Faculty of Earth and Environment  
School of Geography

November 2021

The candidate confirms that the work submitted is her own, except where work which has formed part of jointly-authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

Chapter 6 contains a jointly authored manuscript where Verity Tether is the lead author. The work in Chapter 6 of this thesis has been published as:

Tether, V., Malleson, N., Steenbeek, W. and Birks, D. 2021. Using agent-based models to investigate the presence of edge effects around crime generators and attractors. In: Elffers, H. and Gerritsen, C. (eds) *Agent-Based Modelling for Criminological Theory Testing and Development*. Pp. 45-70.

This research was undertaken as part of Verity Tether's PhD research, and was supervised and supported by Nick Malleson and Daniel Birks. Under the supervision of Nick Malleson and Daniel Birks, Verity Tether had the idea for the article, designed the model, wrote the code, performed the analysis and wrote the report (including data visualisation). Nick Malleson, Wouter Steenbeek and Daniel Birks critically revised it.

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## **Acknowledgements**

The completion of this thesis would not have been possible without the support of several key players.

Firstly, thanks are very much due to my supervisors Alison Heppenstall, Nick Malleon and Dan Birks, who have been nothing short of brilliant for the last few years. I would also like to express thanks to other members of LIDA and the School of Geography who helped in other ways, including Jacqui Manton, for her limitless wisdom in all things PGR; Roger Beecham, for his contribution to my Research Support Group; John Stillwell, for his role as Transfer Examiner; and Ning Liu, for welcoming me into the committee of the Data Science Society.

Secondly, thanks to my boyfriend, Josh Turner, my parents and my sister, all of whom have all been very aware of the challenges of the final year of a PhD. I cannot overstate how grateful I am for the support you've all given me, and for the gin- and chocolate-filled care packages. I would also like to thank my Grandad, for his unending interest and support in my work and career.

Thirdly, thanks to the wonderful friends from both before the PhD and those I met throughout my postgraduate studies. They have all been incredibly supportive and include, but are not limited to, Katrina Dickinson, Jack White, Lauren Dear, Georgie White, Joel Perren, James Brierley and all of B4. Special thanks are definitely due to Amanda Copperwheat, who has been a rock throughout this whole process. I am truly lucky that undertaking this PhD has not only provided me with a qualification and career, but also a wonderful friend.

Finally, thank you to ESRC for funding this project and my secondment to the Department for Work and Pensions.

## **Abstract**

The concept of crime generators and attractors is one which has been widely accepted in environmental criminology since its inception in 1995 by Brantingham and Brantingham. However, despite being well-known and frequently referenced, this concept has been under-investigated when compared with other tenets of this field. Not only does this mean that the theory underpinning this concept is under-developed and sometimes misunderstood, but the potential societal benefits of its understanding are currently limited. Given that the primary difference between crime generators and attractors is the motivation of those offending there, improved understanding of these processes could allow more tailored policing strategies, and thus crime reduction, in these spaces.

This thesis aims to critically appraise key assumptions of crime generators and attractors, in order to gain an understanding of their relevance to modern-day cities. Separated into four parts, this work shall explore this concept theoretically, through a scoping literature review; computationally, through the design and implementation of an agent-based model; and empirically, through analysis of offence data.

The culmination of these bodies of work identifies that there is limited understanding of the processes which lead to the formation of crime generators and attractors. Crime patterns which emerged from the computational research were not found in the corresponding empirical work. This could suggest that greater theoretical understanding of these mechanisms is required. Moreover, although a number of different methods were used to attempt to empirically classify a space as either a crime generator or attractor, the results were inconsistent, further suggesting insufficient understanding of this concept. This thesis proposes the addition of qualitative research to develop knowledge on crime generators and attractors in future.

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## **List of Abbreviations**

**ABM** – Agent Based Model (*or* Modelling)

**CPT** – Crime Pattern Theory

**GIS** – Geographic Information Systems

**GoC** – Geometry of Crime

**IDW** – Inverse Distance Weighted interpolation

**LQC** – Crime Location Quotient (as per literature convention)

**PELT** – Pruned Exact Linear Time algorithm

**WSS** – Within-cluster Sum of Squares

## Chapter 1

### Introduction

#### 1.1 Research Context

Crime is a comparatively rare phenomenon (Prieto Curiel et al., 2018). However, despite its rarity, criminal victimisation can have a profound effect on people's lives. Although mass media publicises the dramatic and shocking offences more than those which are more mundane, the latter are far more common (Felson and Boba, 2010), and are also a source of anxiety for the general population (Ratcliffe, 2015). Whilst studying crime can take many guises, the fundamental aim of any study of crime is the same: reducing victimisation and harm.

It has been repeatedly found that crime occurs neither randomly nor uniformly in space. Indeed, it has been proposed that suggesting that targets and victims are random is "no longer plausible" (Brantingham and Brantingham, 2011 p.79) and that the suggestion of uniformity is "indefensible" (*ibid.*). This is the case at both a multi-national scale as crime trends have been found to vary between countries (e.g. van Dijk et al. (2021)), and at a smaller scale, as the built environment has been found to impact offending (e.g. Iqbal and Ceccato (2016)). Whilst these patterns are all of interest to environmental criminologists, who focus on the environment in which an offence occurs (Wortley and Mazerolle, 2011), understanding those at a micro level is arguably of more theoretical and practical benefit. The concept of "micro" places includes a range of spatial units, including individual addresses and groups of addresses (Groff et al., 2010), and it has been argued that studies at this level are now at the centre of place-based crime research (Newton and Felson, 2015). There are a number of reasons why the analysis of smaller units of analysis could be more meaningful than larger units. For example, it is a general scientific principle that understanding the constituting parts of a concept permit the understanding of the concept as a whole (Bernasco, 2010). Moreover, the use of smaller units can help to avoid analysis using arbitrary administrative boundaries

(*ibid.*). More information on the study of microgeographic patterns of crime is provided in Chapter 2.

The focus of this thesis pertains to the study of crime at a micro level, examining two types of locations that could lead to hotspots of offending. Proposed by Brantingham and Brantingham (1995), **crime generators** are areas such as shopping precincts and office concentrations which many people visit for reasons unrelated to crime. This resulting concentration of people includes potential offenders. Although these people may not have visited the crime generator location with the intention of offending, they encounter opportunities which they then exploit (Brantingham and Brantingham, 1995). In addition to crime generators, they posited that **crime attractors** are locations like some bar areas or drug markets which have a reputation for criminal opportunity to which motivated offenders are drawn to offend (*ibid.*).

The concept of crime generators and attractors has been widely accepted in environmental criminology and is often referenced in research. However, despite this popularity there is a dearth of research into the processes which lead to their existence, and instead these titles are often used as a post-hoc explanation of crime concentration (Davies and Birks, 2021). This means that the mechanisms which underpin crime generators and attractors are not very well understood, and therefore neither is the crime concentration which follows them. This limits the extent to which we are able to apply this theoretical concept to have a more practical purpose. For example, it has been suggested that crime generators and attractors would require different law enforcement approaches (Sosa et al., 2019), as offences which are committed at crime generators are opportunistic, but those which are committed at crime attractors are premediated. However, because crime generators and attractors are not suitably understood, it is not yet possible to accurately identify these hotspots in the real world. As a result, this potential tailoring of law enforcement strategies has not yet come to fruition.

This thesis will contribute to research on crime generators and attractors by exploring the mechanisms which underpin crime trends in these spaces, with a focus on their implications for the spatial distribution of crime. However,

studying crime generators and attractors is challenging. This is discussed in more detail in Chapter 2, but these challenges mainly centre on difficulties in quantifying these spaces and the processes which lead to their existence (Newton, 2018) and in distinguishing between crime generators and attractors in the real world (Yoo and Wheeler, 2019).

Considering these challenges, the use of traditional methods alone is not appropriate for all studies of crime generators and attractors as there are some aspects of this research which they are unable to capture, such as the motivation of offenders at these sites. As a result, this research utilises a combination of theoretical, computational, and empirical methods to study these spaces. This use of multiple methods is referred to as methodological triangulation (or just “triangulation”), and was introduced to social science research in the 1950s (Denzin, 2015). Whilst it was originally considered as a way of validating results, it is now believed to be a way of enriching knowledge (Flick, 2018) and increasing confidence in findings (Heale and Forbes, 2013).

This research incorporates a scoping literature review, an agent-based model and two pieces of empirical analysis to critically appraise the concept of crime generators and attractors. It begins with the scoping literature review, exploring the extent to which the processes behind crime generators and attractors have been researched. This is followed by empirical research, testing methods of classifying spaces as crime generators or attractors. After this, an agent-based model, which is a computational method which utilises autonomous and heterogenous agents that interact with each other and their environment (Bonabeau, 2002; Brantingham et al., 2012), is used to explore the crime patterns which emerge as a result of the mechanisms behind crime generators and attractors. The final analytical chapter consists of empirical work which investigates whether the patterns that emerged from the agent-based model can be identified using traditional methods. Each of these methodological approaches are introduced in more detail in Chapter 3.

## **1.2 Research Aims and Objectives**

The overall aim of this PhD research is to use theoretical, computational and empirical approaches to critically appraise the concept of crime generators and attractors. This shall be achieved through the following objectives:

1. Critically appraise previous research on crime generators and attractors to identify how they are defined and the extent to which their mechanisms have been studied.
2. Investigate previously suggested methods for empirical classification of crime generators and attractors, to explore whether multiple methods identify the same areas as crime generators and attractors.
3. Examine the theoretical mechanisms underpinning this concept using an agent-based model, and their implications for crime distribution.
4. Empirically investigate crime distribution around crime generators and attractors, and identify whether the crime patterns which emerged as a result of the agent-based model are seen in the real world.

The first two objectives critically appraise previous work, examining how these concepts have been interpreted in the extant literature, both theoretically and empirically. The latter two objectives further develop the concept, through the creation of an agent-based model and the subsequent empirical investigation to validate the results.

## **1.3 Thesis Chapter Outline**

Seven chapters follow this initial introduction. Chapters 2 and 3 introduce the relevant literature for this work, relating to the topic and methodology respectively. Following this, as this thesis aims to use different methods to critically appraise the concept of crime generators and attractors, Chapters 4 – 7 introduce distinct pieces of research, each utilising distinctive methods to answer their research questions. These pieces of work have been formatted as four distinct journal publications (complete with reference lists) and are arranged in separate sections to reflect the methodological approach employed in each. Because of this structure, a degree of repetition occurs across the chapters, but this has been minimised where possible. Chapter 8

brings the analysis together to provide the overall conclusions for the thesis. These chapters are now all introduced in more detail.

Chapter 2 provides further background to this research. This includes an introduction to environmental criminology to provide a theoretical basis, as well as a more comprehensive discussion of crime generators and attractors.

Chapter 3 then introduces the methodological approach selected for this thesis. It introduces the individual methods included in this work, discussing their strengths and weaknesses and their previous application in environmental criminology research.

Chapter 4, "The Mechanisms Behind Crime Generators and Attractors: A Scoping Review" aligns with Objective 1. This chapter reports on a scoping review undertaken with the aim of answering the question "*To what extent have the mechanisms behind crime generators and attractors been studied?*". This work analyses the definitions provided for crime generators and attractors, as well as assessing research exploring the mechanisms behind these spaces. This chapter informs the ones which follow it within this thesis. This paper has been uploaded to SocArXiv to disseminate it with the aim of getting additional feedback before submission to a journal.

Chapter 5, "Investigating Crime Generators and Attractors: A Comparison of Classification Techniques" pertains to Objective 2. This chapter details empirical analysis undertaken to compare two classification techniques for crime generators and attractors, exploring whether two different classification methods identify the same areas as crime generators or attractors. This paper has been submitted to PLOS ONE and is currently under review.

Chapter 6, "Using Agent-Based Models to Investigate the Presence of Edge Effects around Crime Generators and Attractors" relates to Objective 3. The agent-based model reported in this chapter formalises the mechanisms behind crime generators and attractors and examines the spatial distribution of crime which emerges as a result of these processes. This work has been published in a peer reviewed book entitled *Agent-Based Modelling for*

*Criminological Theory Testing and Development* (Tether et al. (2021), in Gerritsen and Elffers (2021)).

Chapter 7, “Spatial Distribution of Crime in the Vicinity of Crime Generators and Attractors: an Empirical Investigation”, concerns Objective 4. In this chapter, crime data from Austin, Texas (USA) are analysed to investigate the spatial distribution of crime in the environs of a sample of crime generator and attractor locations identified from the literature.

Chapter 8 contains the discussion and final conclusions of this thesis, including a discussion of the implications of this research, the limitations of this project and recommendations for future work.

The outline above is also explained in Table 1.1. In addition, each chapter (except Chapter 1) will have a preface at the start that will summarise the contents, and a summary at the end to explain how it fits into the overall thesis.

| <b>Chapter Number</b> | <b>Title</b>   | <b>Objective</b> |
|-----------------------|--|------------------|
| <b>1</b>              | Introduction   | NA               |
| <b>2</b>              | Background   | NA               |
| <b>3</b>              | Methodological Approach  | NA               |
| <b>4</b>              | The Mechanisms Behind Crime Generators and Attractors: A Scoping Review                                      | 1                |
| <b>5</b>              | Investigating Crime Generators and Attractors: A Comparison of Classification Techniques                     | 2                |
| <b>6</b>              | Using Agent-Based Models to Investigate the Presence of Edge Effects around Crime Generators and Attractors  | 3                |
| <b>7</b>              | Spatial Distribution of Crime in the Vicinity of Crime Generators and Attractors: an Empirical Investigation | 4                |
| <b>8</b>              | Discussion and Conclusions   | NA               |

**Table 1.1 - Thesis Structure**

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## **Chapter 2**

### **Background**

#### ***Preface***

*Chapter 2 consists of a more detailed background into crime generators and attractors, providing context for the rest of the work which follows in this thesis. Chapter 3 will then present the methodological approach. Section 2.1 will introduce environmental criminology and discuss some key theories which underpin work in this field. Following this, Section 2.2 provides more information on crime generators and attractors, starting with an introduction to microgeographic studies of crime, before going into detail on defining and studying crime generators and attractors, and why it is important to research them.*

#### **2.1 Introduction to Environmental Criminology**

Environmental criminology concerns the study of crime, with a focus on the environment within which the offence occurs (Wortley and Mazerolle, 2011). Whereas traditional criminological approaches are more focused on the offender, environmental criminology is instead focused on the offence itself (Bruinsma and Johnson, 2018; Weisburd, 2015; Wortley and Mazerolle, 2011), aiming to understand it in relation to the time and space in which it occurred (Brantingham et al., 2012). Indeed, as highlighted by Clarke and Cornish (1985), the existence of a motivated offender does not fully explain the occurrence of a crime; additional components need to be explored to understand the offence.

Although crime in relation to geographical space has been studied for centuries (Bruinsma and Johnson, 2018), the name *environmental criminology* was proposed by C. Ray Jeffery in 1971. Jeffery's concept of "environment" in this case considered more than merely the built environment (such as road networks), incorporating ideas such as architecture and social institutions (Andresen, 2010). Since then, this

environmental approach has been suggested to be “the fastest growing approach in criminology” (Wortley and Mazerolle, 2008 p.24). Indeed, between 2000 and 2015 the number of papers published in the five top peer reviewed criminology journals which had space or place as the unit of analysis approximately doubled (Bruinsma and Johnson, 2018).

The study of environmental criminology has led to the identification of a number of theoretical perspectives in the field, including the routine activity approach (Cohen and Felson, 1979), geometry of crime (Brantingham and Brantingham, 1981), rational choice perspective (Clarke and Cornish, 1985) and crime pattern theory (Brantingham and Brantingham, 1993). Although each concept has a specific approach, they share a number of the same themes, such as the notion that changing an environment can influence crime occurrence (Bruinsma and Johnson, 2018) Indeed, Eck and Weisburd (2015 p.7) refer to crime pattern theory and the routine activity approach as “mutually supportive”. Despite this, they highlight that these theories can suggest differing causes for areas of crime concentration. This is exemplified in the upcoming sections which briefly summarise each of these approaches, as they are considered to be key to research in environmental criminology (Brantingham et al., 2008; Eck and Weisburd, 2015).

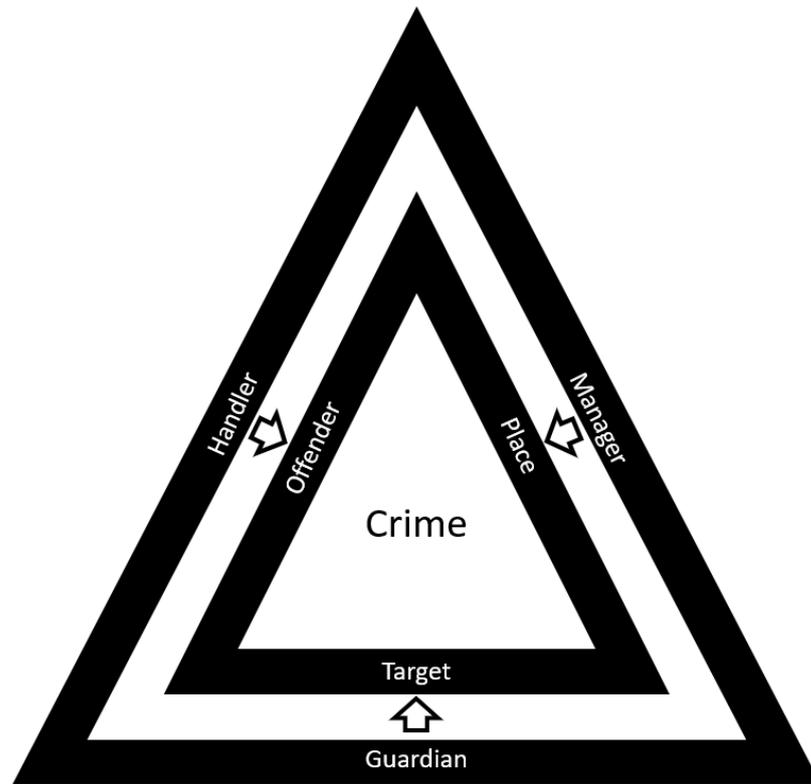
### **2.1.1 Routine Activity Approach**

The routine activity approach was proposed by Cohen and Felson (1979), and was realised in response to the paradoxical increase in crime in the United States of America following the second world war. The premise of the routine activity approach is that the convergence of three elements in time and space lead to the commission of a crime; (1) a suitably motivated offender; (2) an appropriate target; and (3) the absence of a capable guardian (Cohen and Felson, 1979). It was argued that the absence of any one of these elements could prevent an offence from taking place, and that the “routine activities” of people’s everyday life would affect their likelihood of being a victim of crime. Here, routine activities are defined as “any recurrent and prevalent activities which provide for basic population and individual needs, whatever their biological or cultural origins” (Cohen and Felson, 1979 p.593). This approach has been found to be applicable across a variety of

cultures and settings (Felson, 2008), and has been praised for identifying that the confluence of these three components is not random and can be explained (Wortley and Townsley, 2008). It suggests that a place can experience large amounts of crime because of the types of people there acting as targets, and the absence of capable guardians (Eck and Weisburd, 2015).

The routine activity approach has been found to be successful in predicting changes to crime patterns in a number of studies (Franklin et al., 2012; Reynolds, 2013), and changes to citizens' routine activities has been proposed as the reason for changes to crime patterns identified since COVID-19 restrictions came into place (Nivette et al., 2021). Indeed, it has been said that the core tenets of the routine activity approach have become "the primary explanations for what puts individuals at risk of victimization" (Reynolds, 2013 p218). However, it is also not without its limitations. For example, it does not consider the journey to crime, or go into detail about offenders' decision-making processes (Felson, 2011). As a result, it is considered "essential" to combine routine activity approach with other environmental criminology theories (Felson, 2011 p.73).

Since its initial conception, the routine activity approach has been developed and has seen the incorporation of additional elements (Felson, 2011, 2008), such as Eck's idea of the "crime triangle", which incorporated further ideas into the concept of guardianship. This consists of two triangles, one inside the other, as demonstrated in Figure 2.1 (adapted from Felson (2011)). The inner triangle contains the vital elements needed for a crime to occur: an offender, a location, and a target. The outer triangle represents different forms of guardianship (referred to as *supervisors*): handlers, managers, and guardians, who supervise each of the elements of the inner triangle. The crime triangle concept posits that a crime will only occur when none of these supervisors are present.



**Figure 2.1 - Crime Triangle (adapted from Felson (2011))**

### **2.1.2 Geometry of Crime**

The geometry of crime, considered “the most explicitly spatial theory” (Song et al., 2017 p.52), was devised by Brantingham and Brantingham (1981), adapting Lynch's (1960) work for application in analysing crime patterns (Brantingham et al., 2008). Lynch (1960) explored the way that people perceive cities, and proposed five elements that people use to create a cognitive map of an area; nodes, paths, edges, districts and landmarks (Filomena et al., 2019). The geometry of crime uses this concept of nodes, paths and edges to explore the spatial distribution of crime. Whilst Brantingham and Brantingham (1981) suggested a number of rules for the geometry of crime approach (which are covered in more detail in Section 2.1.4), the core premise is that all individuals have an “activity space”, which is made of the activity nodes that they visit, and the paths they take between them, whilst undertaking their routine activities. These can include home, work, and the gym, among others. The area around their activity space that

they are able to see is referred to as their “awareness space”. Brantingham and Brantingham (1981) posited that offenders are likely to commit crime near to their activity and awareness spaces, and that there would be increased concentration of crime around activity nodes.

A critique of geometry of crime is encapsulated in that for crime pattern theory and can be found in Section 2.1.4.

### **2.1.3 Rational Choice Perspective**

The rational choice perspective, originally conceived by Clarke and Cornish (1985), is not a traditional criminology theory, but rather a heuristic device which has been integrated into other theories (Bruinsma and Johnson, 2018; Cornish and Clarke, 2008) and has been applied to a range of criminological studies (Gül, 2009). Whilst the rational choice perspective remains under development (Cornish and Clarke, 2008), it currently has six core tenets, including the belief that criminal behaviour is rational and that decisions are made by the offender for each specific crime (*ibid.*). The latter point leads the authors to advise against using this approach to more general studies of crime, and suggest applying this perspective to individual crime types instead (Andresen, 2010; Cornish and Clarke, 2008). Although one could query how this approach relates to the environment the crime occurs in, rational choice perspective concerns the way in which a potential offender’s mental map of an area affects their decision making (Andresen, 2010).

This concept has the benefit of encompassing all forms of criminality, including impulsivity (Gül, 2009), and has informed the field of situational crime prevention (Gül, 2009; Hayward, 2007). However, there are also a number of criticisms of the rational choice perspective. For example, as offenders do not have perfect knowledge of their environments, their decisions are made on limited, rather than perfect, rationality (Cornish and Clarke, 2008). Moreover, not all crimes are considered rational, such as some violent offences (*ibid.*).

### **2.1.4 Crime Pattern Theory**

Crime pattern theory is considered to be a meta-theory which incorporates the main environmental criminology perspectives introduced above

(Andresen, 2010; Brantingham et al., 2008), and was developed by Brantingham and Brantingham (1993). This concept aims to demonstrate the relatedness between the aforementioned environmental criminology theories (Brantingham et al., 2008). However, despite being similar, these theories explain crime concentration in different ways. A crime pattern theorist would focus on how the offenders discover the location, whereas a researcher following routine activity approach would suggest that behaviour of targets and absence of guardians makes a space problematic (Eck and Weisburd, 2015). Moreover, a rational choice theorist would explore the cognitive environment which affects the decision-making of offenders (Andresen, 2010).

Like geometry of crime, crime pattern theory consists of a series of rules, several of which overlap between the two theories. Table 2.1 includes the rules associated with each; eight for crime pattern theory and ten for geometry of crime. Those which are present in both theories are in italics, enabling the differences to be identified. The wording of the repeated rules is often the same across both theories, as the rules are reported in the same manner for both theories (Brantingham et al., 2008; Brantingham and Brantingham, 2011).

| <b>Crime Pattern Theory (CPT) (from Brantingham and Brantingham (2011))</b>   | <b>Geometry of Crime (GoC) (from Brantingham et al. (2008))</b>  |
|---|--|
| <p><i>Rule 1: People make a series of decisions as they conduct their activities, which become a template once they have been repeated several times. Offenders have a similar template for offending, called a crime template.</i></p> <p><b>This is the same as GoC Rule 4.</b></p> | <p>Rule 1: The environmental backcloth is important as all activities (whether associated with crime or not) occur within a social, economic, political, and physical context.</p> |
| <p><i>Rule 2: Most people operate within a network of others. These networks can influence people's decisions.</i></p>  | <p><i>Rule 2: People have routine activities which occur at activity nodes, and they travel along regular paths to get to them.</i></p>  |

|   |  |
|---|--|
| <p><b>This is the same as GoC Rule 5.</b></p>   | <p><b>This is the same as CPT Rule 5.</b></p>  |
| <p>Rule 3: Aggregate patterns can be identified by combining the individual patterns of those involved.</p>   | <p><i>Rule 3: Both offenders and non-offenders create activity and awareness spaces by moving around space and time. Crimes are likely committed near to these spaces.</i></p> <p><b>This is the same as CPT Rule 6.</b></p>   |
| <p><i>Rule 4: People offend following a triggering event when they are able to find a target fitting their crime template. Each criminal event is added to an offender's accumulated experience and can affect future behaviour.</i></p> <p><b>The first sentence is the same as GoC Rule 8. The second sentence is the same as GoC Rule 9.</b></p> | <p><i>Rule 4: People make a series of decisions as they conduct their activities, which become a template once they have been repeated several times. Offenders have a similar template for offending, called a crime template.</i></p> <p><b>This is the same as CPT Rule 1.</b></p>                      |
| <p><i>Rule 5: People have routine activities which occur at activity nodes, and they travel along regular paths to get to them.</i></p> <p><b>This is the same as GoC Rule 2.</b></p>   | <p><i>Rule 5: Most people operate within a network of others. These networks can influence people's decisions.</i></p> <p><b>This is the same as CPT Rule 2.</b></p>   |
| <p><i>Rule 6: Both offenders and non-offenders create activity and awareness spaces by moving around space and time. Crimes are likely committed near to these spaces.</i></p> <p><b>This is the same as GoC Rule 3.</b></p>  | <p><i>Rule 6: Potential targets have activity spaces which intersect those of potential offenders. They are targeted when an offender has become triggered to commit and offence and the potential target aligns with the offender's crime template.</i></p> <p><b>This is the same as CPT Rule 7.</b></p> |
| <p><i>Rule 7: Potential targets have activity spaces which intersect those of potential offenders. They are</i></p>   | <p><i>Rule 7: High volumes of people using and travelling through nodes lead to the creation of crime</i></p>  |

|  |   |
|--|---|
| <p><i>targeted when an offender has become triggered to commit and offence and the potential target aligns with the offender's crime template.</i></p> <p><b>This is the same as GoC Rule 6.</b></p>   | <p><i>generators. Crime attractors occur when a potential offender's activity nodes contain targets.</i></p> <p><b>This is the same as an element of CPT Rule 8.</b></p>  |
| <p><i>Rule 8: The rules above occur within the built environment. High volumes of people using and travelling through nodes lead to the creation of crime generators. Crime attractors occur when a potential offender's activity nodes contain targets.</i></p> <p><b>The section in italics is the same as CPT Rule 7.</b></p> | <p><i>Rule 8: People offend following a triggering event when they are able to find a target fitting their crime template.</i></p> <p><b>This is the same as the first sentence of CPT Rule 4.</b></p>  |
|  | <p>Rule 9: The trigger for offending usually occurs when the offender is engaging in routine activities. <i>Each criminal event is added to an offender's accumulated experience and can affect future behaviour.</i></p> <p><b>The second sentence is the same as the second sentence of CPT Rule 4.</b></p> |
|  | <p>Rule 10 (rule 1 redux): The backcloth affects both routine activities and offenders' decisions to offend.</p>  |

**Table 2.1 - Crime Pattern Theory Rules Compared with Geometry of Crime Rules**

As one can see from Table 2.1, crime pattern theory and geometry of crime are very similar theories, and the concept of crime generators and attractors can be found in both. Indeed, the two theories appear to have notably more similarities than differences. The primary distinction between them is that geometry of crime highlights the environmental backcloth in Rules 1 and 10,

whereas it is not discussed in as much length in the crime pattern theory rules, and that Rule 3 in crime pattern theory (regarding emergence of crime patterns) does not feature in geometry of crime. This suggests that whilst crime pattern theory was designed to integrate multiple environmental criminology perspectives, it is the geometry of crime which was most integral to its formulation. In practice, this similarity between crime pattern theory and geometry of crime does not appear to have a profound effect, but it is a notable limitation of both concepts. The distinctions between each are not commonly highlighted, and the two appear to be used rather interchangeably in environmental criminology literature. This is unsurprising given the overlap between the rules they follow, but it can lead to confusion surrounding both concepts.

A number of other limitations apply to both crime pattern theory and geometry of crime. For example, both are relatively a-temporal, despite routine activities (featuring in Rules 5 and 2 of crime pattern theory and geometry of crime respectively) having a strong temporal element. Whilst time is acknowledged in some of the rules, it has been argued that crime pattern theory would benefit from being extended to identify not only where crimes occur, but also when (van Sleeuwen et al., 2021). Moreover, Higgins and Swartz (2018) have proposed that the concept of paths and edges (see Section 2.1.2) needs to be updated and combined to create “edgeways”; areas which are used by both residents and outsiders, but lack social control. They posit that these mixed-use areas, such as alleyways and side streets, can act as both paths and edges.

The information in Section 2.1 has provided a background to environmental criminology, permitting understanding of the theories which underpin crime generators and attractors. The next section of this chapter introduces this concept in more detail.

## **2.2 Crime Generators and Attractors**

### **2.2.1 Introduction to Microgeographic Studies of Crime**

These environmental criminology theories, and particularly the works of Brantingham and Brantingham, provided a firm foundation for understanding

spatial patterns of crime (Wortley and Townsley, 2016). However, the study of *microgeographic* patterns of crime did not become of notable interest to criminologists until the late 1980s (Weisburd, 2015). The work of Sherman et al. (1989) is considered to be one of the preliminary papers on crime hotspots (Anselin et al., 2011; Weisburd et al., 2004), coining the term “criminology of place” (Weisburd, 2015). Although the study of microgeographic patterns of crime was still nascent in the early 1990s, with only 2.6% of articles in *Criminology* journal examining this level of spatial granularity (Weisburd, 2015), this burgeoning interest was aided in 1990s with the availability of Geographic Information Systems (GIS) on personal computers, which allowed hotspots to be more easily studied (Wortley and Townsley, 2016). As a result, between 2010 and 2014 more than 6% of articles published in the same journal were examining micrographic patterns of crime (Weisburd, 2015).

Crime concentration has been repeatedly identified within environmental criminology literature (Johnson, 2010). More than two decades after Sherman et al.'s (1989) proposal of criminology of place, Weisburd (2015) introduced the “law of crime concentration at place”, after finding strong support for crime clustering, which he proposed was analogous to physical laws. This law asserts that “for a defined measure of crime at a specific microgeographic unit, the concentration of crime will fall within a narrow bandwidth of percentages for a defined cumulative proportion of crime” (Weisburd, 2015 p.133).

The upcoming sections will go into more detail on crime generators and attractors; two types of areas which lead to crime concentration at microgeographic scales. It will start with a discussion on how to define crime generators and attractors, before going into detail on studying them. It will end with information on why it is important to study these types of spaces.

### **2.2.2 Defining Crime Generators and Attractors**

In examining the effects of the environmental backcloth on microgeographic crime trends, Brantingham and Brantingham (1995) proposed two types of urban space which could lead to crime concentration; crime generators and

attractors<sup>1</sup>. Although a wide variety of definitions have been provided for these types of spaces in the extant literature (see Chapter 4 for evaluation of this), the key mechanisms proposed in the definition of crime generators by Brantingham and Brantingham (1995) can be broken down into their core components. Crime generators, therefore, are:

1. Areas which large numbers of people use.
2. Areas where offenders commit opportunistic offences. They do not specifically go to a crime generator to offend, but encounter opportunities whilst there.
3. Areas which are not inherently criminogenic; these spaces do not necessarily lead to criminal behaviour.

Crime generators are considered to be the result of the overlap of many people's awareness and activity spaces (Brantingham and Brantingham, 2011). As a result of these processes, crime problems at crime generators can be exacerbated by more people using the space (Clarke and Eck, 2003), and are therefore modulated by the accessibility of the location (Demeau and Parent, 2018). Examples of crime generators include sports stadiums and shopping precincts (Brantingham and Brantingham, 1995). Given the rather commonplace nature of these characteristics, it is possible that a great many crime generators exist within any urban area.

On the other hand, the core processes identified for crime attractors by Brantingham and Brantingham (1995) indicate that these areas are:

1. Areas which have reputation for criminal potential.
2. Areas which motivated offenders visit when they wish to commit an offence.

Crime attractors therefore vary depending on the crime an offender is wishing to commit (Demeau and Parent, 2018), and could have a variety of characteristics which attract an offender to them (Boivin and D'Elia, 2017).

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<sup>1</sup> Whilst additional types of crime hotspots have since been proposed, such as crime enablers (Clarke and Eck, 2005, 2003), these have been excluded from the current work in order to focus exclusively on this initial classification and their processes.

The emergence of a location as a crime attractor is caused by offenders' experience and networks (Brantingham and Brantingham, 2011).

However, despite these clearly distinct definitions for crime generators and attractors, Brantingham and Brantingham (1995) stressed that areas are unlikely to be mutually exclusive. They suggested instead that some places could be simultaneously crime generators for some types of crime and crime attractors for others. Indeed, some authors discuss how their study areas can demonstrate elements of both of these types of processes, including Christensen (2008), who was studying the Beerburrum forest district in Australia, and Kurland et al. (2014) who were studying a football stadium.

Moreover, Clarke and Eck (2005, 2003) suggested that a location can evolve from a crime generator into a crime attractor. Both of these papers give the example of new roads leading to more shoppers in an area, which could lead to opportunities for thefts (a crime generator). The success of these crimes could then attract new offenders who are motivated to commit a theft (a crime attractor). Similarly, Newton (2018) highlighted that an offender's awareness of opportunities develops over time, and thus a site which started as a crime generator for them evolves into a crime attractor if they begin to plan their offending. Conversely, Soto and Summers (2020) suggested a situation where a crime attractor develops into a crime generator. They proposed that an offender could visit a red-light district specifically to commit a crime there (a crime attractor), but then identify and exploit additional opportunities for crime (a crime generator). Further details on how crime generators and attractors have been defined in the extant literature can be found in the scoping literature review in Chapter 4.

The concept of crime generators and attractors is also intrinsically linked to that of risky facilities, which suggests that a small number of sites in a group of facilities will experience the majority of the crime experienced by the group as a whole (Eck et al., 2007). For example, a small number of bars sees the majority of crime experienced by all bars in a city. Whilst risky facilities are not the focus of the research found in this thesis, it is important to keep this concept in mind when studying crime generators and attractors.

### **2.2.3 Studying Crime Generators and Attractors**

By conducting the scoping literature review detailed in Chapter 4, which explores the extent to which crime generators and attractors have been studied, it has been identified that there is a dearth of research into this area. This is surprising given how frequently this concept is referenced in environmental criminology literature. This lack of research is particularly noticeable regarding testing and verifying the mechanisms proposed by Brantingham and Brantingham (1995). Indeed, this is illustrated by an example in Chapter 4; when crime generators and attractors were searched for within ProQuest Dissertations database (see Chapter 4 for the search terms used), more than 39,000 papers were identified if the search was undertaken in full text, but only 12 if the search was anywhere except full text. It is suggested this lack of research could be caused by three potential factors; (1) the fact that the concept of crime generators and attractors appears straightforward and thus does not require additional research, (2) the fact that previous researchers have set a precedent by attributing crime concentration to crime generators and attractors, rather than exploring their mechanisms, and (3), that it is challenging to empirically study these processes.

The last point, that empirical investigation of crime generators and attractors is challenging, can be broken down into a number of interrelated aspects. Firstly, crime generators and attractors can be difficult to quantify (Newton, 2018). A number of the mechanisms behind crime generators and attractors, such as the motivation of the offender, the reputation of a space and the number of potential targets there, are challenging to quantify. For instance, the residential population is not an appropriate way to identify the population at a potential crime generator (Malleson and Andresen, 2016). Moreover, obtaining crime data at a suitably accurate geographic scale to study these microplaces can be challenging. For one thing, it can be difficult for police to accurately record the location of offences. For example, if a crime was committed on public transport, it is difficult to pinpoint exactly where that offence occurred (Newton, 2004). Indeed, the geocoding of publicly available crime data in the UK is estimated to be between 60% to 97% accurate (data.police.uk, No date). For another, even if the police are able to

accurately locate the offence, publicly available crime data are often obfuscated to protect the privacy of those involved. Publicly available data in the UK, for instance, has been found to be unsuitable for use at microgeographic levels, as the spatial error at scales such as postcode is considerable (Tompson et al., 2015).

Secondly, as previously highlighted it can be difficult to distinguish between a crime generator and attractor in practice (Yoo and Wheeler, 2019). As discussed in the preceding section, sites are rarely exclusively one or the other, and the nature of a location as either classification can change by crime type or throughout the day (Brantingham and Brantingham, 1995; Feng et al., 2019). Moreover, as discussed further in Chapter 5, there has been very little work undertaken to validate methods of identifying these spaces. As a result, this can complicate the identification of appropriate case studies to study these processes.

Thirdly, understanding of the concept of crime generators and attractors is limited, which will hinder appropriate empirical research into it. Not only is there the aforementioned scarcity of research into the mechanisms behind these spaces, but there is much uncertainty within the extant literature as to which environmental criminology theory the crime generator and attractor concept sits in. Some authors have suggested that this concept is part of geometry of crime (such as Song et al. (2017)), others suggest crime pattern theory (such as Groff and McCord (2012)), and still others have suggested routine activity approach (McCord and Ratcliffe, 2007). Whilst this does not affect the concept in practice, it does indicate that we do not fully understand the processes which lead to crime concentration at these locations. As highlighted in Section 2.1, these theoretical ideas suggest different reasons for the emergence of crime concentration. The fact that crime generators and attractors are attributed to multiple theories indicates that there is no consensus as to what leads to crime concentration here.

Moreover, these terms are not always used consistently in the literature. For example, a number of authors have used the terms “crime generator” or “crime attractor” in ways which do not align with Brantingham and Brantingham's (1995) original proposal. Mawby (2008), for example,

suggested that tourism is a crime generator in Cornwall, UK, and Clancey et al. (2017) referred to a number of things as crime generators, including lengthy commutes, financial pressures and high numbers of young people in an area. Whilst it is possible that these features of a location could lead to more crime being committed, they could not be considered crime generators in the traditional sense as they do not display any of the processes discussed by Brantingham and Brantingham (1995). Whilst this confusion does not hinder empirical investigation in itself, it could impede understanding of this topic, thus reducing the amount of empirical research done to test and verify these proposed mechanisms.

Fourthly, it can be difficult to isolate the effects of specific facilities when studying crime patterns using traditional empirical methods. For one thing, when there are multiple crime generator or attractor locations in an area, it is impossible to attribute an offence specifically to one site instead of the other. As these sorts of locations (especially crime generators) are often located in close proximity to each other, this is a distinct disadvantage when studying these spaces. It is also impossible to isolate the facilities from the environments in which they are situated. Indeed, more crime in a certain area could be attributed to the environment itself, rather than any facilities there (Kurland et al., 2014). As a result, it is not known whether multiple crime generator and attractor sites in close proximity to each other take offenders away from each other, or make an area more criminogenic, and therefore increase crime (Newton, 2018). Research on this has so far been contradictory; whilst Mago et al. (2014), for example, found evidence indicating the former, Bowers's (2014) research, for example, suggested the latter.

One must ask, therefore, what one would have to look for in order to empirically identify a crime generator or attractor. Whilst the most obvious initial answer would be areas of crime concentration, this alone is not sufficient. Although the crime generator and attractor mechanisms usually lead to a crime hotspot, a crime hotspot is not necessarily caused by the crime generator and attractor mechanisms. A number of other processes could be at play leading to those areas of crime concentration, such as the mechanisms behind *crime enablers*, which are locations where poor

management practices lead to criminal behaviour, such as a car park with no attendant (Clarke and Eck, 2005, 2003). As a result, whilst an area of crime concentration could be indicative of the occurrence of crime generator and attractor processes, further exploration is required to identify if that site is experiencing these mechanisms. Yu (2009) demonstrated this with bus stops which experience crime clusters. They suggested that if these bus stops are in areas with a number of services and activities which appeal to a large number of people, they are probably crime generators. However, they suggest that if these bus stops experience a lot of crime but there are no legitimate activities available, that these could be crime attractors.

Although there may not be any notable *physical* distinctions which could be used to distinguish between a crime generator and attractor site, other types of differences have been found between them. First, the type of facility identified as a crime generator will most likely be different from that of a crime attractor. Not only are the former more legitimate establishments, they also usually have a more distinct location, such as a sport stadium or shopping precinct (Brantingham and Brantingham, 1995). Crime attractors, on the other hand, can be more conceptual; areas with reputations for criminal potential do not necessarily take a specific form. This is exemplified in a number of traditional examples of crime attractors, including red light districts and drug markets (Brantingham and Brantingham, 1995). Whilst this is not the case for all potential sites, this distinction is worth noting. Second, differences in distances travelled to these sites are often noted. Although crime generators tend to be visited by people who live nearby as part of their routine activities, offenders who purposely visit crime attractors are usually outsiders, and can travel relatively far to get to them (Brantingham and Brantingham, 1995; Newton, 2018; Spicer et al., 2016). Third, the types of crime which take place at crime generators and attractors has been theorized to be different. Whilst a number of authors have suggested the types of crime which take place at each type of space, there is limited consistency between these suggestions. For example, property crime has been suggested to be indicative of a crime generator by Bowers (2014) and Vandeviver et al. (2019), but a crime attractor by Newton (2018) and Irvin-Erickson and La Vigne (2015). This is discussed in more detail in Chapter 5,

which attempts to analyse crime types to classify sites as either a crime generator or attractor.

#### **2.2.4 Why is it Important to Study Crime Generators and Attractors?**

Although the previous section has demonstrated how challenging it is to study crime generators and attractors, there is a great deal of theoretical value in researching these types of spaces. The preceding sections have demonstrated that there is much confusion and a dearth of research around this topic. Whilst it has been suggested that the concept of crime generators and attractors is too simplistic (Hipp and Williams, 2020), it is argued that the concept itself is still lacking complete understanding. Moreover, crime generator and attractor mechanisms may not translate consistently across different cultures and settings, so a wider literature base across a variety of study locations would be beneficial. To date, the majority of crime generator and attractor research has taken place in western countries, especially USA and Canada, so advancement in knowledge in a non-Western setting in particular would be beneficial.

There is also the potential for much practical benefit of research into these types of spaces. Most importantly, improved understanding of crime generators and attractors could lead to tailoring of law enforcement strategies around these spaces, as understanding the processes which lead to crime occurrence is important for designing law enforcement strategies to reduce it (Birks et al., 2012). Given the potential prevalence of crime generator and attractor locations, it would be beneficial to explore whether a large number of these spaces exist in an urban area, as these tailored strategies could therefore have a great effect on crime occurrence. Increased understanding of crime generators and attractors would also improve understanding of the potential repercussions of these strategies. Brantingham et al. (2008), for example, suggest that a crime reduction strategy at a crime attractor could lead to displacement (the relocation of crime), rather than a reduction in offending. Further exploration of this suggestion would be valuable to inform future law enforcement programmes.

