A SPATIAL CLASSIFICATION OF CRIMINAL OFFENDERS: MOVING BEYOND CIRCLE THEORY WITH AN AGENT-BASED MODEL APPROACH

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DEDICATION

This is dedicated to Ash Mattburn for whose crazy stories helped inspire this thesis.

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I would like to thank my parents, Phoenix and Shirley, for always being there with their unwavering love and support and for teaching me that the right way isn't typically the easy way. To my best friend, Matt, for always knowing the right thing to say, even when it wasn’t the easiest or most polite option. To Dr. Rice for agreeing to step in midway to advise this thesis and ensure its successful completion. To Drs. Crooks, Curtin, and Gill for advising and guiding me throughout this process. To my staff at City Trivia for patiently working around my absences and picking up the balls I dropped. To my boys, Ethan and Cole, whose births delayed this thesis, but are worth every extra second. Finally, thank you to my amazing wife, Angela, because without her perpetual faith and unwavering support this thesis would never have seen the light of day.

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LIST OF ABBREVIATIONS

American Community Survey .... ACS
American Standard Code for Information Interchange .... ASCII
Agent-Based Model .... ABM
Density-Based Spatial Clustering of Applications .... DBSCAN
District of Columbia .... D.C.
Environmental Systems Research Institute .... Esri
Fairfax County (Virginia) Police Department .... FCPD
Geographic Information System(s) .... GIS
Maryland .... MD
Metropolitan Police Department .... MPD
Metropolitan Statistical Area(s) .... MSA
New York (City) Police Department .... NYPD
Office of Management and Budget .... OMB
Overview, Design concepts, Design details .... ODD
Quantum Geographic Information System .... QGIS
Virginia .... VA
Washington (D.C.) Metro Area Transit Authority .... WMATA

ABSTRACT

A SPATIAL CLASSIFICATION OF CRIMINAL OFFENDERS: MOVING BEYOND CIRCLE THEORY WITH AN AGENT-BASED MODEL APPROACH

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This thesis builds a spatial classification of criminal offenders and uses agent-based modeling and spatial analysis to demonstrate the validity of this classification. Existing literature is reviewed for foundation definitions related to the spatial behavior of criminal offenders and for research into spatial types of criminal offenders. Key findings and gaps found in this literature are presented with updated foundation definitions and an updated spatial classification of offenders. An agent-based model is developed as a proof of concept to this spatial classification of offenders and to simulate the emergent behavior of these offender types. The data produced by the agent-based model is used to review Circle Theory and to conduct a spatial analysis of the resulting patterns of criminal offenses. An assessment of Circle Theory is made followed by the first steps in developing a decision tree for classifying spatial types of criminal offenders. These efforts demonstrate the validity of the five proposed spatial offender types; that Circle Theory is fundamentally flawed in its current state but may still have validity in

classifying spatial offender types; and that a criminal offender can be spatially classified through an analysis of their criminal offense locations.

1. INTRODUCTION

In 2008, the Metropolitan Police Department (MPD) in Washington, D.C. instituted driver checkpoints in reaction to high amounts of gun violence in the Trinidad neighborhood (Klein, 2008). The general belief was that non-residents were responsible for this gun violence and that by preventing non-residents from entering the neighborhood, these crimes would be curtailed. In 2014, the Fairfax County Police Department (FCPD) also reacted to the potential of outside offenders with the completion of the new WMATA Silver Line. A new police unit was deployed in the Tysons Corner and Reston neighborhoods in expectation of an increase in the property crime rate that would result with this new mass transportation route (Culver, 2014).

These two seemingly unrelated events paint a picture that criminals commute, just like law-abiding citizens. In the case of the new WMATA line criminals can now commute to Tysons Corner, VA and Reston, VA without a car, whereas before these neighborhoods were largely unavailable without personal transportation.

People generally discuss crime in context with where the crime took place, but not in context with whether the criminals live in their neighborhood. Where do criminal offenders live? When a person is arrested for a crime one of the basic pieces of information collected is their home address. Do people live in the neighborhood where they commit crimes? Do criminals commute in the same fashion as law-abiding citizens? Is it both?

The following thesis considers where arrested persons live. First, a thorough review of the existing research is outlined (see Section 2, Literature Review), followed by an acknowledgment of gaps (see Section 2.13, Key Gaps) and a redefining of key terms such as "commuter", "marauder", "drifter", and "local" as well as the introduction of "routine activities offenders" in the context of individuals committing multiple, or a series of, criminal offenses (see Section 3.3, Spatial Classification of Criminal Offenders). These offender types are grouped into a broader spatial offender classification of criminals with the intent of being able to better understand geographic profiles of criminal offenders.

Next, an agent-based model (ABM) has been built to simulate the behavior of the redefined and additional spatial offender types against the real background of Fairfax County, VA (see Section 4, Objective 2 – Agent-Based Model). Runnings of this model produced theoretical offense locations emerging from the road network and land use of Fairfax County and the behaviors (i.e. rules) of each spatial offender type.

The resulting data is analyzed using the existing Circle Theory (Canter & Larkin, 1993) to reassess this theory against the expanded spatial classification of criminal offenders (see Section 5.2, Circle Theory Analysis). This analysis also begins laying groundwork for building a decision tree to determine an offender's spatial type from a series of offenses, regardless of offense type (see Section 5.3, Spatially Classifying a Set of Offenses). This will ultimately lead to being able to classify real world offenders prior to geographic profiling, thus ensuring that the most fitting law enforcement techniques are implemented in serial crime investigations.

The end goal of this thesis is to bring together the decentralized literature on spatial offender types, create a set of cohesive definitions, implement these definitions into an ABM for validation and verification, to assess this expanded classification against Circle Theory (Canter & Larkin, 1993), and finally to begin the spatial analysis work of applying these definitions to serial offense patterns for spatial classification of serial offenders in geographic profiles for use in law enforcement investigations.

2. LITERATURE REVIEW

2.1. Spatial Theories of Crime

In 1942, Shaw and McKay (1942) published their work on juvenile delinquency's relation to space and forever altered criminological research. This book, in part, demonstrated that juvenile delinquency was highly correlated to several factors including population change, housing, poverty, neighborhood demographics, physical and mental health factors, and other types of crime, specifically crimes committed by adults (Shaw & McKay, 1942: xi). With this revelation, Shaw and McKay proposed that "if we wish to reduce delinquency, we must radically change our thinking about it" (Shaw & McKay, 1942: xiii). The context of this thought change was in line with looking at the social constructs behind delinquency rather than the individual factors, with a strong emphasis on finding a prevention to delinquency rather than a cure. But, out of this high-level perspective, Shaw and McKay (1942: 437-8) also recognized that delinquency in typical urban life, as compared to small town and rural life, was largely associated with two things: economic status of neighborhoods and individual anonymity.

In the 1965 seminal work *Urban Crime Patterns*, Boggs (1965) demonstrated that different neighborhoods are conducive to different types of crimes. Boggs (1965) talked about familiarity with targets and profitableness as factors in an offender choosing a location to commit a crime and suggested that crime occurrence rates should be structured based on environmental opportunities specific to each type of crime. This work also highlighted that residents of urban neighborhoods have limited acquaintance and are thus indifferent to strangers, which would allow strangers to move around unnoticed and unsuspected. Boggs (1965) concludes by placing types of crime into different categories, each of which has different factors related to the type of neighborhood and the offender's familiarity with the neighborhood. In this approach, the relationship between the offender and the target are both relevant to understanding where offenders commit crimes. As a result, Boggs' (1965) work demonstrated that targets are not limited to an offender's neighborhood, but to an offender's familiarity with the target, and by association the target's neighborhood, is a key factor. This approach therefore highlighted the need to collect data about where criminal activity occurs compared to an offender's own neighborhood.

As in Boggs (1965), the Routine Activities Theory (Cohen & Felson, 1979) attempts to explain the relationship between offenders and targets but includes a temporal component to help understand both where and when crimes are committed. This theory states that criminal offenses "required the convergence in space and time of likely offenders, suitable targets, and the absence of capable guardians" (Cohen & Felson, 1979: 588). This theory takes Boggs' (1965) work a step further by not only recognizing the need to look at both offender and target factors, but by adding in the presence of guardians to deter offenders. Using data on rapes, robberies, and assaults, Cohen and Felson (1979: 589) argued that crime rates increase when these three agents converge, thus bringing crime directly into the world of geospatial and temporal analysis. Cohen and Felson (1979: 591) further argue that illegal activities stem from routine, everyday activities, thus the spatial and temporal aspects of a likely offender's day-to-day life has an influence on where and when that individual is likely to commit a crime.

The combination of Boggs' (1965) work with the Routine Activities Theory (Cohen & Felson, 1979) suggests that a likely offender's day-to-day life will help to increase the offender's familiarity with neighborhoods outside of their residence neighborhood. These "routine activities", such as commuting to work or visiting family, could have the potential for a likely offender to gain familiarity with neighborhoods, or "targets", that have a higher "profitableness" than the neighborhood in which the offender resides.

Also attempting to explain why offenses are committed in specific neighborhoods, Kelling and Wilson (1982) published in *The Atlantic* what has become a controversial piece known as Broken Windows Theory. This theory is colloquially described as minor crimes begetting major crimes. The analogy is that if broken windows in a neighborhood aren't repaired, then people are more likely to break more windows and a neighborhood will deteriorate. This theory was implemented by the New York City Police Department (NYPD) through heavy policing of minor offenses (e.g. subway turnstile jumping) with the goal of preventing major offenses. The public perceived the NYPD's actions as being heavy-handed which resulted in controversy surrounding Broken Windows. Looking past this controversy and back to the original research, Broken Windows Theory categorizes people in a single neighborhood into two groups: "regulars" and "strangers"[1], and chronicles different policing strategies for each group. Kelling and Wilson (1982) further discuss the role of a neighborhood's "regulars" as capable guardians and the difference in victimization rates between young me and the elderly due to their activity levels. Both ideas feed into Routine Activities Theory with neighborhood regulars acting as capable guardians in addition to law enforcement and the likelihood of victimization increasing with more active targets having an increased likelihood of converging in space and time with likely offenders.

In 1981, Brantingham and Brantingham (1981a, 1981b) published the book *Environmental Criminology*. In the introduction of this book, they broke crime into four dimensions: law, offender, target, and place. Brantingham and Brantingham (1981a: 7) directly stated that environmental criminology was the study of crime's fourth dimension: place. Within this fourth dimension, for analysis, environmental criminology was divided into three levels: macro-, meso, and micro-analysis (Brantingham & Brantingham, 1981a: 21). The meso-analysis level was described as sub-units that included metropolitan areas, police precincts, census tracts, or as small as individual city blocks. Specifically, research within the meso-analysis level included distribution of criminal targets and offender populations as well as daily routine activities "such as work, school, shopping, and recreation locations" and "of traffic channels". In addition to this division of analysis, Brantingham and Brantingham (1981a: 24) also identified a major

[1] In some literature, the terms "strangers" and "regulars" are used, in other literature the terms "suitable guardians" and "likely offenders", and in other literature "commuters" and "marauders". There is a gap in fully defining these terms and where definitions differ and crossover. This is a gap that is filled by this thesis. For now, the terms used are those used in the specific research being discussed.

flaw in previous waves of environmental criminology research: "the general assumption that criminal residence locations and crime sites were spatially identical".

In the afterword of *Environmental Criminology*, Brantingham and Jeffery (1981) described crime and space in relation to criminological theory. In this work, Brantingham and Jeffery (1981: 237) stated that research into spatial aspects of crime has previously been impeded by "the insistence that only the offender dimension of crime be considered". The authors insisted that the urban form, offender mobility, and the distribution of offenders and targets must be researched.

Expanding on their previous research, Brantingham and Brantingham published *Criminality of Place* (1995) and introduced the concept of "crime generators" and "crime attractors". Crime generators are places that are conducive to certain types of crimes and crime attractors are places that provide opportunities for certain types of crimes (Brantingham & Brantingham, 1995: 7-8). Also discussed in this work were the relations of geographic nodes, paths, and edges to crime (Brantingham & Brantingham, 1995: 10-12). Nodes are places central to people's lives which were close to where they committed offences. Examples of nodes included work, school, recreation sites, and shopping centers. Paths were described as where people spent long hours in routines traveling to and from the nodes central to their lives. These paths specifically include street and transit networks. Brantingham and Brantingham (1995: 12) recognized that movement patterns "must be considered in understanding crime aggregate patterns". Edges were described as either physical (e.g. rivers) or perceptual (e.g. jurisdictional boundary) and are believed to create areas "where strangers are more easily accepted because they are frequently and legitimately present" (Brantingham & Brantingham, 1995: 12).

The above research builds the foundation for needing to understand not only a criminal offender's choice of offense location, but how the offense location relates to the locations in an offender's daily non-criminal routines and movement.

2.2. Cognitive Maps

Understanding how an offender's offense locations relates to their daily non-criminal routines and movement requires understanding how they see the world spatially. This requires an understanding of the offender's "cognitive map", or their mental spatial picture of the world.

In 1973, Downs and Stea (1973b) compiled the first major work on cognitive maps. In the forward of their work, "cognitive maps" were defined as "an abstraction which refers to a cross-section, at one point in time, of the environment as people believe it to be" (Downs & Stea, 1973b: xiv). Their book included the paper *Cognitive Maps and Spatial Behavior* in which Downs and Stea (1973a: 9) stated that "human spatial behavior is dependent on the individual's cognitive map of the spatial environment". A cognitive map is used by someone to know "where certain valued things are" and "how to get to where they are", thus making cognitive maps the "basis for deciding upon and implementing any strategy of spatial behavior" (Downs & Stea, 1973a: 10). Furthermore, cognitive maps provide people with the ability to know where something is, either in relation to where they are now or relative to another familiar location (Downs & Stea, 1973a: 17). Problematically, these places of interest become "so extensive that they cannot be perceived or apprehended either at once or in a series of brief glances" (Downs & Stea, 1973a: 14). As a result, "cognitive maps are complex, highly selective, abstract, generalized representations in various forms" (Downs & Stea, 1973a: 18), thus creating distortions in an individual's cognitive map in either distance or direction (Downs & Stea, 1973a: 19). Add to this distortion the thought that stored knowledge is subject to a time decay, being lost over time, and repetition of spatial experiences are necessary for cognitive maps to be accurate and useful over an extended period. (Downs & Stea, 1973a: 25).