## **Summary**

*This chapter has provided a detailed summary of environmental criminology and crime generators and attractors, which will contextualise the work which follows. Section 2.1 introduced environmental criminology and its core theories. It demonstrated that although there are a number of different theories within the discipline, they are interrelated and focus on the place in which an offence takes place, rather than the psychology of the offender. Knowledge on these theories is vital for the creation of a sound agent-based model, which is found in Chapter 6.*

*Section 2.2 discussed crime generators and attractors; how they are defined, some key difficulties in studying them, and why it is valuable to study them. Not only does this introduce the concept to be explored throughout this thesis, but it also illustrates the motivations and challenges for this research.*

*The following chapter introduces the methodological approach employed in this thesis. Having a greater understanding of environmental criminology and the concept of crime generators and attractors itself will aid the reader in understanding the rationale for the methodologies selected.*

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## Chapter 3

### Methodological Approach

#### ***Preface***

*The chapter that follows introduces the methodological approach employed in this thesis: a combination of theoretical, computational, and empirical research. This chapter does not discuss the details of how each method was undertaken, as this is covered in each of the individual analysis chapters (Chapters 4 – 7), but it shall discuss the strengths and weaknesses of this threefold approach, as well as the strengths and weaknesses of each method selected and how each has been applied to criminological research previously.*

#### **3.1 Introduction**

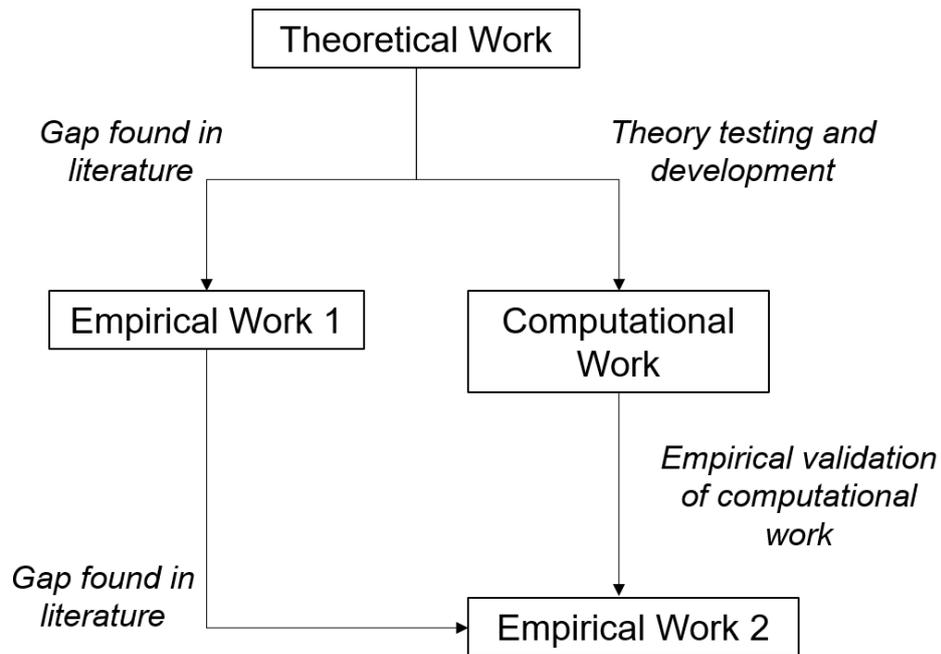
This research uses a threefold methodological technique to critically appraise the concept of crime generators and attractors, combining theoretical, computational and empirical research. The use of multiple approaches to answer a research question is known as *triangulation*, and although triangulation is not without criticism, the combination of different methods generally increases confidence in the findings as they are more comprehensive and rigorous than if one method was used alone (Heale and Forbes, 2013).

There are a number of benefits to using this multidimensional approach, the most notable being that it enables this research to benefit from the strengths of each approach, whilst simultaneously going some way to mitigating the limitations of each. The advantages and disadvantages of each technique will be discussed in the upcoming sections, which will go into more detail of each method used, but a brief example will be provided now to illustrate this. Computational simulations have been referred to as complementary tools to more traditional methods (Eck and Liu, 2008; Townsley and Johnson, 2008), as they can overcome several of the problems of empirical research which

are covered later in this chapter (Eck and Liu, 2008). However, although simulation experiments can surmount some limitations, they are restricted when it comes to comparison of the model results with the real world (Gerritsen and Elffers, 2021b); the area in which empirical work excels. As a result, whilst computational research does not overcome all the disadvantages of empirical work (Birks, 2017) it can go some way to alleviate them, and empirical study can mitigate one of the main limitations of computational simulation.

Not only are the relative strengths and weaknesses of each method identified and manipulated, this approach also grants the exploration of different elements of the crime generator and attractor systems. Creating computational simulations, for example, permits greater understanding and development of theories as the formalisation of the mechanisms included requires a clear idea of the processes at play (Eck and Liu, 2008). Empirical work, on the other hand, allows studies of elements which are outside the remit of the traditional theory, in this case classifying spaces as crime generators and attractors and the offence distribution around both types of space.

As such, these three approaches are used interconnectedly in this work and the results of each impact the decisions made in following pieces of research. In this thesis, the theoretical work informs both the computational work and one piece of empirical analysis. The computational work then informs subsequent empirical research, which then relates back to the other empirical study. The relationships between each piece of research are shown in Figure 3.1, below.



**Figure 3.1 - Relationship Between Papers**

Despite the advantages of the threefold approach, some could argue that the comparison of computational and empirical research is inappropriate, and thus call into question this multidimensional approach. This criticism primarily relates to the difficulty in comparing simulated results with empirical crime data; Eck and Liu (2008) highlight that one of the strengths of computational research is reducing the reliance on potentially inaccurate empirical data. If these data are potentially flawed, they ask, is it an appropriate benchmark for the results of computational work? This must be taken into account when using this triangulation technique.

The following three sections shall go into more detail on each of the methodological approaches employed in this research. They shall discuss the specific methods employed for each piece of research, but not go into detail about how the methodology was undertaken, as this information is provided in the relevant chapters (Chapters 4 -7).

### **3.2 Theoretical Approach: Scoping Literature Review**

The theoretical element of this research, presented in Chapter 4, consists of a scoping literature review to answer the question *to what extent have the*

*mechanisms behind crime generators and attractors been studied?* A scoping review aims to identify all the relevant literature on a particular subject (Arksey and O'Malley, 2005), in this case all work which explicitly studies crime generators and attractors. Although traditional literature reviews can be subjective and biased (Aromataris and Pearson, 2014; Munn et al., 2018), scoping literature reviews are more rigorous and transparent, and aim to be reproducible (Arksey and O'Malley, 2005; Munn et al., 2018). They are particularly helpful when identifying the extent of the extant literature for guiding future research (McKinstry et al., 2014).

There exists a range of approaches for undertaking literature reviews, and whilst they all have different names their key characteristics are consistent (Arksey and O'Malley, 2005). There is particular confusion regarding the differences between a scoping literature review and a systematic literature review, as their differences are fairly subtle. A systematic review, for example, typically aims to answer a more defined question, whereas a scoping review has a broader scope (Arksey and O'Malley, 2005; Munn et al., 2018). Moreover, a systematic review usually aims to assess the quality of work included, whereas a scoping review does not (Arksey and O'Malley, 2005; McKinstry et al., 2014). Given these differences between a scoping review and a systematic review, a scoping review was considered more appropriate for this work. In addition to this, scoping reviews are particularly well-suited to identifying research gaps and clarifying key concepts within literature (Arksey and O'Malley, 2005; Munn et al., 2018). These are both important for research on crime generators and attractors given the frequency with which they are mentioned, but not explicitly studied, in environmental criminology literature.

Despite being a valid approach for reviewing literature (Munn et al., 2018), a limited number of scoping reviews exist in the extant environmental criminology literature. Those which have been published cover a range of topics, such as Comerford's (2021) research on geographic mobility of serial homicide offenders and Snaphaan and Hardyns's (2019) work examining the use of emerging data sources to study theories in this field. It is believed that the use of a scoping review to study crime generators and attractors not only contributes to the dearth of this method in environmental criminology, but

also allows for their theoretical basis to be explored and incorporated into the subsequent computational and empirical studies. Whilst theoretical explanations of concepts can be interpreted in a range of ways (Eck and Liu, 2008) the use of a scoping literature review allows this interpretation to be as rigorous and transparent as possible.

### **3.3 Computational Approach: Agent-Based Modelling**

Computational criminology is a growing field within the discipline, and utilises methods which combine criminology, computer science and applied mathematics (Brantingham, 2011). For the computational component of this research, an agent-based model (ABM) was created aiming to explore the distribution of offences around crime generators and attractors. As with Section 3.2, details of the model shall not be provided here (see Chapter 6 for this information), but the methodology will be introduced.

A model is a simplified version of a reality under investigation (Bandini et al., 2009), and a range of modelling techniques exist to examine phenomena in the social sciences. In this case, agent-based modelling (also referred to as ABM) was selected. ABMs consist of classes of autonomous heterogeneous individuals (agents) who move through and interact with each other and their digital environments according to specific user-defined rules (Bonabeau, 2002; Brantingham et al., 2012). In criminology, the agents could represent a range of individuals, including police, offenders and targets, and the environments could be a small street network, a city or an abstract space (Eck and Liu, 2008). In the model created for this research, offender agents moved around an abstract environment following the mechanisms underpinning crime generators and attractors, as identified through the scoping literature review.

ABM was selected for this work because of several important benefits which meant it was well-suited to the aims of this project. Not only does the creation of computational models such as ABMs permit the testing and development of theory by examining whether a theory leads to the expected outcomes (Birks et al., 2012; Brantingham et al., 2012; Eck and Liu, 2008; Johnson and Groff, 2014), but it also requires the model builder to be explicit

and systematic about the mechanisms being explored (Birks, 2017; Birks et al., 2012; Brantingham et al., 2012; Eck and Liu, 2008; Elffers et al., 2021). The latter ensures that the theoretical mechanisms under scrutiny are well understood and thought-out prior to the research commencing, which is not always the case in other approaches (Birks, 2017). Given the lack of research on the mechanisms behind crime generators and attractors, formalizing, testing, and developing these processes is an important contribution to this field. Moreover, ABM has the advantage of not relying on crime data, which is often not of a sufficient quality to be considered an accurate representation of reality (Eck and Liu, 2008). However, it is important to note that computational simulations are not a replacement for empirical research (Birks, 2017); instead they can be used to complement it, as demonstrated in this thesis.

Moreover, ABM is well-suited to modelling dynamic systems such as crime, which changes over time and space. Whilst it can be interesting to know the crime rate at a certain location at a certain point in time, this fixed value is of limited benefit to those who wish to reduce offending there (Rosenfeld, 2018). Without understanding the crime trend in an area, a snapshot such as this offers little in the way of actionable data. Instead, the use of methods such as ABM can apply criminological theories to crime occurrence patterns to suggest ways to explain them, with the goal of implementing strategies to reduce offending. Similarly, the use of an ABM permits the studying of complex systems. Whilst there is no individual definition for complexity (Bertelsen, 2003; Ladyman et al., 2013), Table 3.1 demonstrates how crime can align with the properties associated with a complex system, as suggested by Ladyman et al. (2013). Although these properties can vary based on the crime type being examined, broadly they help to illustrate the complex properties of crime.

| Complexity property<br>(all from Ladyman et al. (2013)) | Alignment with crime  |
|---|---|
| Nonlinearity  | <p>In a linear system, the outcomes are proportional to the causes underpinning them. However, this is too simplistic to be applied to social systems, primarily as it is not possible to account for individual choice in a linear system (Karmeshu, 2003). Take, for example, handbag theft in a bar. If the system was linear, the probability of a handbag being stolen is proportional to the number of thieves in the bar, so if there are double the number of thieves in the bar, there would be double the amount of handbag theft. This, however, is not the case as in reality handbags would not be left unattended if there are a lot of potential offenders.</p>  |
| Feedback  | <p>Feedback in a system is evident when the manner in which parts of the system interact with each other depends on how it interacted with them previously (Ladyman et al., 2013). Whilst this can be seen in offenders (for example, committing an offence can impact both the offender who committed the crime but also the environment in which it was committed (Sullivan et al., 2012)) it is important to note that feedback alone does not guarantee complexity. To indicate a complex system, the feedback must be in a sufficiently large group to lead to the emergence of patterns at a larger scale (Ladyman et al., 2013). A hypothetical example in crime would be the influence of law enforcement in a heavily policed neighbourhood. In this example, the area has a reputation with law enforcement, so it is heavily policed and there are poor relations between the inhabitants and the police. In response, distrust builds between both groups which can lead to worsening reputation of the area for law enforcement, and thus more policing, which further perpetuates the distrust the inhabitants feel towards them.</p> |
| Spontaneous order                                       | <p>For a system to be complex, behaviour is not completely random, nor is it totally uniform</p>  |

|            |  |
|------------|--|
|            | (Ladyman et al., 2013). Crime has been found to meet these criteria. Consider, for example, the spatial distribution of crime; crime hotspots form in certain areas, and little offending occurs in others.  |
| Emergence  | Emergence is defined by a phenomenon or property occurring due to the interactions of entities in the system, even though the individual entities may not have that property themselves (de Haan, 2006). It has been acknowledged for many years that macro crime patterns emerge from the interaction of many elements, including an individuals' motivation for offending and the opportunities at their location (Sullivan et al., 2012). |
| Numerosity | Anderson (1972) suggested that systems are not complex if merely a small number of elements interact. Instead, the system needs to have many parts and many interactions. Although crime is a relatively rare phenomenon (Prieto Curiel et al., 2018), it takes place across society affecting both offenders and non-offenders, meaning that a large number of agents and processes are involved in this system.                            |

**Table 3.1 - How Crime Aligns with Complexity Properties**

Studying complex systems is challenging using traditional empirical methods, but ABM is well-suited to modelling them. Despite this, there are also a number of limitations to using ABM. First, it is possible that certain model components, such as offenders' decision making processes, are too complex to formalize into a simple rule (Clarke and Cornish, 1985). ABMs are very dependent on any assumptions included or excluded in the model design phase (Davies and Birks, 2021; Johnson and Groff, 2014; Weisburd et al., 2017), and thus formalizations, and other model design decisions, must be carefully planned. Second, it can be difficult to validate the results of ABMs. Theoretical mechanisms, although often tested in isolation in an ABM, rarely act in isolation in the real world (Birks et al., 2012). As a result, obtaining data which is appropriate to use as validation can be challenging. The ABM research included in Chapter 6 uses stylized facts to validate the model results, as recommended by Gerritsen and Elffers (2021). Stylized

facts “stylize[d] away the differences between empirical findings... and concentrates on the common characteristics” (Gerritsen and Elffers, 2021 p.6), looking for general expected trends rather than specific values or findings. Whilst the stylized reality used in the chapter is discussed in more detail in Chapter 6, it has been identified that the concept of stylized facts is flawed; even though a particular pattern occurs in some situations, it is not guaranteed to occur in all (Gerritsen and Elffers, 2021). Moreover, it is challenging to identify a pattern which is sufficiently prevalent in environmental criminology literature for it to constitute a stylized fact (Elffers et al., 2021). As a result, empirical work was also undertaken to validate this work (as found in Chapter 7).

Despite these limitations, ABM is becoming increasingly popular in criminology (Johnson and Groff, 2014) and is one of the more dominant simulation techniques in the discipline (Brantingham et al., 2012; Eck and Liu, 2008). It has been used to explore a range of topics and crime types, including street robbery (Araújo and Gerritsen, 2021; Groff, 2007), corruption (Van Doormaal et al., 2021) and crime displacement (Wang et al., 2014). However, as well as the current research, only one other paper was found using ABM to study crime generators and attractors; Davies and Birks (2021) created a model looking at crime generators, examining the extent to which the mechanisms underpinning crime pattern theory will produce crime generator patterns at a variety of spatial scales. This model used an abstract street network to explore inter-personal victimisation and found that the processes behind crime pattern theory do indeed lead to areas of crime concentration because of the presence of large numbers of people at certain locations. As a result, this research found evidence potentially supporting crime generator mechanisms. However, it is impossible to categorically conclude that an ABM has found evidence for crime generators and attractors. Not only can models only be used to falsify, rather than confirm, theories (Crooks et al., 2008), Davies and Birks (2021) note the complexity in identifying crime generators in their model results. As there are no specific thresholds already in the literature as to how much crime must be concentrated at a site for it to constitute these types of location, identifying crime generators in data (whether computational or empirical) is challenging.

### **3.4 Empirical Approach: Analysis of Crime Data**

Empirical analysis, which uses observations of real-world phenomena to generate conclusions (Patten and Galvan, 2020), is used in two chapters in this work. The first, Chapter 5, examines crime generator and attractor classification methods, applying different techniques to empirical data on incidents reported to a university security team to determine if they categorise sites on the campus in the same way. The second, Chapter 7, explores crime distribution in the vicinity of a number of potential crime generator and attractor sites in Austin, Texas (USA), exploring whether the patterns found in the computational research align with those identified empirically. It also examines whether the crime distribution in the vicinity of these sites could be used to classify them as either type of location.

Although it is beneficial to understand a concept theoretically and computationally, it is important to understand how theoretical concepts influence real-world crime patterns. Indeed, Bottoms (2008) highlights that criminologists cannot avoid engaging with the real world as topics cannot be studied exclusively theoretically. However, Lynch et al. (2017) note that not all empirical knowledge is useful; it must be suitably analysed and interpreted to be valuable to its field. Related to this, there are a number of limitations of doing empirical research in environmental criminology. The predominant one has been touched upon previously in this chapter; that of disadvantages concerning empirical crime data. As well as the well-known limitations of offence data, such as underreporting (Eck and Liu, 2008; Song et al., 2017) and geographical inaccuracies (Kurland et al., 2014; Song et al., 2017), Eck and Liu (2008) highlight that whilst other fields also experience limitations with data, criminology is a field in which people deliberately falsify data, such as offenders misrepresenting facts of an offence. Moreover, empirical research in this field is limited both ethically and logistically as to the amount of manipulation one can do to test theories (Birks, 2017; Eck and Liu, 2008), restricting the variety of testing which can be undertaken. For example, crime prevention strategies can be costly to evaluate (Eck and Liu, 2008), and it is not always ethically appropriate to test crime-related hypotheses in the real world if it means putting people at risk of victimisation.

Finally, although empirical research can appear objective, judgement and subjectivity are intrinsic to this type of research (Orsagh, 1979). Whilst this is not a limitation in itself, or specifically related to empirical work in environmental criminology, it must be considered when examining the validity of these pieces of work.

Empirical research is widely used in criminology. Kleck et al. (2006), for example, on exploring methods in articles published in leading criminology and criminal justice journals in 2001 and 2002, found that 81.3% of papers included empirical studies. Moreover, Weisburd (2015), in his study examining the units of analysis in criminological research, identified that approximately 93% of papers published in Criminology between 1990 and 2014 included empirical units. As one can see, empirical methods dominate research in criminology, and this is also true of work on crime generators and attractors. In the scoping review included in Chapter 4, 98% of the papers incorporated empirical data. As a result, analysis of observed crime occurrence is important to substantiate the theoretical and computational approaches used in this thesis.

## **Summary**

*This chapter has introduced the methodological approach employed in this thesis: the combination of theoretical, computational, and empirical approaches. Section 3.1 covered the theoretical work: a scoping literature review aiming to answer the question to what extent have the mechanisms behind crime generators and attractors been studied? which is found in Chapter 4. This section showed that scoping literature reviews are rare in environmental criminology, and to the author's knowledge, no scoping literature review has been conducted looking into any element of crime generators and attractors.*

*Section 3.2 discussed the computational work in this thesis, the creation of an agent-based model which is found in Chapter 6. It discussed the strengths and weaknesses of this method, and identified the only other example, of which the author is aware, of agent-based modelling being applied to crime generators and attractors.*

*The other methodological approach used in this work, empirical research, was examined in Section 3.3. This approach is used in Chapters 5 and 7. This section highlighted the strengths and limitations of empirical analysis and touched on the prevalence of empirical work in environmental criminology.*

*The following four chapters (Chapters 4 – 7) make up the analysis undertaken for this research. Each chapter will begin with an preface summarising the upcoming research and its contribution to the overall thesis. Each will discuss the data used for the analysis and go into detail on the more specific steps taken in conducting the analysis, before providing results and a discussion.*

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## **Chapter 4**

### **The Mechanisms behind Crime Generators and Attractors: A Scoping Review**

#### ***Preface***

*This chapter forms the theoretical component of this thesis and details a scoping review which answers the question to what extent have the mechanisms behind crime generators and attractors been studied? Following the procedure laid out by the Joanna Briggs Institute for scoping reviews (Tricco, 2017), this research identifies 48 papers for inclusion, and finds a great deal of inconsistency in the definitions of crime generators and attractors. Moreover, of the 48 papers included, only 11 examined the mechanisms behind crime generators and attractors.*

*This chapter aligns with Objective 1 for this thesis: Critically appraise previous research on crime generators and attractors to identify how they are defined and the extent to which their mechanisms have been studied. Not only does this research provide an important foundation for further research into crime generators and attractors, but it also identifies the mechanisms which lead to these spaces, which will then be formalised for the agent-based modelling work found in Chapter 6.*

#### **4.1 Background**

It is well-known that crime is distributed neither uniformly nor randomly in space. On examining the impact of the urban backcloth on crime, Brantingham and Brantingham (1995) identified a potential classification for two types of hotspots based on different types of causal mechanisms: crime generators and crime attractors. Crime generators, they posited, are areas that large numbers of people visit for reasons unrelated to criminal activity, such as public transport hubs. They suggested that potential offenders, who visit the area because of its legitimate use, come into contact with criminal opportunities that they then exploit. Crime generators are not, therefore,

areas that are specifically associated with crime. Crime attractors, on the other hand, are areas with reputations for particular illegal activities, such as drug markets, to which suitably motivated offenders are drawn.

Brantingham and Brantingham's (1995) paper was not the first to consider the reason why certain facilities lead to increased crime. Frisbie et al. (1977, cited by Roncek and Maier (1991)), for example, proposed several potential reasons why areas with bars see more crime than those without. These causes include those latterly suggested by Brantingham and Brantingham (1995) as characteristics of crime generators, such as potential offenders being among the bars' clientele, and crime attractors, such as bars attracting motivated offenders in search of targets. Moreover, since the introduction of crime generators and attractors, additional types of hotspot categorisations have since been suggested, such as crime enablers (Clarke and Eck, 2003), crime radiators (Bowers, 2014) and crime absorbers (*ibid.*). Despite the variety of research on this topic, this work shall focus on Brantingham and Brantingham's (1995) classification of these two types of spaces, due to this thesis' focus on the original concept.

This chapter presents the results of a scoping review examining literature on crime generators and attractors. The motivation for this review is threefold. First, there is a scarcity of research specifically examining crime generators and attractors, rather than merely referencing them. Although the presence of crime generators has been referred to as "undisputed" (Song et al., 2019 p.832), empirical evidence for the existence of crime generators and attractors is limited and is often produced by methods that have limitations (Kurland et al., 2014). In addition to this, the status of a location as either a crime generator or attractor is often suggested as a post-hoc explanation of crime concentration (Davies and Birks, 2021) without much further investigation, leading the concept to be frequently referenced, but relatively under-researched, in environmental criminology. Second, of the research that has been conducted, there is much confusion around what constitutes a crime generator and crime attractor, leading to misuse of terms. Indeed, Newton (2018 p.7) stressed "there is perhaps a need to revisit these definitions". As highlighted in Chapter 2, empirical research into crime generators and attractors is complex, and therefore this is not surprising, but

future research into this concept would benefit from improved understanding of these spaces. Third, further understanding of crime generators and attractors could have a practical implication if used to tailor crime reduction strategies, as it is possible that crime generators and attractors require different law enforcement strategies (Sosa et al., 2019).

Whilst many of the characteristics of crime generators and attractors are consistent across both types of space, their main difference is the motivation of the offender (Newton, 2018); whether the offence was opportunistic or actively sought. As a result, crime control measures could focus on specific aspects of the offence (Sosa et al., 2019), depending on the type of area in question. Moreover, Frank et al. (2011a) suggest that knowledge of these spaces could aid in creating a profile of offenders. For example, if a crime is committed near a specific crime attractor, law enforcement could identify potential characteristics of the offender based on the facilities that attracted them to that space.

In order to fill these gaps in understanding, this scoping review aims to answer the question *to what extent have the mechanisms behind crime generators and attractors been studied?* In this work, the term “mechanism” refers to the processes underpinning crime generators and attractors, highlighted by Brantingham and Brantingham (1995) in the definitions provided in their seminal paper, which are discussed in Section 4.3.1. This chapter has the following objectives:

1. Investigate the extent to which crime generators and attractors have been researched.
2. Explore how crime generators and attractors have been defined in the existing literature, and how these definitions align with their causal mechanisms as posited by Brantingham and Brantingham (1995) .
3. Examine the extent to which the mechanisms behind crime generators and attractors have been investigated.

The structure of the review is as follows. Section 4.2 outlines the methodology, including the search terms, databases used and inclusion and exclusion criteria. Section 4.3 outlines the results. Section 4.4 contains a

discussion of their implications and recommendations for future research, and Section 4.5 draws conclusions.

## **4.2 Methodology**

The approach taken to review the literature on crime generators and attractors follows a scoping review (Tricco, 2017), designed to assess the extent of a body of literature (Munn et al., 2018; Tricco, 2017). Based on the procedure laid out by the Joanna Briggs Institute for scoping reviews (Tricco, 2017), the steps taken to conduct the review were as follows. Details on the key stages will be discussed in the coming sections.

1. Development of a protocol for the review, including its methodology.
2. Refinement of research question and objectives.
3. Identification of inclusion and exclusion criteria.
4. Undertaking of the searches in each database.
5. Use of Mendeley software to check for, and remove, duplicates.
6. Supplementary search using Google Scholar.
7. Title and abstract screening using abstractkr website.
8. Full text screening.
9. Backwards snowball search.
10. Creation of charting form.
11. Data charting.
12. Analysis of data and interpretation of results.

### **4.2.1 Search Strategy**

#### **4.2.1.1 Key Words**

Having formulated the research question, the next step was to identify the key words which would be entered into the selected databases. These were:

1. Terms relating to crime generators and attractors: *crim\**, *generator\**, *attractor\**
2. Terms relating to spatial distribution of crime: *geog\**, *distrib\**, *spatial*, *pattern\**
3. Term relating to the classification of spaces: *classif\**

#### 4.2.1.2 Databases

Owing to the multi-disciplinary nature of this work, a number of different databases were selected that covered several different fields. These are listed in Table 4.1, alongside information on the search undertaken in each. Although every effort was made to conduct the same search across each database, there are some differences that are database-dependent and thus unavoidable.

Where possible, each search for the key words was conducted in the title and abstract, rather than the full text. This decision reflects the fact that when these terms were searched for in ProQuest Dissertations in full text, there were over 39,000 results. When the same search was run looking anywhere except full text, only 12 results were identified. This may indicate the extent to which crime generators and attractors are referenced in research, rather than specifically investigated.

| Database                       | Search Term   | Location of Search   | Data Completed | Count of Results |
|--------------------------------|---|--|----------------|------------------|
| Web of Science Core Collection | TS=(crim* AND (generator* OR attractor*) ) AND TS=(classif* OR pattern* OR geog* OR distrib* OR spatial)                                    | TS = "Abstract, Title, and/or Keywords fields of a record"                             | 09.06.2020     | 86               |
| Scopus                         | ( TITLE-ABS-KEY ( crim* ) AND ( generator* OR attractor* ) ) AND ( TITLE-ABS-KEY ( classif* OR pattern* OR geog* OR distrib* OR spatial ) ) | TITLE-ABS-KEY= A combined field that searches abstracts, keywords, and document titles | 09.06.2020     | 896              |

|   |  |                                   |            |       |
|---|--|-----------------------------------|------------|-------|
| JSTOR:<br>Criminology<br>and Criminal<br>Justice                                | ((crim* AND<br>(generator*<br>OR attractor*))<br>AND (classif*<br>OR pattern*<br>OR geog* OR<br>distrib* OR<br>spatial)) | All                               | 10.06.2020 | 103   |
| JSTOR:<br>Geography   | ((crim* AND<br>(generator*<br>OR attractor*))<br>AND (classif*<br>OR pattern*<br>OR geog* OR<br>distrib* OR<br>spatial)) | All                               | 10.06.2020 | 127   |
| JSTOR:<br>Sociology   | ((crim* AND<br>(generator*<br>OR attractor*))<br>AND (classif*<br>OR pattern*<br>OR geog* OR<br>distrib* OR<br>spatial)) | All                               | 10.06.2020 | 1,545 |
| JSTOR: Law  | ((crim* AND<br>(generator*<br>OR attractor*))<br>AND (classif*<br>OR pattern*<br>OR geog* OR<br>distrib* OR<br>spatial)) | All                               | 10.06.2020 | 1,325 |
| ProQuest:<br>Applied<br>Social<br>Sciences<br>Index and<br>Abstracts<br>(ASSIA) | ((crim* AND<br>(generator*<br>OR attractor*))<br>AND (classif*<br>OR pattern*<br>OR geog* OR<br>distrib* OR<br>spatial)) | “Anywhere<br>except full<br>text” | 09.06.2020 | 11    |
| ProQuest:   | ((crim* AND  | “Anywhere                         | 09.06.2020 | 12    |

|                                  |   |                             |            |  |
|----------------------------------|---|-----------------------------|------------|--|
| Dissertations and Theses A&I     | (generator* OR attractor*) AND (classif* OR pattern* OR geog* OR distrib* OR spatial))              | except full text”           |            |  |
| ProQuest: Sociological Abstracts | ((crim* AND (generator* OR attractor*)) AND (classif* OR pattern* OR geog* OR distrib* OR spatial)) | “Anywhere except full text” | 09.06.2020 | 29   |
| Google Scholar                   | “crime attractor”   | Title                       | 22.06.2020 | 0  |
| Google Scholar                   | “crime attractors”  | Title                       | 22.06.2020 | 19   |
| Google Scholar                   | “crime generator”   | Title                       | 22.06.2020 | 2  |
| Google Scholar                   | “crime generators”  | Title                       | 22.06.2020 | 22 (12 of which were already included from previous Google Scholar searches) |

**Table 4.1 - Details of Database Searches**

Of the final 48 articles included in the analysis, 6 were from grey literature sources, such as PhD theses and conference proceedings.

#### 4.2.1.3 Backwards Snowball Search

Following the full text screening, a backwards snowball search was undertaken to identify any relevant papers which were referenced by those included in this review. For this, the reference list of each article included was examined, and those papers that had “generator(s)” or “attractor(s)” in the title were incorporated for further screening.

#### 4.2.2 Inclusion and Exclusion Criteria

Once the searches had been conducted, title and abstract screening was undertaken by one reviewer (the author). Whilst it is best practice to have multiple reviewers for scoping review screening (Munn et al., 2018), this was beyond the resources of this PhD thesis. Each article was then considered against the predefined inclusion and exclusion criteria. These are listed in Table 4.2 and are as follows:

| Inclusion Criteria  | Exclusion Criteria   |
|---|--|
| Crime generators or attractors must be the clear focus of the narrative, or a section of the narrative.   | Studies not in English   |
| The studies do not have to be investigating “traditional” crime generator or attractor examples (such as those given as examples by Brantingham and Brantingham (1995)), but must identify crime generators or attractors as the focus of the research, regardless of the case study facility under scrutiny. | Studies only looking for hotspots that are not focused on crime generators or attractors                       |
| The research does not have to exclusively study crime generators or attractors.   | Studies which refer to crime generators or attractors in a throwaway manner, without researching them directly |
| The studies can be empirical, theoretical or computational.   | Book reviews   |
| There are no restrictions of time or location of study.   | Undergraduate or master’s level theses   |
| There are no restrictions on crime  | Studies that use crime generators or   |

|               |   |
|---------------|---|
| type studied. | attractors to represent criminal opportunity rather than studying them specifically |
|---------------|---|

**Table 4.2 - Inclusion and Exclusion Criteria**

These inclusion and exclusion criteria are suited to identifying papers which specifically studied crime generators and attractors, which is the aim of this work. However, they could lead to the exclusion of other papers studying elements of these spaces, such as those looking at more general crime concentration, or those which study the mechanisms without specifically declaring their paper to be investigating these spaces. Whilst this is a limitation of this approach, and the review would have been more comprehensive if they were included, the focus of this review is to examine work which has specifically studied these spaces, in part to examine the extent to which they have been the focus of research. As a result, these inclusion and exclusion criteria are considered appropriate for this study.

### **4.2.3 Data Charting**

A data charting form was created used Google Forms to permit consistent data extraction. It covered areas such as whether the research looked at crime generators or attractors (or both), whether the paper examined the mechanisms behind these spaces, and the methods employed. A full list of the fields in the charting form is available in Appendix A.

## **4.3 Results**

Through conducting this scoping review, 48 papers were identified as eligible for inclusion. Figure 4.1 uses a PRISMA template to provide an overview of the number of references obtained at each step of the search process. A complete list of the 48 references is included in Appendix B.

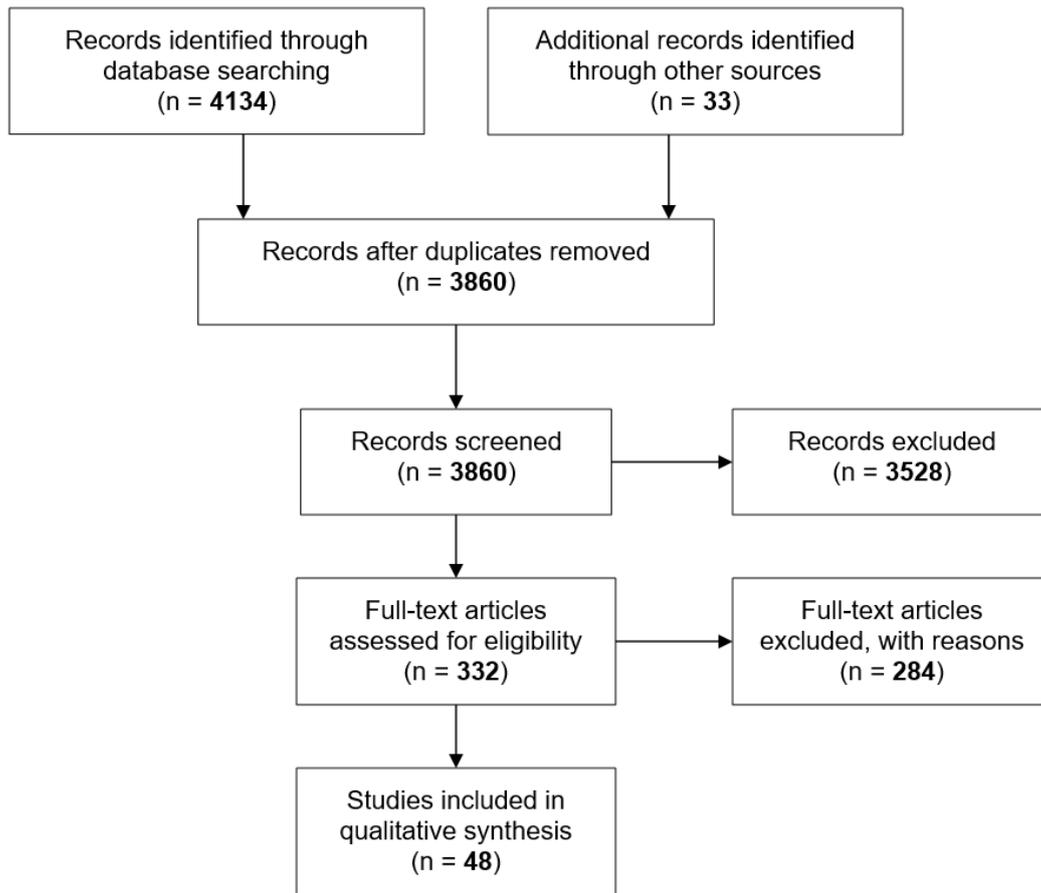


Figure 4.1 - Flowchart of Stages of the Review

### 4.3.1 Defining Crime Generators and Attractors

Although Brantingham and Brantingham (1995) provide definitions of both crime generators and attractors in their seminal paper which are reiterated shortly, these definitions are not used consistently by researchers. The definitions provided in the papers included in this review shall now be examined, in order to assess how the concept of crime generators and attractors has been interpreted, and therefore developed, by these authors, and how they relate to the original definitions provided.

#### 4.3.1.1 Crime Generators

The original definition for crime generators given by Brantingham and Brantingham (1995) is as follows:

*“Crime generators are particular areas to which large numbers of people are attracted for reasons unrelated to any particular level of criminal motivation they might have or to any particular crime they might end up committing...”*

*Mixed into the people gathered at generator locations are some potential offenders with sufficient general levels of criminal motivation that although they did not come to the area with the explicit intent of doing a crime, they notice and exploit criminal opportunities”*

(Brantingham and Brantingham, 1995 p.7)

Whilst this definition appears straightforward (Newton, 2018), the papers included in this review saw a number of variations on this original concept. To explore this variation, this section will start by identifying the core elements of the Brantingham and Brantingham (1995) definition of a crime generator. This work shall then discuss those papers which followed this original definition, followed by those which did not provide a complete definition, or failed to define them at all, before discussing those papers which used a definition which differs from that suggested by Brantingham and Brantingham (1995).

In establishing a definition for a crime generator which is in line with Brantingham and Brantingham's (1995), it was important to identify the key mechanisms proposed in their original definitions. Through examining their paper, three fundamental elements were suggested to explain crime concentration at crime generators: (1) the idea of large numbers of people using the space, (2) the fact that the offenders do not visit the space specifically to commit a crime, but encounter serendipitous criminal opportunities, and (3) that the space is not criminogenic in itself; it does not specifically lead to criminal behaviour.

A number of papers included in this review were found to provide definitions that mentioned all of these fundamental elements, including Contreras (2017), Demeau and Parent (2018) and Groff and McCord (2012). However, this list of fundamental components also highlighted a number of papers which did not define crime generators as thoroughly as in the seminal paper. Yoo and Wheeler (2019 p.2), for example, stated that “Places with a larger number of individuals (the denominator) are often referred to as crime generators”. Whilst this is not untrue, as the first element highlighted above concerns the large quantity of people at the location, one can argue that this is not sufficient for a definition of a crime generator, as it misses the two

other fundamental elements proposed by Brantingham and Brantingham (1995). Similarly, Song et al. (2019 p.833) claimed that “crime generators produce crime because they are widely known and because they provide abundant opportunities”. Whilst, as before, this is not necessarily incorrect, this suggestion misses the second and third factors in the list above. Moreover, one could argue that crime generators do not produce crime concentration because they are “widely known”, but rather because they are *widely used*.

A number of other articles miss one of the points proposed by Brantingham and Brantingham (1995) but incorporate the remaining two. Some, for example, did not include the second point; that the crimes committed at crime generators are primarily opportunistic, including Irvin-Erickson and La Vigne (2015), Drawve et al. (2016) and Adams and Felson (2015). Others, such as Tillyer et al. (2020), Song et al. (2017) and Feng et al. (2019) omit the third element; that crime generators are not criminogenic.

Finally, a number of papers did not provide definitions at all. Whilst some authors seemingly excluded their definition as their research was focused on crime attractors (for example Hewitt et al. (2018), Iwanski et al. (2012) and Reid et al. (2014)), others neglected to provide a definition, despite researching factors concerning crime generators, including Kimpton et al. (2017), Tita and Ridgeway (2007) and McCord and Ratcliffe (2007). Additionally, Han et al. (2019) provided an inaccurate definition for both crime generators and attractors by not separately defining them (“certain facilities play a role of generator or attractor of crime by attracting large numbers of people that may likely be victims or offenders” (Han et al., 2019 p.8)). Whilst this could be considered to include elements of definitions for both crime generators and crime attractors, as defined later, it does not specifically cover any of the three points for a definition for a crime generator which is in keeping with Brantingham and Brantingham's (1995) original concept.

As well as absent and incomplete definitions, there were also a number of papers identified through the review methodology that did not align their definition with any of the mechanisms itemised above. Sheard (1998 p.1), for

example, referred to crime generators as “centers for drugs and crime”, and LeBeau (2012 p.80) claimed that crime generators are “establishments used as a bases [sic] for criminal activities”. Besides these irregular definitions, Breetzke et al. (2019, no page) consider crime generators to be “places to which strongly motivated, intending criminal offenders migrate to because of opportunities for crime”, which is notably more in keeping with the original definition given for a crime attractor (Brantingham & Brantingham, 1995), and does not appear to have any of the features of a crime generator. As a result, the focus of work in Breetzke et al.'s (2019) paper is hereafter referred to as crime attractors.

#### **4.3.1.2 Crime Attractors**

Similarly to crime generators, in order to explore the definitions provided for crime attractors, it is important to first examine their original definition, which shall be used to create an outline highlighting their key mechanisms:

*“Crime attractors are particular places, areas, neighbourhoods, districts which create well-known criminal opportunities to which strongly motivated, intending criminal offenders are attracted because of the known opportunities for particular types of crime”*

(Brantingham and Brantingham, 1995 p.8)

After examining Brantingham and Brantingham's (1995) definition above, the following elements are proposed as integral to a definition of a crime attractor: (1) the reputation of the space as offering criminal opportunities, and (2) the fact that motivated offenders visit them with the specific goal of committing crime. Comparing against these proposed mechanisms, a number of papers provided definitions which were in keeping with Brantingham and Brantingham's (1995) original idea, including LaRue and Andresen (2015), Bowers (2014) and Song et al. (2017).

Moreover, a definition was considered incomplete if it referred to only one mechanism of the two specified. Of the papers examined in this review, four articles overlooked one component. Yoo and Wheeler (2019 p.3), for example, stated “Due to more vulnerable targets within a location, it may be that motivated offenders are attracted to particular areas to commit a crime”. Whilst the second element of the schema, that concerning the luring of

motivated offenders to the space, is clearly included, the first, regarding the reputation of the area, is absent. McCord et al.'s (2007) and Piza and Gilchrist's (2018) definitions also have the same weakness. Boessen and Hipp (2018), on the other hand, refer to the criminal reputation of crime attractor areas, but exclude the concept of drawing the offenders to them.

A number of papers, such as that by Kimpton et al. (2017), Sheard (1998), and Vandeviver et al. (2019), omitted a definition for crime attractors due to their studies' focus on crime generators. Some, on the other hand, neglected to define crime attractors despite their research focusing on them, including Hewitt et al. (2018) and Xu and Griffiths (2017).

Moreover, some papers provided definitions for crime attractors which are not in line with the definition discussed above. Both Song et al. (2013) and LeBeau (2012), for example, primarily defined crime attractors as spaces that provide attractive targets for offenders, overlooking both of the factors in the schema. Interestingly, however, LeBeau (2012) acknowledges that their definition is dissonant with that provided by Brantingham and Brantingham (1995). Malleson and Andresen (2016 p.58) also neglect to incorporate either of these elements into their definition, instead referring to crime attractors as "places that are used specifically for criminal activity", further confusing the concepts.

#### **4.3.2 Causal Mechanisms of Crime Generators and Attractors**

In order to better understand crime generators and attractors, it is important to develop understanding of the proposed causal mechanisms underpinning them. As a result, this work shall look into those papers that specifically explored the elements that would lead to the emergence of a hotspot at a crime generator or attractor, as per the definitions outlined above. Despite the importance of the mechanisms at work, only 11 of the 48 papers examined here discussed them, their second order implications, or elements relating to them. In this section, the contributions that these 11 papers made to understanding of these concepts shall be discussed.

Two papers in this review specifically discussed the mechanisms behind crime generators. Firstly, Newton (2018) discussed the notion of busy-ness at crime generators in his textbook-style paper. The author suggested that a

number of factors need to be considered when discussing this, including the number of people in the space, the density of people in the space, and the length of time they are together. Secondly, Vandeviver et al. (2019) explored the criminogenic effects of stadiums as crime generators, to investigate whether they generate crime only on days when they are used, or if they also provide opportunities which can then be revisited. They identified that stadiums experience both immediate and delayed crimes, and suggested that these two types of criminogenic effect are conceptually distinct. Whilst Brantingham and Brantingham (1995) did note this potential distinction at crime generators, this was not discussed at length and thus benefits from this additional investigation and empirical support.

As well as these papers on crime generators, five articles examined crime attractor mechanisms. Song et al. (2013), for example, in their work into the relationship between crime attractors and mobility, noted that crime attractors do not necessarily lead to crime occurring uniformly around a central point. Instead, they posit, crime attractors' connection to major pathways leads to the emergence of crime ridges that can connect these types of sites. Similarly, both Frank et al. (2011b) and Mago et al. (2014) also consider the impact of attractors on each other. Both examine the attractiveness of shopping malls as crime attractors, focusing on the strength of attraction around malls and the relative attractiveness of multiple crime attractors respectively. Despite their slightly different focus, both of these articles conclude that the presence of multiple crime attractors can change the attractiveness of each. Frank et al. (2011b), for example, identify that malls have different levels of attractiveness depending on their size, with smaller malls acting as weaker crime attractors. They also explore the consequences of the addition of crime attractors in an area, concluding that this addition does not affect all crime attractors equally, with some crime attractor sites becoming stronger and others weaker. Mago et al. (2014), on the other hand, stress that relative attractiveness is subject to a number of factors, finding that stronger attractors were those with better transport links, a wider range of services and in more central locations, rather than purely related to size. Similarly, Iwanski et al. (2012) also identify that multiple

factors contribute to a site's relative attractiveness, including size, accessibility and the criminogenic nature of the surrounding area.

Moreover, both Iwanski et al. (2012) and Frank et al. (2011a) examined offenders' journeys to crime attractors. Iwanski et al. (2012), for example, investigated the impact of crime attractors along a route, rather than the impact at the destination itself, concluding that crime attractors are not necessarily a single node, but rather raise the attractiveness of the whole area in which they are located. Frank et al. (2011a) reach a similar conclusion from their research. By identifying clusters of criminals' intersections, they identify these as potential locations of crime attractors, but stress that the crime attractor is not a single point, but encompasses the surrounding area as well. Whilst this method identified three malls as crime attractors, the authors highlight that not all malls created clusters that were indicative of crime attractors, and therefore not all of a certain facility type could be classified as such.

In addition to these papers that considered the mechanisms of either crime generators or crime attractors, five papers examined them in tandem. Among them is that of Brantingham and Brantingham (1995), who introduced the concept and the mechanisms, demonstrating them empirically as well as theoretically.

A number of papers explored methods of classifying spaces as either crime generators or attractors based on their mechanisms, such as Kurland et al. (2014) and Irvin-Erickson and La Vigne (2015). Similarly, Boivin and D'Elia (2017) tried to distinguish between the two types of space based on measures for risk, effort and reward using methods underpinned by these mechanisms. Whilst some could argue that this means that understanding of the mechanisms themselves is not being explored and developed, but rather used to test pre-conceived ideas of crime generators and attractors, empirical work such as this could be used as a method of testing and validating these concepts. However, it is noted that no validation of these classification approaches was evident through this review.

To summarise, whilst research into the mechanisms underpinning crime generators and attractors would be incredibly beneficial, it appears that

comparatively little work has been undertaken on it, especially for crime generators. As a result, there can be little surprise when authors use irregular definitions or methods to study them, when the foundations for understanding this idea are somewhat limited. If the concept of crime generators and attractors is to be developed further than merely a post-hoc explanation of crime concentration (Davies & Birks, 2021), further understanding is required into these underlying processes.

## **4.4 Discussion**

This scoping review aimed to examine papers that explored the concept of crime generators and attractors to answer the question *to what extent have the mechanisms behind crime generators and attractors been studied?* In order to answer this question, each of the objectives of this review shall be discussed before suggestions for further research and a final conclusion.

### **4.4.1 To What Extent Have Crime Generators and Attractors Been Studied?**

Through this review, it has been identified that crime generators and attractors, although often referred to in environmental criminology, have been relatively understudied. Whilst a great many papers refer to these types of spaces, the number of those that focus on researching and verifying the mechanisms that might underpin them is far lower. Indeed, of the papers that were included here, not all aligned their work with the mechanisms of crime generators and attractors put forward by Brantingham and Brantingham (1995). This will be discussed in more depth in Section 4.4.3, but also calls into question the extent of the scholarship on this topic. Although general studies into these spaces are beneficial to the field of environmental criminology, it is possible that further understanding of these mechanisms would extend the breadth and depth of this topic, and indeed go further in confirming the validity of the concept or the need for its refinement.

This scarcity of in-depth research is a problem theoretically, as it leads to potentially unsubstantiated claims for locations of these types of spaces. However, identifying a crime cluster and simply allocating it to one of these

classifications without exploring it could also lead to practical limitations for law enforcement who could tailor crime reduction strategies to the processes which are suggested to be taking place. Not only could the mechanisms underpinning crime generators and attractors not be at play in that location, and thus the location be incorrectly classified, but there may be processes leading to a different type of crime cluster which is currently unidentified. By labelling this site a crime generator or attractor, these unidentified mechanisms could remain unknown.

One could ask why this is the case; why are crime generators and attractors so often used as a post-hoc explanation for an area of crime concentration (Davies & Birks, 2021) with little research into the concept itself? Firstly, this lack of research could be caused by the seemingly self-explanatory nature of crime generators and attractors. When one examines the mechanisms proposed by Brantingham and Brantingham (1995), they appear easily understood; that crime concentration occurs either where there are a lot of potential targets, or where motivated offenders go because they want to commit crime. As a result of this apparent simplicity, it is possible that researchers feel they have sufficient understanding into these spaces to use these monikers without researching them further. Secondly, it could be the result of previous researchers setting a precedent. If it has become the norm that crime concentrations can be attributed to a crime generator or attractor without much research, this could be seen as common practice and therefore acceptable. Thirdly, it could be because it is challenging to empirically verify these mechanisms. As highlighted previously in this thesis, it is difficult to obtain appropriate data to empirically examine these processes, resulting in limited ways in which to test them. As a result, this concept has remained largely unverified and potentially misunderstood. This is discussed in greater length in the coming section.

Is it possible, however, that all crime hotspots are in fact caused by the mechanisms behind crime generators or attractors, and consequently this frequent use of these labels is correct? One must consider whether there are other mechanisms that could lead to the concentration of crime, or whether those suggested by Brantingham and Brantingham (1995) are applicable to all possible hotspots. This, however, seems unlikely. Not only have other

types of hotspots been proposed (such as crime enablers (Clarke & Eck, 2003)), but there must also be consideration for other mechanisms that have yet to be formally hypothesized. For example, a crime hotspot could emerge where lots of opportunistic crimes occur which are not necessarily related to large numbers of people being present. This sort of hotspot could not be classified as either a crime generator or an attractor but is conceivable if small numbers of victims are repeatedly victimized in the same place, for example. As a result, it seems unlikely that all areas of crime concentration could be considered as crime attractors or generators, adding to the argument that they need to be researched further.

#### **4.4.2 How have Crime Generators and Attractors been Defined?**

This research has demonstrated that Brantingham and Brantingham's (1995) original definitions have been open to much interpretation in later work. In this review, the key components of the definitions of both a crime generator and crime attractor were formalised, and each definition in the papers included in this review were then compared against this formalisation. Doing so, it was identified that whilst some articles defined crime generators and attractors in keeping with the mechanisms proposed in the seminal paper, a number of others gave definitions that were either incomplete or inconsistent with those originally put forward. As a result, when one explores the definitions of crime generators and attractors, the main conclusion is one of inconsistency, as the definitions provided by the authors vary a great deal between papers. But what could be the cause of this disparity? Two potential explanations have been identified.

Firstly, variation could be the result of previous researchers examining crime generators and attractors without providing accurate definitions. Neglecting to define these concepts accurately could have led to further misinterpretation, consequently solidifying further misuse. Even in the articles included in this study, which were selected because of their focus on crime generators and attractors, a variety of different definitions were provided. Indeed, of the 48 papers included in this review (of which one is the original Brantingham and Brantingham (1995) paper), 15 did not reference the seminal work while providing their definitions of the spaces.

Whilst an incomplete definition, or an absent one, does not lead one to automatically assume limited understanding of the topic, it is potentially inappropriate if the variation from the original concept is not justified. However, in papers where the term has been so inaccurately defined, the authors' understanding of crime generators and attractors is called into question, therefore casting doubt over the validity of the conclusions of the paper. Beyond confusing the terminology further, the use of inaccurate definitions has the potential to dilute the literature base if future researchers base their work on these interpretations. As a result, it is recommended that future work follows the formalisation above, based on Brantingham and Brantingham's (1995) original definition, when defining these spaces, to ensure that research is in line with the original concepts and mechanisms. Although it is possible that these original definitions were overly simplified, and thus other definitions could be more useful when examining crime concentration, it seems sensible that these original concepts need to be tested first. Rigorous testing of these initial ideas, through analysis of the mechanisms outlined above, will enable potential gaps in the definitions to be identified, which could allow for their development. Improving understanding of the definitions of crime generators and attractors will not only aid in theoretical comprehension, but it will also assist in the development of methods to empirically identify these spaces in the real world, as it will lead to greater clarity of how the components of each can be explored. As long as the definitions of these types of spaces remain contentious, challenges will persist in classifying a real-world location as either a crime generator or a crime attractor.

Secondly, divergence from Brantingham and Brantingham's (1995) definitions might be caused by the fact that crime generators and attractors are challenging to identify empirically. Not only does this lead to further confusion about their underlying theory, but also means that testing and verifying these mechanisms is challenging. Given that the primary difference between these two types of spaces is offender motivation (Newton, 2018), it is necessary to obtain data on this highly complex topic to accurately differentiate between them empirically. Whilst some have attempted to use proxies for motivation (such as Sosa et al.'s (2019) variable of 'magnetism',

which represented the attractiveness of a casino for crime), this could be most accurately achieved through qualitative work. Indeed, one could question whether proxies such as that used by Sosa et al. accurately reflect offender motivation or merely target attractiveness. However, methods such as interviews with offenders were not used in any of the papers examined in this review. Not only is empirical evidence for the classification of spaces as either crime generators or attractors limited (Kurland et al., 2014), but the two spaces often share many of the same features (Newton, 2018; Song et al., 2019), and can be hard to differentiate in reality (Yoo & Wheeler, 2019). Indeed, this was recognised by Brantingham and Brantingham (1995) in their original paper, who highlighted that spaces are unlikely to be purely crime generators or attractors. As a result, challenges in empirically identifying them and distinguishing between the two could lead to challenges in defining them.

#### **4.4.3 To What Extent Have Crime Generators' and Attractors' Causal Mechanisms Been Studied?**

Not only were the mechanisms underpinning crime generators and attractors missing from several of the definitions provided, they were also absent from the research in many of the papers examined here. Whilst a wide range of work was undertaken across the papers included in this review, the analysis was rarely specific to the formative mechanisms, their characteristics or their second order implications. This means that although a breadth of knowledge has been gained concerning a wide range of locations potentially acting as crime generators or attractors, there is little depth of understanding of these processes. Of those papers that did explore these mechanisms (n=11), some papers were fairly unique in their angle, and other ideas were used in multiple studies. Several papers, for example, explored the impacts of multiple crime attractors near each other, and others examined offenders' journeys to crime attractors. Additionally, a number of papers used elements of these mechanisms to explore methods of classifying spaces as either crime generators or attractors.

Three potential causes for the lack of research into these mechanisms could be suggested. Firstly, the aforementioned problem of inconsistently defining crime generators and attractors could lead to confusion and

misunderstanding of which mechanisms are actually at play in these locations. Until a consistent definition for these spaces can be identified, it is unsurprising that research into these processes is minimal. This paper has attempted to formalise the processes specified in these original definitions, but this wide range of interpretations suggests that the mechanisms are unclear. Secondly, this dearth of research could be caused by challenges in identifying datasets and methodologies to appropriately study and verify these purported processes. Not only do the crime data have to be at a fine level of geographic accuracy, research into this area would also require data on the motivation of the offender, which is not easily obtained. It is possible that more research could have been conducted on these mechanisms if they were easier to quantify. However, as technology and access to novel datasets develops over time, it is possible that this will present less of a problem for the field. Thirdly, as Brantingham and Brantingham (1995 p.9) stressed in their seminal paper, places are “unlikely to be pure attractors or pure generators”. This notion further complicates this idea, which is already challenging to investigate, as even with appropriate definitions, datasets and methodologies, it will be difficult to know the extent to which a location has elements of each of these mechanisms.

Despite these challenges, further understanding of crime generators and attractors will be difficult until these mechanisms have been examined. This review has identified that within the extant literature there is limited research ascertaining if these proposed underlying mechanisms are indeed at play at crime hotspots. Whilst a small number of the papers examined here found crime concentration in areas where crime attractor mechanisms were proposed to be occurring, research exploring crime generator mechanisms was limited. Until these processes have been appropriately tested, we cannot know that crime generators and attractors affect crime patterns or lead to the emergence of crime hotspots in the manner in which they are theorized to, thus throwing some doubt over the existence of crime generators and attractors in the guise in which Brantingham and Brantingham (1995) proposed.

#### **4.4.4 Future Research Recommendations**

Through conducting this scoping review, a number of research gaps have been identified, starting with a scarcity of studies testing the mechanisms underpinning crime generators and attractors. Not only would more research in this area enable the verification, or refutation, of this concept, but it would also enable appropriate definitions for these types of spaces to be identified. When considered in tandem, it is hoped this will lead to improved scholarship in this field.

In addition to these recommendations around basic comprehension of the topic, this scoping review has led to speculation on three additional elements of the concept of crime generators and attractors that could benefit from being explored. Firstly, which characteristics of locations enable the crime generator and attractor mechanisms to turn these sites into crime hotspots? When examining locations that are given as examples of crime generators and attractors, it is evident that not all facilities of that type lead to crime concentration. For example, this was highlighted by Frank et al. (2011a) in their study of shopping malls as crime attractors, who identified that not all shopping malls lead to crime patterns indicative of the crime attractor mechanisms at play, and Groff and McCord (2012), who found that whilst some parks appear to be crime generators, the relationship between parks and crime varies between sites. This suggests that the processes that lead to the emergence of a crime generator or crime attractor do not affect all facilities in the same way. One must question, therefore, what characteristics of a site contribute to the development of a crime generator or attractor? Whilst the characteristics affecting the strength of a crime attractor were discussed by several authors in this review (including Frank et al. (2011b); Iwanski et al. (2012) and Mago et al. (2014)), those for crime generators were only considered by Tillyer et al. (2020), who explored the features that can moderate the effect of crime generators on offences and Irvin-Erickson & La Vigne (2015) who examined crime generating- and attracting-characteristics of metro stations. Moreover, is it possible that these characteristics can lead to subtypes of crime generators and attractors? If these contextual factors do affect the way in which the crime generator and attractor mechanisms lead to crime hotspots, it could be that these two types

of spaces are umbrella terms for a wider classification of types of crime concentration. If this is the case, this could be of interest both theoretically and practically, if crime reduction strategies could be tailored to more specific mechanisms.

Similarly, a second area of research that would be of interest to the field relates to types of crime attractors. Whilst the “traditional” idea of a crime attractor is an area with a reputation for criminal opportunities that lures motivated offenders, it has been suggested that a crime generator can transition into a crime attractor and take on these characteristics as its reputation worsens (Clarke & Eck, 2003). Although it could be argued that the mechanisms underpinning both a traditional crime attractor and this “transition attractor” are the same, this is not necessarily the case. For example, is it reasonable to assume that this new “transition attractor” still experiences opportunistic offences committed by those using the site the way in which a crime generator location is traditionally used, therefore taking on mechanisms of both types of spaces? Or, as the reputation of this transition attractor worsens, do people stop using the site for its original purpose, as suggested by Clarke and Eck (2003)? If this is the case, can the site remain a crime attractor if the original target pool has disintegrated? Unless the type of crime that lures offenders to the site has shifted, it seems unlikely that the mechanisms underpinning a crime generator can transition entirely into those of a crime attractor.

Thirdly, the relationship between crime generators and attractors and types of crime would be an interesting topic for further study. When these types of spaces are discussed in the literature, the term “crime” is often used generally, with little distinction as to the type of offence taking place there. Indeed, whilst some of the papers studied here mentioned that crime generators and attractors could experience different types of crime, this tended to be more in passing than at any length (see, for example, Boessen and Hipp (2018), Bowers (2014) and Demeau and Parent (2018)). Despite this, Brantingham and Brantingham (1995) refer to crime generators as “settings that are conducive to *particular types of criminal acts*” (Brantingham and Brantingham, 1995 p.7, emphasis added), and to crime attractors as “particular places... [to which] intending criminal offenders are attracted

because of the known opportunities for *particular types of crime*” (Brantingham and Brantingham, 1995 p.8, emphasis added). As a result, one can conclude that the type of crime that takes place at both of these spaces is highly specific to that area. Not only is this inferred by the definitions, but it can be suggested that the processes underpinning crime generators and attractors could lead to hotspots for different types of crime (Bowers, 2014; Newton, 2018). Crime generators, for example, regardless of the type of facility being examined, would see a great deal of opportunistic crime which need a large target pool, such as pick pocketing. Crime attractors, on the other hand, would experience large amounts of crime that would require targets to be more actively sought, such as arson. When considering the types of crime that would take place at crime attractors, it seems reasonable to suggest that some crime attractors would be areas which have reputations for highly specific types of crime. As a result, the crime concentration that occurs at these locations, and indeed at crime generators, could be specific to a certain type of crime. Furthermore, as pointed out by Newton (2018) and Irvin-Erickson and La Vigne (2015), it is possible that a location is a crime generator or attractor for a specific crime at a specific time of day, or as posited by Brantingham and Brantingham (1995), that a site can be a crime generator for one type of offence but a crime attractor for another. Further study of crime types at these locations could be a valuable avenue for future research, as potential crime generator and attractor sites could have been missed if analysis focuses purely on concentration of all offences, rather than identifying hotspots of specific crime types.

## **4.5 Conclusion**

To conclude, one must re-examine the research question: *To what extent have the mechanisms behind crime generators and attractors been studied?* This review has identified a dearth of work to support the mechanisms proposed, and therefore limited evidence to confirm the occurrence of these processes at crime hotspots. As a result, this could call into question the existence of crime generators and attractors as hypothesized by Brantingham and Brantingham (1995). Three potential reasons for this

paucity of research were suggested; appropriately defining these types of spaces; identifying suitable datasets and methodologies to verify these mechanisms; and the fact that spaces are rarely exclusively either crime generators or crime attractors. Indeed, the challenge of studying crime generators and attractors empirically emerged several times throughout this research and remains one of the largest hurdles for developing understanding of this concept.

### **Summary**

*This chapter has detailed the methodology and results of a scoping literature review which was undertaken to answer the question to what extent have the mechanisms behind crime generators and attractors been studied? This review has identified a lack of research into these mechanisms, and great inconsistency between definitions for these types of spaces. The use of scoping review methodology enabled this research to successfully meet the first objective of this thesis, to critically appraise previous research on crime generators and attractors to identify how they are defined and the extent to which their mechanisms have been studied, as it permitted the systematic inclusion of papers relevant to this research, and the exclusion of those which do not explicitly study this topic.*

*The results of this chapter inform the subsequent chapters in this thesis, in particular the computational work in Chapter 6. Here, the crime generator and attractor mechanisms identified through this scoping review shall be formalised and used to create an agent-based model. Moreover, through undertaking this scoping review, the lack of validation of classification methods for crime generators and attractors became apparent. This led to the development of the research which forms Chapter 5 of this thesis, comparing two classification techniques. This is the work which follows in the subsequent chapter.*

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## **Chapter 5**

### **Investigating Crime Generators And Attractors on a University Campus: a Comparison of Classification Techniques**

#### ***Preface***

*Through undertaking the scoping literature review in Chapter 4, it was identified that little validation of classification methods for crime generators and attractors exists in the extant literature. This chapter consequently focuses on empirical classification of sites as crime generators or attractors and aims to examine whether two classification methods identify the same crime generators and attractors, acting as proof of concept to validate these approaches. Two proposals are tested; (1) that crime generators have high counts and low rates of crime, but that crime attractors have high counts and high rates (Clarke and Eck 2003, 2005); and (2) that different types of crime take place at each of these locations (Newton, 2018, among others). Not only does this chapter fill a literature gap by attempting to validate these classification approaches, but it also provides a good introduction to the complexities of empirically studying crime generators and attractors.*

*The study used incident data from a university campus security team, as their temporal and spatial accuracy are better than publicly available police data. To test the first method, buildings were identified that had crime counts and rates greater than one standard deviation above/below the mean. To test the second method, crime types associated with crime generators and attractors were identified from the literature, and crime location quotients were calculated for each building.*

*Although both approaches identified at least one crime generator or attractor, no buildings received the same classification by both methods. This demonstrates the complexity in studying these spaces and suggests that these classification methods should only be used with additional validation.*

*The work in this chapter aligns with Objective 2 of this thesis, to investigate previously suggested methods for empirical classification of crime generators and attractors, to explore whether multiple methods identify the same areas as crime generators and attractors. Moreover, it feeds into Chapter 7, which contains the additional empirical work, as it highlights the complexity of identifying empirical case studies of crime generators and attractors. Not only does this impact the selection of case studies for the research in Chapter 7, it also shapes one of the objectives of that work, to investigate another classification method.*

## **5.1 Introduction**

In studying the relationship between crime and the urban backcloth, Brantingham and Brantingham (1995) proposed that crime hotspots can be classified into two types of spaces, each with different causal mechanisms; crime generators and crime attractors. Crime generators, they suggested, are areas that lots of people visit for reasons unrelated to crime, such as public transport hubs. Here, opportunistic offenders commit crimes when they encounter criminal opportunities, even if they were not actively seeking them. As a result, crime generators, which are not inherently criminogenic themselves, become crime hotspots due to the large number of opportunistic crimes that offenders commit, and the crime problem here can become more severe as the use of the area increases (Clarke and Eck, 2003). Crime attractors, on the other hand, are areas with a reputation for criminal potential. These spaces, such as drug markets (Brantingham and Brantingham, 1995), become hotspots of crime as motivated offenders visit them specifically to offend. The crime problem here can worsen if the reputation of the area grows (Clarke and Eck, 2005). Although many of the same elements are present at both crime generators and attractors, the main difference between these spaces is the motivation of the offender (Newton, 2018; Sorg, 2016).

Whilst the conceptual difference between these two types of spaces appears straightforward (Newton, 2018), work on crime generators and attractors is not, and empirical research into this concept is limited (Kurland et al., 2014).

This is particularly the case when it comes to classifying a space as either a crime generator or attractor; although the definitions appear to provide a clear distinction between these two types of areas, identifying them empirically has proved challenging. Indeed, Kurland et al. (2014 p.7) stressed that research supporting the classification of spaces as either a crime generator or attractor is “not unequivocal”. Not only would an improved understanding of the classification of these spaces go some way to testing and validating the processes behind crime generators and attractors, but it could also be used to target crime reduction strategies. Given that the main difference between these two types of spaces is offender motivation, crime generators and attractors could require different law enforcement strategies (Sosa et al., 2019) as areas which experience a lot of opportunistic crime would respond to different policing to those which experience a lot of premediated offending. Consequently, a more developed method for distinguishing between these spaces in the real world could be of benefit to law enforcement.

This work therefore aims to test methods of empirically classifying crime generators and crime attractors by comparing two methods of classification to answer the following research question: will two different classification methods for crime generators and attractors identify the same areas? This paper will act as proof of concept, testing and validating these classification approaches. This shall be achieved through the following objectives:

1. Explore Clarke and Eck's (2003, 2005) proposal that areas with comparatively high counts and low rates of crime are crime generators, and areas with relatively high counts and high rates are crime attractors, by identifying sites in the study area which meet these requirements.
2. Identify clusters of different types of crime, testing the suggestion of the types of crime expected at crime generators or attractors (Newton 2018, among others).

The case study examined will be a university campus in England. This campus, unnamed due to confidentiality agreements, is located within walking distance of a city centre, and was selected because spatially and

temporally accurate data could be obtained from the University's security team on the location of incidents on the campus. This is discussed further in Section 5.3.1. This paper creates maps showing the locations of crime generators or attractors using both of the methods above, and then compares them to identify similarities and differences between the results. The first method is applied by identifying buildings that have crime counts and rates greater than one standard deviation above/below the mean, as appropriate, and the second uses crime location quotients to identify crime hotspots for offences that are indicative of either type of space.

The structure of this paper is as follows. Section 5.2 provides an overview of the background to this research, going into more detail on crime generators and attractors and their classification, as well as crime on university campuses. Section 5.3 then details the data that will be used in this work, and Section 5.4 discusses the methodology. Following this, Sections 5.5 and 5.6 provide the results and discussion respectively, before Section 5.7 provides conclusions.

## **5.2 Background**

### **5.2.1 Challenges in Researching Crime Generators and Attractors**

Although crime generators and attractors have been referred to as the "most salient crime predictors" (Connealy, 2020 p.4) there is a lack of research into this topic. But if this concept is considered so integral to understanding crime concentration, why has it not been the subject of more research? Three potential reasons for this are proposed.

Firstly, although crime generators and attractors can vary in size from small facilities, such as bus stops, to areas of a city, they are traditionally considered to be micro places. Whilst there is no exact definition for the size of a micro place, they range from specific buildings to clusters of addresses (Weisburd et al., 2004). Studying areas at this level of granularity is traditionally more challenging, as the data required are more specific (Connealy, 2020). Fortunately, data that are appropriate for work at this level, such as that with highly accurate geocoding, has become more readily

available over time, enabling research into micro spaces to become more popular (Connealy, 2020).

Secondly, certain elements of crime generators and crime attractors are challenging to research. For example, when studying crime generators, one of the key components is the presence of a large number of people in these spaces. As a result, researchers require data on ambient populations, defined as the number of people within a given space at a particular time (Andresen, 2011; Whipp et al., 2021), in order to understand the number of people at the location. However, this sort of data is rarely readily available (Malleon and Andresen, 2016). Whilst this has restricted research into crime generators, it has been surmountable. To avoid this problem in their research on parks as crime generators, for example, Groff and McCord (2012) examined facilities that bring people to the parks, such as playgrounds, as a proxy for usage to understand how busy the parks would be. When studying crime attractors, researchers face a similar challenge as they require data on offender motivation in order to understand the “luring” of the offender to the attractor space. Without conducting interviews this can be difficult to obtain. A number of authors have instead used offender journey data as a proxy for motivation, inferring the locations of crime attractors by estimating the area that the offender was travelling towards when they committed a crime (Frank et al., 2011b, 2011a; Iwanski et al., 2012). As a result, it is possible that a broader range of research into crime generators and attractors has not been undertaken due to the challenges associated with obtaining data on their integral processes.

Thirdly, in the seminal paper that introduced the crime generator and attractor concept, Brantingham and Brantingham (1995) stressed that spaces are rarely exclusively either a crime generator or a crime attractor, and that spaces could display elements of both. This was later identified empirically by authors such as Irvin-Erickson and La Vigne (2015) who found that transit stations can be identified as either type of space, depending on the time of day being studied. This illustrates the consideration that there could be a spectrum between the two types of spaces, rather than a binary distinction between the two. Indeed, Clarke and Eck (2005, 2003) proposed that a space can transition from a crime generator to a crime attractor as its

reputation as a crime generator grows. As a result, if it is difficult to conclusively identify a facility as either a crime generator or attractor, this might deter researchers from studying them.

Given the frequency at which crime generators and attractors are referred to in environmental criminology literature, it is a surprise that their mechanisms have not been studied more, despite these limitations. The challenges identified here are not insurmountable but require careful consideration when identifying datasets and methodologies. The following research attempts to address these challenges, exploring potential ways in which they can be overcome.

### 5.2.2 Classifying Crime Generators and Attractors

Although spaces are rarely exclusively either a crime generator or a crime attractor (Brantingham and Brantingham, 1995), there is great potential value in classifying them as either one or the other, and a few methods have been put forward to do so. Whilst some of these potential methods are merely mentioned, rather than developed, this variety in methods suggests that a number of potential avenues could be explored when attempting this classification. The following section will introduce the approaches examined in this work and justify their selection. Moreover, a comprehensive list of classification methods identified through a literature search is provided in Table 5.1.

| <b>Reference</b>            | <b>Case Study Facility</b> | <b>Classification Method Used/Suggested</b>  | <b>Method Undertaken/ Proposed/ Mentioned</b> |
|-----------------------------|----------------------------|--|---|
| Clarke and Eck (2003, 2005) | Not Specified              | Calculation of crime counts and rates. The authors suggest that crime generators have a high count and low rate of crime, but that attractors have a high count and high | Proposed                                      |

|                           |                   |   |            |
|---------------------------|-------------------|---|------------|
|                           |                   | rate of offences  |            |
| Bernasco and Block (2011) | Not Specified     | Identification of the location of cash economies, proposing that the presence of these facilities could suggest that a site is a crime attractor  | Proposed   |
| LeBeau (2012)             | Hotels and Motels | Identification of variables relating to the hotels (e.g. room rate) to identify whether they are related to a specific crime types which could indicate either a crime generator or attractor | Undertaken |
| Groff and McCord (2012)   | Parks             | Identification of “activity generators” in parks to identify if they are crime generators   | Undertaken |
| Kurland et al. (2014)     | Football Stadium  | Application of the method proposed by Clarke and Eck (2003, 2005)   | Undertaken |
| Bowers (2014)             | Not Specified     | Study of the crime types around a site, suggesting that property crimes are more prevalent at crime generators and violent crime at crime   | Mentioned  |

|                                    |                |  |            |
|------------------------------------|----------------|--|------------|
|                                    |                | attractors   |            |
| Irvin-Erickson and La Vigne (2015) | Metro Stations | Creation of variables related to the crime generator and attractor mechanisms  | Undertaken |
| Sorg (2016)                        | Various        | Examination of offender journeys, suggesting that the length of the journey could be indicative of a crime generator or crime attractor  | Undertaken |
| Boivin and D'Elia (2017)           | Various        | Examination of offender journeys, identifying elements that affect anyone (crime generators) and those that only effect offenders (crime attractors)                                       | Undertaken |
| Newton (2018)                      | Not Specified  | Study of the crime types around a site, suggesting that some crime types, like pickpocketing, are more prevalent at crime generators and others, like property crimes, at crime attractors | Mentioned  |
| Sosa et al.                        | Casinos        | Creation of a  | Undertaken |

|                        |         |  |            |
|------------------------|---------|--|------------|
| (2019)                 |         | variable representing magnetism and exploration of the reputation of the sites through online reviews  |            |
| Yoo and Wheeler (2019) | Various | Identification of a facility as a crime generator if it is accessible to all, or a crime attractor if it is more specific to homeless people | Undertaken |

**Table 5.1 - Classification Methods for Crime Generators and Attractors in Extant Literature**

From the list in Table 5.1, some papers proposed classification methods that were unique to their research projects and would therefore not necessarily be applicable to a broader range of case studies. In the current research, two more general classification methods were used, which will now be discussed in turn.

The first method is that proposed by Clarke and Eck (2005, 2003), which compares the counts and rates of crime at a site. They posited that crime generators have a high count and low rate of crime, but that attractors have a high count and high rate. This method, they suggested, is particularly useful for comparison purposes when there is an absence of data on offender motivation, as the rankings are relative (Clarke and Eck, 2005). However, this concept is not without limitations, primarily regarding the identification of an appropriate denominator for establishing crime rates (Newton, 2018).

The second approach chosen for examination here concerns the different crime types expected at crime generators and attractors. A number of authors, including Newton (2018) and Bowers (2014), highlighted that different crime types could be associated with these types of spaces.

However, there is little consistency with the offences they posited would occur there. Newton (2018), for example, suggested that crimes that occur more frequently in busy locations, such as pickpocketing, may be indicative of crime generators and that those that are more common at quieter times, such as property crime, could be suggestive of crime attractors. Similarly, Irvin-Erickson and La Vigne (2015) noted that crimes that would require a lack of guardianship, such as vandalism, are more likely to occur at crime attractors. Bowers (2014), on the other hand, suggested that property crimes could be a characteristic of crime generators, whereas violent crimes could occur more at crime attractors, but does not relate this suggestion back to the crime generator and attractor mechanisms. Vandeviver et al. (2019) made a similar point, suggesting that high-volume crime such as property offences could be suggestive of crime generators. This disparity between the offences expected at these sorts of locations demonstrates the confusion around the mechanisms that occur at each. For this current research, however, a list provided by Newton (2018) was developed as his work was supported with justifications based on the crime generator and attractor mechanisms. This is discussed in more detail in Section 5.4.2.

Despite authors suggesting a variety of methods for empirically classifying a space as either a crime generator or attractor, and in some cases applying them to their own research, there has been little work undertaken to validate these approaches. By comparing the two methods discussed above, this research aims to go some way to substantiate them. If the same locations are categorised together, as either an attractor or a generator, by both methods, this could suggest that these methods are suitable for empirically identifying these types of spaces. If the categorisations contradict each other, however, this could indicate that these methods do not appropriately distinguish between the processes for crime generators and attractors proposed by Brantingham and Brantingham (1995).

### **5.2.3 Crime Generators and Attractors on a University Campus**

Given that this work is looking at crime generators and attractors on a university campus, it is important to consider this context when looking at the results of this work. Although crime on American university campuses was

found to have decreased by 31% between 2001 and 2017 (Wang et al., 2020), university campuses have a reputation as crime hotspots (Henson and Stone, 1999). Despite this reputation, however, several papers identified crime occurrence at these locations to be lower than that in their surrounding communities or the wider city in general (Henson and Stone, 1999; Robinson and Mullen, 2001; Volkwein et al., 1995), but this does depend on the campus location (Tomsich et al., 2011). The influence of the wider city has not, however, been found to consistently affect offending; Fox and Hellman (1985) found that the surrounding area does not necessarily impact crime rates, suggesting that university campuses act as isolated units. Of the studies that have been conducted looking into crimes on university campuses, the results have been somewhat varied, and different crime rates have been found between different campuses and across different types of institutions (LaRue and Andresen, 2015; Volkwein et al., 1995). Despite this, one phenomenon was noted across several studies; that university campuses appear to experience more property crime than violent crime (Henson and Stone, 1999; LaRue and Andresen, 2015; Sloan, 1994). It is important to note, however, that work examining crime on campus suffers from the same problem as research on crime elsewhere; the potential risk of underreporting when using official data. Indeed, Robinson and Mullen (2001 p.44) suggested that there could be a “hidden rape problem on campus” due to underreporting of this sort of crime in this setting.

Despite the mixed results of research into campus crime, some authors such as Newton (2018) have suggested university campuses to be crime generators. As highlighted in Chapter 4, the three key components to a crime generator, according to Brantingham and Brantingham (1995) are: (1) the presence of a great number of people, (2) the fact that offenders commit opportunistic crimes here, rather than travel specifically to the site to offend, and (3) the fact that the site itself is not criminogenic. The first point, that many people are present, feels logical for a university campus given the number of students being educated at these locations, and the large number of people who visit these sites (McGrath et al., 2014). Especially when one considers this in the context of the surrounding area (as advocated by Newton (2018)), it is assumed that university campuses generally have

higher population densities than their surroundings. However, it is important to note that this population density is likely to fluctuate over the day, in line with students' movements (Sun et al., 2014). Second, concerning the nature of the crimes committed; although campuses can provide opportunities for motivated offenders (McGrath et al., 2014), it has been identified that many offences committed on university campuses are opportunistic (Henson and Stone, 1999). Finally, concerning the non-criminogenic nature of the sites, it seems a reasonable assumption that the majority of people on a campus are there for legitimate university-related reasons. As a result, all three of the component parts of a crime generator can be met by university campuses, suggesting that they could be classified in this way. There is, however, also the possibility that a university campus, particularly those located in urban environments, could be a crime attractor if they attract offenders from the surrounding area (Fox and Hellman, 1985). There is minimal evidence for this however, as it has been identified that a university campus is not necessarily impacted by its surroundings (Fox and Hellman, 1985).

Is it reasonable, therefore, to examine a university campus not as a crime generator itself, but to explore the potential for crime generators and attractors within it? Newton (2018) has suggested that large crime generators, such as this, could be considered "superfacilities", rather than a single site. He argued that places such as this, alongside having a primary function, comprise a number of smaller facilities as well. It is therefore possible that these smaller facilities could be crime generators or attractors in their own right. Superfacilities have not been the subject of much research, and thus it is unknown how elements such as the size of the university campus effects the processes underpinning crime generators and attractors. However, it will be interesting to examine whether the results of this research are indicative of these mechanisms occurring, thus suggesting that these smaller facilities are indeed these types of spaces. Although not an original aim of this paper, this finding could also provide some verification for the existence of superfacilities.

### 5.3 Study Location and Data

In order to provide context, Figure 5.1 shows the location and use of the buildings across the university campus in England that is the focus of this study.

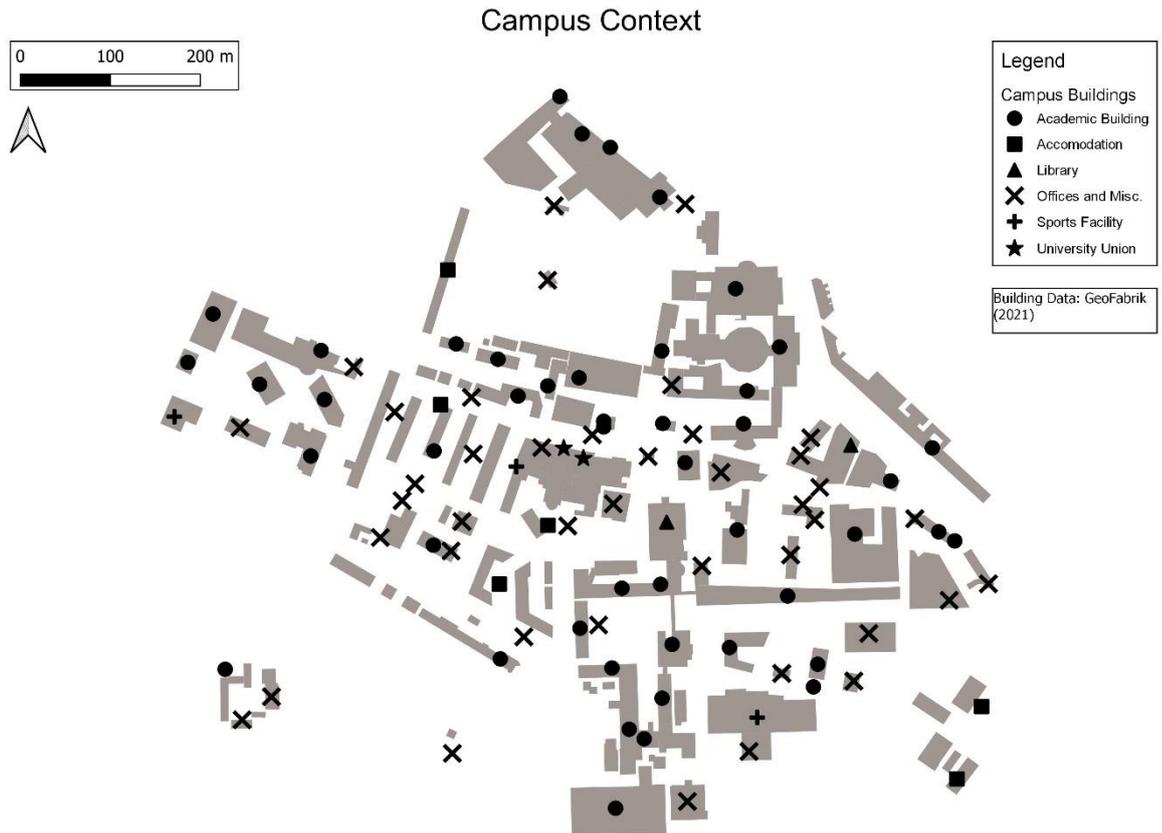


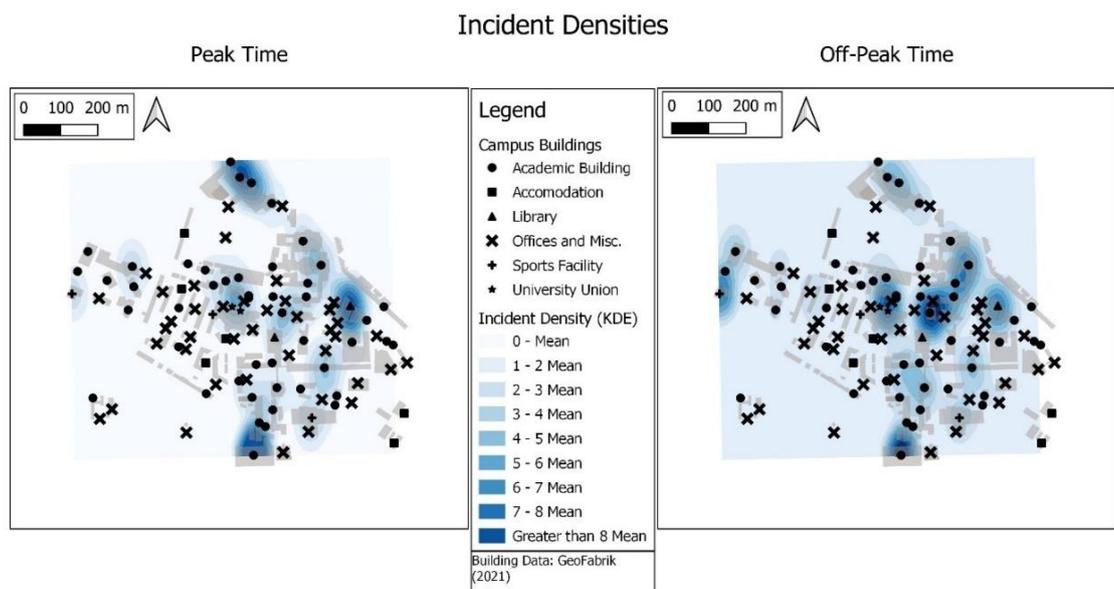
Figure 5.1 - Study Area: Campus Building Locations and Uses. Building Data from Geofabrik (2021)

#### 5.3.1 Incident Data

Incident data were provided by the campus security team, covering all offences reported to security on campus in the time period between 1<sup>st</sup> January 2017 and 1<sup>st</sup> January 2020 (n=563). In addition to incidents reported, this dataset also included those identified by the security team whilst on patrol of the campus, although the data do not distinguish between these two types of report. It also does not distinguish between those offences that were reported exclusively to the security team, and those that were also reported to police. These data were selected for use in this work

primarily because of the temporal and spatial accuracy they provided for each incident recorded. Not only were the locations provided accurate to the specific building in which the incident occurred, but they also had been timestamped. This allows for these data to be analysed at a microgeographic scale, which publicly available police data do not (Tompson et al., 2015)<sup>2</sup>.

A small amount of data cleaning was required to prepare the data for analysis. This included reconciling the building names (for example if a building was called both “The Criminology Building” and “The John Smith Building”), and removing the incidents that were not able to be linked to a specific location (n=63). Figure 5.2 presents the incident density (via Kernel Density Estimation, KDE) for both peak time and off-peak time (see Section 5.3.3 for explanation of these time periods).



**Figure 5.2 - Incident Densities in Study Area in Peak and Off-Peak Times**

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<sup>2</sup> Whilst it would have been beneficial to compare the security team data with police data, this was not possible due to the small size of the study area. Publicly available police data in the UK is too spatially perturbed to compare with data of this spatial scale (Tompson et al., 2015).