Adding to the work of Boggs (1965), Rengert (1981) wrote a critique of the Opportunity Structure Model and discussed the relative attractiveness of areas for criminal activity with respect to criminal residences when controlled for relative mobility. Rengert (1981: 201) concluded that crime targets must be accessible, opportunity is not an objective reality, and inaccessible opportunity is no opportunity at all. Although Rengert (1981) was speaking in general about the physical sense of opportunities, when applied to Downs and Stea's (1973a) work on cognitive maps, it shows that opportunities must be physically accessible as well as accurate enough in an individual's cognitive map to become physically accessible, otherwise there is no criminal opportunity. More plainly said: if the potential offender can't physically find the opportunity, then the crime can't be committed. Rengert (1989: 165) added to this thought process when he wrote that "we needed to know the 'awareness space' of criminals.

Criminal offenders are aware of this need for cognitive maps and awareness space. As noted by Brantingham and Brantingham (1981b), serial offenders actively engage in searches for targets. Through their research, Brantingham and Brantingham (1981b: 35) recognized that this active search expands an offender's awareness space from the nodes and paths in their routine activities to include nearby areas, thus expanding their cognitive map further than their non-criminal awareness space. Both Brantingham and Brantingham (1981b: 36) and Rengert (1981: 167) argued that awareness space varies with a criminal's age, just as with non-criminals. Brantingham and Brantingham (1981b: 42) hypothesized that the specific criminal activity awareness space would be the intersection of an offender's non-criminal awareness space and areas with suitable targets. Furthermore, Brantingham and Brantingham (1981b: 36) hypothesized that in urban areas with popular mass transit, an offender's awareness space would become more nodal with less emphasis on paths than if primary transportation was vehicular, walking, or similar fluid modes of transportation.

The research outlined in this section shows the importance of understanding not just the spatial world, but the spatial world as seen by offenders, while understanding that offenders will seek to improve their spatial knowledge to find better opportunities. One can logically concluded that offenders would stray outside of daily, non-criminal activities to increase their awareness space with the goal of finding physically accessible opportunities to commit crime. Basically, to be a "good" criminal a large awareness space is necessary.

2.3. <u>Anchor Points</u>

The research discussed thus far has focused on an offender's or target's neighborhood and has been the general area of an individual's residence. Although a person's residence is an important aspect in a spatio-temporal analysis of their activities, most people don't spend their entire lives at home. This aspect leads to the concept of anchor points. Couclelis, et al. (1987) posited different anchor point theories and how these points help an individual build a cognitive map, or in Boggs' (1965) words: "familiarity". Anchor points were defined by Couclelis, et al. (1987: 101), as a subset of landmarks (e.g. important buildings in a city). For example, where someone works can be an anchor point, but one that is more personal to an individual and may have minimal significance to other people. Locations of work and home were specifically highlighted as examples of anchor points to specific individuals (Couclelis, et al., 1987: 102). These anchor points are used by individuals to gain familiarity that helps to organize spatial information, navigate, and estimate distances and directions.

Applying the concept of an individual's familiarity with an area around an anchor point to the work of Boggs (1965), Routine Activities (Cohen & Felson, 1979), and Broken Windows (Kelling & Wilson, 1982) shows the need to include other locations in a likely offender's life when analyzing the location, time, and likelihood of offenses. This was concluded by Canter, et al. (2000: 458) when they commented on the value of an offender's "base" (i.e. primary anchor point) only being valuable when that location has some relation to the offender, such as their residence, work, or frequent leisure activity. Bernasco (2010) further demonstrated this point by showing the significance of an offender's former residence to their choice of crime locations.

2.4. Journey-to-Crime

Rhodes and Conly (1981: 167) defined a "criminal commute" as "a theoretical construct in which offenders with diverse motivations to commit crimes are seen to select crime sites of varying distances from their home bases". This theory of a "criminal commute" assumes that criminals travel to locations away from their residence to avoid detection or victimize the best targets. To utilize a criminal commute, offenders take "environmental cues" based on their travels during routine activities to and from work, school, shopping, and recreation (Rhodes & Conly, 1981: 168). While researching this theory, Rhodes and Conly (1981: 184) found that distances traveled tended to increase when the offenders did not know their victims, were older, and had criminal records (i.e. experience).

Researching the journey-to-crime behavior of suburban burglars, Ratcliffe (2003: 5) found that an offender's journey-to-crime was not significantly changed in relation to the jurisdictional boundaries of suburbs. This leads to the conclusion that jurisdictional lines do not factor into the spatial awareness of an offender (Ratcliffe, 2003: 6), thus showing that an offender's journey-to-crime is based less on the political features on a map and more on their awareness space.

Snook (2004) studied the relationship between distances a burglar travels and the burglar's age, method of transportation, and the value of the property stolen. These factors were found to be significantly related to variations in travel distance (Snook, 2004: 63). Although, it was found that the number of crimes in a series, the length of time in a series, and if the burglar had an arrest record were not significantly related to the distances a burglar travels (Snook, 2004: 61). Despite these findings, Snook (2004: 64) acknowledged that this research assumed the burglar's residence was within their criminal activity space, thus this study assumes that all burglars were marauding offenders (see Section 2.6, Commuters vs. Marauders).

Researching journey-to-crime aspects of serial homicide, Snook, et al. (2005: 150-2) found that most serial homicide victims are selected within five kilometers of the offender's residence, older homicide offenders leave bodies closer to their residence, IQ and journey-to-crime distance are positively correlated, and mode of transportation is an important factor.

This journey-to-crime research further demonstrates that factors other than what is traditionally shown on and beyond a map are critical to understanding where an offender commits crimes.

2.5. Routine Activities

Expanding upon the brief discussion above of Routine Activities Theory (see Section 2.1, Spatial Theories of Crime) as a spatial theory of crime, in a follow up study, Clarke and Felson (2008) discussed the compatibility between routine activities and rational choice. In their paper, the authors highlighted that changes in the general population's routine activities resulted in a change in crime rates and that routine activities described behavior at the macro level of a population group (Clarke & Felson, 2008: 8).

In 1985, Rengert and Wasilchick (1985) interviewed residential burglars to determine what lead to the burglars' choice of targets. Their research determined that urban burglaries were generally the result of spontaneous opportunities found during non-criminal routine activities and that suburban burglars generally engaged in a search pattern for targets (Rengert & Wasilchick, 1985: 53). Offenders were found to actively engage in evaluation of targets during non-criminal routine activities (Rengert & Wasilchick, 1985: 57), but since offenders can't evaluate places they've never been (Rengert & Wasilchick, 1985: 54) the burglars in this study found targets from four different types of opportunities (Rengert & Wasilchick, 1985: 67). These four opportunities all result in potential targets for burglaries: (1) situational opportunities occurring during non-criminal routine activities, (2) targets found through evaluation of areas known through routine activities, (3) targets found through exploration, and (4) opportunities found by other people such as friends or dealers in stolen goods (Rengert & Wasilchikc, 1985: 67). Rengert and Wasilchick (1985) saw each of these opportunities as presenting a different spatial pattern and different distances from the offender's residence. Situational opportunities were closest to an offender's residence; evaluation of known areas pushed further away from areas of routine activities; exploration was the farthest away from an offender's residence; and opportunities found by others were randomly distributed in space as these have the least direct association with the offender's routine activities.

In addition to the connection between opportunities and proximity to routine activities, Rengert and Wasilchick (1985: 67) found that routine activities orient offenders towards targets. In studying the burglar's routine activities, it was found that the route from the residence and to recreational activities tended to be longer than the route from the residence and to work (Rengert & Wasilchick, 1985: 69). Additionally, it was found that the burglars studied showed a directional bias for targets oriented along the journey-to-work and that targets were clustered more along this journey than the journey-to-recreation (Rengert & Wasilchick, 1985: 69).

Through studying the spatial patterns of serial murders, Lundrigan and Canter (2001: 595) found that the locations used by these offenders (e.g. victim search, body disposal) were based on past experiences. This study argued that if a serial killer employed pure rational choice for location selection, then there would occur a "commute" to an area with optimal benefits for the crime (Lundrigan & Canter, 2001: 598). But, with routine activities, body disposal would occur along routes familiar to offender in a "marauding" fashion (Lundrigan & Canter, 2001: 598). The authors also believed that a routine activity approach would result in a bias towards the residence at one end of the area of offenses and would create a defined area of criminal activity (Lundrigan & Canter, 2001: 598). Additionally, the authors argued that an offender's career would start off with routine activities and a marauding pattern but would progress to a rational choice model and simulate a commuting pattern (Lundrigan & Canter, 2001: 599).

Two additional studies highlighted the importance of routine activities in an offender's target selection. Eck and Weisburd (1995: 11) noted that the more a single place is a part of people's routine activities, then the more likely this place is to be the scene of a crime (Eck & Weisburd, 1995: 11), thus offenders are also more likely to find these places through their routine activities. Similarly, Godwin and Canter (1997: 36) found that as a serial killer's confidence grows, their offenses become increasingly integrated with their daily lives and routine activities.

Brantingham and Brantingham (2008b) highlighted the need to know an offender's routine activities, not just their residence, through an example of juveniles. Their research further noted that when juveniles hang out at anchor points such as convenience stores or fast food restaurants, then these locations become a node in the routine activities and thus a spatial factor in any resulting criminal activity (Brantingham & Brantingham, 2008b: 270). The above theory, highlighted by this example, shows the targets selected by an offender are just as much a result of their routine activities as the location of their residence. Thus, it is necessary to analyze the pattern of offence locations of a serial criminal in this full context, not just in the context of their residence.

2.6. <u>Commuters vs. Marauders</u>

2.6.1. Background Theory

Brantingham and Brantingham (1981b) outlined many cases for the geometry of crime. The first case was the most basic: a single offender based in a single location with a uniform distribution of targets (Brantingham & Brantingham, 1981b: 30-32). As in basic geometry teachings starting with a circle, this case started with the most basic options and added additional factors with additional cases to the theory. The third case described a single offender with a uniform distribution of targets but based from multiple anchor points (Brantingham & Brantingham, 1981b: 33-37). Again, like in basic geometry teachings moving from a circle to a triangle, this case began to describe offender behavior in terms closer to the behavior of non-offender behavior. With the sixth case, the description of an offender's behavior included an area of criminal activity that is derived from the intersection of an offender's awareness space and areas with non-uniform distribution of targets (Brantingham & Brantingham, 1981b: 42-44). Case 6 showed that crime occurs near areas of activity (i.e. anchor points) and along transportation paths (i.e. roads commonly used in routine activities). These selected cases, and the others not described, demonstrated "that crime occurrence is not the direct result of motivation, but is mediated by perceived opportunity" (Brantingham & Brantingham, 1981b: 54).

With theoretical examples of offender behavior, theories of how to find offenders from these behaviors are needed. LeBeau (1987) believed that criminologists had not fully utilized the geographic techniques available and argued that the use of centrography (i.e. the average coordinates of a set of points) would improve upon environmental criminology. Using centrography to calculate the mean center of a distribution of criminal offenses, LeBeau (1987: 127) recognized that bimodal distributions with a mean center occurring in a void between clusters was a possible result. This bimodal distribution would result in two clusters, each potentially representing a separate anchor point, such as an offender's residence and work (LeBeau, 1987: 127).

2.6.2. Circle Theory

Previous literature shows that analyzing likely offenders based on where they live, work, and are likely to commit crime has viability. This thought was explored in depth with serial rapists in the United Kingdom to determine if there was a connection between an offender's residence and the locations of their offenses (Canter & Larkin, 1993). This research split offenders into two specific categories: commuters and marauders (Canter & Larkin, 1993: 65). To distinguish between these two classes of offenders, the authors developed the Circle Theory. This theory plots an offender's known offenses and the offender's residence. Next, "a circle is drawn with its diameter as the two offences that are furthest from each other" (Canter & Larkin, 1993: 66). The circle would then encompass all the known offenses committed by a single offender. If the offender's residence was within the circle, then the offender is a marauder, otherwise the offender is a commuter.

Adding to the Circle Theory, Canter and Gregory (1994: 170) defined an offender's "home range" and "criminal range". The home range is as "an area well known to the offender, specifically the region surrounding the home or base of operation" and the criminal range is the "finite region which encompasses all of an offender's offence locations". Their paper further clarified that a commuter offender has little to no overlap between the home and criminal ranges and that a marauder offender has an overlap between the home and criminal ranges (Canter & Gregory, 1994: 171).

2.6.3. Circle Theory Studies and Results

The Circle Theory and the distinction between commuter and marauder offenders was tested against known serial offenders in Australia (Kocsis & Irwin, 1997). The study used crime data from a city with a different street layout (planned versus unplanned layouts) than Canter and Larkin's (1993) study and added two additional offense types: arson and burglary. Using the Circle Theory, the results showed that serial rapists and arsonists are more likely to be marauders and serial burglars are evenly commuters or marauders. This research highlighted that connections do exist between an offender's residence and the type of offenses being committed. The authors acknowledged temporal factors may also exist and that the incorporation of additional spatial data, such as highways, may have value as these features affect movement and mental maps.

Not specifically looking at Circle Theory, but researching criminal range, Barker (2000) concluded that burglary in small towns was specifically attributed to "local" offenders. As with Canter and Larkin's (1993) "marauder" offender, Barker found that the offense area for a majority burglary series included the offender's residence (Barker, 2000: 64). This research also found that offense patterns beyond the initial five offenses mirrored the patterns of the first five offenses (Barker, 2000: 64). This shows that a subset of the offense series can be used to determine the pattern of the full offense series, thus allowing conclusions to be made about an offender's behavior even if there are unknown offenses.

Kocsis, et al. (2002) published a further assessment of Circle Theory finding a fifty-fifty split of offenders between commuter and marauder types. Additionally, it was found that an offender's residence tended not to be centrally located within the circle identifying the criminal range (Kocsis, et al., 2002: 52). It was also found that the Circle Theory encompassed most of the offenses, but the offenses were not circularly distributed, but were restricted to specific corridors relating to the location of the offender's residence (Kocsis, et al., 2002: 54-5). The study's conclusions included thoughts that it might be more appropriate to use all offenses to determine the center of an offender's criminal range and that further research into the corridor patterns was warranted. (Kocsis et al., 2002: 60).

Research by Meaney (2004) showed a distinction across offense types, but unlike in Kocsis and Irwin (1997), burglars were more likely to be commuters than marauders and sexual offenders and arsonists were more likely to be marauders (Meaney, 2004: 132).

Researching serial burglars in India, Sarangi and Youngs (2006: 111) found that using Circle Theory resulted in a roughly fifty-fifty split (56.7% marauders) between commuters and marauders. Looking deeper into the subset of offenders classified as commuters, the authors found that only two of the thirteen offenders were properly classified as commuters using Circle Theory (Sarangi & Youngs, 2006: 111). This result was attributed to major pathways having a dominate role in structuring an offender's spatial behavior (Sarangi & Youngs, 2006: 114).

A study of predicting residential locations of offenders found that of the 85% of offenders with a fixed address, only 39% of the data conformed to the Circle Theory (Laukkanen & Santtila, 2006: 79). This study concluded that a larger number of offenses improved the commuter and marauder predictions (Laukkanen & Santtila, 2006: 79). Edwards and Grace (2006: 223) also looked at the effectiveness of Circle Theory in its original form and found contrary results to previous research (Canter & Larkin, 1993; Kocsis & Irwin, 1997) when their data showed that arsonists are equally likely to be commuters or marauders. The study further concluded that the Circle Theory provided little information as to the location of a marauding arsonists home base (Edwards &

Grace, 2006: 224) and recognized that the inclusion of topographic and geographic features could assist in determining an offender's criminal range (Edwards & Grace, 2006: 225).

2.6.4. Circle Theory Relation to Offender Demographics

In the Kocsis, et al. (2002: 51) study no significant differences between commuters and marauders were found across gender, race, or residence location. Similarly, the research by Edwards and Grace (2006: 224) also found that there was no significant distinction between arsonist commuters and marauders when compared by age, number of convictions, and number of offenses. Thus, the study concluded that "no demographic or offence-related variable that was correlated with the marauder versus commuter pattern" (Edwards & Grace, 2006: 224). As with this conclusion, the Laukkanen and Santtila (2006: 81) study found that length of the series of offenses was the best predictor for marauder offenders, not demographics.

Another study considered whether demographics, in addition to offense types, were a factor in distinguishing between commuter and marauder offenders and concluded that female offenders were more likely to be marauders (Meaney, 2004: 128). Although the conclusions varied from previous studies, this study argued that an offender's spatial activity can be distinguished by demographics as well as offense type (Meaney, 2004: 128).

2.6.5. Circle Theory Criticisms and Improvements

A critical analysis specifically identified flaws in the Circle Theory (Paulsen, 2007). The study looked at investigative case data rather than known, convicted offenders, thus incorporating a broad range of offenders. Serial offenders were also defined using multiple offense types instead of a single offense type as in previous studies (Paulsen, 2007: 351). Through this different approach, Paulsen (2007) highlighted flaws in the Circle Theory, specifically in the definitions of commuters and marauders. Commuters were redefined as clusters of offenses away from an anchor point and marauding is indicative of an offender moving out from an anchor rather than committing offenses close to home. It was acknowledged in Paulsen's (2007: 356) conclusions that it is critical to determine whether a serial offender is a commuter or marauder because geographic profiling efforts allow for modeling of marauding offenders, but not commuting offenders. Paulsen (2007: 356) further argued that research into serial offenders should include multiple crime types and cross jurisdictional data.

Kent and Leitner (2007: 149) studied the use of deviational ellipses, not circles, in geographic profiling and acknowledged that the Circle Theory is an implementation of centrography, the effectiveness of which is susceptible to outliers. The authors argued that centrography by itself can not reflect the geography of an environment or an offender's cognitive map and offense locations are "a reflection of the irregularities consistent with the underlying physical and cultural landscapes" (Kent & Leitner, 2007: 150). As a result, the paper concluded that elliptical models are more accurate than circular models, but only successfully encompassed approximately one-third of residences (Kent & Leitner, 2007: 159).

Comparable to the 2007 published work, Leitner, et al. (Unpublished) proposed two additional methods of determining the offender type based on offense locations:

convex hull and ratio. Instead of a circle, the convex hull method connects the offenses on the outside of the distribution so that offense locations are either within the convex hull or mark its corners. The ratio method calculates ratio of the distance between the offender's residence and the furthest offense with the distance between the two offenses location furthest apart from each other. Analyzing the same dataset with the Circle Theory and these two new methods produced different percentages of commuter and marauder offenders.

2.6.6. Beyond Circle Theory's Commuters and Marauders

A 2006 study of predicting residential locations of offenders found that 15% of offenders had no known residential address (Laukkanen & Santtila, 2006: 75). Also in 2006, a study of homicide offenders found that 65% lived at the same address (either living together or in the same multi-unit residential building) as the victim and that 78% of offenders lived within two miles of where the victim's body was discovered (Salfati & Dupont, 2006: 128). These two studies and the resulting statistics demonstrate that there are types of criminal offenders who cannot be classified as either a commuter or a marauder as originally defined by Canter and Larkin (1993).

2.7. Geographic Profiling

Rossmo (1999) defined geographic profiling as "an information management system for serial violent crime investigation that analyzes crime information to determine the most probable area of residence". In the same published book, Rossmo (1999) provides an in-depth discussion of geographic profiling. In this discussion, Rossmo (1999) acknowledges that the simplest cases of geographic profiling find an offender's residence through the spatial mean of a group of offenses, but also acknowledges that this simple pattern is distorted by the real world to include street layouts, traffic patterns, and land use. This is in part because finding an offender's residence relies more on the offender's psychological perception of distance rather than the reality of physical distance, or an offender's "cognitive map". In describing information management systems for geographic profiling, Rossmo (1999) stated that the system must be compatible with the police investigation, will produce a more accurate profile with more offense locations, and may result in multiple peak areas showing multiple anchor points for the offender.

Like Rossmo (1999), Snook, et al. (2005: 162) concluded the success of geographic profiling is dependent on being familiar with an offender's spatial decisions, or again, the offender's cognitive map. Similarly, Strangeland (2005: 462) found that offenders tended to commit crimes along transportation corridors between their residence and work locations and that a map of the offenses revealed an area of routine activities more so than an offender's residence. Strangeland (2005: 468) also noted that assumptions made by investigators about the serial offender's behavior were disproven by the map of offenses, showing that correct interpretation and understanding of a geographic profile can assist in locating an offender.

Some problems of geographic profiling were highlighted by Kocsis and Palermo (2008). In their paper, the need for accurate data and consistent definitions were identified as paramount to the eventual success of geographic profiling (Kocsis & Palermo, 2008: 335). It was stated that geographic profiling has not yet been scientifically validated, but with further development in original, data-driven studies this method can produce valid results that assist investigators in finding offenders (Kocsis & Palermo: 2008, 337).

Van der Kemp and Van Koppen (2008) published a paper fine tuning the use of geographic profiling. Their paper acknowledged that the use of a geographic profile for a drifter offender type would not be valid because a geographic profile is dependent on the presence of a fixed point of operations (Van der Kemp & Van Koppen, 2008: 349). It was also highlighted that previous methods of geographic profiling assume a random distribution of targets and that all directions from a residence have equal opportunity for the offender to commit a crime (Van der Kemp & Van Koppen, 2008: 353). These assumptions were argued to be invalid since journey-to-crime incorporates an offender's routine activities, target availability, and incorporates the geographic landscape (Van der Kemp & Van Koppen, 2008: 353). Furthermore, there is the overlying assumption in geographic profiling that an offender starts (and ends) from their residence, but an offender can start from multiple places such as where they work (Van der Kemp & Van Koppen, 2008: 357). These authors were insistent that if geographic profiling is to fulfill its promise, then these assumptions should be addressed (Van der Kemp & Van Koppen, 2008: 358).

Tackling another assumption of geographic profiling, Leitner and Kent (2009) performed accuracy checks on one data set reviewed in two scenarios. One scenario only included single crime types for an offender, and another scenario included all the crime types from each offender's crime series (Leitner & Kent, 2009: 216-7). It was found that including multiple crime types significantly improved the accuracy of geographic profiles (Leitner & Kent, 2009: 232). The study further showed that when all an offender's crimes, regardless of offense type, were analyzed, a higher proportion of marauding offenders was found within the dataset. This results in more offenders being open to a geographic profile (Leitner & Kent, 2009: 232-3).

Reviewing the geographic profile assumption of all directions from an offender's residence having equal opportunity, Van Daele and Bernasco (2012) studied the directional consistency of offenders. Their research concluded that a substantial proportion of offenders have strong directional consistency with no correlation between the number of offenses committed and this directional consistency. It was found that the further an offender is from their anchor point when offending, the stronger the directional consistency. These findings further support that offense locations are based more on routine activities, transportation networks, and geographic landscape than on a random distribution of targets and an equal likelihood of offending in any direction from an anchor point.

2.8. Crime Displacement

Addressing crime in specific locations raises the concern of displacement. If the presence of suitable guardians is increased in a neighborhood, then will the likely offenders not commit offenses or commit offenses somewhere else? In the case of the latter, crime displacement has occurred. To determine if this displacement occurred, a comparison of crime displacement studies and the tactics used by law enforcement was conducted to determine if certain tactics were conducive to displacement (Eck, 1993).

Although this comparison concluded that displacement may not be a major threat, the study also concluded that displacement should still be taken into consideration (Eck, 1993: 541). Thus, it will be important to monitor for displacement, but not at the sacrifice of reducing crime known to occur at specific locations and at specific times.

2.9. Work Commute

As discussed earlier (see Section 2.5, Routine Activities) with Routine Activities Theory (Cohen & Felson, 1979), the more offenders travel, then the greater likelihood of convergence in space and time with a suitable target in the absence of capable guardians. A study conducted for the United States Census Bureau discussed the general rise in commuting as well as the concept of mega-commuting (Rapino & Fields, 2013). In this context "commuting" refers to an individual traveling between their residence and work (i.e. anchor points). In the case of mega-commuting, this sub-type of commuter travels over 90 minutes and 50 miles to work. Given Paulsen's (2007) modified definition of commuter offenders as clusters away from an anchor point and the consideration of Routine Activities Theory, the question is raised as to how this will affect the number of commuter offenders. With the lack of commuting offender models, minimal analysis across crime types and jurisdictions, and an increased likelihood of commuting offenders being displaced rather than prevented, it is difficult to tell whether this increase of work-related commuters influences crime rates. But it is possible that patterns between increased work commuting and crime rates have previously gone unnoticed and/or unexplained.

2.10. Choice of Data

2.10.1. Arrest Records

Amir (1971) discussed the use of arrest records versus conviction records when analyzing patterns of rape in Philadelphia. Amir (1971: 9) argued that the mortality of cases at each step in the law enforcement process, from arrest to indictment to trial to conviction, resulted in only a selective group of cases to be found in the court records. Furthermore, Amir (1971: 9) observed that arrest to conviction ratios were not constant and could be politically motivated, further diluting the value of analyzing conviction records. Amir (1971: 9-11) concluded that "the class of 'crimes known to the police' is the highest number of crimes reported" and thus arrest records were the best data set, in the imperfect world of criminology, to study.

In line with Amir's (1971) data choices, Ressler, et al. (1988: 66) noted that approximately one-third of sexual homicide cases resulted in plea bargains to lesser crimes, thus distorting statistics on crimes committed versus crimes receiving convictions. Numerous other research studies in this area have used arrest data (e.g. Ratcliffe, 2003).

2.10.2. Multiple Crime Types

In relation to single crime type versus multiple type crime analysis, Leitner, et al. (2009) compared both schools of thought in relation to Bayesian journey-to-crime models. This research looked at a set of known serial offenders and split the data into "single type" and "multiple type". In the "single type" only one type of crime was analyzed for the a given offender. In the "multiple type" other types of offenses committed by the offender were incorporated into the analysis. Leitner and Kent (2009: 232) then performed accuracy checks of the Bayesian journey-to-crime on both sets of data and found that inclusion of multiple type crimes improved accuracy and precision of geographic profiles. The research found a higher proportion of marauder serial offenders in the multiple type series of data, thus indicating that looking at only a single type of crime could produce a false positive that an offender is a commuter (Leitner & Kent, 2009: 232).

2.10.3. Residence at Street Address Level

In *Place Matters* from Weisburd, et al. (2016), it was argued that data should be collected at the lowest possible geographic level. This data then allows for aggregation up to higher levels but collecting data at higher levels does not allow for analysis at lower levels. Weisburd, et al. (2016: 8-9) further stated that collecting specific geographic coordinates for a place represents the lower possible geographic level for study.[2]

2.11. Agent-Based Modeling

As can be seen from the above research, crime is a complex phenomenon. As shown by Paulsen (2007), it is important to be able to identify relevant trends prior to convictions of offenders. Reviewing case data and being able to identify trends and patterns is important to seeking out active serial offenders. Knowing that an offender is a commuter or marauder after their conviction isn't practical to law enforcement

[2] In some jurisdictions (e.g. Montgomery County, MD) publicly available crime data is modified to address privacy concerns. This modification is commonly a rounding of the street address to the nearest hundred (e.g. 123 Main St would be reported as 100 Main St), which limits resolution and the ability to geographically analyze data as argued by Weisburd, et al. (2016: 8-9).

practitioners. Being able to take data and derive actionable knowledge in a timely manner will ultimately assist law enforcement in becoming more capable guardians.