### **5.3.2 Campus Buildings**

In order to map the location of the offences on the university campus, data were required on the location of campus buildings and distinct outside spaces such as plazas, hereafter referred to collectively as “buildings”. A list of all buildings on campus was obtained online, and the grid references for each was obtained from UK Grid Reference Finder (2011). The offence data were then linked with this building data, identifying the number and type of incidents per building on campus. When the building name listed in the offence data did not line up with that from the campus map, search engines were used to identify and align them.

In order to accurately calculate offence rates, an appropriate denominator is required. Whilst crime rates are often calculated using residential population counts, this can be misleading as they do not accurately represent the population at risk (Malleon and Andresen, 2015). This was considered to be a particular issue when examining campus incidents, as the population on a campus is not reflective of its residential population. As a result, estimates for the ambient population were required. However, research into calculating ambient populations is limited (Whipp et al., 2021), and no publicly available data exist that would provide accurate ambient population estimates at a small enough scale for this study. To remedy this, a campus-specific ambient population was calculated for this research. This was done by identifying the capacity of each building on campus, using a range of sources. For most buildings, data could be obtained from the university’s online room booking system, as it provided both the number and size of the rooms that could be booked for teaching. When this was not appropriate, other data sources were used including web pages with information of the buildings and requests for information from relevant departments. When a building’s capacity could not be found through these sources, it was estimated by identifying a known capacity for a building of a similar size.

Although these data have the benefit of being more appropriate for this work than residential population counts, they are not without limitation. The most significant is that using the online room booking system misses any additional rooms in the buildings that are used by staff members and are not

bookable, such as administrative offices. This limitation is consistent across the campus, as only a small number of buildings had their capacities estimated using a different method. This means that although the denominators may be slightly underestimated, they are underestimated almost consistently across the space.

The details of how these data were adjusted to calculate the ambient population for the whole study area is in Section 5.4.1.

### **5.3.3 Peak and Off-Peak Times**

In order to reflect the large variations in population density that occur on a university campus throughout the day (Sun et al., 2014), two time periods were created for these data: peak and off-peak. Peak time was considered to be 9am – 6pm, Monday – Friday in term time, as these are the times in which classes are scheduled, and off-peak was any time around that. The holiday dates for the time period studied were obtained from the university's online almanac, and any day in these windows was identified as off-peak.

Using this classification, incidents were identified as occurring in either peak time or off-peak time, and two different population density values were calculated. Using the capacity data obtained for each building, adjustments were made to represent the busyness of the building in either peak or off-peak time. Whilst no literature could be found on which to base these calculations, the use of the building was considered, as certain building uses would lead to different rates of use at peak and off-peak times. It was proposed that academic buildings used primarily for teaching, for example, would be approximately 50% full in peak time, as not all rooms are always occupied at full capacity. These buildings were then considered to be 15% full in off-peak time, reflecting those who use the buildings in the university holidays. Other types of buildings had different rates for peak and off-peak times, as displayed in Table 5.2.

| <b>Building Type</b>                   | <b>Percentage Full in Peak Time (%)</b> | <b>Percentage Full in Off-Peak Time (%)</b> |
|--|---|---|
| Academic Buildings                     | 50                                      | 15  |
| Accommodation                          | 25                                      | 50  |
| Dining Hall                            | 80                                      | 30  |
| Childcare Centre                       | 100                                     | 10  |
| Conference Building                    | 50                                      | 0   |
| Car Parks                              | 50                                      | 15  |
| Libraries                              | 75                                      | 25  |
| Ceremonial Building                    | 10                                      | 10  |
| Function Building                      | 50                                      | 50  |
| Gyms                                   | 60                                      | 60  |
| Security Office                        | 50                                      | 50  |
| Business Centre                        | 60                                      | 40  |
| Buildings in Construction <sup>3</sup> | 100                                     | 100   |
| Office Buildings                       | 50                                      | 25  |
| Health and Safety Building             | 100                                     | 50  |
| IT Building                            | 75                                      | 75  |
| Theatre                                | 50                                      | 50  |
| University Union                       | 50                                      | 15  |

**Table 5.2 - Busyness Allocated to Campus Buildings by Building Use**

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<sup>3</sup> Buildings in construction were allocated a smaller number based on the estimated number of people working on the construction, rather than the building capacity.

In order to test the appropriateness of these assumptions, a form of sensitivity testing was undertaken, which is used to examine the effect of specific values on model results (Niida et al., 2019). This is discussed in more detail in Section 5.4.1.

## 5.4 Methodology

### 5.4.1 Objective 1: Comparison of Incident Counts and Rates

In order to compare the rates and counts for each building on campus, the ambient population for each area had to be estimated. As highlighted above, population estimates had been created for each building, but a number of offences were also linked to specific outdoor areas, which had no population value. As a result, inverse distance weighted interpolation (IDW) was used to create a raster dataset representing ambient population across the campus. IDW calculates values for unsampled locations using known values nearby. The weights of these nearby locations, which are proportional to their proximity to the unsampled location, can be set using the power coefficient (Gimond, 2021). Here, the power coefficient was set to 2 as per general convention (Liu et al., 2020; Maleika, 2020), but it must be noted that some highlight the lack of scientific reasoning for this selection as a limitation of traditional IDW (Liu et al., 2020). The equation for IDW is:

$$\hat{Z}_j = \frac{\sum_i Z_i / d_{ij}^n}{\sum_i 1 / d_{ij}^n}$$

Where  $\hat{Z}_j$  is the value at unsampled location  $j$ , with power coefficient  $n$  (Gimond, 2021) and known location  $i$ , with  $d$  representing distance between the points  $i$  and  $j$ .

The values created by the IDW were then extracted for each site, to obtain an ambient population figure for each. These values were then used to calculate the offence rate at each site, and the z-scores for both the incident counts and rates for each building were calculated.

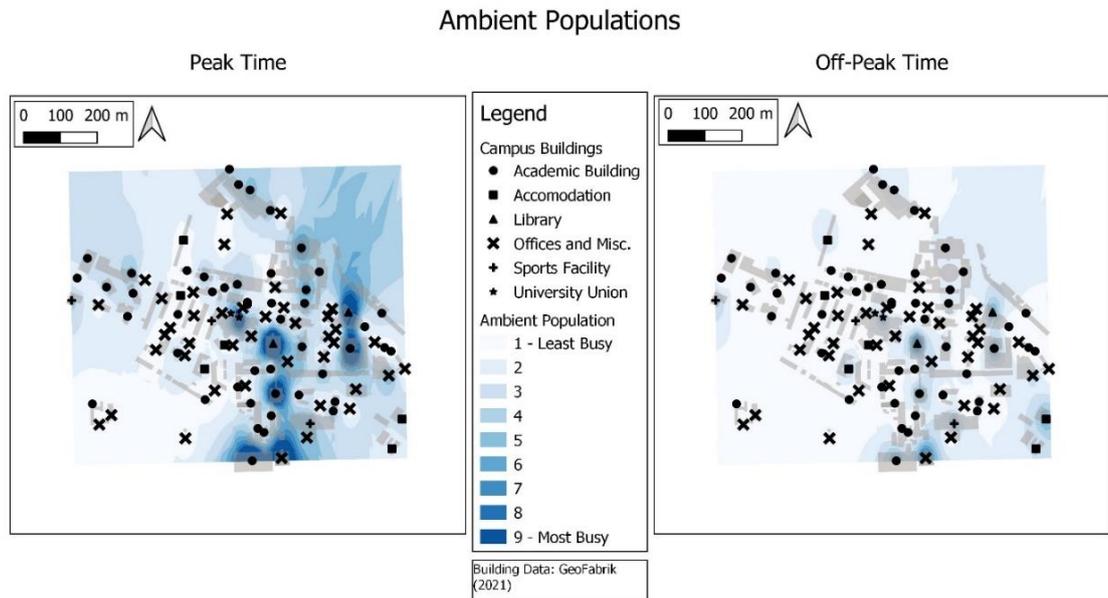
A binary classification identifying areas as either crime generators or crime attractors was then created using the thresholds provided in Table 5.3,

reflecting the concept proposed by Clarke and Eck (2005, 2003). An area was identified as either a crime generator or attractor if it corresponded to both of the conditions below. Whilst these thresholds could be considered somewhat arbitrary, they were selected as they are in line with Clarke and Eck's (2005, 2003) proposal, which did not provide a more specific value for what constitutes, for example, a "high crime rate", and are therefore considered appropriate for this work.

| <b>Type of Space</b> | <b>Counts</b>   | <b>Rates</b>  |
|----------------------|---|---|
| Generator            | High (Greater than 1 Standard Deviation above the Mean) | Low (Greater than 1 Standard Deviation below the Mean)  |
| Attractor            | High (Greater than 1 Standard Deviation above the Mean) | High (Greater than 1 Standard Deviation above the Mean) |

**Table 5.3 - Crime Generator and Attractor Thresholds for Counts vs Rates Method**

In order to assess the appropriateness of the ambient population estimations, this analysis was conducted three times, firstly with the percentage values highlighted in Table 5.2 (later referred to as Option 1), secondly with ten percentage points less for each value (so, for example, academic buildings were considered to be 40% full in peak time and 5% full in off-peak time), and thirdly with ten percentage points more for each value (so academic buildings were considered 60% full in peak time and 25% full in off peak time). The results for all three runs were the same, and thus this method of estimation the ambient population was considered appropriate. The IDW map for Option 1 is shown in Figure 5.3 to demonstrate the ambient population being studied.



**Figure 5.3 - Ambient Population in Study Area in Peak and Off-Peak Times**

### **5.4.2 Objective 2: Offence Types**

In pursuance of compiling a list of offences more prevalent at crime generators or attractors, the table below (Table 5.4) was developed from that of Newton (2018 p.11), with a few changes to reflect this project and the data available. For example, when Newton (2018) suggested that a certain type of offence could span both crime generators and attractors depending on population density, time of day (whether peak or off-peak) was incorporated to reflect this. Moreover, incidents that were not straightforward to classify as either crime generator or attractor offences, such as assault, were removed from this analysis (n=11). Although Bowers (2014) suggest that violent crime could be more common at crime attractors, LeBeau (2012) identifies a relationship between this crime type and crime generators. As a result, it was deemed more appropriate to exclude this small number of incidents from the work rather than potentially skew the results.

| <b>Generator Crimes</b>              | <b>Attractor Crimes</b>              |
|--------------------------------------|--------------------------------------|
| Pickpocketing (any time)             | Criminal damage (any time)           |
| Disorder (peak)                      | Arson (any time)                     |
| Theft from person (peak)             | Theft of/from car/bicycle (any time) |
| Harassment/alarm/distress (any time) | Robbery (any time)                   |
| Hate crime (any time)                | Drug dealing (any time)              |
| Attempted theft (peak)               | Disorder (off-peak)                  |
|                                      | Vehicle crime (any time)             |
|                                      | Theft from person (off-peak)         |
|                                      | Burglary (any time)                  |
|                                      | Attempted burglary (any time)        |
|                                      | Going equipped (any time)            |
|                                      | Attempted theft (off-peak)           |
|                                      | Vagrancy (any time)                  |

**Table 5.4 - Crime Generator and Attractor Offences**

Crime location quotients (LQCs, as per convention) were used to identify whether the offence types at specific buildings suggest that they are a crime generator or a crime attractor. Location quotients, although first used in criminology by Brantingham and Brantingham (1993), have been used in other fields for decades, particularly regional sciences (Block et al., 2012; Brantingham and Brantingham, 1997; McCord and Houser, 2017). LQCs are ratios used to examine the occurrence of crime in one area compared to a wider area (Groff, 2011; Piza et al., 2014), and thus can be indicative of whether a certain type of incident is disproportionately higher or lower than average in a particular location (Brantingham and Brantingham, 1997). Whilst LQCs are therefore appropriate for this work as they permit the identification of areas of over- or under-representation of crime generator or attractor offences (Wuschke et al., 2021), they are not without their limitations. A primary drawback of this method is the lack of generalizability of the results; as they are a ratio of the specific building to the rest of

campus, these results cannot be compared with other buildings of similar uses on other campuses (Groff, 2011).

In order to calculate the LQCs for the buildings on campus, the following equation was used:

$$LQC_{i_n} = \frac{\frac{C_{i_n}}{C_{t_n}}}{\frac{\sum_{n=1}^N C_{i_n}}{\sum_{n=1}^N C_{t_n}}}$$

where  $n$  is the building being studied,  $N$  is the total number of university buildings  $C_i$  is the count of offence type  $i$ , and  $C_t$  is total number of offences of all types.

The resultant LQCs were examined to identify buildings that displayed a disproportionate amount of either crime generator or attractor offences. Buildings that experienced no incidents, or only one, were excluded from analysis, as areas that contribute very little to the overall crime problem can skew results (Block et al., 2012). These potential crime generators and attractors were then compared to those identified through the methods for Objective 1, to identify whether the buildings were classified in the same way using these two methods.

## 5.5 Results

### 5.5.1 Objective 1: Comparison of Offence Counts and Rates

As proposed by Clarke and Eck (2005, 2003), the classification method that shall be examined first explores the possibility that crime generators see high counts, but low rates, of crime, and that crime attractors see both high counts and rates of offences. This is summarised in Table 5.5.

| Type of Space | Counts | Rates |
|---------------|--------|-------|
| Generator     | High   | Low   |
| Attractor     | High   | High  |

**Table 5.5 - Clarke and Eck's (2005, 2003) Suggestion of Counts and Rates for Crime Generators and Attractors**

Through this method, no crime generators were identified on the campus, and only one crime attractor. Figure 5.4 shows the location of the crime attractor, which is an outdoor plaza in peak time. This result is unexpected, as it was expected that a number of crime generators would be identified on the campus.

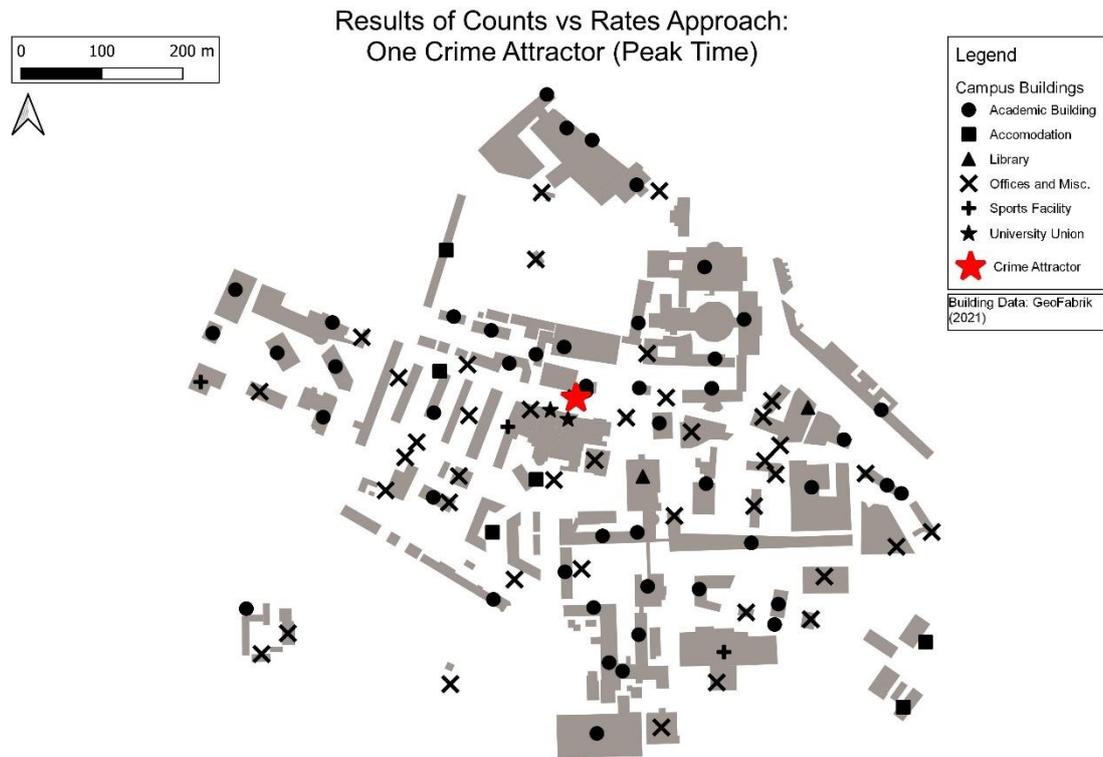


Figure 5.4 - Results of Counts vs Rates Approach: One Crime Attractor Identified

### 5.5.2 Objective 2: Offence Types

The calculation of crime location quotients was used to identify whether any areas of campus saw noticeable specialization in offences that are associated with either crime generators or attractors. This calculation produced a value for each building for both crime generator and attractor offences. To interpret these values, a classification proposed by Miller et al. (1991) shall be used. Whilst this classification was suggested for use in location quotients studying industrial sectors' representation in the county, it has been used for crime location quotients (see, for example, Andresen et al. (2009)). This classification suggests that the LQC values be interpreted as shown in Table 5.6.

| <b>LQC Value</b> | <b>Interpretation</b>          |
|------------------|--------------------------------|
| < 0.7            | Very underrepresented          |
| 0.71 – 0.90      | Moderately underrepresented    |
| 0.91 – 1.10      | Average representation         |
| 1.11 – 1.30      | Moderately high representation |
| > 1.31           | Very high representation       |

**Table 5.6 - LQC Value Interpretation proposed by Miller et al. (1991)**

Given that the offence types included in the LQC calculations were identified as more likely to occur at these sorts of spaces, a building shall be considered to be a crime generator or attractor if it falls into the highest classification in this table; that of very high representation. Although it could be argued that this threshold is fairly arbitrary, there are no specific values for what constitutes a crime generator or attractor (Davies and Birks, 2021), so a quantifiable figure for crime specialisation does not exist. As a result, these values are considered appropriate for identifying offence type specialisation as it means that the building sees more than 30% more crime generator or attractor offences than the rest of campus.

#### **5.5.2.1 Crime Generator Offences**

The results of the LQC calculations for crime generator offences are displayed in Figure 5.5 and Figure 5.6. Figure 5.5 shows the counts of the buildings that were allocated to each classification in Table 5.6, and Figure 5.6 locates each building on the campus map. Buildings that saw no incidents, and which were therefore not included here, are not shown on the map.

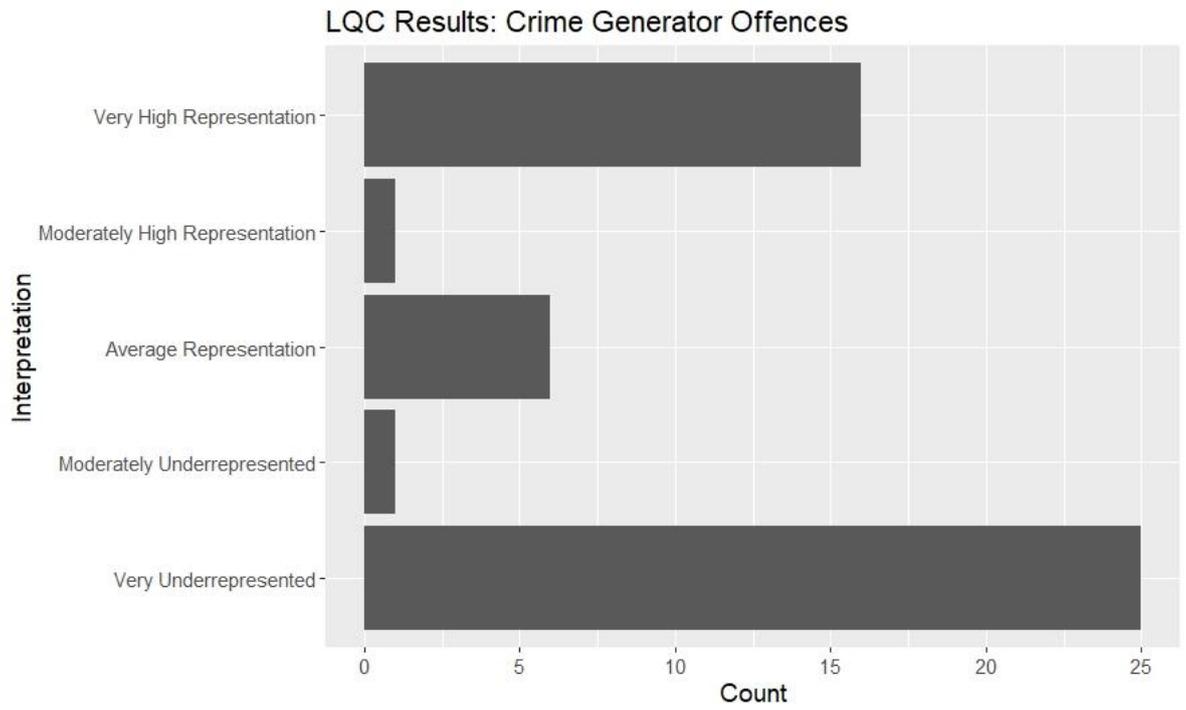


Figure 5.5 - LQC Results: Counts of Crime Generator Offences by Interpretation

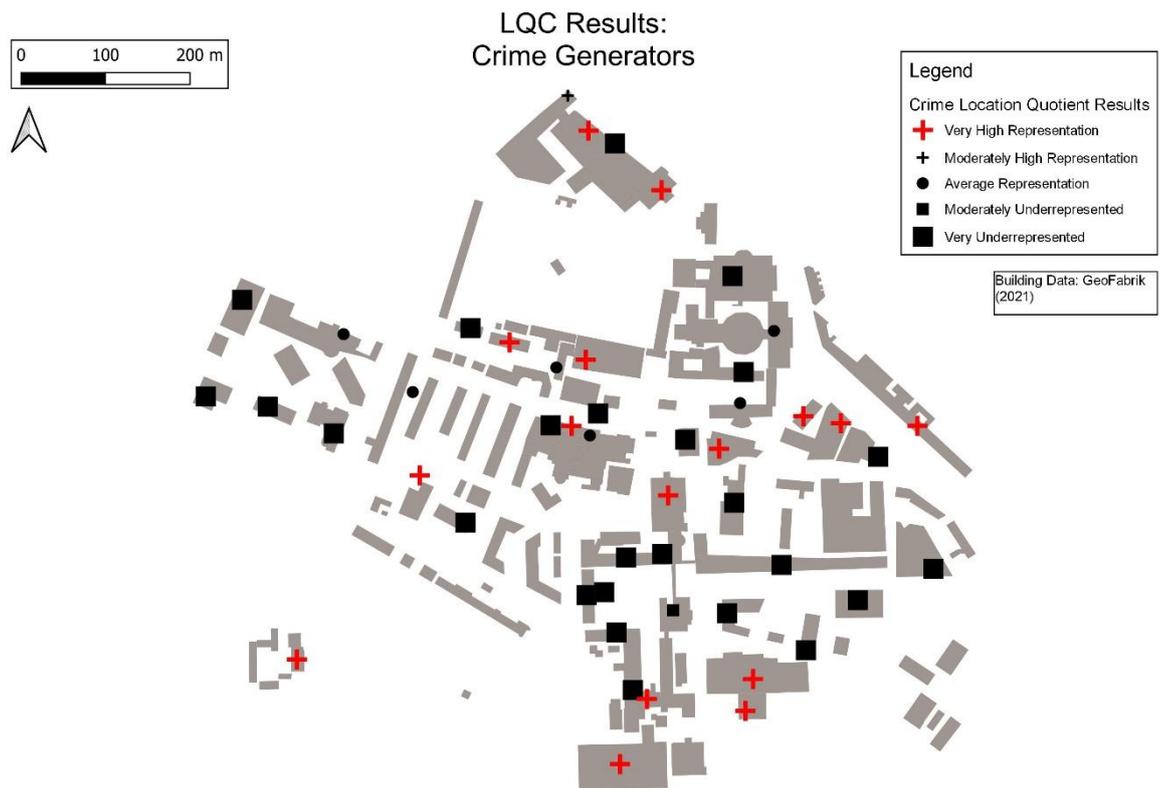
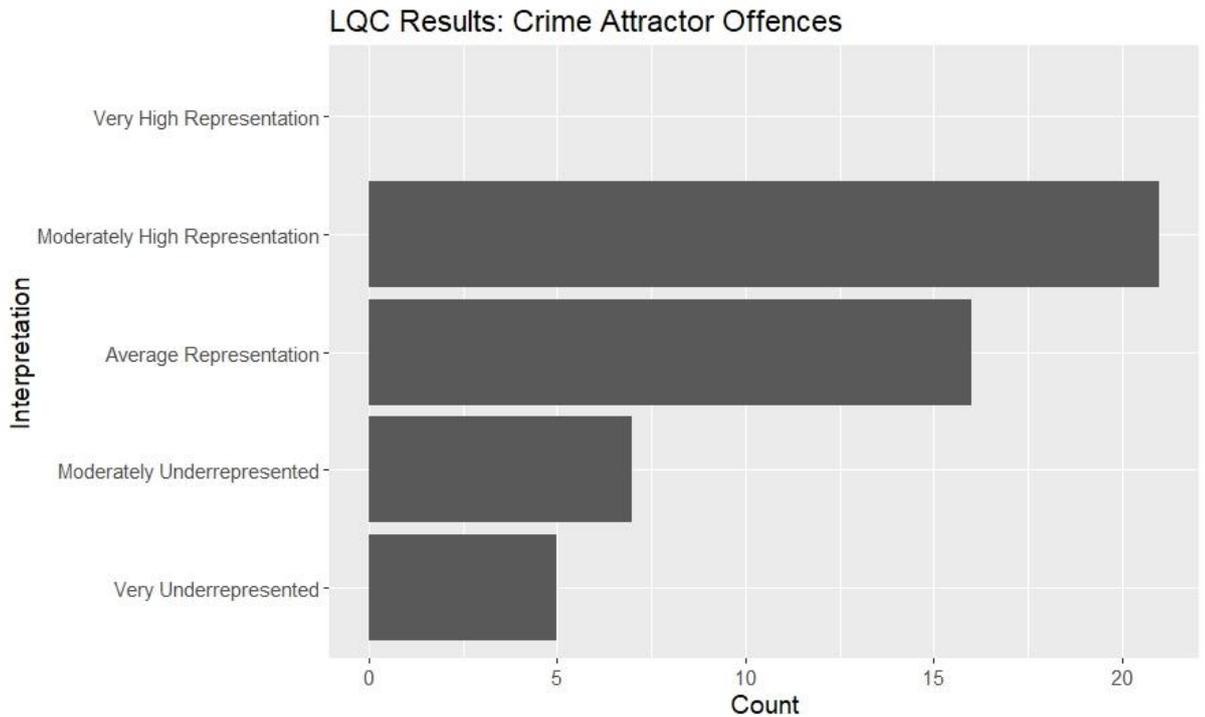


Figure 5.6 - LQC Results: Crime Generator Locations in Study Area

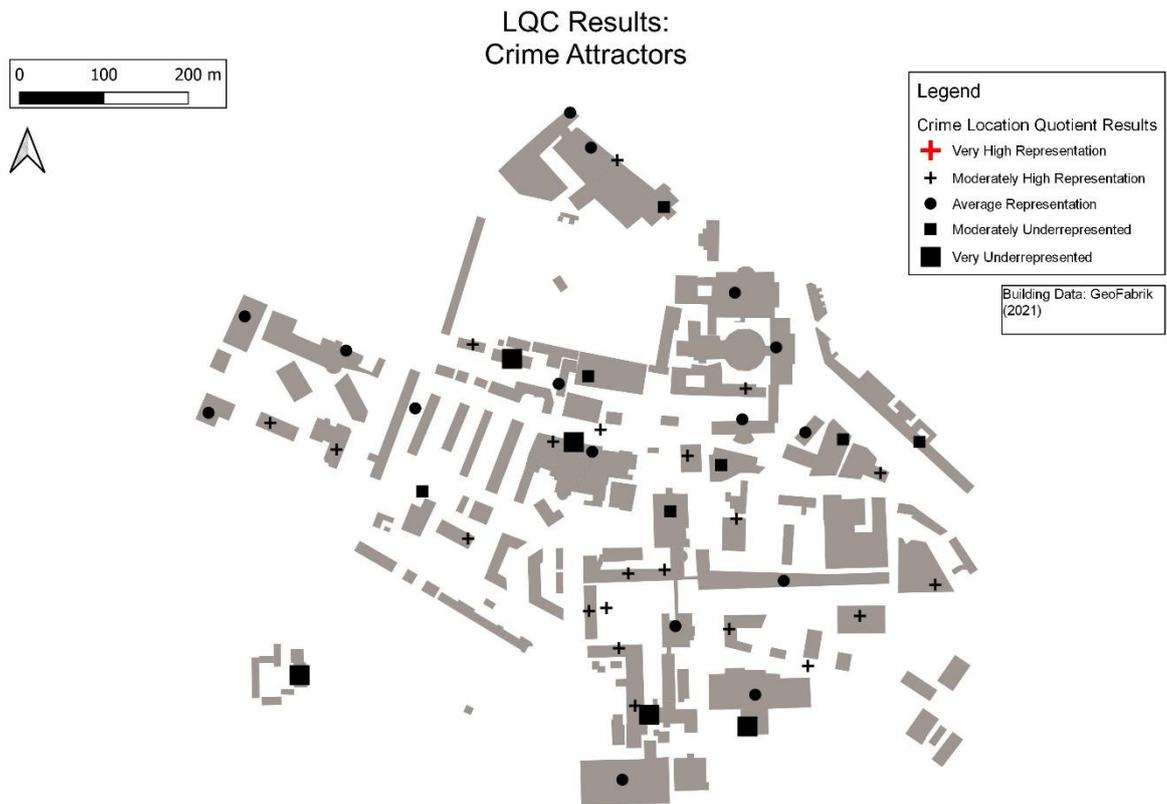
As one can see, there appear to many buildings that have *Very High Representation* of crime generator offences, and even more that are *Very Underrepresented* by these incident types, with a smaller number of buildings that align with the campus-wide patterns for crime generator offences. As stated above, it is possible that any building that has a *Very High Representation* of these types of offences could be crime generators, thus indicating potentially a large number of this type of space on this university campus.

### 5.5.2.2 Crime Attractor Offences

Figure 5.7 displays the results of the LQC analysis for crime attractor offences in a bar chart, and Figure 5.8 displays them on a map.



**Figure 5.7 - LQC Results: Counts of Crime Attractor Offences by Interpretation**



**Figure 5.8 - LQC Results: Crime Attractor Locations in Study Area**

Here, unlike the LQCs for crime generators, no buildings are found to have *Very High Representation* of crime attractor offences, even though almost half ( $n=21$ ) have *Moderately High Representation*. As a result, these findings do not clearly indicate any of these buildings to be crime attractors. A number of buildings ( $n=18$ ) had an LQC for 1.22 for these incidents, indicating that they see 22% more attractor offences than the rest of campus. Although this classifies them as *Moderately High Representation*, and therefore not high enough to be considered a crime attractor according to the identified threshold, these buildings still appear to see a fairly high occurrence of these types of offences.

## 5.6 Discussion

This work aimed to answer the following research question: *will two different classification methods for crime generators and attractors identify the same areas?* To summarise the results of this research; the comparison of the

counts vs rates method, proposed by Clarke and Eck (2005, 2003), suggested only one site to be a crime attractor (an outdoor plaza in peak time) and none to be crime generators, whereas the study of offence type indicated 16 buildings to be crime generators, but no crime attractors. These results therefore demonstrate that no buildings were found to have the same classification in both methods. This disparity could indicate that one or neither of these methods are best suited to empirically identifying crime generators or attractors.

It is interesting that the counts vs rates approach did not identify any crime generators in the study area. Given that it appears logical that a university campus is a crime generator in itself, it was expected that a number of crime generator sites would have been identified. It is possible that the thresholds identified for this analysis (in Table 5.3) restricted the classification of these areas, and different thresholds (such as 0.5 standard deviations above/below the mean) may have led to the identification of sites as crime generators. This reintroduces another complication of the study of these spaces; as there is no specific definition for a crime hotspot (Chainey et al., 2002), it is difficult to suggest how much crime has to occur at a site before it constitutes a concentration caused by the crime generator or attractor processes. It could be that there were crime generator and attractor processes at work at other buildings on this campus, but they did not lead to a crime hotspot that was suitably apparent to be identified by this analysis because of the thresholds selected for this research. Whilst this is not necessarily a limitation of the current research, which was aiming to test the classification methods rather than specifically identify crime generators or attractors, it could be a problem for those wishing to empirically classify sites as these types of spaces.

When examining the buildings identified as crime generators by the offence type analysis to explore any potential similarities between them, a number of features become evident. Firstly, when one looks at the use of these buildings, it is clear that building use alone cannot be used to identify crime generators; these buildings include a variety of uses, including a library, a dining hall, and academic buildings. Whilst some of these sites have additional features, such as cafés, these are not found to be consistent

across all these locations. Moreover, in examining the capacity values allocated to these sites, it was found that the crime generators were not simply the largest building on campus. This suggests that building size can also not be used to identify crime generators on this university campus. Indeed, there are no features that appear to be consistent across all the crime generator sites identified.

The fact that no crime attractors could be found in the offence type analysis, even though the comparison of counts and rates identified one, is intriguing. As highlighted previously, many buildings on campus were identified as having *Moderately High Representation* of crime attractor offences. As a result, rather than crime attractors being considered in binary terms, that is, that a site is either a crime attractor or it is not, this could suggest that these sites have crime attracting qualities, or are less concentrated forms of crime attractors. Indeed, if this approach was considered, it could offer support for the aforementioned concept of the crime generator and attractor spectrum and could be aligned with the idea that spaces are not exclusively crime generators or crime attractors (Brantingham and Brantingham, 1995). However, there is evidence to suggest that the latter is not the case; of the sites that had *Moderately High Representation* for crime attractor offences, all were *Very Underrepresented* by crime generator offences. This suggests that even though these buildings were not clearly defined crime attractors, they also do not display crime generator processes and thus the two could be more mutually exclusive than first theorised.

Given that each approach identified *either* crime generators (offence type) or a crime attractor (counts vs rates), but not both, it could be the case that each method is more suited to identifying the processes specific to one type of space. It is possible, for example, that examining the offence types associated with crime generators accurately isolates the mechanisms underpinning these spaces, whereas the crime attractor mechanisms are too complex to attribute solely to offence type. Similarly, the assumptions on which the counts vs rates approach is based could correctly identify crime attractors but be unsuited to crime generators. Further exploration of these mechanisms would be beneficial to identify whether this is the case.

In exploring these two potential methods for classifying crime generator and attractor areas, this work has further illustrated the complexities in categorising these types of spaces and studying them empirically. There are many inconsistencies between the results of these two methods that could call into question their validity if they were considered independently, suggesting that these methods should not be used individually to classify spaces as crime generators or attractors without some other form of validation. Future research incorporating the addition of other techniques to explore these results would increase their validity and allow exploration into the inconsistencies between the results. Moreover, the results of the offence type analysis may suggest support for the existence of a crime generator and attractor spectrum, which would also benefit from further study.

Whilst every effort has been made to ensure this research is as accurate as possible, limitations remain. For example, although the data have come from a reliable source, it has been demonstrated that they suffer from the aforementioned limitation of underreporting and could therefore not represent the true picture of incidents on campus. Moreover, whilst IDW was used to calculate ambient population from point data, this may not accurately reflect the way in which people move around the university campus. Whilst this was appropriate for the scope of this work, further investigation into ambient populations would be of benefit. In addition to this, as is the case with other research set on a university campus (Henson and Stone, 1999), the small sample size means that these results may not be generalizable, and the proximity of the campus to the city centre could have affected the offending that takes place here (Tomsich et al., 2011). Finally, the use of a number of arbitrary values in quantifying crime generators and attractors was unavoidable. Although the concept of these types of spaces appears relatively unambiguous (Newton, 2018), this work identified challenges in quantifying them. Whilst decisions were backed up by literature or by results of sensitivity analysis where possible, the arbitrary nature of some of these decisions remains. Clearly, empirical research on crime generators and attractors is in its infancy and is likely to remain so until more defined methods for measuring them are identified.

## 5.7 Conclusion

*Will two different classification methods for crime generators and attractors identify the same areas?* This research found the answer to this question to be no, as even though both approaches identified at least one crime generator or attractor, no buildings received the same classification by both methods. Indeed, one technique identified only crime generators, whilst the other identified only one crime attractor. These results further demonstrate the complexity in studying crime generators and attractors empirically and suggest that these classification methods should not be used to identify these spaces without additional validation. As a result, further research into crime generator and attractor classification methods is recommended, in order to further explore the inconsistent results identified by these two methods, and to develop scholarship on quantifying these types of spaces.

### **Summary**

*This chapter has tested two methods for empirically classifying spaces as crime generators or attractors, acting as proof of concept to validate these approaches. No buildings received the same classification by both methods, suggesting that either one, or both, of these methods do not accurately identify crime generators or attractors. As a result, it suggests that additional validation methods should always be used when empirically classifying crime generators or attractors. This research has successfully met the second objective of this thesis, which was to investigate previously suggested methods for empirical classification of crime generators and attractors, to explore whether multiple methods identify the same areas as crime generators and attractors. In addition to meeting this objective, it has also illustrated some of the challenges in empirically studying crime generators and attractors.*

*The results of this chapter inform the subsequent empirical work in this thesis, which is found in Chapter 7. Not only do these results demonstrate the difficulty in identifying case studies for crime generators and attractors, but it also leads the research in Chapter 7 to also seek to explore an additional classification method.*

*The following chapter contains the computational work in this thesis, the agent-based model.*

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## Chapter 6

### Using Agent-Based Models to Investigate the Presence of Edge Effects around Crime Generators and Attractors

#### **Preface**

*This chapter contains the computational part of this thesis; the agent-based model. This work explores the relationship between crime generators, crime attractors and edge effects; the suggestion that boundary areas between spaces experience more crime events than internal zones. This chapter utilises agent-based models to test whether these theoretical concepts can be considered in conjunction, with the aim of exploring whether the mechanisms which underpin generators and attractors can also lead to the emergence of edge effects. Whilst results of this study suggest that they cannot, they do identify clear differences in the spatial distribution of crime both inside and outside these spaces. To that end, in these experiments simulated crime generators produced increased numbers of crimes, both internally and externally, which decayed over distance from the crime generator. Conversely, crime remained consistent outside simulated crime attractors with only the facility itself seeing increased offending. This chapter discusses how these findings contribute to theory development, and how they may support empirical studies that seek to better understand the mechanisms that underlie real world concentrations of crime.*

*The work found in this chapter is aligned with Objective 3 for this thesis, to examine the theoretical mechanisms underpinning [crime generators and attractors] using an agent-based model, and their implications for crime distribution. It is supported with knowledge obtained from undertaking the scoping review which is found in Chapter 4, and also relates to the empirical work found in Chapter 7, which explores whether the crime distribution patterns which emerge from these models can be found empirically.*

## 6.1 Introduction

The understanding that crime is found clustered in geographic space is well-established in criminological literature (Herbert and Hyde, 1985), following centuries of investigation into the relationship between crime and space (Ratcliffe and Breen, 2011). Analysis of these clusters has led to the identification of different causal mechanisms underpinning their locations, and the consequential classification of two different types of crime clusters; crime generators and crime attractors (Brantingham and Brantingham, 1995). Crime generators are places in a city which are used by a large number of people for activities unrelated to crime (Clarke and Eck, 2003), thus creating a number of criminal opportunities for opportunistic offenders. Examples of crime generators could include railway stations (Kurland et al., 2014) and parks (Groff and McCord, 2012). The large number of offences experienced here is primarily due to the high concentration of people (Clarke and Eck, 2005), and consequently the crime problem can be exacerbated by increased use of the space (Clarke and Eck, 2003). Crime attractors, on the other hand, are areas of the city that lure motivated offenders with the potential for criminal opportunity, and are exemplified by areas infamous for illegal activities. Crime problems here are aggravated by the growing reputation of the area (Clarke and Eck, 2005), and as a result, crime attractors are considered to be the result of offenders' experiences and networks (Brantingham and Brantingham, 2008). Examples of crime attractors can include red light districts (Brantingham and Brantingham, 2008, 1995; Clarke and Eck, 2005, 2003) and drug markets (Brantingham and Brantingham, 1995). Both crime generators and crime attractors can range in size from individual buildings, to a small area of a city (Bernasco and Block, 2011; Houser et al., 2019).

Another well-established concept in the investigation of crime concentration is that of the effect of edges on crime patterns. Initially conceptualised as the "border-zone hypothesis" by Brantingham and Brantingham (1975), this has identified that boundaries between areas, whether physical or perceived, experience more crime events than internal zones. Several explanations of this phenomenon have been proposed, including the frequent and legitimate

presence of strangers in these areas (Brantingham and Brantingham, 1993), the absence of formal guardianship here (Kim and Hipp, 2018) and the ability to exit the area quickly after committing a crime (Herbert and Hyde, 1985; Kim and Hipp, 2018). The effect of edges has been examined at a variety of scales, including a macro-level study of the city by Shawn and McKay (1942, cited by Rengert et al., 2012), and a meso-level investigation of communities by Rengert et al. (2012).

Whilst much research, detailed later, has been undertaken to investigate crime patterns around criminogenic facilities, very few pieces of work have specifically examined the relationship between crime generators and attractors and their edges. Moreover, those studies which have examined this have not studied the boundaries of the generator or attractor *itself*. Instead, Song et al. (2017), for example, considered the impact of crime generators and attractors on edge effects, comparing edge effects in areas within 500m of a generator/attractor, with those further away. Likewise, Kim and Hipp (2018) studied the impact of the proximity to highways and parks, among other city features, on crime rates, examining these features as the boundaries themselves, rather than a criminogenic facility.

Not only has the relationship between these topics been seldom studied, there has been little theoretical investigation into the mechanism of how crime generators and attractors could lead to the emergence of edge effects. Indeed, Kim and Hipp (2018) stress the need to examine the mechanisms behind edge effects on offending, and Song et al. (2013) highlight that further research into edges is vital to theoretical understanding of areas which experience many crime events. More generally, Weisburd (2015) has stressed the need for theory development in studies investigating crime at very small geographic units; the so-called *geography of place*.

### **6.1.1 The Present Research**

Consequently, this work aims to investigate the emergence of edge effects around crime generators and attractors, in order to test whether these theoretical concepts can be considered in conjunction with one another. Agent-based models of crime generators and attractors shall be created to identify the potential presence of edge effects around these spaces,

exploring whether the mechanisms underpinning crime generators and attractors do, or do not, lead to the occurrence of increased crime events at their boundaries. Abstract environments shall be used, as seen elsewhere in computational criminology (such as in Birks et al. (2014, 2012)), allowing these theoretical concepts to be investigated without the additional complexity of a real geographic space.

Not only does this work fill the aforementioned literature gap on testing of these concepts, but there are also a number of strengths of using agent-based models to theoretically test this relationship, over empirical analysis. Song et al. (2018), for example, identified limitations in defining an edge in real-world space and finding appropriate data for analysis, but the abstract nature of these models means that the complexities of this definition, as discussed later in this chapter, are avoided. Moreover, empirical research into crime generators and attractors is not without methodological limitations (Kurland et al., 2014). As noted by Ratcliffe (2012), for example, in their investigation on violence around bars, Homel and Clark (1994) did not specify the precise area “around” the bar which they would be studying.

Whilst that is an example of a project-specific limitation, there are also more general challenges encountered when undertaking research into crime generators and attractors; Holloway and McNulty (2003 p.206), for example, following their investigation into crime patterns around public housing projects, note that “project-to-project differences” related to elements like specific design details can lead to different patterns around the sites. Although Holloway and McNulty did not specify these sites as crime generators or attractors, this point is also pertinent to this area of research. This particular limitation, however, has been mitigated in this research; by creating an abstract environment for the theoretical testing, the differences between individual crime generator and attractor sites can be reduced. Furthermore, when investigating the impact of criminogenic sites on their vicinities, Ratcliffe (2012) identified problems with the often-used empirical method of concentric buffers, such as the confounding effect of clustering of bars in space. When this is the case, it is challenging to identify which crimes can be attributed to which bars, rendering identification of the effects of each site difficult. The use of agent-based models, however, allows a

single crime generator or attractor to be present in a space, eliminating this potential problem.

Despite these strengths of agent-based modelling, it is also important to consider the limits of using this methodology for this theory testing. Groff (2007), for example, highlights that agent-based models do not empirically test a theory, but examine the extent to which it is possible. Moreover, Crooks et al. (2008) stress that theories cannot be confirmed, only falsified. As a result, testing of this theory should not stop if edge effects are identified, and this work should act rather as a basis for further research.

The following chapter is separated into four main sections. Firstly, the background section comprises a literature review which will provide a more in-depth introduction into crime generators and attractors, as well as edge effects and crime distribution around these facilities. After this, the Methodology shall discuss the model specifications and stylized facts used in this work. Results and Discussion shall follow, ending with an overall Conclusion.

## **6.2 Background**

### **6.2.1 Crime Generators and Attractors**

As highlighted in Chapter 2, the concept of crime generators and crime attractors is underpinned by ideas from crime pattern theory, geometry of crime and routine activity approach. As a result, crime generators and attractors are not considered to be part of one theory over the other, and the theoretical explanations of this phenomenon are instead used interchangeably. Despite this potential ambiguity, and the aforementioned methodological limitations in studying these spaces empirically, this concept has nevertheless been widely accepted in environmental criminology (Kurland et al., 2014).

Although relatively few studies (when compared with the overall literature base on the topic) have attempted to quantify the differences between crime generators and attractors (Newton et al., 2014), some authors have acknowledged ways in which they could be distinguished. Several authors

have suggested that crime generators and attractors would see different types of crime, such as Bowers (2014) and Newton (2018). Clarke and Eck (2005, 2003), on the other hand, contend that these facilities can be distinguished based on their crime rates; although both types of spaces would experience high counts of crime, crime generators would see low crime rates, as there is a large number of potential targets. Conversely, crime attractors would have far higher crime rates, as there are relatively fewer targets available. Ratcliffe (2012) offers a further distinction, suggesting that crime attractors diffuse crime into their vicinities, whereas crime generators do not have this effect. More information on classifying crime generators and attractors can be found in Chapter 5.

Since the introduction of the crime generators and attractors concept in 1995 (Brantingham and Brantingham, 1995), it has not been without criticism. A number of authors have, for example, questioned the existence of two types of clusters. Clarke and Eck (2003, 2005), for instance, suggested the existence of a third: crime enablers. These, they claimed, are spaces where crimes occur due to poor management practices, which lead to minimal regulation of criminal behaviour (Clarke and Eck, 2005, 2003). A location can become a crime enabler rapidly, such as by the removal of a car park attendant (Clarke and Eck, 2005), or slowly, if place management gradually deteriorates (Clarke and Eck, 2005). Crime enablers have, however, been excluded from this research, as this thesis is focusing on the two cluster types initially conceptualised by Brantingham and Brantingham (1995).

Moreover, the distinct nature of generators and attractors as separate entities has also been challenged (Brantingham and Brantingham, 1995, 1993; Frank et al., 2011; Kurland et al., 2014 etc.). Irvin-Erickson and La Vigne (2015), for example, in their study of transit stations, stress that a transit hub can be identified as both a generator and an attractor, concluding that time of day is central to which cluster type it can be considered to be. Moreover, Clarke and Eck (2003, 2005), suggested that a facility can transition between each of these types of space. An example of a shopping area is given by Clarke and Eck (2003; 2005); a shopping centre is traditionally considered to be a crime generator (Brantingham and Brantingham, 1995), but as more people visit the centre, the opportunity for

crime increases, potentially attracting new offenders, and consequently rendering it a crime attractor.

### **6.2.2 Edge Effects**

As previously stated, the idea of edge effects, underpinned by concepts from crime pattern theory (Rengert et al., 2012), claims that more crime occurs in the space between two adjacent, yet dissimilar, areas than in the internal zones (Brantingham and Brantingham, 1975). These edges are considered to be the boundaries between two different areas of a city, where the change between these two spaces is sufficiently clear to be discernible (Brantingham and Brantingham, 1993). Whilst this can be a physical boundary, such as a railway or a lake, it can also be a conceptual boundary between two areas (Brantingham and Brantingham, 1975). As a result, these edges can be either well-defined or subtle (Song et al., 2017, 2013). As this work is exploring an abstract space, the edges examined here represent any form of boundary as it is impossible to discount one form or the other from investigation into crime generators and attractors. Whilst, for example, it is possible that crime attractors could primarily be bounded by conceptual edges, due to their largely unofficial and undefined nature, crime generators, on the other hand, may see more defined borders; spaces like parks (given as an example of a crime generator by Groff and McCord (2012)), shopping precincts (Brantingham and Brantingham, 1995) or high schools (Kurland et al., 2014) can have more clearly delimited boundaries than areas such as drug markets, as an example of an attractor (Brantingham and Brantingham, 1995).

Although the effect of crime clustering at edges has been investigated less than that between crime and other environmental features (Kim and Hipp, 2018), a number of studies have found empirical evidence for edge effects. The first work investigating this phenomenon was that of Brantingham and Brantingham (1975), which was motivated by concepts from both criminological and sociological literature, both of which pointed to increased crime at area boundaries. Applying this theory to the city of Tallahassee, they identified higher burglary rates in blocks which bordered edges, which they defined using demographic data. Similar patterns have also been found

in work by researchers such as Kim and Hipp (2018), who examined crime at both physical and conceptual edges in Southern California, USA; Song et al. (2013), who identified 64% higher crime in conceptual edge areas compared to interior areas in Burnaby, Canada; and Song et al. (2017), who found increased evidence for edge effects near crime generators in parts of Metro Vancouver, Canada. Despite this, however, an investigation by Herbert and Hyde (1985 p.265) in Swansea, UK, found “discernible but inconsistent” evidence for edge effects, leading to the suggestion that it may not be appropriate to apply this concept to all contexts (Herbert and Hyde, 1985).

### **6.2.3 Crime Distribution around Crime Generators and Attractors**

Crime generators and attractors tend to be investigated as criminogenic facilities, with minimal consideration of the space in which they are located (Boessen and Hipp, 2018). Additionally, as highlighted by Bowers (2014), there has previously been little distinction between crimes that occur within the crime generator and attractor, and those that occur in their vicinity, despite Brantingham and Brantingham's (1995 p.13) claim that many of the crimes which occur at facilities such as crime generators “in fact occur at the edges of the high activity location”. It seems logical, therefore, that the immediate environment of these spaces is intrinsically connected to the facility itself (Ratcliffe, 2012), and consequently ought to be considered collectively.

However, the consequences of crime generators and attractors on crime in their surroundings have not been found to be consistent. Some researchers propose that crime generators and attractors would lead to more crime in their vicinity. Boessen and Hipp (2018), for example, in their study of crime in blocks adjacent to parks, identified that crime in this area increased, in line with the principle of edge effects. Additionally, it has been suggested that offenders commit crime whilst *en route* to a generator or attractor (Bernasco and Block, 2011; Bowers, 2014; Frank et al., 2011). Given that one of the explanations proposed for edge effects is the frequent presence of strangers in these areas, it seems likely that this could lead to increased criminal activity in the areas bordering crime generators and attractors. This

suggestion has been countered, however, with the possibility that, in some situations, the social ties associated with the facility would lead to increased guardianship by residents, thus reducing crime in this surrounding zone (Boessen and Hipp, 2018). Moreover, Ratcliffe (2012) has suggested that crime generators and attractors could lead to different crime patterns in their vicinity; that attractors may transmit crime into areas nearby, but that generators would not cause this spreading.

Evidently, the relationship between these spaces and their surrounding neighbouring areas is complex. However, the majority of work investigating their wider effects has identified higher volumes of crimes in areas which are in close proximity to these facilities. Bernasco and Block (2011), for example, found that blocks in Chicago which contain a crime generator or attractor have the highest robbery count, those adjacent have fewer, and those which are further away have fewer still; so-called *distance decay*. Furr- Holden et al. (2016) also identified this pattern around a variety of facilities, and Groff and Lockwood (2014) found that street segments which are exposed to certain types of facilities see increased crime, but that these effects decrease with distance from the street segment. Other researchers have discovered this trend around a particular kind of facility, such as Fagan and Davies's (2000, cited by Bowers, 2014)) investigation of violent crime around public housing projects, and Roncek and LoBosco's (1983, cited by Ratcliffe (2012)) study of offences in the vicinity of high schools. The impact of drinking establishments on crime has also been found to replicate this pattern in a number of pieces of work, including that of Groff (2011), Kumar and Waylor (2003) and Ratcliffe (2012). Indeed, Ratcliffe (2012 p.115) highlights that high density for violent crime tends to cluster around alcohol establishments, and "declines rapidly" as one moves further from these facilities.

Other pieces of research have, however, found evidence which contradicts this pattern. Holloway and McNulty (2003), for example, examined the impact of public housing on crime in Atlanta, and identified that whilst some of these projects exhibit distance decay, others show either less pronounced effects, or none at all, stressing the variability around different facilities. Moreover, Griffiths and Tita (2009) found no evidence of distance decay in

homicides around public housing in Los Angeles, and Boessen and Hipp (2018) found that blocks near to parks generally experience less crime than those further away.

Consequently, it is a combination of this complexity, lack of theoretical investigation and the aforementioned limitations to empirical analysis which is the driving force behind this theory testing. As stressed by Boessen and Hipp (2018), improved understanding of the context of crime generators, and thus also attractors, is needed, in order that the wider effects of these facilities on crime patterns can be understood.

## **6.3 Methodology**

The model presented in this chapter was created using NetLogo, a program which has been used in previous criminological research (such as Weisburd et al. (2017) and Collins et al. (2017)). NetLogo consists of a two-dimensional grid of cells called “patches”, and mobile agents referred to as “turtles”. In this model, only one type of agent is represented; offenders. Three different model configurations were created; a traditional crime generator and a traditional crime attractor, in both of which offender movement was underpinned by theory, alongside a control model in which movement was random. The latter was used to assess the impact of the crime generator and attractor on the base case.

This section shall provide detail of the specification of these models, as well as the stylized facts used to assess their results.

### **6.3.1 Model Specification**

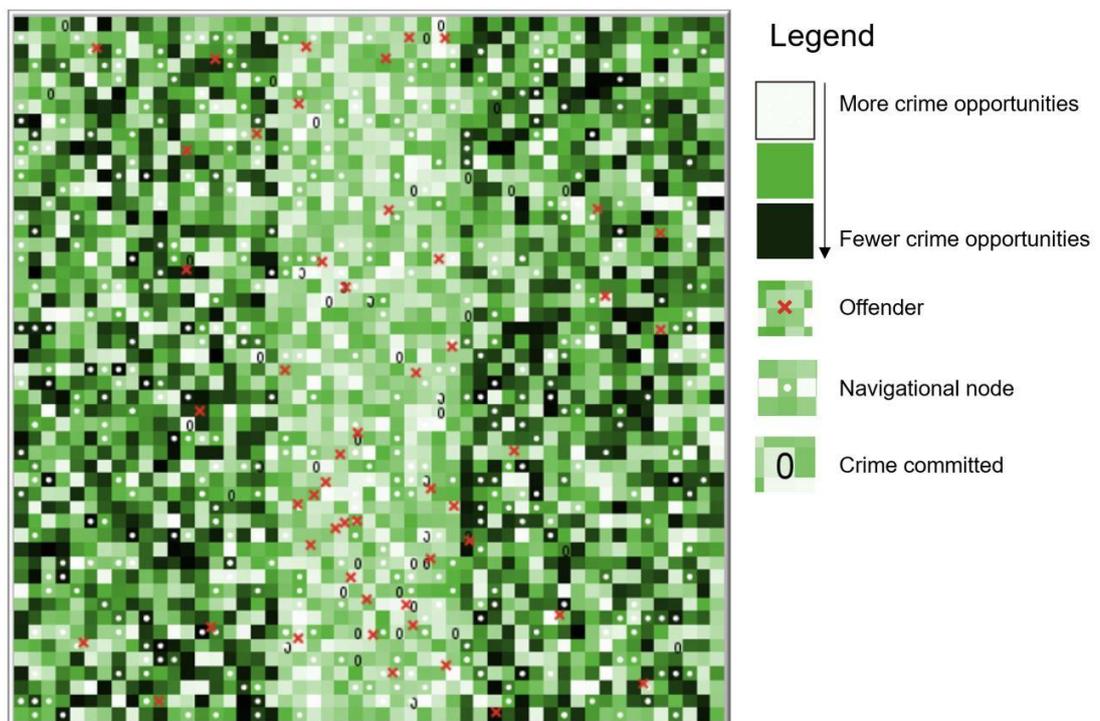
#### **6.3.1.1 Model Environments**

As previously stated, the environments modelled here were all abstract representations of reality, in order to reduce the additional complexity of a real-world geography (Elffers and van Baal, 2008). The environment was designed as a torus, to prevent the clustering of agents within the centre of the model; if the agents reach the right hand side of the model environment, for example, they emerge from the left rather than bouncing off it.

Features which remained consistent across all three model environments are criminal opportunity and the presence of navigational nodes, as follows:

### **Criminal Opportunity**

Upon initialization, each patch in the environment was allocated a value in the range [1,100], representing the potential for criminal activity, where the higher value signifies more opportunity. Higher opportunity is represented on Figure 6.1 with a lighter coloured patch. This value was integral to the mechanism which leads to crime being committed, which is discussed later in this chapter.



**Figure 6.1 - Model Environment Example**

Although crime type can be separated into property crime and interpersonal crime, the concept of “crime” in this model represents either of these forms. Given that crime generators and attractors are likely to experience different types of offences (Bowers, 2014; Newton, 2018), and that the environments modelled here are abstract, this was considered to be more appropriate than selecting one crime type over the other. By not including the additional complexity of victim behaviour, the model is better able to highlight the core

mechanisms that influence the patterns of crime around generators and attractors.

A brief summary of each model environment is as follows:

- Control model: The control model represents an environment with no specific crime generator or attractor, suggesting distributed criminal opportunities with minimal clustering. In this model, the criminal opportunity was randomly allocated across the environment, within the range [1,100].
- Crime generator model: Within the generator model, a central band of the environment represented the generator area, as demonstrated in Figure 6.1. This strip was used to represent this space, rather than a circular area, to simplify the analysis of results. Using a circular central area, rather than a strip, would not influence the conclusions drawn. All patches here had a random criminal opportunity value in the range [50,100], compared with those outside to the space, which had random values in the range [1,100].
- Crime attractor model: The attractor model used the same central band as the generator model to demarcate the attractor area, as demonstrated in Figure 6.1, with the same range of opportunity values. The difference between the two areas was in how they influence the behaviour of agents, as discussed below.

### **Navigational Nodes**

As seen in other agent-based models in criminology such as Birks et al. (2014, 2012) and Groff (2007), a set of navigational nodes were created to represent transport intersections. This network of nodes, which were randomly distributed across the environment, were used by agents to navigate the space.

As proposed by the routine activity approach, each agent was allocated a set of “routine nodes” in the models, as well as a home node, where they started the simulations. These routine nodes represented those places visited more frequently, such as work and shopping facilities (Frank et al., 2011), and were consequently visited more often than nodes which were not considered routine. In the control and attractor models, ten percent of all

nodes were randomly allocated to each offender upon initialization as their routine nodes. This value was chosen arbitrarily, as no literature could be found which was able to improve the estimate of how many places a person routinely visits. In the generator model, aligned with the theoretical mechanisms underpinning these spaces, all navigational nodes located within the generator space also formed part of the offenders' routine nodes, as well as the random ten percent. As the latter were randomly allocated, some could be located within the generator area. This could lead to the agents having varying numbers of routine nodes between runs; if an offender's randomly selected ten percent fell inside the generator area, they had fewer routine nodes in the outside space than an offender whose random routine nodes were all outside the generator. The number of routine nodes, however, does not significantly impact agents' movement, and is not as important as their location; it is the central clustering which is fundamental to the generator mechanism. The distribution of these nodes, as well as the home node, is demonstrated in Figure 6.2 and Figure 6.3; examples of the generator and attractor environment respectively.

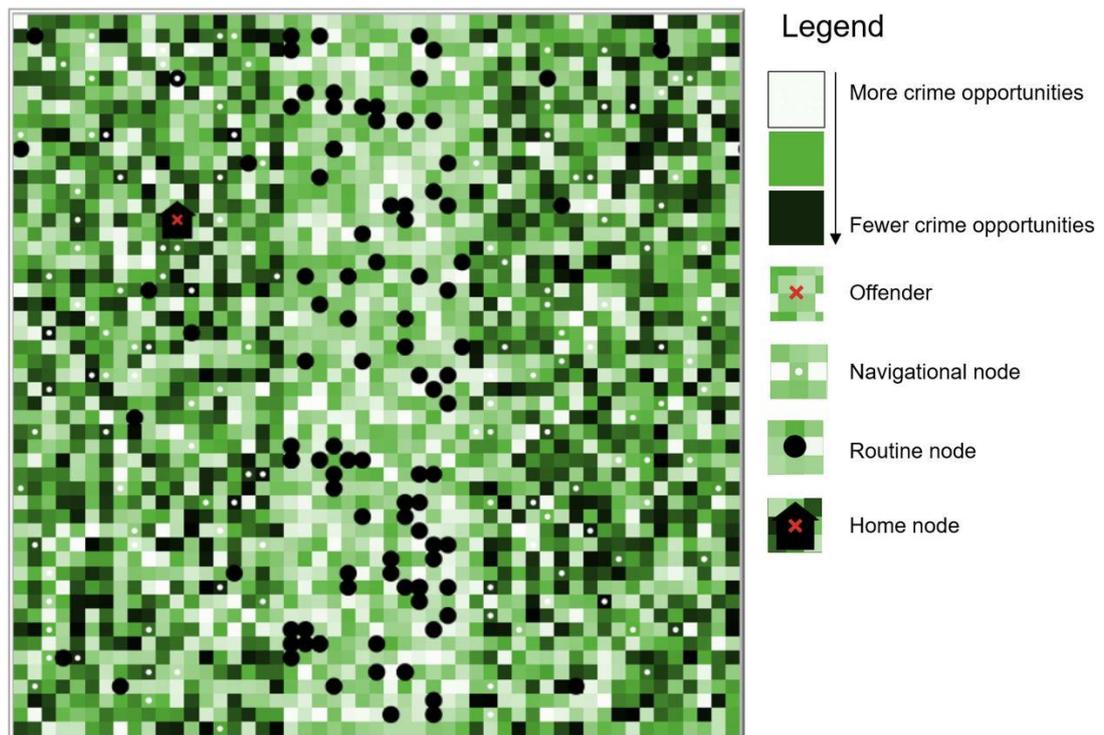


Figure 6.2 - Generator Model Environment Example

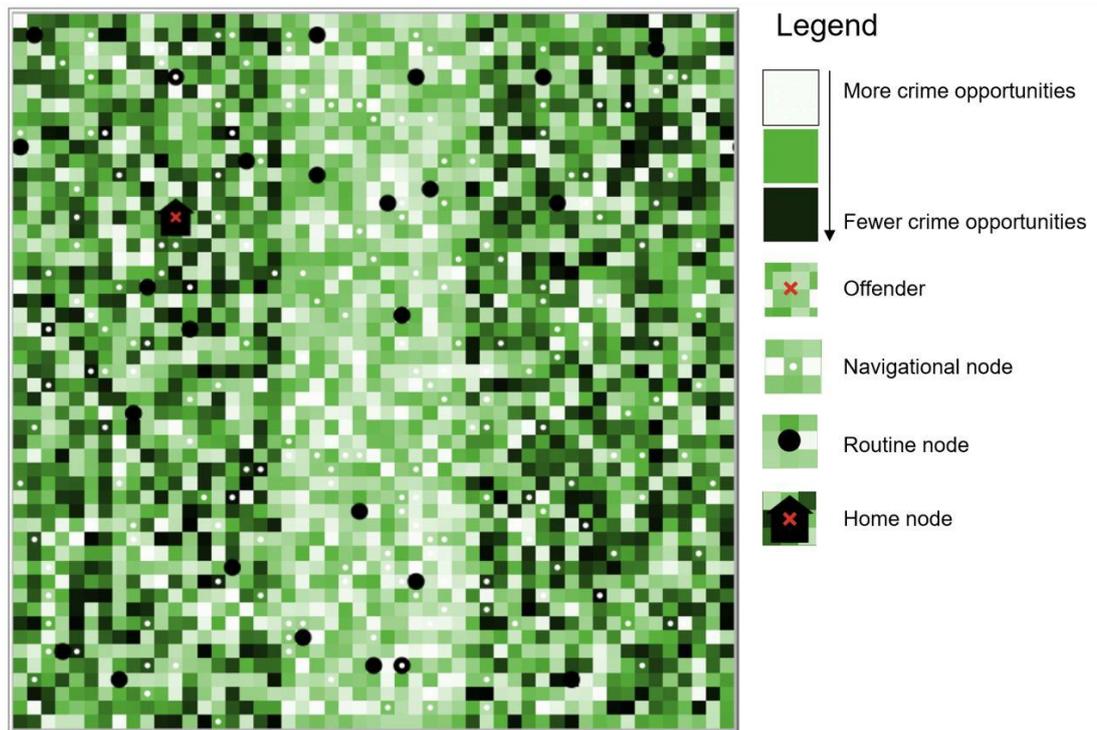


Figure 6.3 - Attractor Model Environment Example

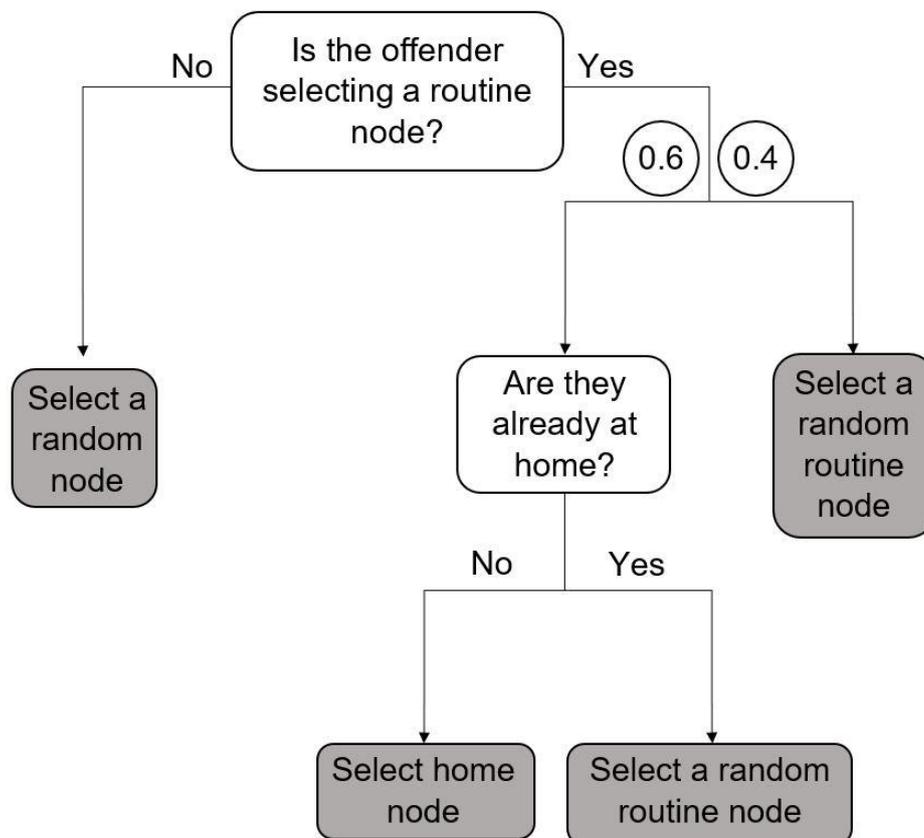
### 6.3.1.2 Agent Specification and Behaviour

In these models, each agent had a value representing their motivation to commit a crime, which was in the range [1,100]. Upon initialisation, all offenders were allocated a random value for this variable. The motivation variable fluctuated with each step of the model, either increasing or decreasing each offenders' motivation, creating some offenders who were more motivated to commit a crime than others. This variable was limited to the range [0,100]. Committing a crime reduced this motivation variable by ten percent, representing satiety. A more specific value could not be identified in a literature search.

In all environments, the offenders moved around the environment via the navigational nodes. To move, the agents randomly selected a node to be their destination, moved towards it via the shortest path between the nodes until it is reached, then selected a different destination node. The model user is able to select the frequency with which the destination node is a routine node. In the model runs which created the results discussed in this chapter, every node visited was a routine node, in order to most accurately represent

routine activities theory. However, more random navigation of the environment could be an avenue for further research.

In the control and generator models, when an offender selected a routine node as their destination, there was a 60% likelihood of selecting the home node over any other routine node, in order to represent increased time spent at home. If the offender was already at their home node and must select another routine node, they selected one at random. This is demonstrated in a flow chart in Figure 6.4. In the attractor model, however, this behaviour was over-ridden when the criminal motivation of an offender crossed the threshold of 75. Once this value had been reached, the offender selected a destination node within the attractor area, modelling the theoretical “luring” of the offenders to the space. When this variable was under 75, the movement was the same as that of the control and generator environments. This threshold was selected arbitrarily as a more precise value was not found in a literature search.



**Figure 6.4 - Offender Movement Flowchart**

The likelihood that a crime will be committed in a specific location  $(x,y)$  at a specific time  $(t)$  is a product of the probabilities that a suitably motivated

offender is in an area with suitably high opportunity. It is calculated as follows, with  $\lambda$  representing a scaling value, as discussed later, and  $p$  representing probability:

$$p(\text{commit})_{(x,y,t)} = p(\text{motivation})_{(x,y,t)} * p(\text{opportunity})_{(x,y,t)} * \lambda$$

Whilst there could be some merit in incorporating a temporal element to this model, such as agents spending longer at home than at other nodes, this has not been included here. Given that agents do not interact, and consequently do not need to be synchronised, it was deemed unnecessary for this model. This would, however, be an interesting addition for further research.

### **6.3.1.3 Simulation Experiments**

As the model is stochastic, a number of separate simulations were executed for each experiment to remove the effect of any skew that might occur in an individual run. Each simulation was run for each environment 1,000 times, lasting 3,000 iterations each. There were 250 navigational nodes in each environment, and 50 offenders. The random seed was set to a constant value upon initialization, to ensure that the same layout of (randomly distributed) criminal opportunity and navigational nodes will be tested under each scenario, allowing for more direct comparisons between the results of each environment. Once the environment had been initialised, the random seed was given a new (random) value, so that each simulation will produce different results.

### **6.3.2 Analysis Methods**

After the model had been executed 1,000 times for each environment, the total count of crimes per patch was exported from NetLogo. To visualise the distribution of crime within the generator or attractor spaces, relative to the areas surrounding them, two different methods were utilised; scatter plots and choropleth maps. Prior to this, however, boxplots were created to examine variance between the model runs.

### 6.3.2.1 Scatter Plots

In order to graphically display the crime distribution on a scatter plot, transects for each step along the x axis were created. The average number of crimes along each transect was then counted, demonstrated graphically in Figure 6.5, which shows 6 of the transects and the total crimes committed along each. This enabled the creation of a scatter plot for each environment, showing the number of crimes which occurred by each step across the x axis. It is expected that the control area model would create a scatterplot which is fairly uniform across the environment, but the generator and attractor environments would both see increased crime within their boundaries, signifying the clustering of crimes in the generator or attractor space. The area of interest in this work, however, are the edges of these spaces, and whether these areas experience more crime than the interior.

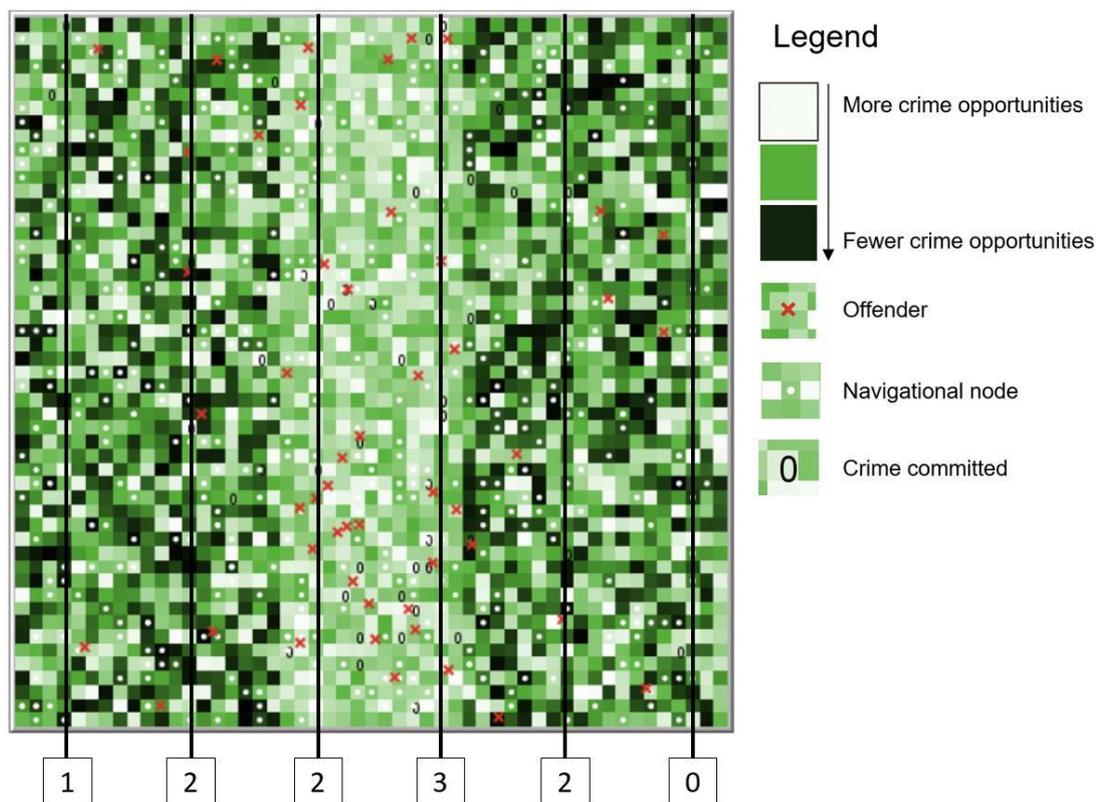


Figure 6.5 - Transect Example

By counting the number of crimes which are committed along each transect (showed in the box below each), the total number per step along the x axis is obtained. This can then be converted into a scatter plot. This figure shows a sample of 6 of the transects.

### 6.3.2.2 Choropleth Maps

Whilst the strength in the scatter plots lies in its ability to simplify the data, clearly demonstrating the trend along the x axis, this could mask any patterns which occur along these transects. As a result, the average number of crimes per patch was calculated for each environment, and then converted into a raster grid, to enable a clear visualisation of the crime patterns across the whole environment in the form of a choropleth map.

### 6.3.3 Stylized Facts

In order to validate the results, they were compared with a stylized fact; that of crime concentration. It is well-known that the spatial distribution of crime is neither random nor uniform, instead concentrating in space and time (Farrell, 2015; Frank et al., 2012; Wortley and Mazerolle, 2008 etc.). Indeed, Kinney et al. (2008) stress that the distribution of crime follows a power law; that crime is intensely concentrated in some locations, and tapers away to few crimes in others. Although crime concentration has been identified at a range of spatial scales (Johnson, 2010), this work concerns microgeographic spaces, and is thus examining what Weisburd (2015) termed the *law of crime concentration at place*.

Research into crime at microgeographic places began in the late 1980s (Weisburd, 2015), with the term *criminology of place* being coined in 1989 by Sherman et al. (Weisburd, 2015). Since then, interest in this field has grown, and a number of studies have identified clustering at this small spatial scale (see Weisburd (2015) for a detailed review on this subject).

Because studies of crime concentration have developed in a somewhat piecemeal manner, it has been highlighted that some concepts and terms can be imprecise (Farrell, 2015). Despite this, it is considered appropriate as stylized reality for this work. Not only is empirical evidence indicative of crime concentration consistently found (Johnson, 2010), but Weisburd (2015) identified sufficient evidence to liken the clustering of crime at micro-places to a physical law, identifying that crime concentration consistently remains within a limited bandwidth. Moreover, Weisburd (2015 p.135) suggests that crime concentration at place is “[p]erhaps the first and most important empirical observation in the criminology of place”.

As a result, in order to corroborate the theory examined here, spatial concentration of crime must be identified by the results of the model, with both the generator and attractor models leading to the creation of crime clusters. However, as stressed by Crooks et al. (2008), validity of a model should not be considered in binary terms. Accordingly, presence of crime concentration will not automatically validate these models, rather suggesting a strong degree of validity.

### **6.3.4 Sensitivity Testing**

In order to test whether various settings and variables within the model were appropriate, sensitivity testing was undertaken. When specific tests were run, settings were adjusted, and run 100 times for each environment, for 3,000 iterations each. The sensitivity testing of this model focused on three primary parameters within the code:

#### **6.3.4.1 Scaling Value**

Within the equation to calculate the probability of committing crime a scaling value,  $\lambda$ , is used to uniformly reduce how frequently crimes are committed. A number of different scaling values were tested, in 0.01 increments between 0.01 and 0.09, as well as having no scaling value, in order to examine the on the crime patterns. It was identified that all values, including not using a scaling value at all, produced the same patterns in their outputs, and thus the specific value used is not of note. As a result, 0.05 was selected as this value, in order to make offences fairly infrequent, as the higher the number of crimes committed, the more computationally expensive it was to run the model.

#### **6.3.4.2 Motivation Variable**

In order to assess the appropriateness of the motivation variable, tests were undertaken to explore how its value on initialization varied the result. Giving all offenders the same value upon initialisation was found to lead to the same patterns as giving them a random value. As a result, the latter was selected, as it is more realistic, reflecting the population's varying propensity to commit crime (Brantingham and Brantingham, 1981)

Another feature examined was the effect of offending on the agents' motivation; whether it should reduce following an offence. The patterns for the control and generator models remained the same in either scenario, but those of the crime attractor became more similar to those seen from the generator model, which shall be discussed shortly. Following a literature search, it was decided to retain the reduction of agents' motivation in these models. Not only does this more accurately reflect human behaviour by ensuring the agents do not offend constantly, it also permits the consideration of fluctuating personal circumstances and their impact on offender desistance (Clarke and Cornish, 1985; Farrall and Calverley, 2006).

#### **6.3.4.3 Navigational Nodes**

Given that a large number of navigational nodes would be more computationally expensive than a small number, tests were run to identify a suitable value for this variable. The use of a smaller number of nodes (50) led to wider variance in model results, whereas a larger number (500) led to more reliable results. Consequently, an intermediate value (250) was selected as a good compromise between reliability and computational expense.

### **6.4 Results**

In order to examine variance between each of the 1000 model runs, boxplots were made of the results of all three environments, by transect. As many of the patches did not have a crime committed on them, the large number of zeros in the data was suppressing meaningful patterns. As a result, any zero value was removed. Figure 6.6, Figure 6.7 and Figure 6.8 are the resultant box plots, and demonstrate that although a few outliers occurred, the majority of the model runs experienced relatively little variance.

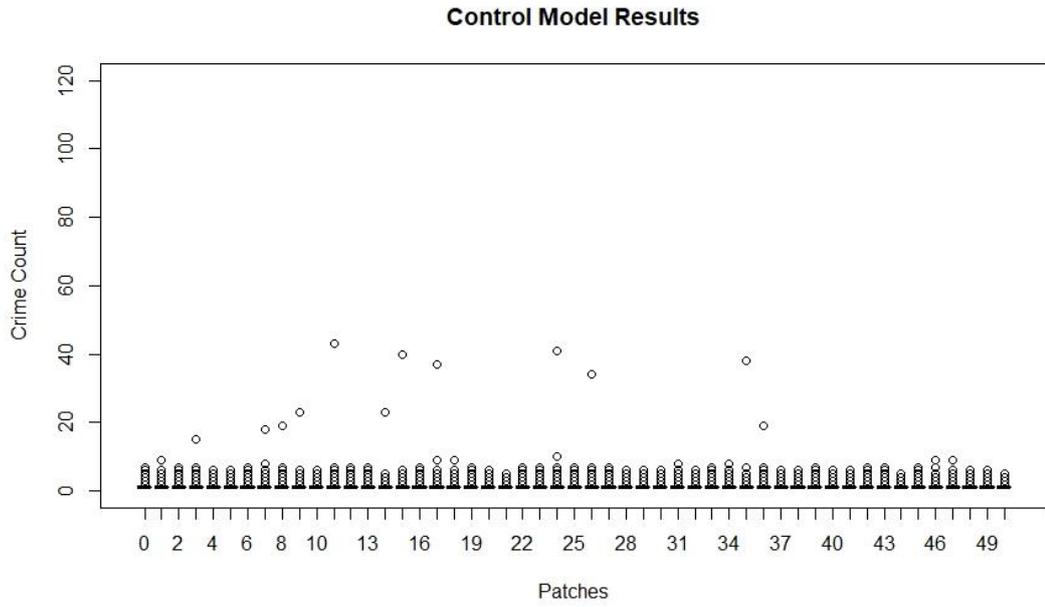


Figure 6.6 - Control Model Boxplots

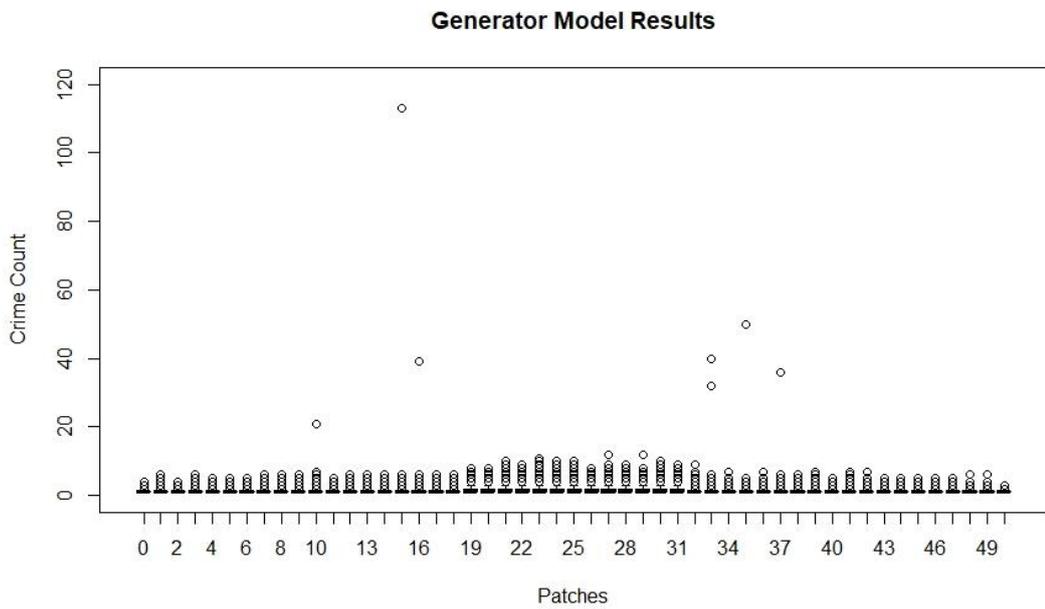


Figure 6.7 - Crime Generator Model Boxplots

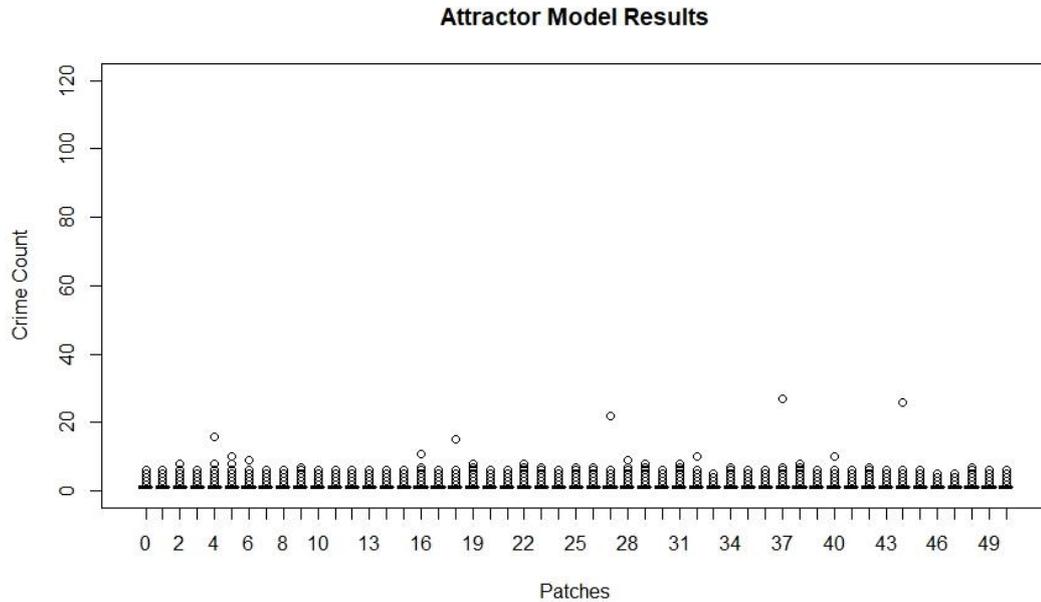
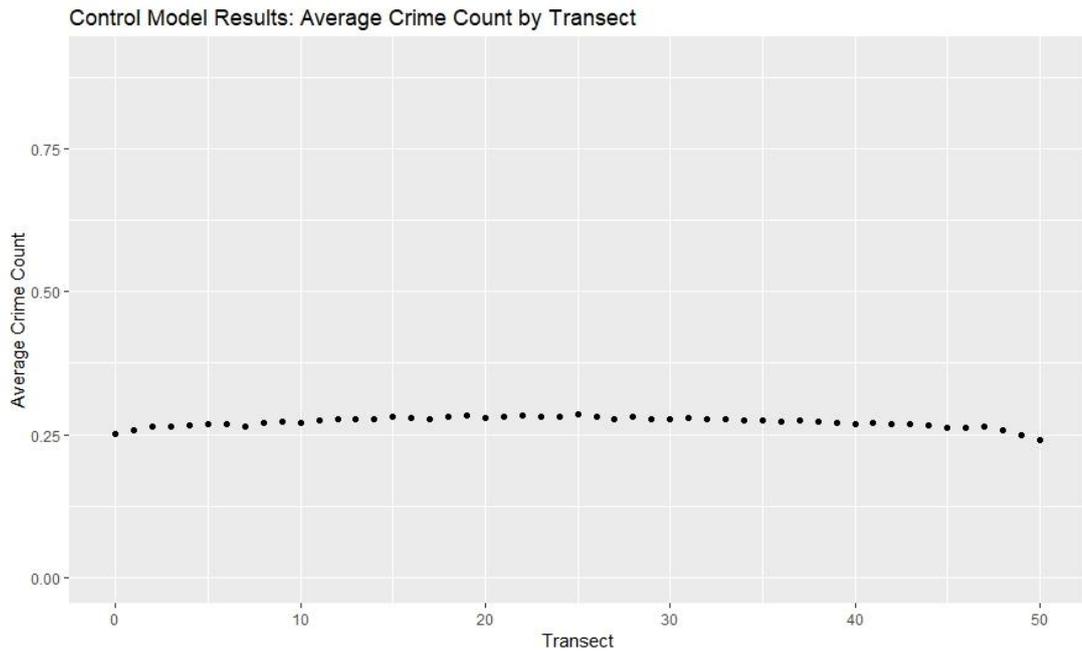


Figure 6.8 - Crime Attractor Model Boxplots

### 6.4.1 Control Model

Figure 6.9 presents the results of the model runs for the control area, showing the average crime count per transect of the environment. These results demonstrate, as expected, a fairly even distribution of crime across the environment with no noticeable clusters. There are, on average, around 0.27 crimes per patch across each transect, but this increases slightly to 0.285 in the centre, and declines slightly at the left- and right-most edges of the environment to 0.25 and 0.24 respectively. Due to this small range of values, the choropleth map of these results has not been included here.