Agent-Based Models (ABM) have great potential for meeting this requirement. In an ABM, "fundamental social structures emerge from the interaction of individual agents" (Axtell & Epstein, 1994: 28). By assigning agents simple rules, complex behavior can be exhibited, modeled, and studied. Crime data can be used to generate stylized facts to compare against the outputs of an ABM to determine a baseline level of accuracy in the model's results (Meyer, 2011). This allows for the reasonable possibility that feeding crime data into an ABM in a timely manner can highlight the emergence of crime patterns in a timely manner that would allow law enforcement to react efficiently and effectively. Furthermore, "to really understand the dynamics of crime patterns, and to be able to properly represent the underlying theories, it is necessary to represent the behavior of the individual system components (i.e. people) directly" (Malleson, et al., 2018: 2). An ABM is uniquely qualified to directly represent people.

An early example of using an ABM to research crime was applied towards residential burglary offenses in the United Kingdom (Malleson, et al., 2010). This model considered both environmental (location of wealth) and behavioral (what causes a person to take an action) factors to demonstrate how likely offenders are to commit a burglary on specific residential locations. The model showed burglars are likely to move off known paths to victimize wealthier targets. Malleson, et al. (2010) acknowledged that the quality of criminal agents in an ABM can be improved through the inclusion of crime statistics. The model built by Malleson, et al. (2010) was an important first step by implementing the concept of Routine Activities Theory into an ABM, but only included likely offenders and suitable targets. The presence of capable guardians was not included. Furthermore, the model simulated a gridded network of streets, without the inclusion of different modes of transportation or speed of different routes.

Another important step in modelling crime was an ABM that tested various policing strategies in a virtual environment using generated artificial street-crime data (Devia & Weber, 2013). Since testing policing strategies in the real world has real potential to directly affect people's lives, at times it could be impractical or unethical to test unproven theories. Contrary to this is the need to test theories to demonstrate effectiveness. Thus, Devia and Weber (2013) simulated the implementation of various policing strategies in an ABM to demonstrate effectiveness and viability. This was done through models of fictitious cities and real cities that provided a realistic urban backdrop. Police agents were modeled with the purpose of dissuading criminals, not capturing, and included different patrol types with different speeds (e.g. foot and vehicle). With these police agents, different strategies of police distribution were tested for effectiveness. Through this modeling, Devia and Weber (2013) found that uniform and random distribution of police agents performed best in every scenario and that hot spots distribution was the least effective policing strategy. The model also showed that the type of patrol was largely irrelevant to a likely offender's decision: a cop is a cop. With models of realistic urban backdrops, offenders without regard to type of crime, and the use of different policing strategies, Devia and Weber's (2013) model largely improved the burglary model built by Malleson, et al. (2010). The need for realistic was further emphasized by Malleson, et al. (2018: 12) stating that "models cannot assist planners… with changes in policy" unless "agent-based models require a spatial environment that more realistically represents the real world".

Despite this large step forward, one of the pieces not incorporated were the geographic boundaries required of law enforcement (e.g. jurisdiction, precincts, sectors), but not required of offenders (e.g. the ability to leave a city or jurisdiction). Another piece not incorporated in this model was the ability for offenders to evade, law enforcement to pursue, and the ability of both to learn from mistakes and successes and adjust to an evolving environment or threat. Furthermore, in consideration of Leitner and Kent's (2009) Bayesian journey-to-crime analysis, the incorporation of a full range of crime types from actual crime data could produce even better analysis of the effectiveness of police strategies.

Crime is driven by a complex mix of influences thus the ability of ABMs to "concentrate on individual-level behaviors" make this type of modelling "ideally suited to modelling crime" (Malleson & Evans, 2014: 41). Crime is a complex system with emergent properties and overall crime rates cannot be attributed to any individual part of the system. It's also difficult to predict crime hot spots in advance, thus resulting in police resources being reactive instead of predictive. Thus, with the incorporation of Routine Activities Theory for modeling crime, is it possible for crime models to shift away from aggregate models and towards models that operate on the individual level? Malleson and Evans (2014) justify the use of ABMs in modeling crime because of the ability to model theories and carry out experiments that would otherwise be impractical or unethical. Specifically, offender agents can reflect a variety of behaviors as needed, the environment can be changed due to crime data and in turn influence agent behavior. Furthermore, this allows for the ability to capture emergence (e.g. city-wide crimes rates) and move to a more predictive law enforcement effort.

2.12. Key Findings

2.12.1. Crime and Place (home range, criminal range, anchor point, target)

As described by Brantingham and Brantingham (1981a: 7), environmental criminology is the study of crime's fourth dimension: place. Within this dimension, this thesis focuses on the meso-analysis level of metropolitan areas (i.e. the Washington, DC metro area) that include the subunits of police precincts, census tracts, city blocks, and specifically the routine activities of criminal offenders (Brantingham & Brantingham, 1981a: 24). These subunits include the basic geographic features on points (i.e. nodes), lines (i.e. paths), and polygons (i.e. edges).

Nodes are central to people's lives and include specific places such as work, school, recreation sites, and shopping centers (Brantingham & Brantingham, 1995: 12). Nodes regularly frequented by people are "anchor points" (Couclelis, et al, 1987: 101). For example, a traditional anchor point could be a person's home or place of work but can also include the homes of friends and relatives as well as regular locations for leisure activities such as a park or bar.

Paths are routes of routine travel to and from nodes. Specifically, these include the geographic lines where people spend time in routine travel between their anchor points and are most commonly street networks and mass transportation routes such as bus and subway lines (Brantingham & Brantingham, 1995: 12). In the context of crime, these paths are used for an offender's "journey-to-crime" or "criminal commute" (Rhodes & Conly, 1981: 167).

Edges are boundaries, whether physical (e.g. a river) or perceptual (e.g. jurisdictional boundary), where there's a distinction between two areas that change is noticeable. These edges are believed to create areas where strangers are more easily accepted and thus experience higher rates of crime (Brantingham & Brantingham, 1995: 12).

2.12.2. Crime and Person

Delinquency in urban life is largely associated with individual anonymity (Shaw & McKay, 1942: 437-8) and because residents of urban neighborhoods have limited acquaintances, there is an indifference where strangers to a neighborhood are often ignored (Boggs, 1965: 905). Different law enforcement strategies are required for policing the "regulars" of a neighborhood versus "strangers" to a neighborhood (Kelling & Wilson, 1982).

Anonymity, regulars, and strangers are the view of the person from the neighborhood. From the person's perspective, "familiarity" of a neighborhood is how criminal targets are discovered (Boggs, 1965: 907). This is partially described by Routine Activities Theory which states that familiarity comes through a person's every day, routine activities and that non-criminal activity influences when and where a likely offender will commit a crime. Specifically, Routine Activities Theory states that criminal offenses occur with the "convergence of likely offenders, suitable targets, and the absence of capable guardians" (Cohen & Felson, 1979: 589).

These "routine activities" create a "cognitive map" in an offender's mind. Defined in part as an "abstraction... at one point in time of the environment as people believe it to be" (Downs & Stea, 1973a: xiv), cognitive maps are used by people as the "basis for deciding upon and implementing any strategy of spatial behavior" (Downs & Stea, 1973b: 10). In the context of likely criminal offenders, opportunities to commit crimes must be physically accessible as well as accurate enough in an offender's cognitive map to be believed to be physically accessible (Rengert, 1981: 201). For example, a bag of money could be lying on the street (i.e. physically accessible), but if a likely offender can't remember how to get to the street, then the offender's cognitive map isn't accurate enough for the offender to steal the bag of money.

Offenders know this. As a result, serial offenders (versus the random passerby who might grab the bag of money) regularly engage in active searches around the areas of their routine activities to improve their cognitive maps. These searches expand an offender's cognitive map, or "awareness space", out from the nodes and paths used during routine activities, thus including nearby areas (Brantingham & Brantingham, 1981b: 35).

2.12.3. Connecting Person to Place

A person's, specifically a likely criminal offender's, routine activities connect the person to the place that leads to the commission of a crime. The process of assessing crime information to derive an offender's routine activities, and hopefully one of their anchor points, such as their residence, is "geographic profiling" (Rossmo, 1999). It is believed that with enough information about a series of crimes committed by a single offender, the offender's anchor points and awareness space can be derived. By understanding an offender's cognitive map and their spatial decisions, successful predictions can be made towards assessing where the offender lives or works (Snook, et al., 2005: 162). This viability of geographic profiling has been demonstrated in a study showing that offenders tend to commit crimes along the paths between their residence and work (Strangeland, 2005: 462).

2.12.4. Types of Spatial Offenders

Brantingham and Brantingham (1981b) outline several different cases to describe the geospatial patterns of offenders. Most relevant to this thesis were three of these cases: Case 1 described a single offender with a single anchor point surrounded by a uniform distribution of targets (Brantingham & Brantingham, 1981b: 30-32); Case 3 added multiple offender anchor points to Case 1 (Brantingham & Brantingham, 1981b: 33-37); and Case 6 described criminal activity as the intersection of an offender's awareness space with areas on non-uniform target distribution (Brantingham & Brantingham, 1981b: 42-44). These cases became practical with the inclusion of centrography to find an offender's anchor point among a distribution of criminal offenses, specifically recognizing that this calculation may result in a bimodal model highlighting multiple anchor points, such as work and residence (LeBeau, 1987: 127).

Case 1 (Brantingham & Brantingham, 1981b: 30-32) was combined with LeBeau's suggestion of centrography to develop the Circle Theory of commuter and marauder offenders (Canter & Larkin, 1993). This theory proposed that if a geographic circle were drawn around the outside points in a criminal offense series, then the offender's anchor point (specifically their residence) would be located within the circle. If this were true for a series of criminal offenses, then the offender was classified a "marauder", otherwise the offender was classified a "commuter" (Canter & Larkin, 1993: 65).

This theory was expanded with the terms "home range" and "criminal range". The "home range" is the "area well known to the offender, since it is the region surrounding the home or base from which he operates", whereas the "criminal range" is the "finite region which encompasses all offence locations for any particular offender" (Canter & Gregory, 1994: 170). These terms were used to further expand the concept of "commuters" and "marauders", where commuting offenders have little to no overlap between these two ranges and marauding offenders have overlap between these two ranges (Canter & Gregory, 1994: 171). This expanded definition was confirmed by additional research specifically stating that commuters move outside of their home range to commit offenses and marauders move out from and return to their base of operations when committing offenses (Kocsis & Irwin, 1997: 198).

The literature shows that in addition to commuters and marauders there are two additional offender types: locals and drifters. A study of crime in rural areas recognized that burglary was generally committed by local offenders, or offenders whose residence was close to the site of the criminal offense (Barker, 2000: 62). Another study recognized the presence of drifter offenders, or those offenders without a fixed residential address or base of operations (Van der Kemp & Van Koppen, 2008: 349).

Circle Theory differentiates between commuters and marauders by drawing circles around a series of known offenses (Canter & Larkin, 1993). The presence of the offender's residence inside or outside of the circle classifies the offender as a commuter or marauder. The definitions of "home range" and "criminal range" moved Circle Theory beyond the simple geographic concept of a circle by showing that an overlap between these two ranges classified an offender as a marauder and that little to no overlap classified the offender as a commuter (Canter & Gregory, 1994; Kocsis & Irwin, 1997). Additional work proposed using convex hulls and ratios around a series of offenses to more accurately classify commuters and marauders (Leitner, et al., unpublished).

2.12.5. Why is this Important?

As highlighted in Routine Activities Theory, the more offenders travel, the greater the likelihood of a convergence in space and time with a suitable target in the absence of capable guardians (Cohen & Felson, 1979). Commuter and marauder offenders, combined with routine activities theory and the U.S. Census Bureau's research showing the rise of "mega-commuters" suggests that criminal commuting will also rise, and marauding offenders will be found farther and farther from their place of residence. Furthermore, as shown in research on cognitive maps, as people travel farther on a day-to-day basis, their cognitive maps will become larger (Downs & Stea, 1973a; Downs & Stea, 1973b). Applied to likely offenders, this indicates that home ranges and criminal ranges will also grow, thus increasing the number of suitable targets available to like offenders (Cohen & Felson, 1979).

2.12.6. Data

When analyzing criminal offenders, arrest records are the best data set as "the class of crimes known to the police is the highest number of crimes reported" (Amir, 1971: 9-11) and due to offenders pleading guilty to lesser offenses than the offense actually committed (Ressler, et al., 1988: 66). It has been shown that when analyzing the offenses of a specific individual, geographic precision is more accurate when all crime types are included, versus a single offense type (Leitner & Kent, 2009). Thus, it becomes important to include all potential offense types in a geographic profile rather than looking at a siloed single offense type profile. Thus, collecting data at the lowest geographic level allows for better analysis when looking for a specific piece of geographic data. Data can be accurately aggregated up to higher levels (lower precision) but cannot be accurately aggregated down to lower levels (higher precision). This shows that it is important to collect data at the level of a specific street address rather than a general street block, neighborhood, zip code, etc. (Weisburd, et al., 2016: 8-9).

2.13. Key Gaps

Research into the spatial aspects of crime has previously been impeded by what Brantingham and Jeffery (1981: 237) described as "the insistence that only the offender dimension of crime be considered". This is still true today as it was in 1981 as is shown by research that fails to take into consideration other spatial aspects of crime, specifically the environment in which crimes take place. This continual oversight in considering spatial factors beyond the location of an offender's target is a gap in research.