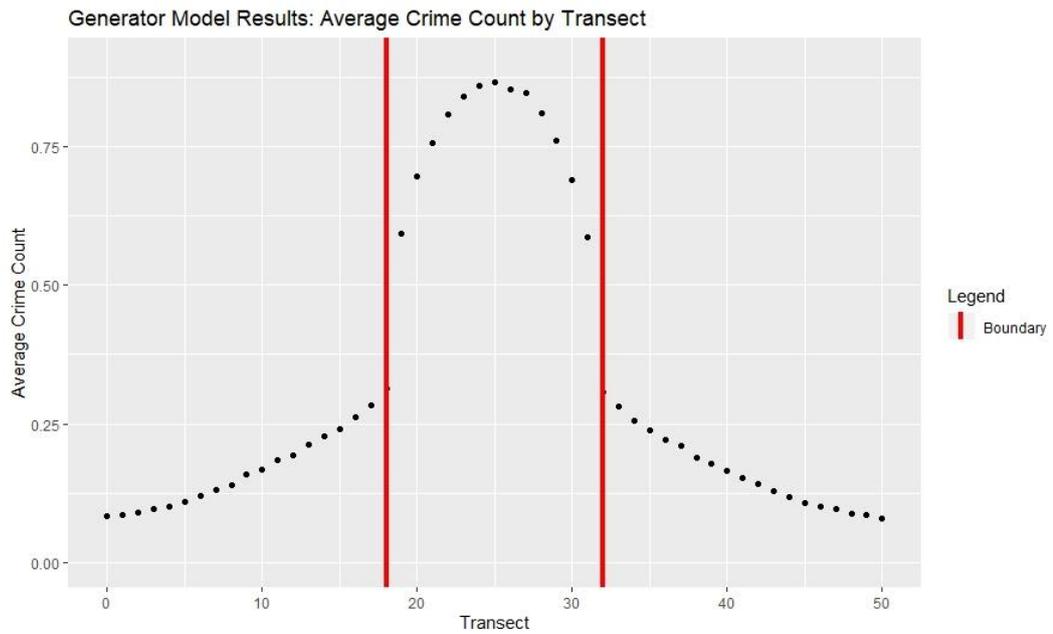


**Figure 6.9 - Control Model Scatter Plot**

As no clusters are evident here, these results indicate that any clustering identified by the generator and attractor models is solely the result of the mechanisms which underpin them.

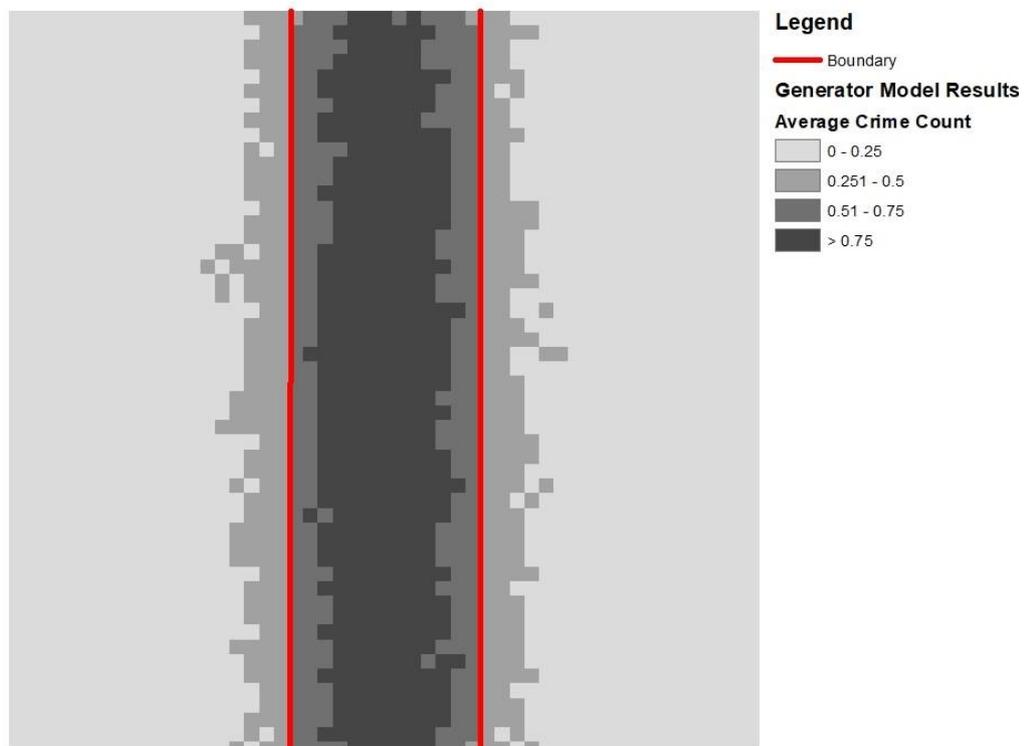
#### **6.4.2 Crime Generator Model**

The results of the model runs for the crime generator model identify a vast increase in crime within the generator space, as one can see from Figure 6.10, the scatter plot for this model. On both sides of the boundary of the area, 0.31 crimes are committed per patch, which almost doubles to 0.59 crimes in the adjacent transects. The crime count then increases steadily, reaching its peak in the centre of the space, where 0.86 crimes are committed per patch.



**Figure 6.10 - Crime Generator Model Scatter Plot**

From this and the choropleth map for the crime generator model, Figure 6.11, the absence of edge effects is apparent. In fact, the reverse is true, that the internal edges of the generator space see the lowest amount of crime in the area.



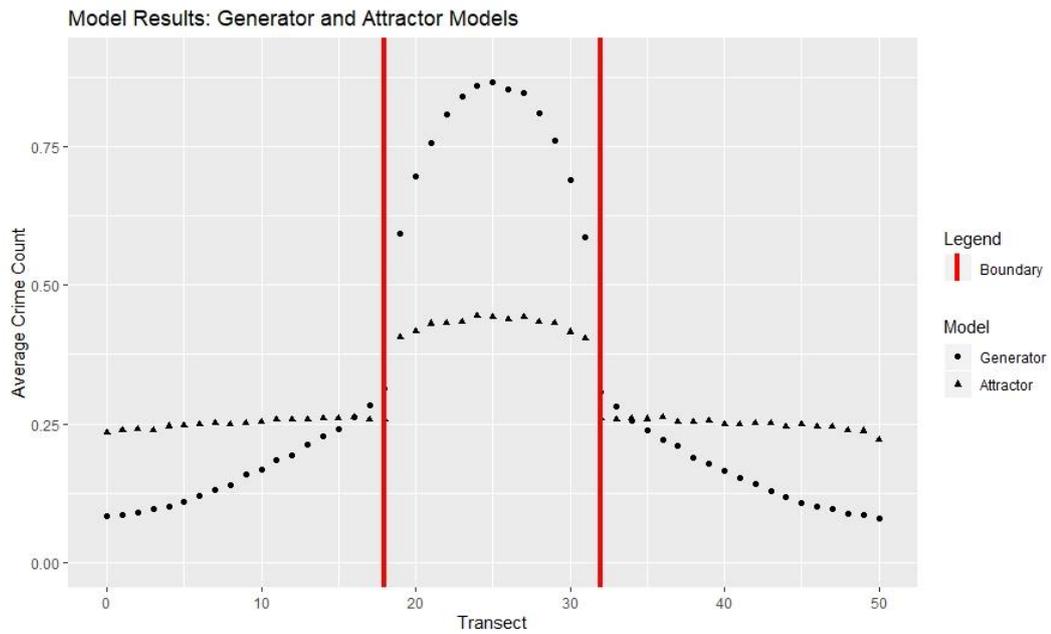
**Figure 6.11 - Crime Generator Model Choropleth Map**

The crime patterns identified outside the generator space are also of note. Particularly evident in Figure 6.10, there is very steady distance decay. On average, offending declines by 0.013 crimes per patch as one moves each transect away from the generator space. This distance decay, combined with the steady increase of crime towards the centre of the generator space, suggests that the presence of a crime generator in an area could lead to stark clustering of crime.

In order to corroborate or reject this finding, these results must be compared with the aforementioned stylized reality; that of crime concentration. Crime concentration is evident in both graphs for this model, consequently suggesting that the results identified here are valid; that edge effects are not present around crime generator. However, as previously discussed, the need to consider validity in non-binary terms is relevant here. Whilst this indicates that the results of this work are valid, and that there is no potential relationship between edge effects and crime generators, additional research is needed in order to corroborate this further.

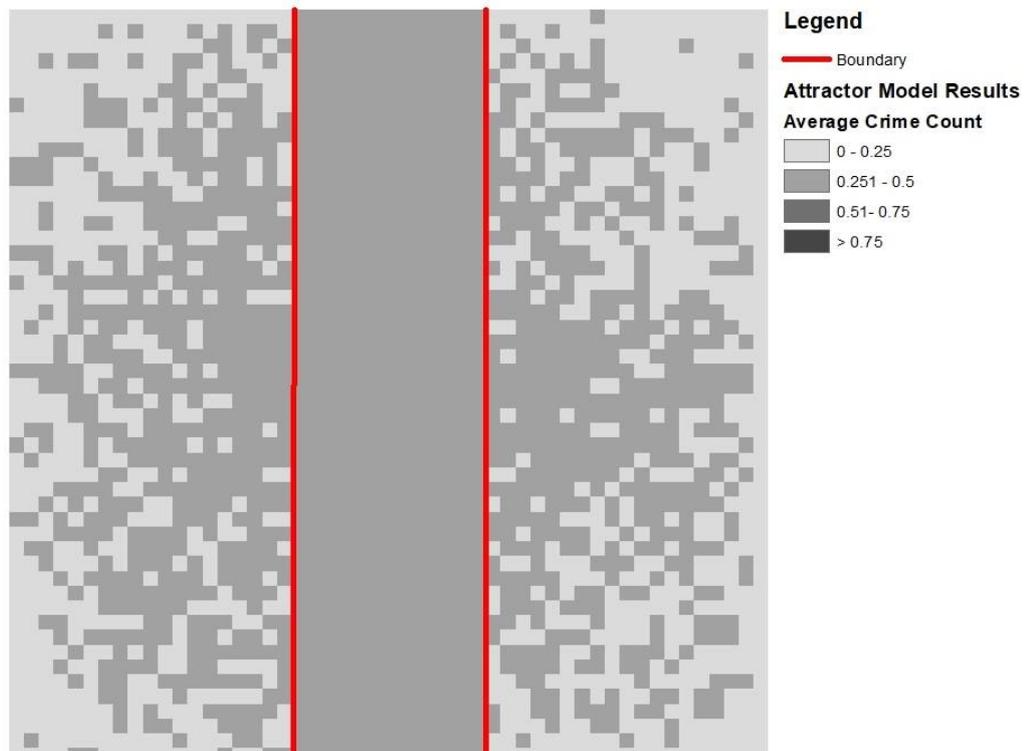
### **6.4.3 Crime Attractor Model**

As displayed in Figure 6.12, the scatter graph of the attractor model results overlaid onto the generator results, this simulation also identified an increase in crime occurrence within the attractor space, albeit to a lesser extent than those of the generator model. Unlike the crime generator, which sees a vast increase in crime occurrence towards the centre of the space, offending within the crime attractor occurs at a more consistent rate across the space, increasing only slightly towards the centre; from 0.405 at the internal boundaries, to 0.44 in the centre. However, similarly to the crime generator, edge effects are not present in this model.



**Figure 6.12 - Crime Generator and Attractor Model Results**

In the space outside the crime attractor, similar patterns are identified to those of the control model, where offending remains fairly consistent across the external space. Indeed, not only is the pattern similar, but the values are also comparable; around 0.25 crimes per patch. Whilst there is a slight decline evident in the transects furthest from the attractor, this is minimal. This decline is, however, evident in Figure 6.13, the choropleth map for the attractor model, where one can see noticeably less crime in the corners of the environments.



**Figure 6.13 - Crime Attractor Model Choropleth Map**

Although the crime generator saw crime almost double from the external to internal spaces, the attractor model does not identify such a harsh increase, instead increasing by approximately 0.15 crimes per patch. This model still does, however, reproduce the stylized reality of crime concentration, therefore validating the model. As a result, no potential relationship between edge effects and crime attractors can be concluded.

## **6.5 Discussion**

The aim of this work was to use agent-based models to identify whether edge effects, in the form of increased crime around the edges of a space, occur around crime generators or crime attractors. However, neither the generator nor attractor model suggested that offending spikes on their edges. In fact, the edges of these spaces saw less crime than the centres, as offending increased with each step towards the centre of both of these areas. As a result, following validation of the models through stylized reality, this theory testing has suggested that, in this instance, the mechanisms underpinning crime generators and crime attractors alone do not lead to the

emergence of edge effects around these spaces. If empirical evidence can also be found for this, it could have implications for policy, as it suggests that the internal areas of these facilities could require more guardianship than the edges.

However, it is not merely offences around the edges of these spaces which are interesting here. These models identified differing crime patterns for each type of space, both internally and externally. Inside the generator, for example, offending was found to increase steadily towards the centre of the space, where it reached its peak. Given that theory dictates that the majority of the crime problem experienced at generator locations is caused by more people using the space (Clarke and Eck, 2003), this suggests that the centre of the generator was the most heavily travelled area of the model. The inside of the attractor, however, saw far less variation, despite also increasing a little towards the centre. Indeed, the frequency of crime occurrence within the attractor area is fairly stable across the space. Moreover, the extent to which crime increases at the boundary of these spaces also differs; whilst offending almost doubles when one enters the generator space, the increase at the boundary of the crime attractor is less pronounced.

Furthermore, despite the fact that work on crime generators and attractors has rarely examined the vicinity of the facility under scrutiny (Boessen and Hipp, 2018), the patterns identified outside these spaces are also of note, as they suggest clear differences outside the generator and attractor. Whilst the model for the crime attractor found that offending outside this space is consistent with the control model, being fairly uniform with minimal fluctuation, that for the crime generator identified clear existence of distance decay occurring in this area. As previously highlighted, a number of projects have identified the presence of distance decay around facilities (see, for example, Bernasco and Block, 2011; Bowers, 2014; Furr-Holden et al., 2016; Groff, 2011; Holloway and McNulty, 2003; Kumar and Waylor, 2003; Ratcliffe, 2012), and thus this finding is in line with previous empirical investigations.

Could these patterns be used to quantify real-world generators and attractors? As previously stated, a limited number of classification methods

have been proposed, and even fewer have been tested. However, the results of this analysis suggest that the spatial crime patterns in their vicinity, as well as those within the crime generator and attractor spaces themselves, are highly different. As a result, for example, the presence of clearly defined distance decay around a facility could suggest that it is a crime generator, rather than a crime attractor. This shall be tested in the empirical work in Chapter 7. Furthermore, these patterns could also suggest that an area which has many crime generators could see greater clustering of crime than an area with many crime attractors.

Moreover, these results appear to refute Ratcliffe's (2012) suggestion that crime attractors radiate crime into their surroundings, whereas crime generators have no contagious effect. However, given that the focus of Ratcliffe's work was not on the distinction between these spaces, but their influence on their vicinity, the underlying mechanisms examined here were not tested. This again suggests that these mechanisms need to be explored further, in order to improve our understanding of them in a variety of settings.

However, this work is not without limitations, the most notable being the lack of testing for statistical significance. In an attempt to mitigate this, hot spot analysis, in the form of Getis-Ord  $G_i^*$  analysis, was conducted using a GIS to identify areas of which saw statistically significant crime hot spots. However, because this software was unable to identify the environment as a torus and thus the algorithm presumed a boundary around it, the patterns identified at the edges were incorrect. Future work would benefit from the application of tests to identify statistical significance.

## **6.6 Conclusion**

Whilst this work aimed to investigate crime patterns on the edges of crime generators and attractors, the results across the whole environment were notable, identifying clear differences in the spatial distribution of crime both inside and outside these spaces.

This discovery could have broad practical implications, as well as contributing to theory development. If it is possible to identify whether a space is a crime generator or attractor, policing strategies planned for the

area could be tailored to the mechanisms which are leading to offences occurring there. In order to develop this idea, further empirical analysis on crime generators and attractors is required to examine whether the theoretical presence of this pattern matches that identified empirically.

### **Summary**

*The work in this chapter has met Objective 3 of this thesis, to examine the theoretical mechanisms underpinning this concept using an agent-based model, and their implications for crime distribution. It has explored whether the processes which lead to the emergence of crime generators and attractors also lead to edge effects. The results of this work suggest that they do not. However, despite this, these findings suggest differences in the spatial distribution of crime inside and outside these types of spaces.*

*The subsequent chapter uses more traditional methods to explore whether these crime distribution patterns can be identified empirically. However, edge effects shall not be investigated further in this thesis. They were not evident through this computational work, and due to aforementioned challenges in studying them empirically, it is considered out of scope of this project to explore them further.*

### **Chapter 6 References**

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## **Chapter 7**

### **Spatial Distribution of Crime in the Vicinity of Crime Generators and Attractors: an Empirical Investigation**

#### ***Preface***

*This chapter constitutes one part of the empirical analysis in this thesis. It investigates the spatial distribution of crime around a sample of locations identified as crime generators and attractors in the literature using changepoint analysis and k-means clustering. It aims to (1) compare these empirical results with those found by the agent-based model in Chapter 6, (2) explore whether the spatial distribution of crime around crime generators and attractors could be used to distinguish between them, and (3) identify any potential reoccurring patterns which could be indicative of subgroups of these spaces. This research has identified that whilst both crime generators and attractors lead to crime concentration, they do not lead to vastly different crime distribution, and no subgroups can be identified based on their crime distribution patterns. Moreover, these results differ greatly from those found in Chapter 6. This disparity in results could indicate either that understanding of these processes is lacking within the discipline, the formalisation of these mechanisms in the agent-based model was incorrect, or that this empirical work has not managed to suitably isolate the effects of the facilities from the environment.*

*The work found in this chapter aligns with Objective 4 of this thesis, to empirically investigate crime patterns distribution around crime generators and attractors, and identify whether the crime patterns which emerged as a result of the agent-based model are seen empirically. Not only does this chapter relate to Chapter 6 (the agent-based model), but it is also connected to Chapter 5 (testing the classification methods) as it experiments with using crime distribution patterns to distinguish between crime generators and attractors.*

## 7.1 Introduction

Within the field of environmental criminology, crime generators and crime attractors have been referred to as “the most salient crime predictors” (Connealy, 2020 p.4). Proposed by Brantingham and Brantingham (1995), crime generators and attractors categorise different processes which could lead to the emergence of crime hotspots. Crime generators, they suggested, are facilities or areas of a city that are not necessarily associated with crime, but which many people visit, such as shopping areas (Brantingham and Brantingham, 1995). Potential offenders also frequent these places because of their legitimate use, but encounter and exploit opportunities for crime whilst there or at a later date. Conversely, crime attractors are areas which have a reputation for crime which attract suitably motivated offenders, such as red-light districts (Brantingham and Brantingham, 1995).

Whilst it has been suggested that understanding the impact of facilities on crime occurrence is important for studying crime concentration (Groff and Lockwood, 2014), empirical research investigating crime generators and attractors is limited. This is potentially because it is challenging to find empirical data to appropriately verify their mechanisms, as discussed in Chapter 2. Because of the challenges of empirical investigation, a selection of computational papers have instead explored these processes and are indicative of support for the existence of these processes. Davies and Birks (2021), for example, found that the mechanisms underpinning a crime generator led to areas of crime concentration using an agent-based model (ABM), and the work in Chapter 6 used an ABM to identify that these processes not only led to crime concentration in an abstract space, but also to different offence patterns in their vicinities. Moreover, Reid et al. (2014) simulated offenders’ journeys to crime and found that a number of crimes are committed in the vicinity of the paths to crime attractors, not just at the attractor sites themselves. These works suggest that the crime generator and attractor mechanisms can shape offending not just within the site itself and in its immediate vicinity, but in its surrounding environs as well. As with all models, however, these results are highly dependent on the assumptions

excluded or included in the model (Johnson and Groff, 2014; Weisburd et al., 2017), and must therefore be treated with caution.

Despite being frequently mentioned in environmental criminology research, crime generators and attractors are not well understood and often their definitions are ambiguous (Newton, 2018). Indeed, the suggestion that a place is a generator or attractor is often provided as a post hoc explanation for crime concentration (Davies and Birks, 2021), rather than being studied themselves. As a result, there are a number of areas in the extant literature which are particularly lacking which would benefit greatly from further study. For example, there is limited understanding of how to classify a real-world site as either a crime generator or attractor. Moreover, even though a range of literature has found that crime generators and attractors do not affect crime occurrence uniformly (see, for example, Frank et al. (2011) and Groff and McCord (2012)), there has been little research into the potential existence of subgroups of these spaces which could affect the offending which takes place there. Not only would further theoretical and empirical research go some way to clarifying and validating these concepts, but it also has the potential to inform crime reduction strategies which could then be tailored to address the different processes which lead to the development of these hotspots (Sosa et al., 2019).

This research aims to investigate spatial crime patterns in the vicinity of potential crime generators and attractors identified from environmental criminology literature. This work has three main objectives. First, to examine whether the patterns identified empirically around sites suggested to be crime generators and attractors match the results of those found computationally in Chapter 6. The second objective of this research is to explore whether crime generators and attractors create different crime distribution patterns, and whether these could be used to distinguish between these types of spaces. The third is to identify whether any recurring patterns exist, which could suggest subgroups of crime generators and attractors.

The structure of this chapter is as follows. Section 7.2 provides background to this research, offering more detail on crime generators and attractors.

Subsequent sections detail the case studies selected for this analysis, as well as the datasets and methodologies used. This is followed by the results and discussion.

## 7.2 Background

The initial formalisation of crime generator and attractor processes were provided by Brantingham and Brantingham (1995), although the idea of facilities affecting crime patterns was not new at this time. In examining these definitions, the scoping review found in Chapter 4 proposes that the processes from the original definitions of crime generators and attractors can be identified and itemised. These mechanisms have been listed in Table 7.1. Despite these distinctions, Newton (2018) suggests that the main difference between these types of space is offender motivation; offenders specifically visit crime attractors with the goal of committing a crime, whereas at crime generators, the main types of crime committed are opportunistic.

| <b>Crime Generator Mechanisms</b>   | <b>Crime Attractor Mechanisms</b>                                       |
|---|---|
| That large numbers of people use the space  | That these areas have reputation for criminal opportunities             |
| That offenders do not go to these spaces to commit a crime, but encounter unexpected opportunities which they exploit | That motivated offenders go to these areas specifically to commit crime |
| That these spaces are not criminogenic in themselves  |   |

**Table 7.1 - Crime Generator and Attractor Mechanisms specified by Brantingham and Brantingham (1995)**

However, even though the difference between crime generators and attractors appears relatively distinct, it has been suggested that locations which could be considered either type of space are rarely exclusively one or the other (Brantingham and Brantingham, 1995). This has been demonstrated by a number of authors, such as Christensen (2008), who lists the ways in which the Beerburrum forest district in Australia acts as both a crime generator and crime attractor, in line with the processes identified by

Brantingham and Brantingham (1995). Moreover, it has been proposed that crime generators and attractors can evolve between one another (Clarke and Eck, 2005, 2003).

Additionally, whilst specific types of facilities are often given as examples of either crime generators or attractors, it is important to note that not all facilities exhibit the same patterns. Frank et al. (2011), for example, in their study of shopping malls as crime attractors, identified that not all of their case study areas suggested the existence of crime attractor mechanisms. A number of authors have examined the characteristics which can affect a site's strength as either a crime generator or attractor, such as Mago et al. (2014), who suggested that the relative attractiveness of a crime attractor is affected by a number of different factors, such as better transport links, and Tillyer et al. (2020), who identified that the effects of crime generators is exacerbated in disadvantaged areas. Despite these examples, this remains a relatively understudied topic. Therefore, is it possible that rather than two types of spaces, crime generators and attractors<sup>4</sup>, there are instead subgroups of these spaces which lead to different offending patterns? For example, are there locations which are mainly crime generators, where primarily opportunistic offences occur, and others which are crime generators which have some (potentially crime type-specific) crime attracting qualities, to which some offenders are drawn? This remains largely unknown and will be explored in this paper.

Despite the fact that crime generators and attractors should not be considered only in binary terms, the ability to empirically identify the dominant (if any) mechanisms responsible for a particular crime concentration would be of great practical benefit, allowing law enforcement strategies to be tailored to the processes which lead to offending. A limited number of papers have experimented with methods of classifying these spaces. Clarke and Eck (2005, 2003) proposed that crime generators will

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<sup>4</sup> Whilst it is acknowledged that other types of spaces could exist, such as crime enablers (Clarke and Eck, 2005, 2003), this work focuses on the original two concepts proposed by Brantingham and Brantingham (1995).

have high counts but low rates of crime, whilst crime attractors will have high counts and high rates of crime; and Irvin-Erickson and La Vigne (2015) created a range of variables related to crime generator and attractor mechanisms with the aim of distinguishing between them when examining metro stations. Clarke and Eck's (2005, 2003) suggestion would allow one to classify a site as a crime generator or attractor based on previous offending which has occurred there, and focuses exclusively on the number of potential targets and offenders as an indicator of crime generator or attractor mechanisms at play. On the other hand, although Irvin-Erickson and La Vigne (2015) considered previous offences whilst creating their classification, they also examined other characteristics which relate to the crime generator and attractor processes. These include the connectedness of the station to the rest of the transit system, which they suggest could indicate a large number of potential targets and offenders, and the remoteness of the station, as they highlight that more isolated stations have been found to experience more crime than those which are less remote.

### **7.2.1 Identifying Crime Patterns around Crime Generators and Attractors**

As highlighted by Ratcliffe (2012), Brantingham and Brantingham's (1995) seminal work on crime generators and attractors made several references to the importance of geographical context. As a result, Ratcliffe claims that "the idea of crime generators and attractors is thus not just tied to the specific location, but the area in immediate vicinity to the particular land use" (Ratcliffe, 2012 p.103). In this section, the distance of influence around crime generators and attractors is first discussed, before examining the spatial crime patterns identified around these facilities. Although it is acknowledged that crime generators and attractors could be associated with different types of crime (Newton, 2018), the majority of research into them looks at more general crime trends. Therefore, whilst it is possible that the spatial distribution of crime could vary by crime type, this is not explored in this study which instead focuses on the overall spatial patterns of crime.

When examining the impact of a facility on spatial distribution of crime, it is important to consider it in the context of its surroundings, both physical, such

as surrounding facilities and the road network, and intangible, such as the demographics of the area and the crime trends in the city as a whole (Boessen and Hipp, 2018; Brantingham and Brantingham, 1995). This context must be kept in mind when considering the findings of these pieces of research as it could call into question the generalizability of these results, and whether the results can be attributed solely to the facility under scrutiny. Indeed, establishing which crimes can be attributed to a particular facility (or set of facilities) remains a fundamental problem for those who seek to study potential crime generators and attractors. Moreover, the dynamic nature of crime patterns must also be considered. As the way people use space and facilities fluctuates through the day, consistent temporal patterns cannot be expected, especially around sites such as bars which have distinct opening hours (Newton, 2018). Clearly the processes which underpin the emergence of crime generators and attractors are therefore affected by a variety of factors which are individual to each site. This complexity adds to the difficulty in studying the spatial distribution of crime around these locations.

#### **7.2.1.1 Distance of Influence around Crime Generators and Attractors**

Unsurprisingly, across the literature a number of different distances have been identified to be the sphere of influence around a crime generator or crime attractor, ranging between 25ft (8m) and 1.5km.

The smallest distance at which facilities were found to impact crime occurrence was identified by Xu and Griffiths (2017) who observed that shootings are most concentrated within 25ft (8m) of foreclosures, liquor stores, grocery stores and bus stops. They identified, however, that each of the sites have different patterns as one moves further from the facility; grocery stores and liquor stores, for example, are found to have an impact for up to 255ft (78m), whereas foreclosures have limited impact further than 25ft (8m) away. McCord and Ratcliffe (2007) also found different facilities to experience different crime patterns in their surrounding area using crime location quotients. Whilst they identified that clusters of drug arrests were found within 400ft (122m) of cheque-cashing centres, subway stations, beer establishments and pawnshops, their analysis identified that halfway houses, homeless shelters and drug-treatment centres actually experienced

lower crime occurrence in their immediate environs. Instead, these sites were found to experience more crime a little further away; 400-800ft (122-244m) from halfway houses and 800-1200ft (244-366m) from drug-treatment centres and shelters, which they suggest could be caused by a potential place management effect (Eck, 1995). This pattern has been referred to as spatial lag, and suggests that whilst many targets are present in the immediate vicinity of certain facilities, there are also capable guardians who deter offending occurring in their most immediate vicinity (Newton, 2018).

A number of studies looking at parks identified that their sphere of influence is also relatively small. Adams and Felson (2015), for example, identified that crime is concentrated within 50ft (15m) of parks. They found that outside this initial concentration, crime reduces by 70% between 50ft (15m) and 200ft (61m) away from these sites, but increases again between 400ft (122m) and 500ft (152m). They did not, however, suggest possible explanations for this pattern. Groff and McCord (2012) also concluded that crime clusters in and around parks and their surrounding streets, but identify a significant decrease in crime occurrence between 0 and 400ft (122m) of a park, before increasing again between 400ft (122m) and 800ft (244m), and then again decreasing between 800ft (244m) and 1200ft (366m). This finding, they suggest, could be caused by nearby residents taking action to prevent crime problems associated with the park from affecting them. This increase around 400ft (122m), identified by both of these studies of parks, is one of the few consistent findings identified in published literature. There are also similarities to the findings of McCord and Ratcliffe (2007), which could be attributed to a place management effect. However, Boessen and Hipp (2018) found that a block within 400ft (122m) of parks generally sees *fewer* robberies, homicides, motor vehicle thefts and larcenies than other blocks, but that the nearby demographics and land uses affect this. The authors suggest that parks build community capacity for social control, and are therefore protective for the communities in which they are situated. It is therefore interesting to note the differences in conclusions between these three papers. This inconsistency could be caused by a number of factors, such as different datasets and methodologies, or even cultural and societal differences between the case study areas. There is clearly a need for more

work in this area, to identify consistent results and add clarity to an already complex field.

A few other papers studied the influence of facilities over a larger geographical space. Ratcliffe (2012 p105), for example, in exploring "how far around a node will there be a discernible increase in crime?", found that 83.5% of violent crimes were within 1500ft (457m) of an alcohol outlet, but noted that the majority clusters within 330ft (101m). Additionally, Kurland et al. (2014), whose work examined crimes around a stadium, identified increases in offending up to 1.5km from the site on days when matches were on. Despite this, they also note that 60% of crimes occurred within 500m of the stadium on these days. Similarly, Vandeviver et al. (2019), who were also examining a stadium, elected to study a buffer area of 1.25km, and found that the stadium's closure led to a crime reduction of 7% more in this area than the city-wide trends. They also point out that similar results are obtained when this study area is smaller, (500m, 750m, and 1000m), but these results are not provided. Moreover, Contreras's (2017) research suggests that the presence of medical marijuana dispensaries on a block could impact crime patterns for half a mile (805m) surrounding it. Reid et al. (2014) identify a similar sphere of influence when looking at offences around travel paths to crime attractors, as they found that approximately 70% of crimes are found within 1km of the offenders' routes. More notably, they also found that 30% of crimes studied were within 50m of these paths, suggesting that the area closest to the paths has the most intense clustering of crimes.

This suggests that while the effects of a crime generator or attractor can be felt several hundred meters away from the facility, there is a correlation between offending and distance from the site. Although many papers identified this to be the case, a specific distance of influence of crime generators and attractors cannot be identified, as this varied a great deal between facility types. However, this is unsurprising given the differences in environments around these sites given the aforementioned differences in networks, geodemographics and surrounding facilities which could all impact the sphere of influence of a crime generator or attractor.

### **7.2.1.2 Crime Patterns around Crime Generators and Attractors**

Section 7.2.1.1 examined the distance over which crime occurrence would be affected by the presence of a crime generator or attractor, whereas this section details the spatial patterns of crime around these types of sites. As highlighted above, the impact of a crime generator or attractor on its immediate surrounds cannot be automatically assumed. Indeed, a number of possibilities have been suggested as to the relationship between crime generators and attractors and their environs. For example, Bowers (2014) used spatial regression to explore whether these facilities attract offenders to commit crime within them, thus reducing the risk of crime in the immediate area, or whether they instead 'radiate' risk into their surroundings. She concluded the latter, as did Bernasco and Block (2011) in their study of crime generators and attractors in Chicago.

When studying the patterns of crime around their various case study facilities, a number of papers encountered distance decay, which is that crime rates reduced as one moved further from the site in question. Ratcliffe (2012), for example, identified this spatial pattern in violent crime around alcohol outlets, as did Xu and Griffiths (2017) in their study on a number of features identified as crime attractors. This pattern was also found by Bernasco and Block (2011); blocks (defined generally as "an area that is encompassed by four streets" (Bernasco and Block, 2011 p.53)) which house a crime generator or attractor have the highest robbery counts, those adjacent have fewer robberies, and those further away have fewer still. Not only did these empirical methods lead to the identification of distance decay, but computational research has had similar results too. Reid et al.'s (2014) work using computational models to simulate movement of offenders in comparison with the actual crimes they committed also found evidence of this phenomenon around paths offenders use to travel to crime attractors. Similarly, Chapter 6 of this thesis used an agent-based model and identified distance decay around crime generators. The combination of these findings offers evidence to confirm that the influence of crime generators and attractors is greatest in its immediate surroundings (Newton, 2018).

As well as these papers which identified distance decay, several found mixed results. McCord and Ratcliffe (2007), for example, found this pattern around some of their case study facilities, but not others. Similarly, Boessen and Hipp (2018) identified that motor vehicle theft patterns exhibit distance decay around parks, but that this pattern does not hold true for all crime types. Additionally, Groff and McCord (2012) did not find the distance decay they had expected in their studies of crime around parks, instead finding that a range of offences decreased in the first 400ft (122m) from a park, before increasing between 400 and 800ft (122 – 244m), as highlighted in the previous section.

In short, the mixed nature of these results means that it is currently challenging to confidently conclude that crime generators and attractors lead to specific crime distribution patterns. Whilst it appears that distance decay often occurs around crime generators and attractors, some of the research covered here identified this not to be the case. Even within the same study, different crime types have created different patterns, and the same type of facility was found to have different results across different papers. This suggests that it is not yet possible to generalize the patterns found around these spaces, as the results have been somewhat inconsistent, potentially caused by the complexity highlighted in Section 7.2.1. Moreover, even if the patterns identified had been consistent, it is also possible that the studies are not varied enough for any findings to be generalizable to all crime generators or attractors. All the empirical studies examined here, for example, are from western countries, with the vast majority based in cities in the USA. Given the social nature of the processes underpinning crime generators and attractors, it is possible that different patterns would emerge as a result of different cultural norms. In addition, there is little consideration of the aforementioned effects of crime generators and attractors over time; given that the population flows to these spaces would fluctuate throughout the day, the crime patterns experienced in their vicinity could change over time as well.

### 7.3 Case Studies

Although spaces are rarely either a crime generator or attractor (Brantingham and Brantingham, 1995), a number of case studies have been selected for this work as either crime generator or attractor examples. The reasoning for their selection and classification is highlighted in Table 7.2. Three facility types have been selected for each type of space, in order to reduce reliance on a single case study example.

| Type of Space   | Case Study                                  | Authors who give this case study as an example of a crime generator/attractor                                   | Why this case study is an appropriate crime generator/attractor   | Other notes  |
|-----------------|---|---|---|--|
| Crime generator | Schools                                     | Houser et al. (2019), Murray and Swatt (2013) and Song et al. (2019).   | Schools bring together a great number of students and staff. Song et al. (2019) highlight that both high schools and elementary schools can be considered to be crime generators, as high schools congregate large numbers of teenage students who can be both offenders and victims, and that elementary schools lead to large numbers of parents and other carers at the start and end of the school day. | Schools could also be considered to have crime attracting qualities. As Murray and Swatt (2013) highlight, schools might be a relatively unique sort of crime generator. They suggest that during school hours, staff act as guardians and thus dissuade offending, but that there is minimal guardianship in their vicinity after school is over, which could be attractive to motivated offenders. |
|                 | Entertainment venues (cinemas and theatres) | Brantingham and Brantingham (1995), Newton, (2018) and Spicer et al. (2016).                                    | Entertainment locations naturally draw a large crowd for their legitimate purposes, and some of these attendees could commit opportunistic offences.  | NA   |
|                 | Stations                                    | Bernasco and Block (2011), Newton (2018) and Song et al. (2019) have all proposed variations on transport hubs. | Transport hubs are particularly busy during rush hour, and travellers may be less vigilant whilst trying to find their destinations, leaving them more  | Newton (2018) stressed that facilities like subway stations experience a great deal of temporal variation in their   |

|                 |                        |  |   |  |
|-----------------|------------------------|--|---|--|
|                 |                        |  | open to victimisation (Song et al., 2019).  | flows of people, which can affect its crime generating characteristics.  |
| Crime attractor | Bars                   | Brantingham and Brantingham (1995), Contreras (2017) and Feng et al. (2019). | Bars and bar districts have been considered to have a number of crime attracting qualities, including the patrons carrying cash (Contreras, 2017; Ratcliffe, 2012) and potentially making good targets if they are drunk (Ratcliffe, 2012).   | It is likely that bars experience some of the processes of crime generators given the large numbers of people who frequent them.         |
|                 | Drug treatment centres | Groff and Lockwood (2014) and McCord et al. (2007).                          | The people who frequent these facilities could both be vulnerable targets and people with criminal records (Groff and Lockwood, 2014; McCord et al., 2007). Moreover, as they are frequented by drug users, they could attract drug dealers and lead to the emergence of a drug market (McCord and Ratcliffe, 2007) | These locations could be crime generators because of the large number of people who attend them (Groff and Lockwood, 2014)               |
|                 | Homeless shelters      | McCord et al. (2007), Newton (2018) and Yoo and Wheeler (2019).              | The patrons of these facilities are more vulnerable to being a victim of crime, and more likely to have history of offending (McCord et al., 2007). Similarly to drug treatment centres, homeless shelters could be frequented by drug users, consequently attracting drug dealers (McCord and Ratcliffe, 2007)     | As with the other examples of crime attractors, the large number of people using these facilities could lead to opportunistic offending. |

**Table 7.2 - Details of Case Studies**

As highlighted above (and in Chapter 5 of this thesis), it is challenging to empirically identify locations as crime generators or attractors. This is, of course, a distinct limitation to any empirical work seeking to study these types of spaces. However, it is hoped that the use of a thorough literature

review, combined with the use of three case study types for both crime generators and attractors, will reduce the effect of this limitation.

The following sections shall detail the analysis undertaken for this work, starting with the data used before discussing the methods utilised in order to achieve the aim of investigating spatial crime patterns in the vicinity of potential crime generators and attractors.

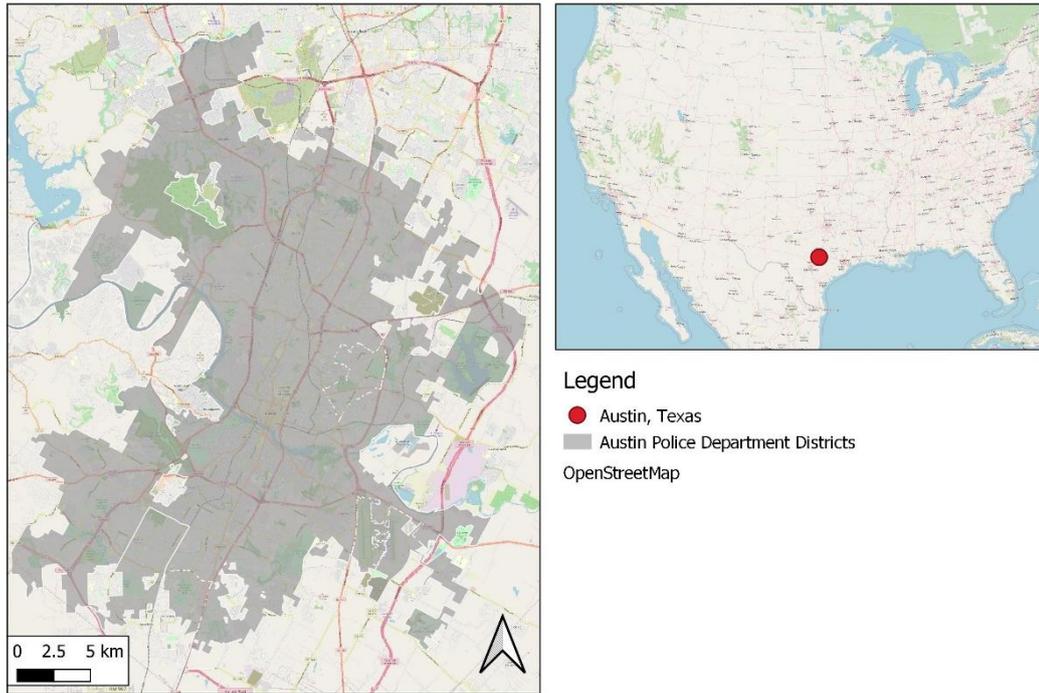
## **7.4 Data**

### **7.4.1 Boundary and Backdrop Data**

The geographic focus for this research is Austin, Texas (USA). Austin was chosen as the site of this work primarily because offence data could be obtained at a suitable geographic scale to enable analysis of the spatial patterns of offences around facilities. The boundary of the city, and therefore the study area under scrutiny in this work, was obtained from the city's open data portal and shows the Austin Police Department Districts (Austin Police Department, 2021a). This dataset was validated against a jurisdiction map for the city (City of Austin, 2013) to ensure completeness. The subsequent study area is displayed in Figure 7.1.

Whilst Austin was not the focus of the agent-based model in Chapter 6, and the results are therefore not directly comparable, it was decided that it was an appropriate dataset to use for this work. In order to build the model, the environment had to be simplified and thus was built using an abstract environment. No empirical crime data exists which can be compared exactly with this, as all locations have the aforementioned specific complexities that come with real-world locations, such as road networks and demographics. As a result, the data from Austin, being at a suitable granular level, were considered appropriate for this research as they are no less (or more) comparable than any other empirical dataset at this level of granularity.

Study Area: Austin, Texas



**Figure 7.1 - Study Area: Austin, Texas**

### 7.4.2 Offence Data

Offence data for Austin was obtained from the city's open data portal (Austin Police Department, 2021b). This dataset contains records of incidents since 2003 that the city's police department responded to and wrote a report for, and contains information on the location, date and time of the offence, as well as the type of offence and other details. In order to capture and smooth out seasonal trends, the data for offences which took place between 1<sup>st</sup> January 2017 and 31<sup>st</sup> December 2019 were downloaded (n = 311,457). Although more recent data was available, it was decided to exclude 2020 onwards in order to avoid any changes to crime patterns caused by the COVID-19 outbreak and behavioural responses to it. Analysis was conducted incorporating violent, property and drug offences (n=165,025). Sexual assaults were removed from this dataset as the City of Austin do not provide accurate geocoding on this offence (Fenimore, 2020), and other crime types were removed if they were unlikely to be affected by crime generators and attractors (such as identity theft). As a result, the offences which were retained in the dataset were either considered to be the function of offenders finding targets in space, or specifically mentioned in crime

generator or attractor literature (i.e., drug offences, as drug markets are considered to be examples of crime attractors (Brantingham and Brantingham, 1995)). As with all police recorded crime data, there are a number of well-known limitations to using this data, such as underreporting of offences by victims (Brantingham and Brantingham, 1997; Song et al., 2017) and potential geocoding inaccuracies (Kurland et al., 2014). However, this data source was found to have inaccuracies in geocoding in only 0.408% of offences (Fenimore, 2020) and consequently it was deemed appropriate for this work in the absence of any more accurate datasets.

### **7.4.3 Case Study Location Data**

As discussed in Section 7.3, six case study facilities have been selected for analysis in this work: three crime generators (entertainment sites, schools and stations) and three crime attractors (bars, drug treatment centres and homeless shelters). Whilst it is difficult to empirically identify a site as a crime generator or attractor, these have been selected based on a literature search and are considered appropriate for this analysis. 270 sites were identified as crime generator case studies, and 264 as crime attractors.

#### **7.4.3.1 Crime Generator Case Study: Entertainment Sites (n=17)**

In order to obtain the location of entertainment sites in Austin, OpenStreetMap data were downloaded from Geofabrik (2021) (correct as of 07.02.2021). This download contained a number of different files, and the locations of 17 cinemas and theatres were obtained from the Point of Interest data. These OpenStreetMap data were validated using the Google Maps, whereby a sample of facilities were examined across both platforms to ensure that their locations were consistent.

#### **7.4.3.2 Crime Generator Case Study: Schools (n=165)**

The data on the location of schools came from two sources. The aforementioned Point of Interest OpenStreetMap data were used alongside data on the locations of schools and facilities from Austin Independent School District (2020). These two datasets were merged to create a more complete dataset on the schools in the city. Validation of this subsequent dataset was undertaken to ensure completeness with a sample of school

locations identified and validated against Google Maps. Data cleaning was also undertaken, removing points from the dataset which satisfied the following criteria:

- Those which were duplicated when the datasets were merged
- Those which did not represent school buildings (such as school car parks)
- Those which represented future school sites
- Those which represented preschools
- Those which represented university buildings
- Those which were outside the study area

The resulting dataset included elementary schools, middle schools, high schools and smaller education facilities such as dance schools. This process produced a dataset containing the locations of 165 schools.

#### **7.4.3.3 Crime Generator Case Study: Stations (n=88)**

Data on the locations of transit stations in Austin were obtained from Texas Open Data Portal (2020). This dataset included a variety of public transportation stops, including bus stops, metro stations and rail stations. The types of stops included in this analysis are metro stations and rail stations which fall within the study area, hereafter referred to as “stations”. Again, in order to validate this data, the location of a sample of these transit stations was identified using Google Maps, which was then compared to this dataset to ensure accuracy. This process produced a dataset containing the locations of 88 stations.

One immediate limitation of this dataset is that many of the metro stations are found in pairs, one on each side of the road. When this is the case, it is impossible to identify which station a crime could be attributed to. This must be considered when analysing these results, as the crimes around some stations may actually be the result of the presence of their neighbour.

#### **7.4.3.4 Crime Attractor Case Study: Bars (n=196)**

The sites of bars and pubs (henceforth referred to as “bars”) was obtained from the aforementioned OpenStreetMap Point of Interest data. Validation of this dataset was done using Google Maps; a selection of bars was identified

in the dataset and it was ensured that they were in the location as depicted in Google Maps.

#### **7.4.3.5 Crime Attractor Case Study: Drug Treatment Centres (n=49)**

Drug and other addiction treatment centres (henceforth referred to as “drug treatment centres”) were identified through an internet search. A list of all sites found was compiled, and the coordinates for each site were obtained from Google Maps. The use of multiple websites to compile this list was used as validation.

#### **7.4.3.6 Crime Attractor Case Study: Homeless Shelters (n=19)**

In order to obtain the location of homeless shelters in the city, a similar approach was used to the method for drug treatment centres; an internet search was undertaken and the coordinates for each homeless shelter were obtained from Google Maps. As before, this list was validated through the use of multiple internet pages.

### **7.5 Methodology**

Three methods were employed in order to meet the objectives of this research. First, concentric circle buffers were used to identify the amount of crime near a facility, and how this changes as one moves further away from the site in question. Second, changepoint analysis was employed to identify distances at which changes in patterns occur around these spaces, examining whether crime generators and attractors influence crime distribution patterns differently. Finally, k-means clustering was utilised to investigate the possible existence of groups of facilities that have similar patterns of spatial distribution of crime. All of these methods were undertaken on the complete dataset discussed in Section 7.4.2. These methods shall now be discussed in more detail.

#### **7.5.1 Concentric Circle Buffers**

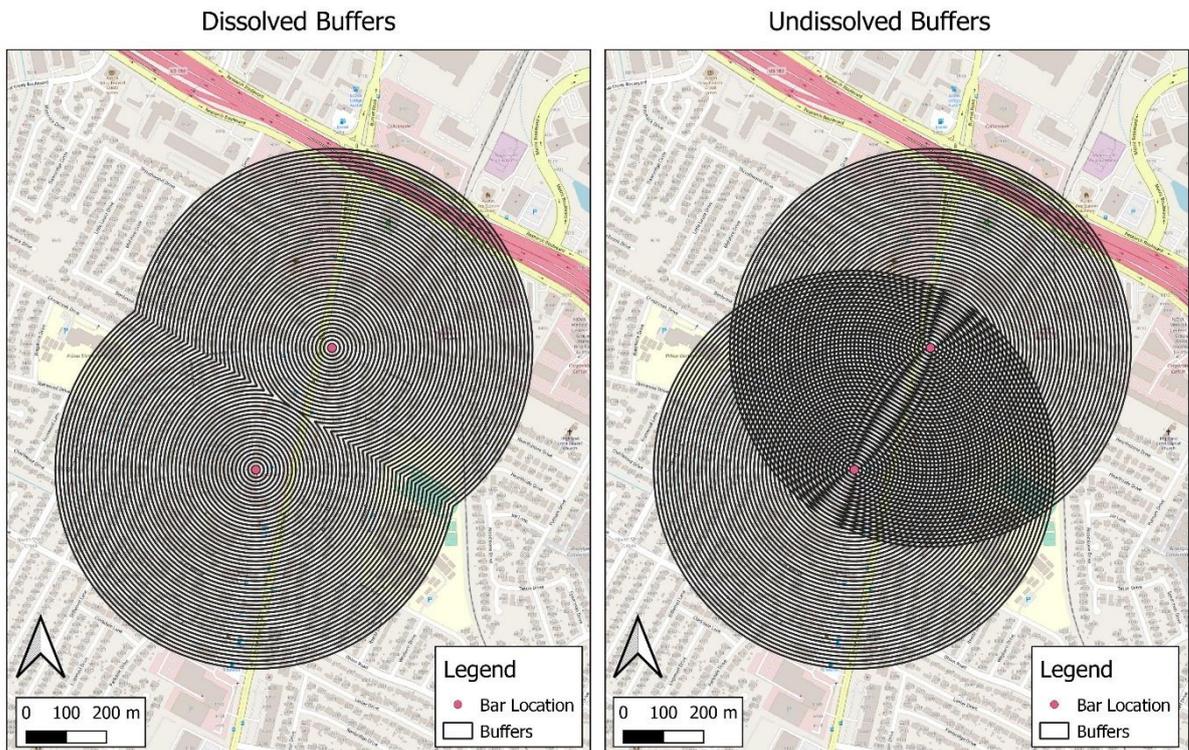
This research utilised concentric circle Euclidean distance buffers, referred to as the “traditional method for quantifying the impact of facilities” (Groff, 2011 p.159). Concentric circle buffers were created up to 500m from the facility in 10m increments using an algorithm created by Vesanto (2018).

This distance was selected following the aforementioned literature search; although some studies identified sites to impact crime patterns over a longer distance, the majority found the distance of influence to be less than 500m. The crime density (offences per meter squared) in each buffer was calculated in order to permit comparison between them, and each value was multiplied by 1000 to facilitate analysis. This was undertaken for several different arrangements of facilities. Firstly, all crime generators and crime attractors were merged into datasets, so that the analysis could be conducted around all crime generator facilities and all crime attractor facilities. As well as this, the analysis was undertaken twice for each facility type; using both dissolved and undissolved buffers. When the analysis was undertaken with the facilities dissolved, this allowed the pattern across all types of that facility to be examined, but when the facilities were undissolved, this identified the patterns for each facility individually<sup>5</sup>. This is demonstrated graphically in Figure 7.2.

Whilst some suggest that a limitation of concentric circle buffers is that they do not incorporate road networks and other barriers (Groff, 2011), any bodies of water identified in OpenStreetMap data (Geofabrik, 2021) were removed from these buffers to reflect the size of the buffer where crime could feasibly take place. Although this meant that crimes which occurred on bridges were not included, it was considered more accurate to remove this area than to include these few offences.

---

<sup>5</sup> In order to examine the variance between facilities in each case study group, boxplots were made for each buffer distance for each facility type. These can be found in Appendix C.



Base Map Source: OpenStreetMap

**Figure 7.2 - Dissolved vs Undissolved Buffers**

### 7.5.2 Changepoint Analysis

Changepoint analysis is used to identify a point in a dataset where the properties before and after this point differ (Killick, 2017). This method is primarily used with time series data, but has been used in other applications, such as to identifying breakpoints in crime density between buffers around facilities by Ratcliffe (2012). In this research, the breakpoints for crime generator and attractor facilities were examined to explore whether these types of spaces lead to different patterns.

Using the changepoint package in R (Killick and Eckley, 2014), the Pruned Exact Linear Time (PELT) algorithm (Killick et al., 2012) was used to identify changes in the variance of the crime density between buffers as one moves further away from a crime generator or attractor facility. The PELT method was selected for this work due its speed and accuracy (Dorcas Wambui, 2015), and because it can identify multiple changepoints in a dataset.

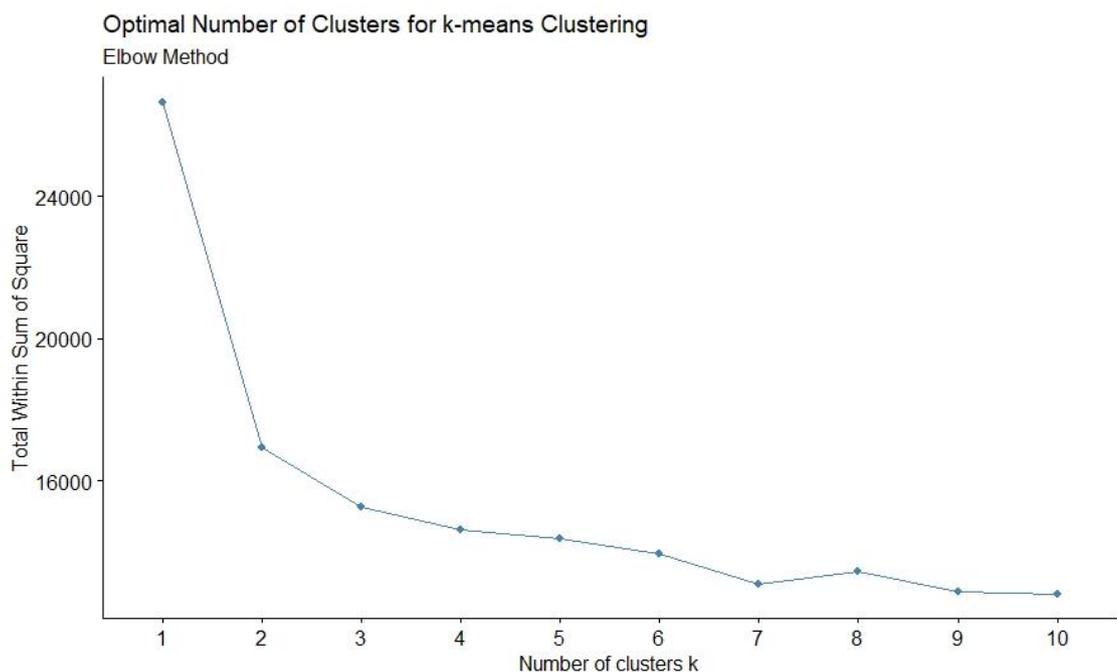
### 7.5.3 K-Means Clustering

K-means clustering was used to identify whether any subgroups of crime generators and attractors could be identified within this dataset based on the crime densities in their buffers. For this part of the analysis, all 534 facilities

were analysed together, to explore whether subgroups would naturally emerge, rather than pre-separating them into the two types of space.

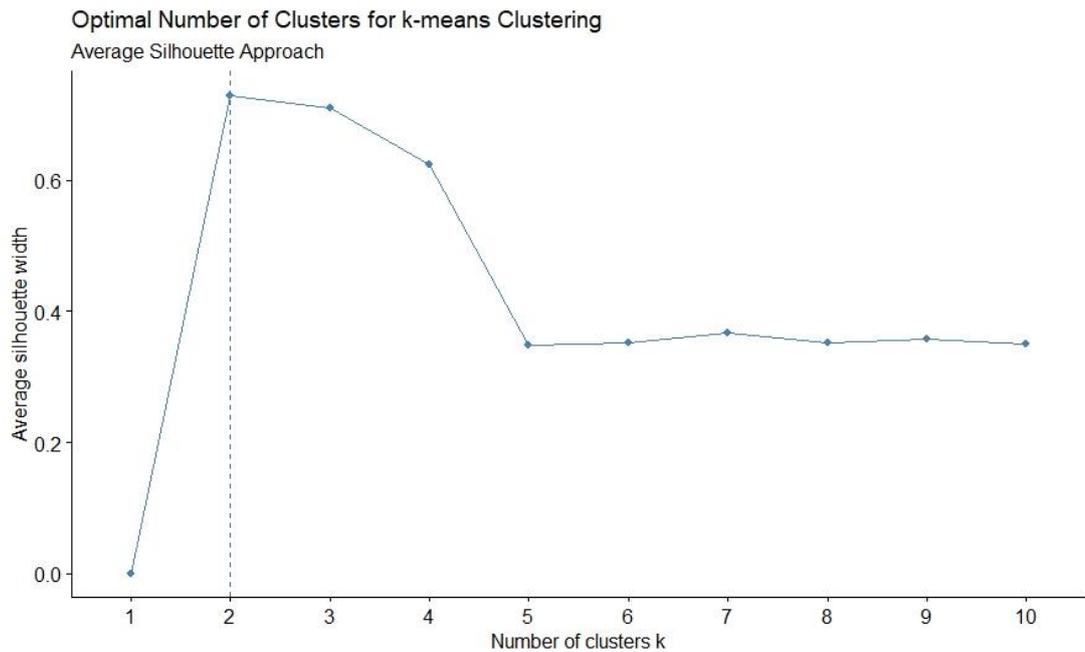
Traditionally, a “cluster” of crimes is considered to be a geographic cluster; a large number of crimes in a particular area (Nath, 2006). However, the use of k-means clustering in this work refers to the identification of crime patterns which are not spatial, creating clusters of similar events and ensuring that intra-cluster variation (also referred to as the total within-cluster sum of squares (WSS)) is minimized (Kassambara, 2017).

Before the k-means clustering could be undertaken, however, it was necessary to identify how many clusters into which to divide the data. Three methods were applied to the full dataset to calculate this. Firstly, the elbow method was used, which examines the total WSS as a function of the number of clusters (Kassambara, 2018a; Sakar, 2019). The aim with this approach is to select the number of clusters which means that the addition of any further clusters would not greatly improve the total WSS; the “bend” in the elbow. The results of this method are displayed in Figure 7.3. This method appeared to indicate that 2 is the optimal number of clusters, but this answer is not definitive, as 3 or 7 could also be correct. Indeed, the somewhat ambiguous nature of the elbow method has been highlighted as one of its limitations (Gove, 2017; Kassambara, 2018a; Sakar, 2019).



**Figure 7.3 - Optimal Number of Clusters: Elbow Method**

Additional methods were therefore also implemented, as recommended if the elbow approach has not clearly indicated the correct number of clusters (Gove, 2017). As a result, the average silhouette approach was also used, which identifies how well each facility (in this case) fits within its cluster (Kassambara, 2017). The results of this method are displayed in Figure 7.4. Here, the optimal number of clusters is shown as a peak in the data, which in this case is 2.



**Figure 7.4 - Optimal Number of Clusters: Average Silhouette Approach**

In order to verify these results, a final method was used, the NbClust() function in R (Charrad et al., 2014), which uses thirty indices to identify the optimal number of clusters (Kassambara, 2017, 2018a). The results of this method are shown in Table 7.3, and also suggest 2 to be the optimal number of clusters as it identifies that twelve indices proposed 2 to be the most suitable number.

| <b>Number of Clusters</b> | <b>Count of Indices which Propose This Number of Clusters</b> |
|---------------------------|---|
| 0                         | 2   |
| 2                         | 12  |
| 3                         | 7   |
| 4                         | 1   |
| 7                         | 1   |
| 10                        | 3   |

**Table 7.3 - Optimal Number of Clusters: NBClust() Function Results**

As a result, the k-means clustering algorithm was run setting the number of clusters to 2. The Hartigan-Wong algorithm (Hartigan and Wong, 1979), shown below, was used for this work, using 25 random starts as recommended by Kassambara (2018b). This algorithm defines the intra-cluster variation as the sum of the squared Euclidean distances between items and the corresponding cluster centroid, where  $x_i$  is the data point belonging to the cluster  $C_k$ , and  $\mu_k$  is the mean value of the points assigned to that cluster (Kassambara, 2018b)

$$W(C_k) = \sum_{x_i \in C_k} (x_i - \mu_k)^2$$

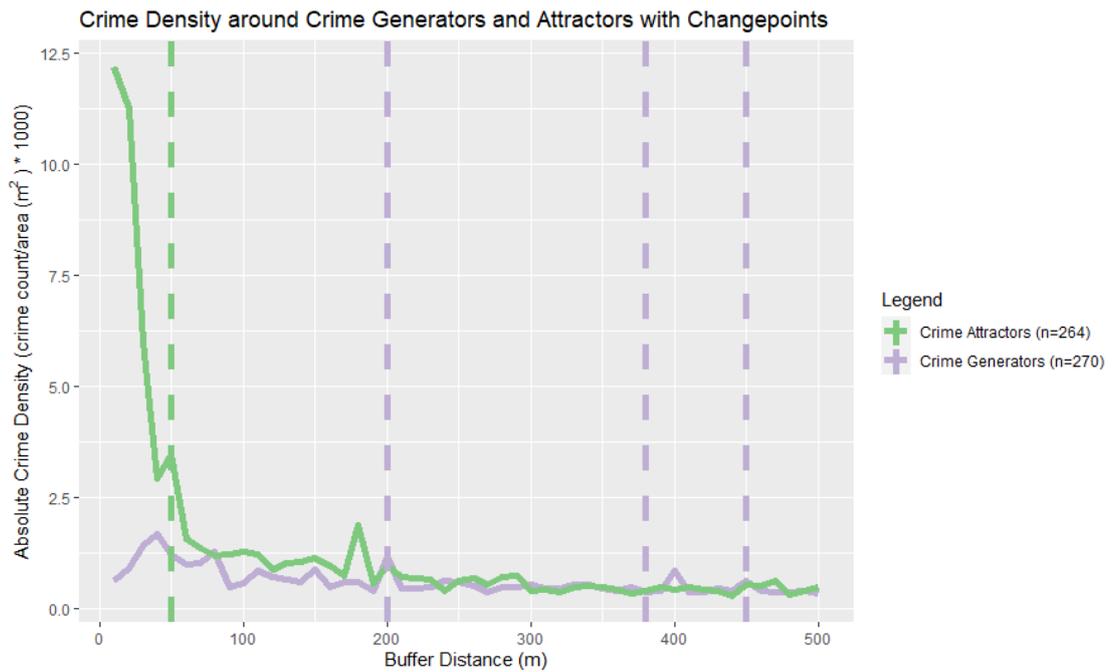
As k-means clustering will consequently be undertaken looking for 2 clusters, it seems unlikely that subgroups of crime generators or attractors will be identified here as there does not appear to be a great deal of variation within the data which would indicate this. However, this analysis may provide some insight as to whether the crime patterns in the vicinities of crime generators and crime attractors can clearly distinguish between the two types of spaces.

## **7.6 Results**

### **7.6.1 Concentric Circle Buffers and Changepoint Analysis**

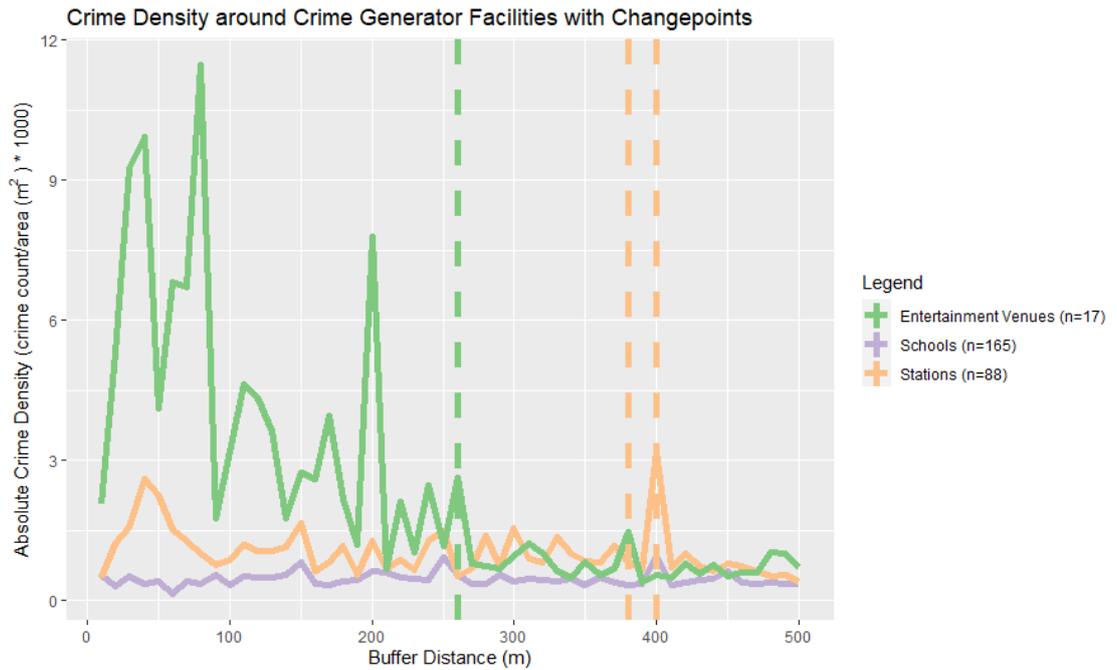
The following results show the crime density in the buffers around the facilities under scrutiny, as well as the points at which the crime densities change. Figure 7.5 shows the crime density in the buffers around all crime generator facilities and all crime attractor facilities, as well as the changepoints. As one can see, a distance decay pattern is evident around crime attractors, particularly in the first 50m, where the decline is very harsh. Even after this point, however, gentle distance decay is evident across the rest of the study area. Moreover, more crime is seen at crime attractor facilities than crime generators until around 200m away from the site. The crime generator facilities, on the other hand, appear to see slightly increased crime density as one moves up to 50m away from the site, before also experiencing gradual distance decay. By 300m away from the facility, however, both crime generators and crime attractors are experiencing similar values for crime density.

These types of facilities have different numbers of changepoints at different distances from the facilities. For crime attractor facilities, only one changepoint is found at 50m. This changepoint clearly identifies the location at which the steep decline in crime density transitions to a gentler distance decay, and where the crime density is far lower. For the crime generator facilities, on the other hand, a difference in crime densities was found 200m, 380m and 450m away from the sites. At 200m, the rate of distance decay decreases to a shallower gradient. Between 380m and 450m, the crime density sees more variation, with some steep increases, before continuing to decline from 450m onwards.



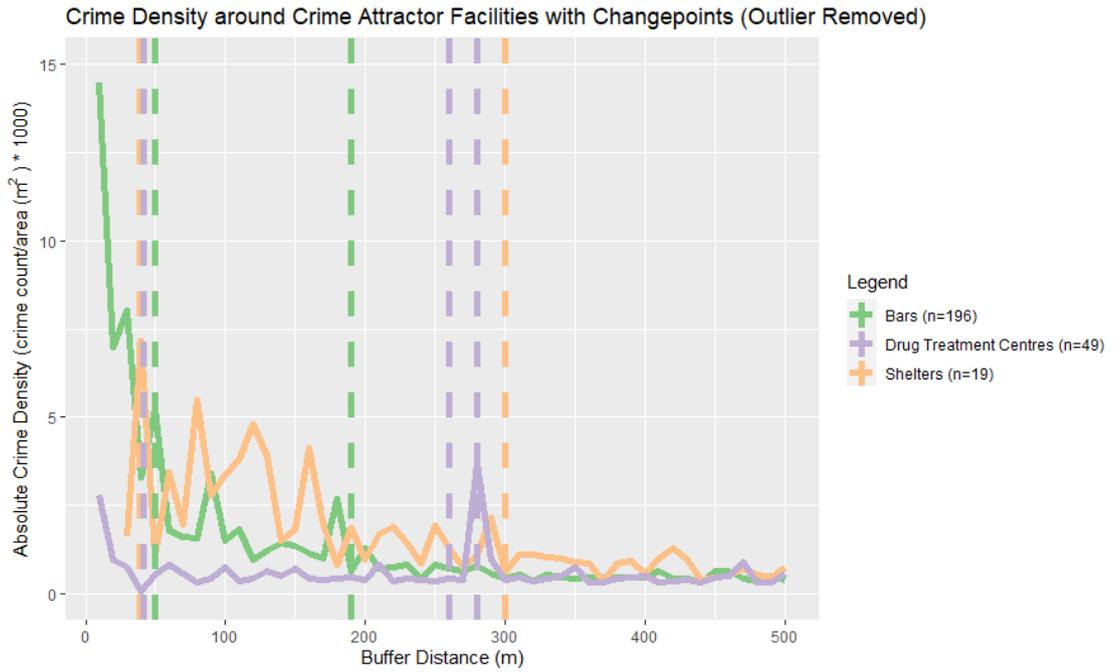
**Figure 7.5 - Crime Density around Crime Generators and Attractors with Changepoints**

When this data is disaggregated by facility type, as displayed in Figure 7.6 and Figure 7.7, one can see that crime generator facilities (Figure 7.6) have a varied distribution of crime densities, with only entertainment venues having a distance decay pattern. Whilst stations do also exhibit distance decay, this is only from 50m away, as this immediate vicinity actually sees increasing crime with distance from the sites. In addition, the crime densities experienced are relatively low, with both schools and stations rarely going over 2.5/1000 offences per meter squared. Moreover, each of the crime generator case studies had a different number of changepoints. Schools, for example, had no changepoints, suggesting that their crime density is regularly stable over the 500m study area. Entertainment venues had one changepoint at 260m, which seems to suggest the end of the distance decay; the crime densities after this point are relatively stable. The final crime generator case study, stations, had two changepoints, at 380m and 400m. This does, however, appear to be reflective of a high value at 400m, rather than a vastly different pattern. Prior to 380m, stations experience steady distance decay, but after 400m this appears to become steeper towards the edge of the study area. It would be interesting to repeat this analysis with a larger study area, to examine whether this pattern continues with increased distance from stations.

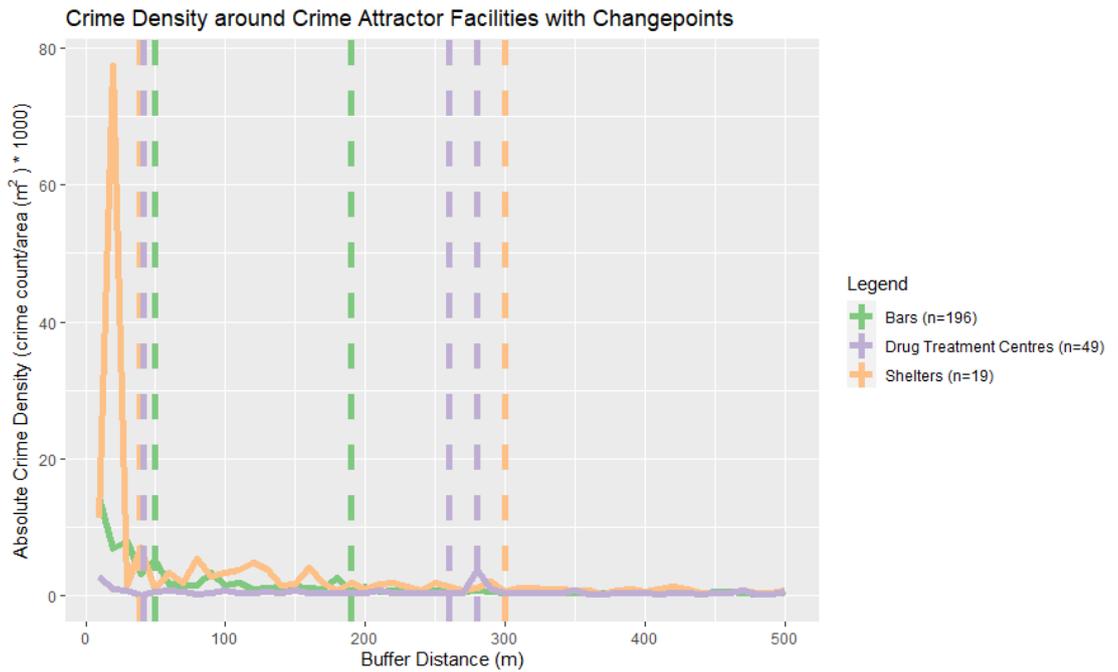


**Figure 7.6 - Crime Density around Crime Generator Facilities with Changepoints**

Contrary to this, the crime attractor facilities (in Figure 7.7) studied experienced higher crime densities, particularly in their immediate vicinities, which declined rapidly within 50m and continued showing distance decay. Moreover, homeless shelters appear to be compatible with the place management effect proposed by Eck (1995), as crime density dramatically peaks in the 10-20m buffer, rather than that incorporating the facilities and their 10m surroundings. This value has been excluded from Figure 7.7 as it complicated visualising the rest of the data but is displayed in Figure 7.8. Interestingly, however, none of the other facility types appear to experience this phenomenon.



**Figure 7.7 - Crime Density around Crime Attractor Facilities with Changepoints (Outlier Removed)**



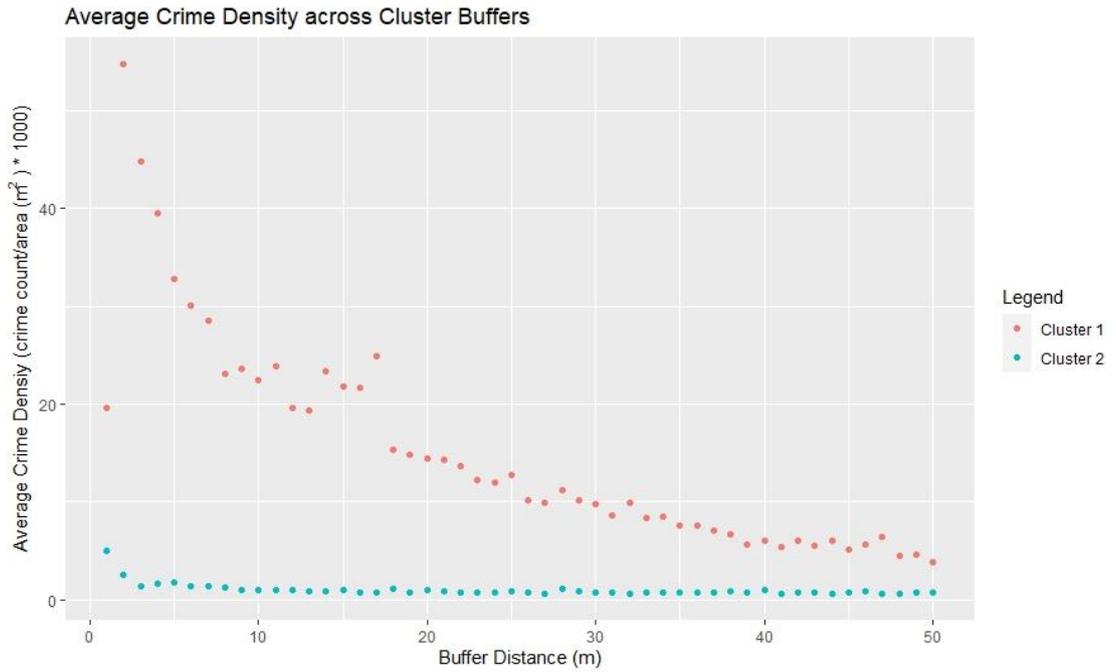
**Figure 7.8 - Crime Density around Crime Attractor Facilities with Changepoints (with Outlier)**

When one looks at the results of the changepoint analysis for the crime attractor facilities, each has at least two changepoints. Bars, for example, were found to have two changepoints, one at 50m and one at 190m. Each of these changepoints identifies a point at which the distance decay appears to

become less steep. A similar pattern is seen in the results for shelters, which have one changepoint at 40m and one at 300m. However, the results for the drug treatment centres do not appear to show the same pattern. The first changepoint, at 40m, does show the similar change in steepness of the distance decay, as after 40m the distance decay is minimal. The other changepoints, however, at 260m and 280m, appear to be similar for that of stations, and may be the result of an anomalous crime density value at 280m. The crime density after 280m appears to be very similar to that between 40m and 260m.

### **7.6.2 K-Means Clustering**

The use of k-means clustering in this work aims to explore whether subgroups of crime generators and attractors can be found based on the distribution of crime in their surroundings. By undertaking k-means clustering, two groups of facilities were identified based on the crime densities in their buffers. Figure 7.9 shows the average crime densities across each facility included in each cluster. As one can see, both clusters experience distance decay across the study area, and the primary difference between them is that facilities located in Cluster 1 see a considerably higher crime density than Cluster 2. Moreover, whilst not all facilities in this cluster experience this phenomenon, on average the facilities in Cluster 1 experience a pattern which is comparable with the place management effect (Eck, 1995), as the density of crimes within the first buffer is lower than that in the following buffers. As a result, it appears that the crime distribution pattern itself does not differ a great deal between these two groups, and rather the classification has been made based on crime density values instead of varying patterns. The structures of these clusters, in the form of the types of facilities in each, are identified in Table 7.4.



**Figure 7.9 - Results of K-Means Clustering: Average Crime Density across Cluster Buffers**

| Facility Type                             | Cluster 1            |                             |                                 | Cluster 2            |                             |                                 |
|---|----------------------|-----------------------------|---------------------------------|----------------------|-----------------------------|---------------------------------|
|   | Count within cluster | Percentage of Cluster 1 (%) | Percentage of Facility Type (%) | Count within cluster | Percentage of Cluster 2 (%) | Percentage of Facility Type (%) |
| <b>All Generators</b>                     | 7                    | 11.11                       | 2.59                            | 263                  | 55.84                       | 97.41                           |
| <b>All Attractors</b>                     | 56                   | 88.89                       | 21.21                           | 208                  | 44.16                       | 78.79                           |
| <b>Schools (generator)</b>                | 2                    | 3.17                        | 1.21                            | 163                  | 34.61                       | 98.79                           |
| <b>Stations (generator)</b>               | 1                    | 1.59                        | 1.14                            | 87                   | 18.47                       | 98.86                           |
| <b>Entertainment Venues (generator)</b>   | 4                    | 6.35                        | 23.53                           | 13                   | 2.76                        | 76.47                           |
| <b>Bars (attractor)</b>                   | 51                   | 80.95                       | 26.02                           | 145                  | 30.79                       | 73.98                           |
| <b>Drug Treatment Centres (attractor)</b> | 0                    | 0.00                        | 0.00                            | 49                   | 10.40                       | 100.00                          |
| <b>Shelters (attractor)</b>               | 5                    | 7.94                        | 26.32                           | 14                   | 2.97                        | 73.68                           |

**Table 7.4 - Structure of Clusters Identified through k-means Clustering**

As highlighted previously, the use of k-means clustering to identify two distinct clusters within this data could have distinguished between crime generators and attractors based on the crime densities in their buffers, if the different mechanisms led to different crime distribution patterns. On examining the results, one can see that 88.89% of the facilities located in Cluster 1 are crime attractors, potentially indicating that Cluster 1 is “the crime attractor cluster”. However, Cluster 2 has a relatively even split, with only 10% more crime generators than crime attractors, suggesting that this cluster could not be considered purely “the crime generator cluster”. Moreover, 100% of the drug treatment centres, which the literature suggests are crime attractor facilities, are found in Cluster 2, again demonstrating that this cluster does not exclusively contain crime generators. Despite this, more than 97% of all crime generator facilities are found within Cluster 2, suggesting that whilst crime attractor facilities are also located in this cluster, the crime distribution patterns demonstrated by these crime attractor facilities are consistent with those typically demonstrated by crime generators.

### **7.6.3 Agent-Based Modelling Recap**

As these results will be compared with those from the agent-based modelling work in Chapter 6, these results are briefly re-summarised here. The agent-based model examined crime generators and attractors in an abstract space, and identified that crime generators experienced more offending than crime attractors, and that they led to a distance decay pattern. Crime attractors, on the other hand, were found to produce a uniform amount of crime in their vicinities which did not fluctuate a great deal with distance from the crime attractor itself.

## **7.7 Discussion**

In order to answer the first objective of this work, whether the crime density patterns identified here match those found in the agent-based models (ABMs) in Chapter 6, the results of the concentric circle buffers shall be analysed. When comparing the results of this research for crime generators to that of the ABM, these results are not a complete match. This work found

far less crime at crime generators than crime attractors, and even found crime in the immediate vicinity (40m) to increase. However, from 50m onwards, the crime generators did experience distance decay, as predicted by the ABM work, albeit weaker than identified by the computational work. When examining the results for crime attractors, these results also do not appear to match the results of the agent-based model. Whilst the ABM found no real evidence for distance decay around these spaces, this empirical research identified a steep decline in crime densities, particularly for the first 50m around a crime attractor site. From 50m onwards this does reduce to a gentler decline which can be seen across the study area.

What are the implications of these opposing results? Whilst both the models and the empirical analysis identified crime concentration to occur at crime generators and attractors, the patterns identified varied significantly. The agent-based models in Chapter 6 stripped these mechanisms down to their most basic elements, in order to study them without the complications seen in real-world criminology. However, the fact that the patterns identified by the ABM contradict the results found empirically could suggest that either; (1) the discipline's understanding of these mechanisms is incomplete; (2) the formalisation of these processes in the ABM was incorrect; or (3) this empirical work has been unable to suitably disentangle the impact of these facilities from potential external influences. Further research into this area would be beneficial, and two potential approaches are suggested. First, the ABM could be developed, to examine which changes need to be made for the results to match those found empirically. This approach would not only aid in the study of crime patterns around these spaces, but also develop deeper understanding of crime generator and attractor processes. Indeed, one development which could be suggested is rerunning the agent-based model, without the reduction of offender motivation following offending. As discovered through the sensitivity testing, removing this function left the results of the crime attractor simulations closer to those of the crime generator, and thus could go some way to bringing the results of the computational and empirical work together. Second, additional crime generator and attractor case studies could be selected and empirically studied, to examine whether other sites lead to the same results identified

here. If a range of facilities across a variety of locations can be found with similar results, this could lend credence to the suggestion that the crime generator and attractor mechanisms are not suitably understood. If, however, other facilities are found to experience different crime patterns, this could suggest that the crime patterns around crime generators and attractors are too affected by external influences to be generalizable to either classification. If this is the case, this remains a useful finding, as it indicates that these patterns are not indicative of the motivations of offenders offending at specific sites.

Related to this, the second aim of this work was to explore whether the offence patterns created by crime generators and attractors can be used to distinguish between these types of spaces. The concentric circle buffers highlighted few actionable differences between crime generators and attractors, as the patterns exhibited by both types of spaces were relatively similar. However, all the crime attractor case studies demonstrated rapid decline in crime density in the immediate 50m around them, which was not seen around crime generators. This steep distance decay in the immediate vicinity of a facility could be indicative of crime attractor mechanisms at play, as it demonstrates that offenders have gone specifically to the site to offend. This conclusion was also confirmed by the changepoint analysis, which identified that all the crime attractors experience a change in pattern within 50m of the facility, whereas crime generators do not see a change until at least 260m away. As a result, whilst further research is recommended into this topic, it could be the case that a steep decline in offences in the immediate vicinity of a facility suggests that crime attractor processes are at work. However, this is a tentative suggestion, given that not all three of the methods here identified this. The results of the k-means clustering suggested that these patterns could not be used to distinguish between these types of spaces, as this method did not differentiate between crime generators and attractors when allocating the facilities to each cluster. Whilst Cluster 1 primarily comprises crime attractors, this seems to be based on high crime density in general rather than a specific crime pattern, and thus crime distribution patterns may not be a suitable method for classifying these spaces.

The final aim of this research was to explore crime patterns around crime generators and attractors to identify whether any recurring patterns emerge from k-means clustering, which could suggest subgroups of crime generators and attractors. However, the use of three different methods for finding the optimal number of clusters for the dataset identified that this data was most appropriately allocated into two clusters. This suggests that distinct subgroups of crime generators and attractors cannot be identified through the study of their crime patterns. Although almost 90% of the facilities in Cluster 1 were crime attractors, this appears to be caused by the high crime density, rather than the patterns themselves. Whilst this could indicate that some crime attractors have more intense crime attracting properties than others, this alone does not appear sufficient to indicate a subgroup of this type of space. Instead, it demonstrates that some facilities see more crime than others, which is similar to a well-established concept in environmental criminology referred to as “risky facilities” (Eck et al., 2007 p.226), whereby “for any group of similar facilities (for example, taverns, parking lots, or bus shelters), a small proportion of the group accounts for the majority of crime experienced by the entire group”. Whilst, therefore, patterns of crime density do not lead to the identification of subgroups of crime attractors, it would be interesting to see if other variables, such as prevalence of specific types of crime, could be indicative of subgroups of these spaces, or whether additional clusters could be found within the facilities included in Cluster 1.

These results do, however, assume that the selection of case studies for this research accurately identified crime generator and attractor facilities. If one looks at the concentric buffer results for entertainment venues (in Figure 7.6), for example, which are identified as a crime generator in the literature, the patterns are more similar to the facilities identified as a crime attractor (as in Figure 7.7). Although this facility type does not see the aforementioned immediate drop in crime density associated with other crime attractors in this study, its results are dissimilar to the other crime generators. There are at least two possible explanations for this. Either it is not possible to distinguish crime generators and attractors by their crime patterns and this is purely coincidence, or entertainment venues have more

crime attracting qualities than first thought. If the latter is the case, this could change the findings of this work. For example, it would suggest that any facility with notable distance decay appears to be a crime attractor, and that crime generators see, on average, more uniform crime density in their surroundings. Whilst this is fundamentally the opposite of the results of the agent-based modelling work in Chapter 6, this does appear consistent with the mechanisms under scrutiny. It is possible that if offenders go to a particular crime attractor to commit an offence, that the opportunities they are seeking may not extend far out from the site itself, so the offending occurs very close to it. It appears logical that this pattern would not occur at a crime generator: as a crime generator leads to crime concentration because of the large amount of opportunistic offending there, this could extend further out from the site as crime opportunities could become apparent outside the site as well as within it. Despite this, evidence has been found for offences being committed en route to crime attractors (Frank et al., 2011a), which would dispel this explanation. Further research is therefore needed to explore this; if a wider range of crime attractor case studies lead to these patterns, this could be indicative of entertainment venues acting more as this type of site, and could potentially corroborate this pattern occurring at crime attractors. This example highlights part of the challenge of studying crime generators and attractors empirically. Whilst it is important to empirically verify the mechanisms proposed by Brantingham and Brantingham (1995), there are a number of challenges to doing so, such as the aforementioned issue of disentangling the effects of the facilities from their surroundings and identifying appropriate case study areas for these spaces.