2.13.1. Definitions of Offender Types

Spatially, offenders were described by Brantingham and Brantingham (1981b) in the context of where they are based and the distribution of their targets. Behaviorally, offenders were described by Boggs (1965) as "strangers" and by Kelling and Wilson (1982) as both "regulars" and "strangers". With the introduction of Circle Theory, offenders were described both spatially and behaviorally as "commuters" and "marauders" (Canter & Larkin, 1993). These two terms have been generally adopted with revisions (Kocsis & Irwin, 1997), but Circle Theory has not been found to consistently differentiate "commuters" from "marauders".

In the original Circle Theory research, care was taken to define commuters and marauders, and the resulting research of serial rapists in Great Britain were found to be 87% marauders (Canter & Larkin, 1993: 67). In a follow up study of Circle Theory, arson and burglary offenses were reviewed in New South Wales, Australia, in addition to serial rape, and marauders were found to be 71% of serial rape cases, 82% of arson cases, and 48% of burglary cases (Kocsis & Irwin, 1997: 202). In a third study, marauders were found to be 35% of burglaries, 90% of arsons, and 93% of sexual offenses in Sydney, Australia (Meaney, 2004: 128). In Orissa, India, serial burglars were found to be 56.7% marauders (Sarangi & Youngs, 2006: 111). In 2017, 50% of arsonists in New Zealand were found be marauders, making the division an even split (Edwards & Grace, 2006: 223).

This body of research shows a large range between results of marauders: sexual offenses ranging from 71% (Kocsis & Irwin, 1997: 202) to 93% (Meaney, 2004: 128), arson ranging from 50% (Edwards & Grace, 2006: 223) to 90% (Meaney, 2004: 128), and burglaries ranging from 35% (Meaney, 2004: 128) to 56.7% (Sarangi & Youngs, 2006: 111). Additionally, the research in Orissa, India was reviewed offender by offender and researchers found that the Circle Theory incorrectly classified about 85% of marauders (Sarangi & Youngs, 2006: 111). To further complicate commuter and marauder classification, a study in Helsinki, Finland found that 61% of data did not conform to the Circle Theory and that 15% of offenders had no fixed residential address (Laukkanen & Santtila, 2006: 79). This highlights that "drifter" and "local" are not addressed in Circle Theory and have not been defined within the context of "commuters" and "marauders".

This is not to say that Circle Theory efforts are invalid, but as acknowledged in the original Circle Theory paper: circles are a simplification and this model is very restrictive spatially (Canter & Larkin, 1993: 68). This next step was taken in a critical analysis of Circle Theory where investigative case data was used and serial offenders were defined based on all offenses committed, not just specifically rape, arson, or burglary (Paulsen, 2007). The result was an improved definition of commuters and marauders, but still lacked inclusion of drifters and locals into the spatial theory of offender behavior. Next steps were also taken on improving the method in identifying commuters and marauders by advancing the spatial simplification of circles to use deviational ellipses (Kent & Leitner, 2007: 149) and convex hulls and ratios (Leitner, et al, unpublished).

It is time to use the success of defining offenders as "commuters" and "marauders" to incorporate "drifters" and "locals", incorporate a full range of case data available when creating geographic profiles, and advance the simplification of Circle Theory to better model true geographic layouts. This thesis will address these gaps.

3. OBJECTIVE 1 – EXPANDING COMMUTERS AND MARAUDERS

The first objective of this thesis is to expand the "commuter" and "marauder" offender types into a complete spatial classification of criminal offenders. This expansion continues the modification and refinement of general theories of criminal offenders in the same way that Kent and Leitner (2007) modified Circle Theory to use directional ellipses.

As discussed in Section 2.6, Commuters vs. Marauders, there are strong definitions for "commuter" and "marauder" offenders (Canter & Larkin, 1993) and these definitions have been updated over time with additional research (Paulsen, 2007). When these definitions are taken in context with similar research involving the spatial behavior of criminal offenders (Kelling & Wilson, 1982; Kocsis & Irwin, 1997), a variety of terms are being used with little consensus among definitions. This section will take the previous body of research and bring together the existing terms and definitions for spatial offenders while adding additional terms from existing research to fill in the current gaps (see Section 2.13, Key Gaps). This integration (see Section 3.2, Updated Foundation Terms) can then be used to further facilitate in-depth research into the spatial classification of criminal offenders, specifically through the spatial behavior of serial criminal offenders. The resulting set of spatial classification terms (see Section 3.3, Spatial Classification of Criminal Offenders) can then assist in moving forward the existing research into commuter and marauder and other spatial classification types of criminal offenders.

3.1. Current State of Research

From the work about serial offenders from Ressler, et al. (1988) and Douglas, et al. (1997) to Geographic Profiling from Brantingham and Brantingham (1981a, 1981b), Rossmo (1999) and more, a tremendous body of research is available. This research has created an excellent foundation for understanding the spatial aspects of criminal profiling, but the research is siloed into specific areas with little consistency in definitions. Clear, agreed upon definitions in this field of work is crucial to exchanging knowledge and ensuring the same understanding is being passed from the researcher to the consumer of the research. This is currently not the case in geographic profiling, specifically in commuter and marauder research. For example, the terms action space and awareness space are interchangeable in some research, but have separate, distinct definitions in other research (see Section 3.1.4, Action Space and Awareness Space). This lack of clarity creates confusion and can result in research that is neither reproducible nor accurate. While researching commuter and marauder offenders, it became evident to the author that clear and consistent definitions were critically needed before adding to the body of research. Please note that this attempt to clarify terms and definitions is not meant to take away from the work done by others. This is only meant to bring together the excellent research thus far and to create a consensus understanding for moving forward. This is not an attempt to rebuild a car, but an attempt to ensure that all cars drive on the road with an agreed upon understanding of the how traffic should flow.

3.1.1. Serial Offender

Serial murderer - three or more separate events with an emotional cooling-off period between homicides (Ressler, et al., 1988: 139)

Serial arsonist - three or more separate fire setting episodes with a characteristic emotional cooling-off period between fires (Douglas, et al, 1997: 186-7)

The definitions of these two types of serial offenders are essentially the same, but with one distinction: serial offense is defined within only one type of offense. This would theoretically require the need for a new definition of serial offender for every offense type: serial burglar, serial rapist, serial jaywalker, etc., etc. Although extremely useful when researching one specific type of criminal offense, this creates a stovepipe of serial offender definitions which does not allow for the consideration of criminal offenders who commit multiple types of crimes, but only criminal offenders who commit crimes of each defined type. This ignores an entire set of serial criminals who commit more than one type of criminal offense.

3.1.2. Geographic Profiling

Geographic profiling - An information management strategy for serial violent crime investigation that analyzes crime site information to determine the most probable area of offender residence (Rossmo, 1999).

This definition of geographic profiling is restricted to serial offenders who commit violent crimes and limits the scope of the geographic search to the offender's residence. In criminal profiling, a serial offender is generally defined as an offender who has committed a series of three or more offenses with an emotional cooling off period between each offense (Ressler, et al., 1988: 139; Douglas, et al, 1997: 186-7). By restricting geographic profiling to violent offenses, the number of offenders is limited to those who have committed more than three violent offenses and ignores non-violent offenders and any non-violent offenses an offender may have committed. This subset of offenses would specifically eliminate the inclusion of burglary offenses, a non-violent offense, which is a large part of commuter and marauder research (Rengert & Wasilchick, 1985; Barker, 2000; Sarangi & Youngs, 2006). Although a good start, this current definition potentially eliminates valid data from the body of research.

By specifically attempting to determine only the offender's probable area of residence, this definition assumes that offenders always travel to and from their residence when committing offenses. This further assumes that offenders use their residence as a base for committing criminal offenses. As with looking at only serial offenders committing a subset of offense types (e.g. *violent* offenses), this definition becomes too restrictive and immediately limits data from research which might help provide a better understanding of the spatial behavior of criminal offenders.

3.1.3. Activity Space

Activity space - the set of locations associated with a household's day-to-day activities (Brown & Moore, 1970: 8)

Activity space - the subset of all urban locations with which the individual has direct contact as the result of day-to-day activities (Horton & Reynolds, 1971: 86)

Activity space - the subset of all urban locations with which the offender has direct contact as the result of day-to-day activities (Capone & Nichols, 1975: 47)

Activity space - those areas that comprise a person's habitual geography, made up of routinely visited places and their connecting routes (Rossmo, 1999 citing Jakle et al, 1976)

Activity space - the set of normal nodes and the normal paths between them (Brantingham & Brantingham, 2008a: 84)

Activity space - an individual's set of contemporaneous activity nodes and the paths between them (Bernasco, 2010: 393)

The concept of "activity space" first appeared in research into the residential movement patterns of families within a single urban environment. As initial defined by Brown and Moore (1970: 8), activity space was generally used to describe the spatial locations for the "day-to-day activities" for the people in a single household. Research from Horton and Reynolds (1971: 86), moved this concept from a single household's spatial behavior to that of specific individuals. The research of Capone and Nichols (1975: 47) moved activity space from the general individual specifically to a criminal offender. All three of these definitions of "activity space" were essentially the same but applied to different research areas. In later research, Rossmo (1999), Brantingham and Brantingham (2008a: 84), and Bernasco (2010: 393) defined "activity space" in the geographical profiling arena and, naturally, provided a more geographical definition to activity space by applying the concept to nodes and paths/routes.

Each of these six different, yet similar, definitions of "activity space" are valid, but having multiple definitions of the same concept can create an air of confusion when attempting to work with law enforcement practitioners. Thus, it is important that this term receive clarity, cohesiveness, and simplification going forward, but still give credence to the pre-existing research efforts.

3.1.4. Action Space and Awareness Space

Action space - that part of the limited environment with which the individual has contact (Wolpert, 1965: 163)

Action space - the set of place utilities which the individual perceives and to which he responds (Wolpert, 1965: 163)

Awareness space - those locations within the total urban space about which the intended migrant household has knowledge (Brown & Moore, 1970: 7-8)

Action space - the collection of urban locations about which the individual has information (Horton & Reynolds, 1971: 37)

Awareness space - the parts of the city criminals have some knowledge about (Brantingham & Brantingham, 1981b: 35)

Action space - used extensively in "Notes on the Geometry of Crime" but refers to Horton and Reynolds' work (Brantingham & Brantingham, 1981b: 35)

Awareness space - all the locations about which a person has knowledge above a minimum level even without visiting some of them (Rossmo, 1999 citing Clark, 1990)

Awareness space - the area normally within visual range of the activity space (Brantingham & Brantingham, 2008a: 84)

Awareness space - a person's current activity space as well as his or her activity spaces in the recent past, including the area normally within visual range of these activity spaces (Bernasco, 2010: 393)

As with activity space, action space in its current form was originally conceptualized in relation to household relocation (Wolpert, 1965: 163). The terms "action space" and "awareness space" were muddied when Brown and Moore (1970: 8) stated in a footnote that "...our concept of awareness space conforms to Wolpert's concept of action space". Further dilution of a difference between "action space" and "awareness space" occurs when Horton and Reynolds (1971: 36) also used a footnote to reformulate Wolpert's definition of "action space" by stating that the term is the same as Brown and Moore's definition of "awareness space".

In the spatial research of crime, the use of "awareness space" dominates (Brantingham & Brantingham, 1981b: 35; Rossmo, 1999; Brantingham & Brantingham, 2008a: 84; Bernasco, 2010: 393), but deviates from Wolpert's (1965: 163) definition of "action space". To further complicated matters, both terms are used independently to mean two different types of space. For example, Brantingham and Brantingham (1981b: 35) provide a definition of "awareness space", but no definition of "action space". Instead, the first use of "action space" has a footnote (Brantingham & Jeffery, 1981: 239) that refers the reader to Horton and Reynolds' (1971: 37) discussion of action space. As previously mentioned, Horton and Reynolds stated that "action space" is the same as "awareness space". This in affect created two separate terms, with two separate uses, but equated the two terms to each other. Thus, logically "action space" and "awareness space" are the same, but in practice have different meanings and uses. A separation and clear definition of these two terms would be beneficial for future research into geographic profiling.

3.1.5. Home Range and Criminal Range

3.1.5.1. Home Range

Home range - the area to which an animal usually confines its daily activities (Merriam-Webster, 2019b)

Home range - the area around the home (Canter & Larkin, 1993: 65)

Home range - an area well known to the offender, since it is the region surrounding the home or base from which he operates (Canter & Gregory, 1994: 170)

Home range - an offender's net spatial knowledge around their base (Kocsis & Irwin, 1997: 198)

Home range - a complex of those objects and places that provide the everyday necessities and everyday experiences of living (Barker, 2000: 60)

Home range - an offender’s net spatial knowledge around their base (Kocsis et al., 2002: 44)

Home range - an area familiar to the offender in which they operate in all noncriminal activities (Edwards & Grace, 2006: 220)

Home range - areas in which an offender habitually moves to conduct his/her (non-criminal) activities (Sarangi & Youngs, 2006: 107)

In the original paper describing Circle Theory and outlining the concept of commuters and marauders, Canter & Larkin (1993: 64, 65) introduced the specific term "criminal range", as a derivation of the ecology term "home range". The term "home range" is well established in ecology, with its first use, as documented by Merriam-Webster (2019b), occurring in 1905. This term is muddied slightly in geographic profiling by being aligned specifically with an offender's home (Canter & Larkin, 1993: 65). Later definitions of home range in geographic profiling research equate this term with an offender's daily activities, as defined by Merriam-Webster (2019b), but references an offender's spatial knowledge as part of the home range (Canter & Gregory, 1994: 170; Kocsis & Irwin, 1997: 198; Barker, 2000: 60; Kocsis et al., 2002: 44). Later definitions retract from spatial knowledge and stick with definitions more aligned with Merriam-Webster (2019b) but specify that the home range includes non-criminal activities (Edwards & Grace, 2006: 220; Sarangi & Youngs, 2006: 107).

For the geographic profiling field of research, a consensus definition in line with the commonly accepted ecological definition is necessary to ensure clarity across research disciplines. It is also necessary to separate this definition from the specific "residence" (i.e. home, as defined by Canter & Larkin, 1993: 65) and instead link the definition to the general "anchor point" as well as to clarify that the definition refers to daily activities and/or spatial knowledge of a criminal offender.

3.1.5.2. Criminal Range

Criminal range - an area in which offences are committed that has some non-arbitrary relationship to an offender's fixed base (Canter & Larkin, 1993: 65)

Criminal range - area in which crimes are committed (Canter & Larkin, 1993: 65)

Criminal range - a finite region which encompasses all offence locations for any particular offender (Canter & Gregory, 1994: 170)

Criminal range - the spatial area in which crimes are committed (Kocsis & Irwin, 1997: 198)

Criminal range - defined area where offences are committed (Kocsis et al, 2002: 44)

Criminal range - the spatial area in which crimes are committed (Kocsis et al., 2002: 44)

Criminal range - the greatest distance an offender is willing to travel to commit an offence (Meaney, 2004: 123)

Criminal range - a region that includes all offence sites of the offender (Edwards & Grace, 2006: 220)

Criminal range - areas in which an offender commits crimes (Sarangi & Youngs, 2006: 107)

The term "criminal range" as a concept has roots in previous research (Capone & Nichols, 1975; Brantingham & Brantingham, 1981b; Rengert & Wasilchick, 1985), but the phrase wasn't formally coined until Canter and Larkin's (1993: 65) commuter and marauder research. This term is necessary for geographic profiling to help conceptualize the spatial regions in which an offender commits crimes, but the body of research lacks a consensus definition. This is evident from the absence of "criminal range" from the glossary in Rossmo's *Geographic Profiling* (1999).

In the various definitions listed above, all are derivative of Canter and Larkin's (1993: 65) original definition and have the general statement that the term includes the area in which an offender commits crimes. The specific terminology varies, but the general concept is basically agreed upon and is in line with the spirit of the original definition. To improve clarity, a formalized definition would be helpful, and one which remains true to the parent term "home range". This formalization of "criminal range" with a consensus definition is important to ensure the furthering of geographic profiling research.

3.1.6. Commuters and Marauders

Commuter - the offender travels from his (sic) base into an area to carry out his crimes (Canter & Larkin, 1993: 65)

Commuter - there will be no clear relationship between the size and location of the criminal domain and the distance it is from any given offender's home (Canter & Larkin, 1993: 65)

Commuter - operate in significantly smaller geographic ranges with more clustered offense locations (Paulsen, 2007: 354)

Marauder - the base acts as a focus for each particular crime (Canter & Larkin, 1993: 65)

Marauder - there is a large or total overlap of the home range and criminal areas (Canter & Larkin, 1993: 65)

Marauder - crime series occur over a significantly larger area and are less clustered (Paulsen, 2007: 353)

Recognizing that it is much harder to create theory than it is to test and criticize theory, Circle Theory (Canter & Larkin, 1993) is a good start to defining offenders from a spatial behavioral context. Circle Theory introduced the concept of commuter and marauder offenders with initial definitions and proposed an initial, simple method of classifying these offenders based on the spatial distribution of offenses in relation to an offender's residence. Until now, the definitions of commuter and marauder have been married to Circle Theory and subsequent research has been inconclusive of the percentage of marauders and commuters across single offenses types. This inclusion has prevented the resulting definitions and classification methods from progressing independently, thus resulting in inconclusive and inconsistent conclusions on the validity of Circle Theory and the concept of commuters and marauders within the field of geographic profiling. The rigidity of the developed commuter and marauder definitions using single offense types and the use of residence as the only anchor point has hindered the development of this area of research. The definitions need to become more flexible and inclusive.

As stated by Canter, Circle Theory was only the beginning: "...although we don't plan our activities to sit inside a circle, we do operate over an area of familiarity. It is probably quite a complicated patchy shape, this area. The circle is just the simplest shape to take as a starting point" (Canter, 1994: 143).

3.1.7. Next Steps

It is time to move beyond the starting point of a circle (Canter, 1994: 143) and use more advance spatial analysis techniques and additional data to improve Circle Theory. New methods of classifying commuters and marauders must account for physical geography (e.g. rivers, mountains), urban geography (e.g. transportation networks, mass transportation), and temporal factors (e.g. traffic, time of day). In the geospatial realm, these methods need to consider the directionality of an offender's travel with respect to the spatial and temporal factors affecting the offender's location. In the criminal justice realm, these methods need to consider all the offenses, regardless of type, believed to have been committed by the offender.

But, without improvements to the commuter and marauder definitions, improved classifications methods cannot be developed. Separating the terms and definitions from the initial theory used to classify commuter and marauder offenders will allow the definitions to be used for testing as improved classification methods are developed. These two pieces should progress independently.

3.2. Updated Foundation Terms

3.2.1. Serial Offender

By updating the definition of "serial offender" to include multiple offense types, the class of serial offenders broadens to an offender who has committed ANY criminal offense within the temporal definition of a series. As shown by the research from Leitner and Kent (2009) this modification will improve the geographic profiling of criminal offenders.

Thus, the following update to the term "serial offender" is proposed:

Serial offender - a criminal offender who commits three or more separate offenses with a characteristic emotional cooling-off period between offenses

By including multiple offense types, this updated definition will "increase" the number of serial offenders. As shown in the research of serial offenders in Baltimore County, MD (Leitner & Kent, 2009: 214) a data set of 3,484 series of crimes involving three of more incidents split the series into 72.8% with multiple types of crimes and 27.2% with single type of crime. It is important to note that by altering a definition that will give the appearance of an increase in serial offenders, resistance may occur as this can alter statistics reported by law enforcement agencies. This concern is valid but should be superseded by the need to properly classify criminal events to improve research and develop better law enforcement practices that can help reduce crime, which would ultimately improve crime statistics and create safer communities.

3.2.2. Geographic Profiling

The true purpose of geographic profiling is to use an offender's spatial history to deduce the offender's location, all with the intent of apprehension and to prevent further victimization. Thus, to produce the best possible results, geographic profiling efforts must be made with the goal of finding ANY of an offender's anchor points whether it be their residence, the home of their family or friends, their place of work, a favorite restaurant, or any other location important in an offender's daily life. As in the previous discussion on the definition of serial offenders, all offenses, regardless of type, should be used when compiling an offender's geographic profile. This allows for improved profiling (Leitner & Kent, 2009). For example, a serial rapist may break into a home, not find a suitable target, and leave without committing rape. Current definitions would exclude this home break-in from geographic profiling, because it is a property crime and not a violent offense, despite the spatial validity of this offense when profiling a serial offender's actions.

By incorporating all the offender's anchor points, offense types, and locations in a geographic profile with the previously discussed update of "serial offender", an updated definition of "geographic profile" becomes necessary. This can be done by removing the words "violent" and "residence" from Rossmo's (1999) definition (and updating the resulting grammar) to account for any of an offender's anchor points and both violent and non-violent offense types.

Thus, the following update to the term "geographic profile" is proposed:

Geographic profile - An information management strategy for serial crime investigation that analyzes crime site information to determine the most probable location of an offender.

3.2.3. Activity Space

Early definitions of "activity space" use the phrase "day-to-day activities" (Brown & Moore, 1970: 8, Horton & Reynolds, 1971: 86; Capone & Nichols, 1975: 47). In the context of criminal spatial theory, "day-to-day activities" are now referred to as "routine activities" (Cohen & Felson, 1979). Later definitions of "activity space" begin to include the geographic elements such as routes (Rossmo, 1999) and paths and nodes (Brantingham & Brantingham, 2008a: 84; Bernasco, 2010: 393).

To account for the current terminology, the inclusion of geographic elements, and use by law enforcement practitioners, the following updated definition is proposed:

Activity space - the subset of locations, routes, and areas an individual has direct contact with during their daily routine activities.

3.2.4. Action Space and Awareness Space

Originally the terms "action space" and "awareness space" were essentially synonymous (Brown & Moore, 1970: 7-8; Horton & Reynolds, 1971: 37). As these terms were adopted into use for criminal geographic profiling, different uses began to emerge (Brantingham & Brantingham, 1981b: 35). But this emergence appeared to be gradual and not realized by researchers while other developments in the science were being made.

To alleviate further confusion, the existing definitions and the context in which both terms are used were reviewed to propose the following definitions:

Action space - the subset of locations, routes, and areas where an individual conducts an activity

Awareness space - the subset of locations, routes, and areas about which an individual has knowledge

3.2.5. Bringing Together Activity, Action, and Awareness Space

These three terms are similar, and as such it is helpful to understand the differences. An individual's awareness space (outer ring in Figure 1)[3] includes the places where that

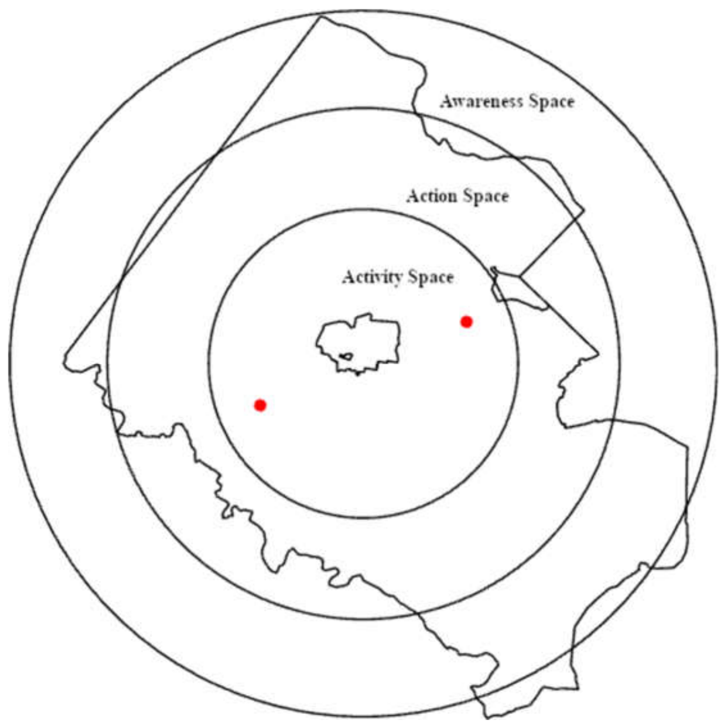

Figure 1: Awareness, action, and activity space

[3] In Figure 1, an outline of Fairfax County, VA is used to articulate awareness, action, and activity space. The two red dots denote anchor points (i.e. residence and work). These anchor points are within an individual's activity space (inner ring). The figure shows a hypothetical show of activity space, followed by action space (middle ring), and lastly an individual's awareness (outer ring).

person has some knowledge and can make references, regardless of whether the place is a part of their daily lives or can be described in detail. A subset of awareness space, an action space (middle ring in Figure 1) includes the places where an individual does something, whether it is regularly or only one time. Activity space (inner ring in Figure 1) is a further subset of awareness space and a subset of action space. This is where most individuals live on a day-to-day basis and includes home, work, regular recreation and shopping, family and friends, and the routes and paths between these locations. This describes an individual generally, but specifically to a criminal offender these spaces can be taken in consideration of the criminal mindset of target seeking behavior.

3.2.6. Unknown Space

Missing from the definitions of awareness, action, and activity space is every place else. No matter how much spatial knowledge an individual has, there will always be unknown space. Thus, the following definition is proposed to describe this space of negative knowledge:

Unknown space - the subset of locations, routes, and areas about which an individual has no knowledge, awareness, or contact.

3.2.7. Home Range and Criminal Range

3.2.7.1. Home range

Since "home range" is a well-defined term in ecology (see Section 3.1.5.1, Home Range), it is important that this is reflected in the term's use in geographic profiling. It is also important to prevent confusion by clarifying the use of "home" in "home range" and a criminal offender's home (i.e. residence) as an anchor point. To address the first concern, the following (slight) modification is proposed for the use of "home range" within the criminal geographic profiling field of research:

Home range - the area to which a criminal offender usually confines their daily non-criminal activities

To prevent confusion between the "home" in "home range" and an offender's home as an anchor point, the use of "residence" needs to become prominent when referring to where an offender lives. This helps provide clarity in discussions with a term that has less ambiguity when discussing anchor points.

Dropped from this definition of home range is the inclusion of "net spatial knowledge" as referenced in the definitions from Kocsis and Irwin (1997: 198) and Kocsis, et al. (2002: 44). This was removed because it is not included in the ecological definition but is included in the definition of "awareness space" discussed above. Additionally, a criminal offender's "net spatial knowledge" isn't necessarily limited to the areas of their daily activities, thus including this part of the definition can result in a misrepresentation of an offender's home range.

This definition also deviates from the initial commuter and marauder research referencing the space specifically around an offender's home (Canter & Larkin, 1993: 65; Canter & Gregory, 1994: 170). In the original research, the world was envisioned as simplistic circles and this work is attempting to move away from this starting point by incorporating more dynamic spaces and regions. Thus, looking at the immediate space surrounding just an offender's residence is no longer beneficial, as eluded to in the previously referenced quote from Canter that "the circle is just the simplest shape to take as a starting point" (Canter, 1994: 143).

3.2.7.2. Home Range vs Activity Space

With this updated definition, "home range" now becomes incredibly close to "activity space". The key difference is that activity space refers specifically to the routes, paths, and specific locations. Home range refers to the general macro space and the day-to-day movement within that space. Also, the "home range" refers to the possible extent of the space an offender travels in daily activities, whereas "activity space" refers to places where the offender conducts activity.