Whilst every effort has been made to ensure the accuracy of this research, four primary limitations need to be considered. The first concerns the generalizability of the research. This work has used case studies of crime generators and attractors which are specific facility types in one city in America. It is possible that either the facilities selected, or the study setting, are not representative of crime generators and attractors as a whole. As a result, this research could benefit from being repeated using other crime generator and attractor examples in different locations. The second, which

has been touched on previously, is that it can be challenging to understand whether high crime densities around a facility are caused by the facility itself or other environmental characteristics (Boessen and Hipp, 2018; Kurland et al., 2014). A large number of facilities was chosen for analysis in this work to attempt to mitigate against this, but it is acknowledged that this problem remains, and will remain a challenge when undertaking empirical research in this field. Third, this research is based on static snapshots rather than the development or use of the crime generator or attractor over time. Whilst this contribution to the literature will go some way to developing understanding of the spatial patterns around these types of sites, it does not investigate the temporal variations in these patterns. Future work would therefore benefit from exploring to what extent these patterns are influenced by the temporal flow of the population. Finally, this analysis looked at a broad range of crime types. As highlighted in Chapter 5, the types of crime committed at crime generators and attractors could vary. Whilst it was decided to study all crime types in this work so as to not skew the results by including, for example, more crime generator offences than attractor, future work would benefit from focusing in on specific types of crime for similar studies.

### **Summary**

*This chapter has used empirical methods to explore crime distribution patterns around crime generator and attractor case studies, identified from the literature, and has met Objective 4 of this thesis, to empirically investigate crime distribution around crime generators and attractors, and identify whether the crime patterns which emerged as a result of the agent-based model are seen empirically. This work has identified that crime generators and attractors do not lead to vastly different crime distribution patterns. The exception to this is that crime attractors see a rapid decline in crime density in their immediate vicinity, whereas crime generators do not experience this drop. It is possible that this could be used to identify crime attractors empirically if this result is also identified in further studies.*

*These results are not consistent with those of the agent-based modelling work in Chapter 6. This disparity in results could indicate either that*

*understanding of these processes is lacking within the discipline, that the formalisation of the mechanisms in the agent-based model was incorrect, or that this empirical work has not managed to suitably isolate the effects of the facilities from the environment. As a result, further studies developing the agent-based model would be of benefit to explore the changes required to bring the results of the model in line with those found through empirical analysis, as would additional empirical research against which to compare these results.*

*Not only has this work allowed comparison between the computational findings of the agent-based modelling work with empirical data, it has also contributed to the literature by investigating the existence of subgroups of crime generators and attractors based on their crime distribution patterns. Whilst no subgroups appear evident in this work, further analysis exploring the use of different variables would be valuable.*

*This is the final analytical chapter in this thesis. The following chapter contains a discussion of the overall findings of this research, as well as its contribution to literature, research limitations and future research recommendations.*

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## **Chapter 8**

### **Discussion**

This thesis sought to use theoretical, computational and empirical approaches to critically appraise the concept of crime generators and attractors. Its objectives were to:

1. Critically appraise previous research on crime generators and attractors to identify how they are defined and the extent to which their mechanisms have been studied.
2. Investigate previously suggested methods for empirical classification of crime generators and attractors, to explore whether multiple methods identify the same areas as crime generators and attractors.
3. Examine the theoretical mechanisms underpinning this concept using an agent-based model, and their implications for crime distribution.
4. Empirically investigate crime distribution around crime generators and attractors, and identify whether the crime patterns which emerged as a result of the agent-based model are seen empirically.

To conclude this thesis, the structure of this chapter is as follows. Firstly, a summary of each of the analytical chapters will be provided, including the extent to which each chapter met the thesis objectives listed above. Following this, the next sections will detail this work's contribution to the literature, and limitations of each piece of research. The penultimate section shall cover suggestions for future research, before final concluding remarks.

#### **8.1 Thesis Summary**

In order to provide context for the following discussion, each of the analytical chapters shall now be summarised here, including the extent to which they met the objectives above. In addition to these summaries, a theme which emerged consistently throughout the thesis, that crime generators and attractors are challenging to study, shall also be discussed.

### **8.1.1 Chapter 4: Scoping Literature Review**

This scoping literature review aimed to answer the question to *what extent have the mechanisms behind crime generators and attractors been studied?*. It explored the variety in definitions for crime generators and attractors, as well as critiquing research studying their mechanisms. It found that there is a dearth of research into these mechanisms and discussed the inconsistency amongst authors defining these types of spaces. It suggested three potential reasons for the paucity of research into this area: (1) the lack of consistent definitions for crime generators and attractors, (2) challenges identifying appropriate datasets to study them, and (3) the fact that crime generators and attractors are not mutually exclusive. This detailed exploration of these mechanisms not only provides a rigorous literature base for this thesis, but also informed the formalisation of the processes for the subsequent agent-based modelling chapter.

The work in this chapter aligned with the first objective of this thesis: to *critically appraise previous research on crime generators and attractors to identify how they are defined and the extent to which their mechanisms have been studied*. This research accomplished this objective through the use of the scoping review methodology; by identifying and including papers which specifically explored crime generators and attractors, this work focused only on those which were relevant to this objective, despite identifying the great extent to which this concept is mentioned in research. Whilst there were limitations with this method, which are discussed in Section 8.3, the scoping review methodology was identified as the most appropriate for this objective as it allowed, to the best of the author's ability, all the relevant literature to be systematically examined and critiqued in an unbiased manner.

### **8.1.2 Chapter 5: Empirically Testing Examining Classification Approaches**

Chapter 5 aimed to explore whether two methods for empirically identifying crime generators and attractors would categorise locations on a university campus in the same way. The two approaches which were studied are able to be applied to a wide variety of facilities (that is to say, not specific to an individual case study), and were:

- That crime generators have high counts but low rates of crime, but that crime attractors have high counts and high rates (Clarke and Eck, 2005, 2003).
- That crime generators and attractors experience different types of crime (Newton, 2018; Bowers, 2014, among others).

Surprisingly, however, these two approaches did not give any locations the same classification. This could suggest that either one or both of these methods are not suitable for empirically locating crime generators and attractors, and that neither should be used in isolation without further validation.

The work in Chapter 5 aligned with Objective 2 in this thesis: to *investigate previously suggested methods for empirical classification of crime generators and attractors, to explore whether multiple methods identify the same areas as crime generators and attractors*. The results of these different approaches were not found to complement each other, but this objective was clearly met through this work, as it permitted the testing and exploration of the different classification approaches. This finding has implications for the practical application of the crime generator and attractor concept, as it suggests that the discipline currently has no reliable way to identify these spaces in the real world. Whilst this work would have benefitted from the addition of other classification techniques so that more than two approaches could be tested, this research acts as a good base for further investigation.

### **8.1.3 Chapter 6: Agent-Based Modelling**

The work in this chapter has met the third objective above: to *examine the theoretical mechanisms underpinning this concept using an agent-based model, and their implications for crime distribution*. More specifically, it aimed to investigate the crime distribution on the edges of crime generators and attractors, exploring the potential occurrence of edge effects around these types of spaces. However, even though edge effects were not found, the distribution of crime across the rest of the model environment (both within, and external to, the crime generator or attractor) differed depending on the type of space being modelled. For example, the model identified that crime occurrence increases towards the centre of a crime generator site, but

remains relatively stable within a crime attractor. Moreover, distance decay was evident outside the crime generator in the model, but the crime distribution outside the crime attractor was relatively stable across the environment. As edge effects were not identified through this research, it was decided to not investigate them further in this thesis, but the crime distribution patterns which emerged from these models informed the subsequent empirical research in Chapter 7.

#### **8.1.4 Chapter 7: Empirically Examining Crime Distribution around Crime Generators and Attractors**

The content of this chapter followed the agent-based modelling research, and it had three chapter-specific objectives which were aligned with the overall thesis objective that it met. Its first chapter-specific objective was to explore whether the crime distribution patterns identified in the agent-based model could also be found empirically, but, interestingly, the results were inconsistent. For example, distance decay was found around crime generators, as in the agent-based model. However, whilst the model identified that crime generators would see more crime than crime attractors, the empirical work found the opposite to be true. Moreover, although distance decay was not found around crime attractors in the agent-based models, it was very evident around crime attractors in this empirical work. There are several potential reasons why the model results did not match those found empirically. For example, the crime generator and attractor mechanisms may not have been correctly formalised in the agent-based modelling work, or the effects of surrounding facilities may have been too prevalent in the empirical work. This is discussed in more detail in Section 8.2.3.

The second chapter-specific objective of this research was to identify whether crime generators and attractors demonstrate different spatial crime distributions, and whether these could be used to distinguish between these types of locations, which relates to the work in Chapter 5. Whilst few notable differences were found between the offence distribution patterns, all the crime attractor case studies saw a rapid decline in crime density in the first 50m outside them, which was not evident around the crime generators. This suggests that rapidly declining offending immediately outside a space could

be indicative of the crime attractor mechanisms. However, the k-means clustering did not identify distinct groups of crime generators and attractors based on these patterns, so these results are not conclusive.

The third chapter-specific objective of this work was to identify whether any recurring patterns exist in the offence distribution around crime generators and attractors, which could indicate the existence of subgroups among them. However, the k-means clustering found that the optimal number of clusters was two, rather than a larger number which could indicate the existence of subgroups. Whilst this does not mean that subgroups of these types of space do not exist, it suggests that they cannot be identified through their crime distribution alone. This analysis did, however, find that some facilities experienced more crime than others of the same type, which aligns with the concept of risky facilities (Eck et al., 2007).

Whilst the work in Chapter 7 has a number of components, the research relating to the first objective is aligned with thesis Objective 4, to *empirically investigate crime distribution around crime generators and attractors, and identify whether the crime patterns which emerged as a result of the agent-based model are seen empirically*. This work suggests that further research is needed to explore what changes need to be made to the agent-based model, or the empirical work against which it is compared, to obtain similar results both computationally and empirically.

### **8.1.5 Obstacles to Studying Crime Generators and Attractors**

As highlighted throughout this thesis, conducting research into crime generators and attractors is not without a number of obstacles. Although this is not specifically aligned with one of the thesis objectives, this theme emerged consistently and would benefit from being discussed. Firstly, there are hurdles related to acquiring adequate data. As noted by Pratt (2016 p.42), “when going about testing criminological theories, finding the right data is critical”. However, finding suitable data to explore these spaces is challenging. Not only is it difficult to obtain crime data at a suitably granular spatial and temporal scale, it also is difficult to obtain data on two integral components to crime generators and attractors: offender motivation and ambient populations. Through this thesis, papers have been identified which

used novel datasets and methods to combat this (such as Sosa et al.'s (2019) *magnetism* variable when looking at casinos), but this difficulty in quantifying these components remains a major obstacle to understanding these types of spaces.

Secondly, certain elements related to the theory of crime generators and attractors are obstacles to further research. Throughout this work (in particular in Chapter 4), it has been noted that these spaces and their mechanisms are not consistently defined. Whilst this is not necessarily a hinderance in itself, as the original concept put forward by Brantingham and Brantingham (1995) could be incorrect, it could lead to more confusion around the concept and research into broader, and perhaps less relevant, topics. One could argue that the notion of crime generators and attractors should not be developed using alternate definitions until we have tested and refuted the original mechanisms. Indeed, Pratt (2016 p.36) suggests that in criminology “we have arguably reached a point where the production of new theoretical explanations is outpacing the production of empirical tests of the core propositions of the theories that we already have”. Whilst this was not in reference to crime generators and attractors specifically, it could apply in this instance. In addition to challenges defining crime generators and attractors, it is also difficult to identify them empirically (as demonstrated in Chapter 5). Although some methods have been put forward to do so, prior to this thesis there had been no validation conducted on these methods and so their appropriateness can be called into question. Related to this, the fact that a space is unlikely to be exclusively either a crime generator or a crime attractor further impedes research, as it complicates operationalisation of the theory.

Whilst this thesis, and other pieces of research, have demonstrated that these obstacles can be overcome, they are important to consider when planning research on crime generators and attractors. Although the concept of these types of space appears straightforward, conducting rigorous research to understand their processes and potential impacts is not. This thesis has demonstrated the value of using triangulation to combine the strengths and weaknesses of different research methods to study these spaces and recommends a similar approach for future research.

## **8.2 Contribution to Literature**

In this section, the contribution to literature of the work in this thesis shall be discussed. As well as contributing to the overall literature base on crime generators and attractors, these contributions can broadly be collated into three headings, which will be discussed in turn:

- Formalising, testing, and developing understanding of crime generator and attractor mechanisms.
- Testing classification approaches for crime generators and attractors.
- Using a multi-method approach to studying crime generators and attractors.

### **8.2.1 Formalising, Testing, and Developing Understanding of Crime Generator and Attractor Mechanisms**

As identified through the scoping literature review in Chapter 4, there is a dearth of research looking into crime generator and attractor mechanisms. This thesis, however, helps to develop understanding of this concept by identifying the papers which examine these processes. Whilst crime generators and attractors are often mentioned in the extant literature, this scoping review identified only those which specifically focused their research on crime generators and attractors. Although this number of papers was relatively small compared to those which *mention* the concept, collating these papers into one source to examine their contribution to the literature is beneficial for future research into crime generators and attractors.

Moreover, the scoping literature review was able to inform the decision-making when creating the agent-based model found in Chapter 6. The creation of this model permitted the formalisation of the mechanisms for both crime generators and attractors. Although crime generators have been explored in an agent-based model previously (Davies and Birks, 2021), this is, as far as the author is aware, the first time that agent-based modelling has been applied to crime attractors at all, and the first time that an agent-based model has been used to study both types of spaces. The formalisation of these processes is an important contribution to literature, as it demonstrates one possible way of explaining the crime generator and

attractor mechanisms in a way that lends itself to implementation in a computer simulation. Indeed, Gerritsen (2015) highlights that formalisation of a concept and the use of agent-based modelling experiments can lead to more insight into a phenomenon.

Following the formalisation of these concepts, the agent-based modelling research also permitted testing of the crime generator and attractor mechanisms, and the use of stylized facts corroborated the results of these models and went some way to validating them. However, it has been suggested that stylized facts are flawed methods of validating agent-based models (Gerritsen and Elffers, 2021b), and the results of Chapter 7, where empirical data were tested to identify whether the same results were found, disagreed with the findings. Accordingly, although these models find support for the existence of crime generators and attractors as hypothesized by Brantingham and Brantingham (1995), which is a useful contribution to literature in itself, they would benefit from additional exploration and testing.

As a result, this thesis has contributed in multiple ways towards the literature on the processes underpinning crime generators and attractors. The theoretical and computational work was particularly beneficial to this field as these areas of the literature are particularly lacking. Although additional research would be beneficial, this thesis has gone some way to develop the theoretical understanding of this topic.

### **8.2.2 Testing Classification Approaches for Crime Generators and Attractors**

Although empirical research on crime generators and attractors is the most prevalent (when compared with theoretical and computational studies), the work included in this thesis is the first that the author is aware of whereby crime generator and attractor classification techniques were compared and tested against one another. Whilst this research identified that these classification techniques may be flawed and need additional validation, this is an important contribution to the literature as it suggests that we are not necessarily ready yet to use these specific approaches to identify crime generators and attractors empirically. Future validation is therefore recommended, before these classification approaches are used in a

practical way. Moreover, it is recommended that all classification approaches are used in conjunction with another for validation purposes.

Not only does this contribute to the theoretical understanding of crime generators and attractors, but this finding could also have practical implications. As highlighted across this thesis, crime generators and attractors could require different law enforcement strategies. However, until it is possible to empirically identify these types of space, this concept cannot be practically applied.

### **8.2.3 Using a Multi-Method Approach to Studying Crime Generators and Attractors**

In addition to the content of the research papers included in this thesis, the triangulation approach to studying crime generators and attractors also has a valuable contribution to environmental criminology literature. No other examples could be found where this approach had been taken to studying environmental criminology to the same extent, and as demonstrated in Chapter 3, there are a number of benefits to using triangulation. In this case, it permitted a broader and deeper dive into this criminological problem, covering a wider range of research themes than one method alone, and allowed certain obstacles of the concept to be overcome. For example, although it is difficult to obtain data on a number of components of crime generators and attractors, the use of agent-based modelling techniques meant that empirical data was not always required for this research.

Moreover, the misalignment of the results of the agent-based model and the empirical investigation provides a good example of why triangulation is valuable in environmental criminology. The agent-based model used the theoretical mechanisms identified through the scoping review to inform formalisation, but the results of this computational work did not align with those identified through empirical analysis. As highlighted above, this could be for a number of reasons, and could be related to each stage of the work which was involved. For example, it is possible that the first stage, the scoping literature review, did not suitably identify the mechanisms due to a lack of clarity in the current literature base. Moreover, the agent-based model might have been mis-specified and therefore did not fully capture the

theoretical mechanisms of these spaces. Finally, the empirical results against which these models were compared could be responsible. Not only could the well-known limitations of crime data have led to inaccurate results, but it could also be the case that external influences in the environment around the case study sites skewed the results, or that the case studies selected were not appropriate examples of crime generators and attractors. Further research into both the agent-based model, to test the assumptions and the formalisation of the processes, and the empirical analysis, to analyse other case study sites, would be of benefit to identify potential sources of this inconsistency. Without the use of triangulation, this inconsistency would not have been as apparent, highlighting that it is a valuable method of validating results.

### **8.3 Research Limitations**

The research included in this thesis is, of course, not without limitation. Although several limitations were highlighted in each chapter, the following section shall identify the most notable for each piece of research.

A general limitation of this thesis is that this research was not focused on a specific type of crime. As highlighted in Chapter 5, it is natural that not all offence types would be prevalent at both crime generators and attractors, and indeed some locations may be crime generators or attractors only for specific types of crime. However, as this thesis is focused more on the general mechanisms behind these types of spaces, it was decided not to focus solely on one crime type case study. This could mean that crime-specific patterns or conclusions were missed, but it was decided that this would be more beneficial for the wider literature base than focusing on a narrow case study.

In the scoping literature review in Chapter 4, the inclusion and exclusion criteria may not have been sufficiently broad to encompass papers on a wider variety of topics, such as more general ones on crime concentration. However, this decision was made as this review aimed to only incorporate those papers which were specifically researching crime generators and attractors, not merely identifying them as a result of crime concentration.

Moreover, only papers written in English were included. Whilst this is commonplace in scoping and systematic literature reviews, and was necessary due to the author's language skills, it does potentially leave large areas of the literature unexamined. A final limitation relates to the fact that only one reviewer (the author) selected the papers which would be included in the review. Best practice would suggest that two reviewers do this in order to reduce subjectivity, but this was not possible due to the resources of this project.

In the computational work found in Chapter 6, the primary limitation relates to how the mechanisms of crime generators and attractors were formalised. As with all agent-based models, the results of this work are heavily dependent on the elements that are included or excluded in this formalisation. Whilst the mechanisms described by Brantingham and Brantingham (1995) were carefully followed when designing the model, it is difficult to turn complex human behaviour into code and thus could have been formalised incorrectly. Further research validating these results and designing additional models would help reduce this limitation.

Despite the empirical chapters (Chapters 5 and 7) both using empirical data, each has its own limitations. The classification research (in Chapter 5), for example, saw a number of assumptions underpinning the analysis, including what values would constitute "high rates" of crime. Whilst decisions were backed up by literature or data wherever possible, this limitation was unavoidable. Chapter 7, on the other hand, was limited by challenges identifying appropriate case study facilities. As demonstrated in Chapter 5, it is difficult to identify crime generator and attractor facilities, so selecting case studies for this work was problematic. It is hoped that the selection of three types for each type of site, backed up by literature, would mitigate any issues if these sites were not appropriate. Indeed, the results of the work suggest that one of the case studies selected (entertainment venues) may be more likely to fall into the other category (crime attractor, as opposed to crime generator from the literature).

## 8.4 Future Research Recommendations

As highlighted throughout this thesis and in Section 8.1.5, there are a number of difficulties to quantitatively studying crime generators and attractors. This can range from theoretical issues surrounding inconsistent definitions to data issues such as obtaining data on offender motivation. As a result, rather than discuss specific areas for future research (which have already been highlighted towards the end of Chapters 4, 5, 6 and 7), this section shall primarily discuss the strength of using qualitative methods to supplement quantitative studies of crime generators and attractors in future. This section shall first briefly discuss how qualitative research has been used in environmental criminology in the past, before demonstrating how qualitative methods could be used in studies of crime generators and attractors. In addition, it shall briefly discuss the benefit of using natural experiments in studying crime generators and attractors.

Whilst quantitative methods dominate in environmental criminology (Oliveira, 2019), qualitative methods can be used to answer questions on individuals' experiences of places and events (Winchester and Rofe, 2010) and thus seem well-suited to the discipline. Indeed, although quantitative and qualitative methods are usually kept apart in social science research (Olson, 2004), Oliveira (2019) advocates for the use of qualitative methods to compliment quantitative research on crime patterns.

The papers which do use qualitative methods in environmental criminology cover a range of topics and use a range of methods. For example, Wood et al. (2015) use focus groups to understand how foot patrol policing in violent areas of Philadelphia contributes to 'capable guardianship'. The use of these focus groups allowed the researchers to discuss elements such as different policing styles and microplaces of harm that the police officers are aware of. Indeed, this research leads Wood et al. to suggest that methadone clinics are crime attractors, although this was not discussed at length in this work. The work of Ceccato (2019) could also be applied to studies of crime generators and attractors. She combined police data, photographs and observations obtained from fieldwork protocols (forms used to record information obtained from observations or interviews (Creswell, 2013)) to

study safety conditions in subway stations, shopping centres and parks. The work of Beauregard et al. (2007), on the other hand, does not seem immediately applicable to crime generators and attractors, as they use data from police reports and interviews with offenders to create a descriptive model of the hunting process of serial sex offenders, based on the rational choice perspective. However, this sort of research would be valuable in understanding offenders' decision-making processes when seeking a crime attractor location.

This demonstrates that qualitative methods have already been used to study elements of crime generators and attractors, but it is believed that these methods could be applied to some of the components of these spaces which make them so difficult to study, as discussed in Section 8.1.5. As with the other methodological approaches utilised in this thesis, the addition of qualitative research methods would add new strengths (and weaknesses) to this research, potentially allowing these elements to be explored. For example, oral methods (such as interviews or focus groups) with offenders would permit the researcher to explore motivation for offending in certain areas, or the effect of an area's reputation on their offending decision-making. Moreover, interviews/focus groups with law enforcement officers could allow the researcher to identify areas of a city with reputation for criminal potential, conceivably permitting the identification of crime attractors. However, there are limitations to using qualitative methods which must be noted. These approaches are time intensive and would result in relatively small sample sizes. Moreover, it can be challenging to obtain participants for the research, particularly offenders. In addition to these difficulties, even if one were able to conduct interviews with offenders, this research can suffer from intentional or unintentional falsification (Beauregard et al., 2007). Despite these limitations, it is believed that incorporating qualitative research, particularly in the form of interviews and focus groups, into the study of crime generators and attractors in future could go some way to mitigating the challenges in obtaining data on these types of spaces and could help substantiate this concept.

The use of mixed methods research to investigate crime generators and attractors would be particularly beneficial in natural experiments, which are

defined as “events, interventions or policies which are not under the control of researchers, but which are amenable to research which uses the variation in exposure that they generate to analyse their impact” (Medical Research Council, No date). This has been done in previous studies on crime generators and attractors, such as Soto and Summers' (2020) research looking at the impact of the closure of brothels as crime attractors, and Kurland et al.'s (2014) study of crime around stadiums. One potential location for a natural experiment studying a crime attractor is the Managed Area for sex work in Holbeck, Leeds. This area has had reputation as a red-light district for many years, and from 1<sup>st</sup> October 2014, sex workers were able to sell their services between 7pm and 7am, without being apprehended by the police (Longman and Hatchard, 2016) in a select industrial area of the city. The scheme was suspended in March 2020 in response to coronavirus restrictions, and it was discontinued in the summer of 2021 (Beecham, 2021). There are several features of the Managed Area which make this an interesting case study as a crime attractor. Not only is it managed by the police, and consequently has had an element of its criminality reduced, it is also a crime attractor with a clearly defined boundary, which is rare for areas of this sort. These boundaries allow for clear investigation of the effects of high-level intervention in a crime attractor; an area of the literature which is currently limited. Mixed methods research into both the introduction and closure of this novel crime attractor could be an interesting area for further research.

## **8.5 Concluding Remarks**

This thesis aimed to use theoretical, computational and empirical approaches to critically appraise the concept of crime generators and attractors. Through the culmination of the research in this thesis, it has been identified that there is currently limited understanding of the processes which lead to crime generators and attractors, as hypothesized by Brantingham and Brantingham (1995). Not only did the scoping review identify that there has been limited research looking into the mechanisms which underpin these spaces, the crime patterns which emerged in the agent-based model were not found in the corresponding empirical work. Similarly, two

approaches for empirically identifying crime generators and attractors found different results, further suggesting limited comprehension of the processes which underpin these spaces. Whilst no evidence was found to disprove the concept of crime generators and attractors, the results of this work were somewhat inconsistent, and suggest that more research is needed. Indeed, until these spaces are better understood, it is unlikely that their full societal benefit, in the form of tailored law enforcement strategies, will be felt. This thesis proposes the addition of qualitative research to develop the concept, as it will permit these spaces to be studied in a manner which has not been hitherto attempted.

## Chapter 8 References

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## **Appendix A**

### **Scoping Literature Review: Charting Form Fields**

The content of this appendix relates to Chapter 4 – the scoping literature review. The following list contains the fields in the charting form which was used to extract data from the papers included in the scoping literature review:

#### **Administrative fields:**

- Date of data extraction
- Paper title
- Author(s)
- Year of publication
- DOI
- Type of publication (journal article, book chapter etc)

#### **Study characteristics fields:**

- Brief description of study
- Aims/objectives of study
- Where is the study based (geographically)?
- Looking at crime generators/attractors/both
- Type of facility examined
- Justification for this as a crime generator/attractor
- What crime types were examined?
- What crime data was used?
- When was the crime data from?
- Number of facilities examined
- Where was the facilities data from?

#### **Content fields:**

- Does this paper look at crime distribution around a crime generator/attractor?
- If it does look at the crime distribution, what does it find?

- Does this paper try to classify crime generators/attractors?
- If it does classify crime generators/attractors, how does it do this and what does it find?
- Does this paper advance understanding of the mechanisms of crime generators/attractors?
- If it does look at the mechanisms of crime generators/attractors, what does it find?

**Analysis and Results fields:**

- What methods of analysis do the authors of this paper use?
- What were their key results?
- How does this work advance knowledge on crime generators/attractors?
- Any other important comments?

**Definition fields:**

- Do the authors reference the Brantingham and Brantingham (1995) paper when defining generators/attractors?
- Crime generator definition
- Crime attractor definition

## **Appendix B**

### **Scoping Literature Review: Papers Included**

The content of this appendix relates to Chapter 4 – the scoping literature review. The following list contains the 48 papers which were eligible for inclusion.

Adams, W., Felson, M., 2015. Are Parks Crime Generators? An Exploratory Analysis of Crime and Parks in Houston, Texas. DOI: 10.13140/RG.2.1.4730.8005

Bernasco, W., Block, R., 2011. Robberies in Chicago: A Block-Level Analysis of the Influence of Crime Generators, Crime Attractors, and Offender Anchor Points. *J. Res. Crime Delinquency* **48**, 33–57. <https://doi.org/10.1177/0022427810384135>

Boessen, A., Hipp, J.R., 2018. Parks as crime inhibitors or generators: Examining parks and the role of their nearby context. *Soc. Sci. Res.* **76**, 186–201. <https://doi.org/10.1016/j.ssresearch.2018.08.008>

Boivin, R., D'Elia, M., 2017. A Network of Neighborhoods: Predicting Crime Trips in a Large Canadian City. *J. Res. Crime Delinquency* **54**, 824–846. <https://doi.org/10.1177/0022427817705935>

Bowers, K., 2014. Risky Facilities: Crime Radiators or Crime Absorbers? A Comparison of Internal and External Levels of Theft. *J. Quant. Criminol.* **30**, 389–414. <https://doi.org/10.1007/s10940-013-9208-z>

Brantingham, Patricia, Brantingham, Paul, 1995. Crime generators and crime attractors. *Eur. J. Crim. Policy Res.* **3**, 5–26.

Breetzke, G.D., Fabris-Rotelli, I., Modiba, J., Edelstein, I.S., 2019. The proximity of sexual violence to schools: evidence from a township in South Africa. *GeoJournal*. <https://doi.org/10.1007/s10708-019-10093-3>

Cohen, J., Gorr, W.L., Olligschlaeger, A.M., 2007. Leading indicators and spatial interactions: A crime-forecasting model for proactive police

deployment. *Geogr. Anal.* **39**, 105–127. <https://doi.org/10.1111/j.1538-4632.2006.00697.x>

Connealy, N.T., 2019. Can we Trust Crime Predictors and Crime Categories? Expansions on the Potential Problem of Generalization. *Appl. Spat. Anal. Policy*. <https://doi.org/10.1007/s12061-019-09323-5>

Contreras, C., 2017. Block-Level Analysis of Medical Marijuana Dispensaries and Crime in the City of Los Angeles. *Justice Q.* **34**, 1069–1095. <https://doi.org/10.1080/07418825.2016.1270346>

Demeau, E., Parent, G., 2018. Impacts of Crime Attractors and Generators on Criminality in Montreal. *Can. J. Criminol. Crim. Justice* **60**, 387–412. <https://doi.org/10.3138/cjccj.2017-0028.r1>

Drawve, G., Moak, S., Berthelot, E., 2016. Predictability of gun crimes: a comparison of hotspot and risk terrain modelling techniques. *Polic. Soc.* **26**, 312–331.

Feng, J.X., Liu, L., Long, D.P., Liao, W.W., 2019. An Examination of Spatial Differences between Migrant and Native Offenders in Committing Violent Crimes in a Large Chinese City. *Isprs Int. J. Geo-Inf.* **8**. <https://doi.org/10.3390/ijgi8030119>

Frank, R., Andresen, M.A., Cheng, C., Brantingham, P., 2011a. Finding Criminal Attractors Based on Offenders' Directionality of Crimes, in: 2011 European Intelligence and Security Informatics Conference. Presented at the 2011 European Intelligence and Security Informatics Conference (EISIC), IEEE, Athens, Greece, pp. 86–93. <https://doi.org/10.1109/EISIC.2011.34>

Frank, R., Dabaghian, V., Reid, A., Singh, S., Cinnamon, J., Brantingham, P., 2011b. Power of Criminal Attractors: Modeling the Pull of Activity Nodes. *Jasss- J. Artif. Soc. Soc. Simul.* **14**. <https://doi.org/10.18564/jasss.1734>

Groff, E., McCord, E.S., 2012. The role of neighborhood parks as crime generators. *Secur. J.* **25**, 1–24. <https://doi.org/10.1057/sj.2011.1>

Han, S., Nobles, M.R., Piquero, A.R., Piquero, N.L., 2019. Crime Risks Increase in Areas Proximate to Theme Parks: A Case Study of Crime Concentration in Orlando. *Justice Q.* 1–20. <https://doi.org/10.1080/07418825.2019.1677935>

Hewitt, A.N., Beauregard, E., Andresen, M.A., Brantingham, P.L., 2018. Identifying the nature of risky places for sexual crime: The applicability of crime pattern and social disorganization theories in a Canadian context. *J. Crim. Justice* **57**, 35–46. <https://doi.org/10.1016/j.jcrimjus.2018.03.003>

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Kinney, J., Brantingham, P., Wushcke, K., Kirk, M., Brantingham, P., 2008. Crime Attractors, Generators and Detractors: Land Use and Urban Crime Opportunities. *Built Environ.* **34**, 62–74.

Kurland, J., Johnson, S.D., Tilley, N., 2014. Offenses around Stadiums: A Natural Experiment on Crime Attraction and Generation. *J. Res. Crime Delinquency* **51**, 5–28. <https://doi.org/10.1177/0022427812471349>

LaRue, E., Andresen, M.A., 2015. Spatial Patterns of Crime in Ottawa: The Role of Universities. *Can. J. Criminol. Crim. Justice* **57**, 189–214. <https://doi.org/10.3138/cjccj.2013.E47>

LeBeau, J.L., 2012. Sleeping with strangers: hotels and motels as crime attractors and crime generators, in: *Patterns, Prevention, and Geometry of Crime*. Routledge, pp. 99–124.

Mago, V.K., Frank, R., Reid, A., Dabbaghian, V., 2014. The strongest does not attract all but it does attract the most - evaluating the criminal attractiveness of shopping malls using fuzzy logic. *Expert Syst.* **31**, 121–135. <https://doi.org/10.1111/exsy.12015>

Malleson, N., Andresen, M.A., 2016. Exploring the impact of ambient population measures on London crime hotspots. *J. Crim. Justice* **46**, 52–63. <https://doi.org/10.1016/j.jcrimjus.2016.03.002>

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## **Appendix C**

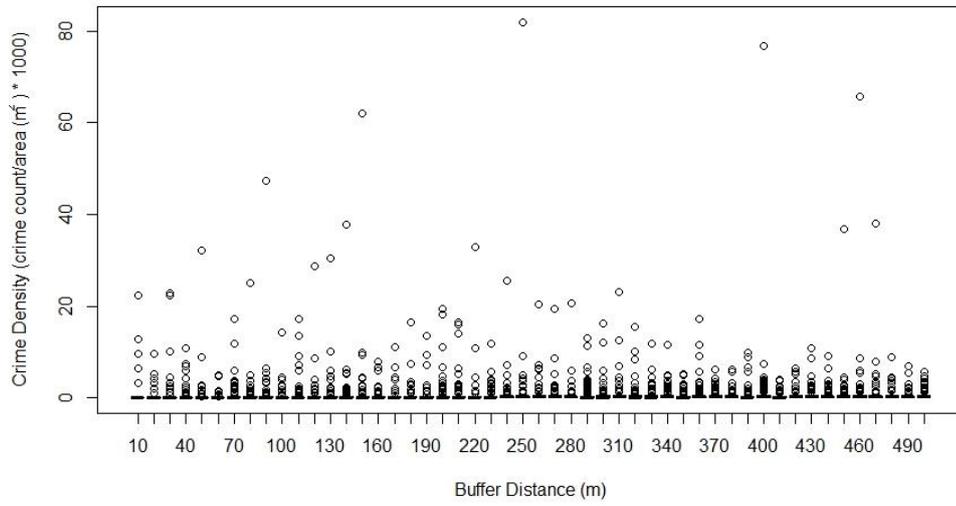
### **Empirical Data Analysis: Boxplots**

The boxplots found here relate to Chapter 7, which consists of empirical analysis of crime data to investigate the spatial distribution of crime in the vicinity of potential crime generators and attractors identified from the literature.

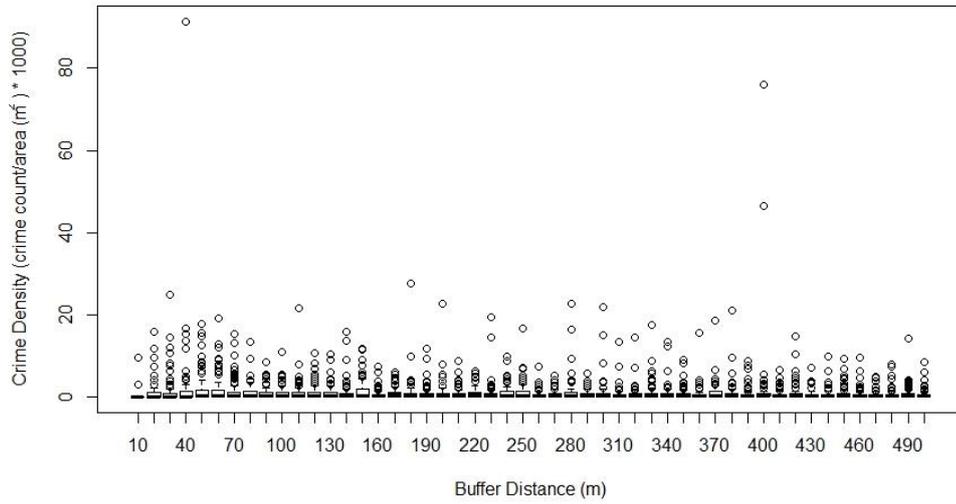
Figure C. 1 shows the boxplots for crime density around the crime generator facilities, and Figure C. 2 show that around the crime attractor case studies. These boxplots indicate that both the crime generator and attractor facilities saw a moderate amount of variance. This is particularly true of homeless shelters and bars, both of which saw more extreme outliers.

It is important to note that any discrepancies that may appear to exist between these boxplots and the graphs found in Chapter 7 are caused by the different data format used. In the graphs found in Chapter 7, the dissolved buffer method was used to obtain the crime density in each buffer around all of one facility type as a whole. In these boxplots, on the other hand, the undissolved buffer method was used to obtain the crime density in each buffer around each facility individually.

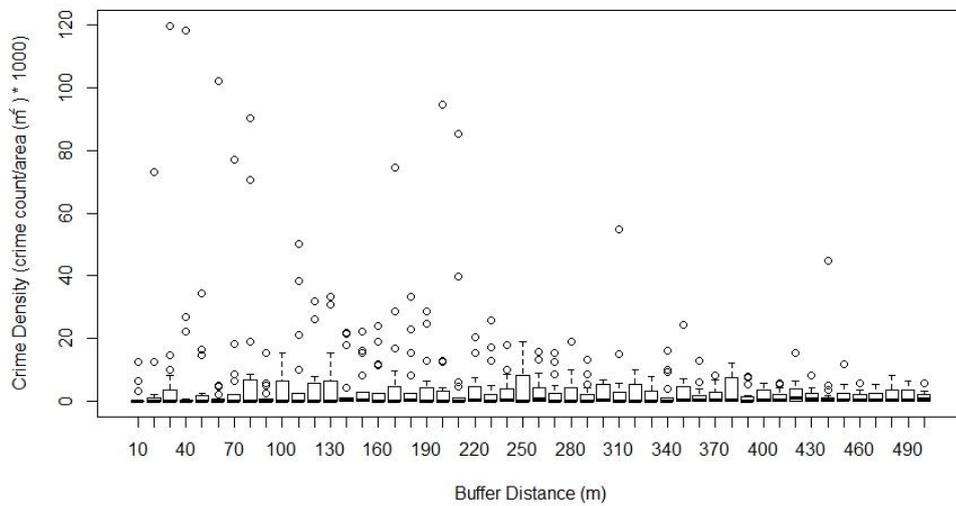
### Schools Boxplots



### Stations Boxplots

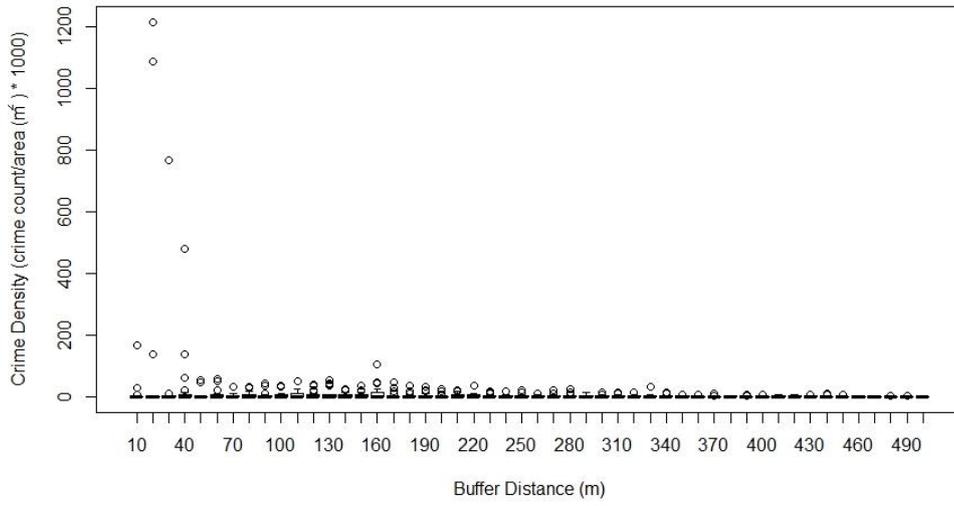


### Cinemas Boxplots

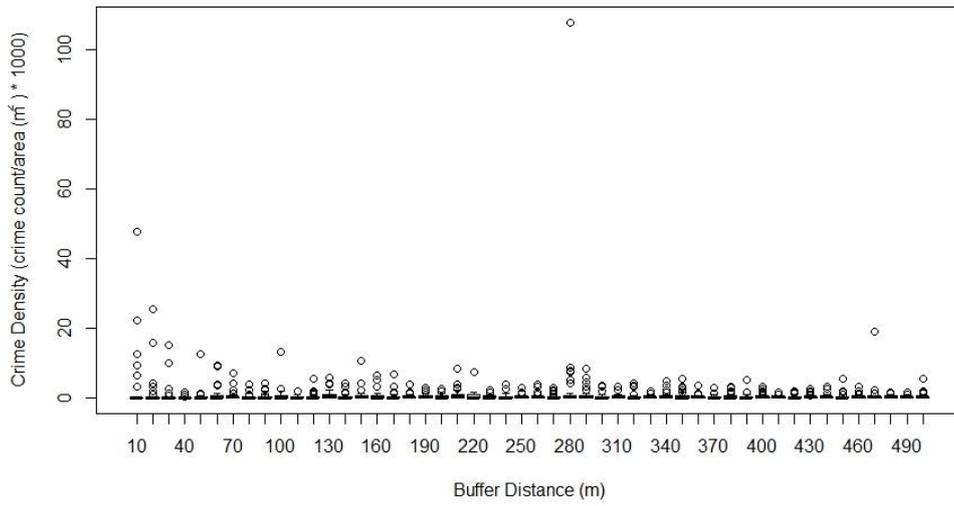


## C. 1 - Crime Generator Boxplots

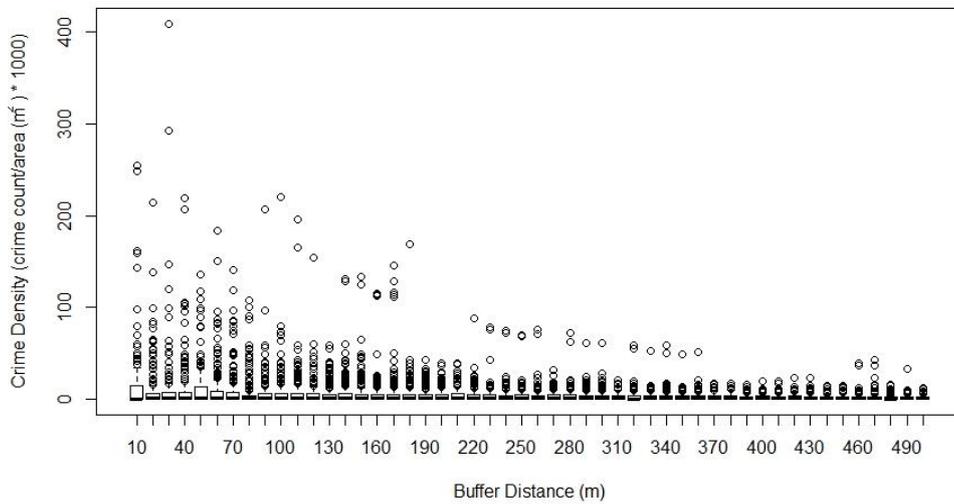
### Shelters Boxplots



### Drug Treatment Centres Boxplots



### Bars Boxplots



## C. 2 - Crime Attractor Boxplots