3.2.7.3. Criminal Range

The phrase "criminal range" has its roots in the ecological "home range", thus the definition should reflect this similarity. As such, the proposed definition of "criminal range" is a simple modification to the "home range" definition above.

Criminal range - the area to which a criminal offender usually confines their criminal activities

Previous definitions of "criminal range" all refer to an area in which criminals commit offenses (Canter & Larkin, 1993: 65; Canter & Gregory, 1994: 170; Kocsis &

Irwin, 1997: 198; Kocsis et al, 2002: 44; Edwards & Grace, 2006: 220; Sarangi & Youngs, 2006: 107). This definition makes the same statement but uses the pre-existing definition of "home range" as its basis.

The one exception is the definition of "criminal range" used by Meaney (2004: 123) that refers to the greatest distance an offender is willing to travel to commit an offense. Since this definition is an outlier to the other definitions, it was set aside for the above proposed definition. In Meaney's (2004: 123) definition, "range" is used as a linear distance versus a two-dimensional space as with the other definitions. A separation between the space within which a criminal commits crime and the maximum distance willing to travel is important but is beyond the scope of this discussion and will be set aside for a moment.

3.3. Spatial Classification of Criminal Offenders

Circle Theory (Canter & Larkin, 1993) only defines two of the terms associated with the spatial behavior of a criminal offender. Two other terms regularly appearing in the literature are "local" and "drifter". These terms should be included in the class of terms with "commuter" and "marauder" as they also describe the spatial behavior of offenders. Additionally, these four terms are missing an important class of offenders: the routine activities offender, where offenses are committed within the geographic area of an offender's routine activities.

The definitions of these five terms should be based on established theories, such as Routine Activities Theory (Cohen & Felson, 1979), and the "victim search process" or "victim attack method" (Rossmo, 1999), not on a specific classification method, such as

Circle Theory. These definitions should also be defined more broadly by criminal activity and more specifically on spatial activity: regardless of offense type. Accounting for these updates and additional terms can be done by moving from discussing specifically "commuter and marauders" towards discussing more generally an offender's "spatial behavior".

The groundwork for these broader definitions was established using case examples of offender spatial behavior as defined by Brantingham and Brantingham (1981b). Additionally, these terms should be mapped to similar terms previously used in the literature (e.g. Kelling and Wilson's (1981) "regulars" and "strangers" and Rossmo's (1999) "hunters", "poachers", and "trollers") to help understand crossover, gaps, and which terms should be used with which scenarios.

3.3.1. Commuter Offender

The term "commuter" conjures a vision of driving to and from work. This concept is viewed similarly by a criminal offender as it is to a normal law-abiding citizen: there's a destination to reach where money can be "earned". Originally, a commuter offender was defined similarly to a typical work commute (Canter & Larkin, 1993: 65), but the method in which a commuter offender is determined strayed from the traditional image of a commuter. What is lost in this original definition is the concept that criminal offenders may have a traditional commute in addition to their criminal commuter and that these two journeys may be intentionally separated by the offender. This thesis helps clarify the theory behind a commuter offender, bringing this type of offender more in line with a "traditional" work commute in the hopes of finding a method to categorize criminal offenders as commuters or not.

3.3.1.1. Existing Definitions:

Commuter - the offender travels from his (sic) base into an area to carry out his crimes (Canter & Larkin, 1993: 65)

Commuter - there will be no clear relationship between the size and location of the criminal domain and the distance it is from any given offender's home (Canter & Larkin, 1993: 65)

Commuter - operate in significantly smaller geographic ranges with more clustered offense locations (Paulsen, 2007: 354)

3.3.1.2. Updated Definition:

Commuter - a serial offender whose journey-to-crime purpose is to commit a criminal offense against a specific target at a specific location, regardless of the offender's routine activities

3.3.1.3. Why the Change?

The updated definition above puts more specificity to Canter and Larkin's "travel from his (sic) base into an area" (Canter & Larkin, 1993: 65). Canter and Larkin's definition is a good start but is overly broad and can truly define any offender's journey-to-crime. Removed from the updated definition is the reference to an offender's home as this location may not be the launching point for a commuter offender. The launching point could be any anchor point relevant to the commuting offender's life, to include a criminal base of operations unrelated to where the offender lives, works, plays, or other routine activities. But the updated definition retains the core point: there is no clear relationship between the location of offense and the location of the offender's anchor point. Addressing Paulsen's (2007: 353) "smaller offense areas and more clustered crime locations", looking at a commuting offender's crimes could show clustered offenses, possibly in multiple locations, but if an offense location isn't returned to, then this may show the appearance of random offense locations throughout a geographic area.

More colloquially, a commuting offender can be likened to the quote generally misattributed to Willie Sutton's choice of target locations: "because that's where the money is" (Mikkelson, 2008).

3.3.1.4. Examples:

- A burglar who is directed by their fence to a location for a specific item to steal
- A celebrity stalker who shows up at a movie premiere knowing the celebrity will be there
- An individual who visits a red-light district to solicit prostitutes or to purchase illegal narcotics

3.3.1.5. Comparison to Other Offender Types

The purpose of the journey to crime for a commuter offender is the least like the other offender types as the purpose of the journey is the crime itself and that a specific target is to be victimize, which is known in advance. In the case of the other offender types, targets are searched for whether intentionally or opportunistically. A commuter knows the target in advance and plans accordingly. This target may have little to no relation to any part of the commuter offender's routine activities (see Section 3.3.3, Routine Activities Offender), may not be anywhere near an anchor point as with local offenders (see Section 3.3.4, Local Offender), and the journey has a specific purpose unlike with marauding offenders (see Section 3.3.2, Marauder Offender). As with the other offender types, the commuter differs from a drifter (see Section 3.3.5, Drifter Offender) in that a commuter uses an anchor point for the origination and destination of the offense.

3.3.1.6. Context in Research

3.3.1.6.1. Regular vs Stanger:

A commuting offender is likened to that of a "stranger" (Boggs, 1965; Kelling & Wilson, 1982), someone who is in an area unrelated to their routine activities or normal anchor points and will generally not be recognized by locals. This is different from a commuter offender becoming familiar with a target location to gather information for assisting in the victimization. In these situations, the offender is likely to use false information to mislead others, whereas the places where the offender is a regular would be where the offender is known by their real identity during their routine activities.

3.3.1.6.2. Victim Search Method:

This type of offender is most closely tied to the search behavior of a hunter or poacher (Rossmo, 1999), someone who sets out specifically to find a target. The key difference is that a commuter offender is going to a specific geographic location because of a target known in advance, whereas a traditional hunter or poacher is searching for a target during their journey.

3.3.1.6.3. Victim Attack Method:

A commuter offender does not fall cleanly into one of Rossmo's victim attack methods (Rossmo, 1999). Rossmo's general intent in defining victim attack methods was to apply to an offender who is in search of a target. Since the commuter offender isn't searching for a target but is traveling to a specific location to victimize a target, this category is a bit out of place for this type of offender. But, to align this offender type with current research, the closest is the attack method of a raptor where the offender attacks a victim upon encounter as a commuter would indeed victimize the target upon encounter as this is the purpose of the journey-to-crime. Additionally, a commuter offender could be likened to the attack method of a stalker in that the offender would travel to the target and then need to follow the victim further before committing the intended offense.

3.3.1.6.4. Urban Site:

A commuter offender would typical commit an offense in an area known as a crime attractor. A crime attractor is specifically defined as an area to which offenders are attracted because of known opportunities (Brantingham & Brantingham, 1995: 8). This fits perfectly with the intent of a commuter offender as the journey-to-crime would be conducted by "strongly motivated offenders (who) will travel relatively long distances in search of a target" (Brantingham & Brantingham, 1995: 8). Again, think of this in context of Willie Sutton (see Section 3.3.1.3, Why the Change?).

3.3.1.6.5. Geometry Case:

Many of the basic search areas defined by Brantingham and Brantingham (1981b) apply to commuting offenders. Case 2 defines a basic search area with a cluster of offenders, a uniform distribution of targets, and offenders starting from a home location, or anchor point (Brantingham & Brantingham, 1981b: 32). When applied to commuting offenders the Case 2 search area gives the appearance of a red-light district: clustered offenders, uniform distribution of targets, offenders coming from an anchor point. But this case does not fully describe a commuting offender's search area. Case 5 describes a selective search area for multiple offenders, specifically a non-uniform distribution of targets with a uniform distribution of offenders (Brantingham & Brantingham, 1981b: 40). An example of this search area applied to commuting offenders would be a high valued target, such as an expensive piece of artwork, that all potential offenders desire. The targets in this example (i.e. high value artwork) are going to be distributed randomly based on personal collections, museums, corporate collections, etc., but potential offenders would be a normal subset of the population. Basically: the target drives the offense. Offenders will go to, or "commute to", the target location for that specific target, not just for any target of value. In Case 8 a dynamic search area is described where awareness space changes over time (Brantingham & Brantingham, 1981b: 45). This applies to commuting offenders as well but is easier to consider in the reverse.

3.3.1.7. Purpose of Journey-to-Crime

The purpose of the journey-to-crime for a commuter offender is solely to victimize a specific target selected in advance to the journey (see Section 3.3.1.2, Updated Definition:). This is indeed the offender's commute as likened to the traditional work commute of a law-abiding individual.

3.3.1.8. Anchor Points

The anchor points used by a commuter offender in their routine activities have no relation to the location of the target. A commuting offender will seek a target based on the desire to victimize the opportunity regardless of the distance to and from the offender's traditional anchor points, specifically their residence. But, the traditional anchor points for a commuter offender will be used, in any combination, as the origination and destination for the journey-to-crime.

3.3.1.9. Awareness Space

The awareness space of a routine activities offender only changes when their routine activities change (see Section 3.3.3, Routine Activities Offender). But for a commuting offender, the awareness space changes with the desired target. A commuting offender will learn about an area if the target is worthwhile. In the example of a celebrity stalker, if a celebrity frequents a certain restaurant, then the commuting offender would learn about the area around the restaurant regardless of their current familiarity. Because the specific target is the goal, awareness space would dynamically change to accommodate the specific target.

3.3.1.10. Directionality

In a series of commuting offenses, directionality, with respect to geography may not be inconsistent as the commuter offender has specific targets regardless of the starting anchor points. For the same reason, distance-to-crime may vary and show little pattern across the series. This could result in a series of offenses that appear random in direction, location, and distance from a commuting offender's anchor points.

3.3.1.11. Summary

Three components define a commuting offender: (1) the journey-to-crime has the specific intent of committing a criminal offense, (2) the target is specific and known in advance, and (3) the target has no correlation to the offender's routine activities or daily life. This clarity is intended to help standardize a method of classifying serial offenders as commuter offenders in the hopes of modeling behavior to aid in offender apprehension and ultimately reduce victimization.

3.3.2. Marauder Offender

The concept of a marauder offender as originally defined by Canter and Larkin (1993: 65) has great potential in classifying a serial offender for geographical profiling. This potential is being squandered by a lack of updated definitions and understanding of this type of offender. In the term's definition, as provided by Merriam-Webster, a marauder is "one who roams from place to place making attacks and raids in search of plunder" (Merriam-Webster, 2019c). This conjures up images of pirates roaming the seas in search of lost, buried treasure, an image that is directly in line with the original intent of defining this type of offender, but not with the existing definitions. This section seeks to bring the definition of a marauder offender more in line with this intent and the general understanding of a marauder.

3.3.2.1. Existing Definitions:

Marauder - the base acts as a focus for each particular crime (Canter & Larkin, 1993: 65)

Marauder - there is a large or total overlap of the home range and criminal areas (Canter & Larkin, 1993: 65)

Marauder - crime series occur over a significantly larger area and are less clustered (Paulsen, 2007: 353)

3.3.2.2. Updated Definition:

Marauder - a serial offender whose journey-to-crime will be to seek targets, will begin and end at the same anchor point, will have inconsistent directionality across the offense series, is independent of the offender's routine activities, will not have a specific target selected in advance, and is not bound by awareness space

3.3.2.3. Why the Change?

Previous definitions of marauder are largely useful, specifically that the "base" (i.e. anchor point) "acts as a focus" for the journey-to-crime and that a serial offender's offenses will include a larger area and be less clustered. The updated part of the marauder definitions brings in clear terminology (e.g. anchor point, journey-to-crime, directionality) and makes it clear that this type of offender does not have a specific target selected in advance. Additionally, it is necessary to make clear that a marauder's criminal range is not bound by the home range or awareness space. Without this distinction there is a gap in offender types. This updated definition attempts to include all offenders who use an anchor point and seek targets without a specific target selected in advance, regardless if awareness space restricts this search.

3.3.2.4. Examples

- A serial rapist searching for a victim
- A criminal gang look for a victim for gang initiations
- A graffiti artist looking for new bridges and buildings to tag

3.3.2.5. Comparison to Other Offender Types

A marauder offender is close to a drifter (see Section 3.3.5, Drifter Offender), but with fixed anchor points and is generally the opposite of a commuting offender (see Section 3.3.1, Commuter Offender). Like a drifter, a marauder offender roams in search of a target, but returns to their origination anchor point at the end of their roaming. Like a commuting offender, a marauder has a single anchor point for their origination and destination, but unlike a commuter, the marauder has no target selected at the onset of the journey-to-crime. The marauder is dissimilar to local (see Section 3.3.4, Local Offender) and routine activities (see Section 3.3.3, Routine Activities Offender) offenders as the marauder is willing to go outside their awareness space in search of a target, but may be confused with these types as a target may be found, and victimized, before a marauder leaves their awareness space.

3.3.2.6. Context in Research

3.3.2.6.1. Regular vs Stranger:

A marauder is more likely to be a stranger depending on how far the offender roams before finding a suitable target. Since the marauder is willing to leave their awareness space in search of a suitable target, this offender type is less likely to be mistaken for a regular than the local offender and may be confused for a regular depending on the set of offenses being analyzed.

3.3.2.6.2. Victim Search Method:

This is a hybrid of the hunter and poacher victim search method (Rossmo, 1999Hunters start out from their residence whereas poachers start from an anchor point other than their residence. (With the updated definitions, these two methods essentially become one.) The marauder starts out from an anchor point, regardless of its type, thus meets the criteria of both a hunter and a poacher.

3.3.2.6.3. Victim Attack Method:

A marauder's method of attack could be classified as either a raptor or stalker (Rossmo, 1999: Target and Hunt). The raptor attacks a victim upon encounter, whereas the stalker follows a victim upon encounter and attacks a later time. Because a marauder's journey is intended to seek a target, the circumstances surrounding the encounter with a target would dictate if the marauder commits an offense upon encounter or followed the target waiting for an opportune moment.

3.3.2.6.4. Urban Site:

Marauders are more likely to commit an offense in an area considered a crime generator. These areas are defined as creating opportunities for potential offenders with an increased concentrations of people and/or targets (Brantingham & Brantingham, 1995: 7-8). Although the purpose of a marauder's journey is to find a target, a specific location needs to generate opportunities for a marauder to commit an offense. Secondarily, the area of offense may be a crime neutral area, or a place that doesn't normally produce criminal opportunities, but a location found by the marauder while searching for targets. Conversely, a crime attractor is an area known for target opportunities and visited for this purpose (Brantingham & Brantingham, 1995: 7-8). If this were the case, then the offender would be a commuter, not a marauder, because they are travelling to the area because of the "attractive" opportunities.

3.3.2.6.5. Geometry Case:

The purpose of a marauder's journey is to find a target. This type of offender exhibits the basic search pattern as described by Case 1 and Case 2 in Notes on the Geometry of Crime (Brantingham & Brantingham, 1981b: 30-32). These two cases are similar in describing a uniform distribution of targets and the use of a single "home location" (i.e. anchor point) for the beginning and end of the journey-to-crime. The difference being that Case 1 describes a single offender, whereas Case 2 describes a cluster of offenders. When describing marauders, this difference is irrelevant. A marauder is defined as assuming a uniform distribution of targets, thus the lack of a selecting a specific target and the inconsistent directionality from anchor point to location of offense. If this uniform distribution was not assumed, then the offender would have a specific target location and would become a Commuter offender.

3.3.2.7. Purpose of Journey-to-Crime

For a marauder, the purpose of the journey-to-crime is solely to seek out targets. The offender's target or location of target are not known in advance and the journey is not part of a routine activity journey. This is contrasted with a commuter offender whose purpose for the journey-to-crime is also to seek out targets, with the location of target being known, but not necessarily the specific target.

3.3.2.8. Anchor Points

A marauder's anchor point, whether it be home, work, or a place of entertainment, is both the start and end of the journey-to-crime. A marauder roams from an anchor point specifically in search of a target with the expectation of returning to that same anchor point after committing an offense or not finding a suitable target.

3.3.2.9. Awareness Space

As originally described by Canter and Larkin (1993: 65), a marauder's criminal range and home range were largely the same. In this updated definition this can still be the case, but a marauder may roam beyond their home range to continue searching for a suitable target. The boundary of awareness space doesn't dissuade a marauder for continuing to search for a suitable target. This awareness space may form the basis of the beginnings of search, but the marauder's desire to victimize isn't necessarily bound by awareness space.

3.3.2.10. Directionality

One major factor not considered by previous research is the geography of the area and the assumption that a marauder can go in any direction. Both physical (e.g. freeways) and geographic (e.g. rivers) boundaries can prevent travel in any direction and the directionality of an offender must be reviewed in this context or the offender could be mistakenly classified. With respect to geography, the directionality of a marauder will be inconsistent. A consistent directionality would indicate that the offender has a destination in mind for target search and would be considered a commuter or is offending along paths of routine activity and would be consider a routine activities offender (see Section 3.3.3, Routine Activities Offender). The marauder searches for targets in a pattern with inconsistent directionality, but if considered without respect to geography, directionality may give a false perception of consistency. Largely, the directionality of a marauder should be without a discernible pattern and in as many possible directions from the anchor point.

3.3.2.11. Summary

Due to the perceived randomness of a marauder's offense locations, it is believed that this spatial type of offender cannot be modeled thus making geographical profiling impossible. By further understanding and defining a marauder offender this offender type will become easier to classify, thus avoiding the use of resources not helpful in the apprehension of marauders. It is also hoped that further understanding will lead to a method of geographically profiling marauders and developing a method to model and apprehend this type of offender.

3.3.3. Routine Activities Offender

Prior to this work, there was no specific definition of a routine activities offender in the manner that there are definitions for commuter and marauder offenders (Canter & Larkin, 1993). The existing definitions for this classification work with the overall idea of routine activities in relation to criminal offenses but does not define the actual offender who offends under the routine activities concept. This is a small distinction, but an important one when looking at the spatial behavior of a criminal offender.

3.3.3.1. Existing Definitions:

Routine Activities - Most criminal acts require convergence in space and time of likely offenders, suitable targets and the absence of capable guardians against crime. (Cohen & Felson, 1979: 558)

3.3.3.2. Updated Definition:

Routine Activities Offender - a serial offender who identifies potential targets during their non-criminal, day-to-day activities, but that are outside of the home range of their anchor points.

3.3.3.3. Why the Change?

Before expanding the types of spatial offenders, this type of offender would have been mixed with marauder offenders. Marauders were described as having "a large or total overlap of the home range and criminal areas" (Canter & Larkin, 1993: 65). This definition has been pulled out of marauder offenders and used to create routine activities offenders. Target selection for routine activities offenders is derived from cognitive maps built during routine activities. Potential targets are identified while moving between anchor points, thus offenses will be committed in between the home ranges of a routine activities offender's anchor points. Thus, the "home range" and "criminal areas" of a routine activities offender will overlap minimally, if at all. Additionally, marauder offenders were described as committing a "crime series occur over a significantly larger area and are less clustered" (Paulsen, 2007: 353). Again, because routine activities offenders identify potential targets while traveling between anchor points, any resulting crime series could cover a larger area depending on the distance between anchor points.

Further research, beyond the scope of this thesis, would need to be conducted to determine if this is accurate and if the crime series of a routine activities offender is indeed less clustered. Consideration would also need to be given to the activities in this offender's routine being centered "mentally" and not necessarily centered "spatially" around anchor points.

3.3.3.4. Examples

- A burglar who identifies houses while traveling between work and home (e.g. Fairfax County's Kirby Road Burglar)
- A robber who targets victims on buses and/or subways while traveling between home and recreation areas (e.g. 2017 Metro bus crime waves)
- A rapist who identifies victims while travelling between work and home and follows them until a suitable location for victimization (e.g. Strangeland, 2005)

3.3.3.5. Comparison to Other Offender Types

The primary difference between a routine activities offender and a commuter (see Section 3.3.1, Commuter Offender), marauder (see Section 3.3.2, Marauder Offender), or local (see Section 3.3.4, Local Offender) offender is that the purpose of the journey-to-crime for a routine activities offender is not the crime itself, but is the offender's day-to-day routine activities. For commuter, marauder, and local offenders the purpose of the journey-to-crime is the crime. Additionally, a routine activities offender has different origination and destination anchor points before and after the offense. For commuter, marauder, and local offenders the origination and destination are the same anchor point.

3.3.3.6. Context in Research

3.3.3.6.1. Regular vs Stranger:

A routine activities offender is a stranger as this offender type seeks targets along the paths between, not around, their anchor points. If this type of offender is seen regularly at places in between anchor points, then a routine activities offender could be mistaken for a regular.

3.3.3.6.2. Victim Search Method:

A routine activities offender uses a troller victim search method. A troller is defined spatially as the offender whose journey-to-crime occurs during routine activities and as an offender who seeks opportunistic victims (Rossmo, 1999). Troller is very similar to routine activities offenders with the exception that trollers are defined as opportunistic. Routine activities offender may identify a target and return a later a time to victimize the target but could also be opportunistic.

3.3.3.6.3. Victim Attack Method:

This type of offender uses a hybrid of attack methods, depending on the type of crime being committed. The raptor attack method is used when targets are victimized upon encounter and the stalker attack method is used when a target is found, but the location is not desirable, resulting in the offender following the target until a more suitable location is found (Rossmo, 1999). As a result, the raptor attack method is more likely to be used in property offenses as these types of targets don't generally walk away. For offenses against persons either the raptor or stalker attack method could be used depending on the circumstances in which the target was found.

3.3.3.6.4. Urban Site:

As with a marauder offender (see Section 3.3.2, Marauder Offender), a routine activities offender is most likely to commit offenses at sites that are crime generators. This type of sites are areas that produce crime through a certain number of people and opportunities being present in the same place at the same time (Brantingham & Brantingham, 1995: 7). This is exactly the situation described by Cohen and Felson (1979) and when considered in the context of a typical work commute and rush hour, leads to a routine activities offender being able to discover opportunities without having to conduct a traditional search as with the commuter and marauder offenders. Crime generator sites are also described as areas where offenders aren't necessarily in the area to commit a crime but would do so when presented with an opportunistic target, whether in the moment or by returning to the target area at another time (Brantingham & Brantingham, 1995: 7-8). Again, this falls exactly in line with a routine activities offender who is travelling between two anchor points, sees a potential target, and either commits the offense in the moment or returns later at a better time.

3.3.3.6.5. Geometry Case:

Routine activities offenders are conducting non-criminal (i.e. normal) activities between different locations. This falls in line with Case 3 and Case 6 (Brantingham & Brantingham, 1981b: 33-36). Case 3 describes a single offender who is not tied to a single location as their starting point and consists in an area of uniform target distribution. This maps to a routine activities offender having multiple locations (i.e. anchor points) as their starting point, whether it be home, work, a favorite restaurant, or a family member's home. Case 6 describes a geographic area that is a subset of awareness space (i.e. area traveled between anchor points) and location of targets (Brantingham & Brantingham, 1981b: 42-44). Specifically, Case 6 states that crimes are committed near areas of activity, or in the case of a routine activities offender, areas between anchor points near routes traveled.

3.3.3.7. Purpose of Journey-to-Crime

For a routine activities offender, the purpose of the journey-to-crime is originally to travel between anchor points and not to commit a crime. The path of this journey may remain the same if an opportunity is found in direct line with the transportation routes used in the offender's routine activities where the offender can commit the offense and continue to their original destination. Alternatively, the path of this journey could alter if the offender were to take a side route to seek targets in an area near or along the transportation routes between their origination and destination. It is further possible that the target is discovered during the routine activities journey and then victimized another time, producing a journey-to-crime with a single anchor point as the origination and destination, such as with a commuter offender.

3.3.3.8. Anchor Points

The origination and destination anchor points are different for a routine activities offender. This is the basis of this type of offender. As targets are discovered, and sometimes victimized, during an offender's routine activities, multiple anchor points must be involved in this type of offender's journey-to-crime.

3.3.3.9. Awareness Space

A routine activities offender's awareness space will consist of the traditional home ranges surrounding their anchor points as well as the areas on and near the transportation routes between these anchor points. As such, this awareness space will be much larger than that of offender types who use a single anchor point as both the origination and destination for a journey-to-crime. This larger awareness space would likely result in a greater knowledge of targets and a better ability to victimize opportunities in the absence of capable guardians but would also be a larger area than the home ranges of this offender's anchor points.

3.3.3.10. Directionality

The directionality of a routine activities offender will be highly dependent of the offender's routine activities. In the case where the offender has very static anchor points, such as a single work location, then the directionality will be consistently between the residence and work anchor points. If an offender has numerous anchor points, an inconsistent residence, or regularly travels to customer sites then directionality could appear to be widely inconsistent. But in the simplest case of a standard home-work-home commute, the directionality would point towards either the residence or work anchor point.

3.3.3.11. Summary

Defining and understanding this spatial type of offender is critical for conducting geographic profiles. It is believed that, as with local and marauder offenders, geographical profiling is possible for routine activities offenders, but a full understanding of this offender type is necessary for proper classification and thus accurate geographic profiling. This section is intended to be the next step towards this success.

3.3.4. Local Offender

As described by Kelling and Wilson (1982), locals (i.e. regulars) are those individuals known to an area. Offenses committed by locals are typically easier to determine the offender and are generally solved quickly and without much investigative efforts by law enforcement. Thus, this type of offender can be generally dismissed in research and not considered when reviewing the spatial behavior of offenders. This section is intended to clearly define this spatial type of criminal offender and ensure that it is included when discussing the spatial nature of a serial offender.

3.3.4.1. Existing Definitions:

Regulars - undefined (Kelling & Wilson, 1982)

Local offenses - relatively higher concentration of unplanned/affective crimes (Rhodes & Conly, 1981: 170)

Local insiders - undefined (Brantingham & Brantingham, 1995: 8, 9)

Local burglars - undefined (Barker, 2000: 62)

Local - centered on the residence and surrounding neighborhood (Rossmo, 1999: Predator Patterns)

Local travel distances - undefined (Lundrigan & Canter, 2001: 601)

Local activity - undefined (Snook, 2004: 53)

Local neighborhood - undefined (Snook, 2004: 64)

Local insiders - undefined (Brantingham & Brantingham 2008a: 89)

3.3.4.2. Updated Definition:

Local - a serial offender who commits crimes at or within close proximity of one or more anchor points

3.3.4.3. Why the Change?

Likened to "regulars" (Kelling & Wilson, 1982) and "local insiders" (Brantingham & Brantingham, 1995: 8, 9), this is an individual who is a part of the community which they are victimizing. This would include crimes such as domestic disputes and workplace theft. The current body of research defines local offenders as those committing an offense within a "buffer zone" or "safety zone" to their residence. Although there is no clear consensus as to the size of this zone, research suggests the radius is about one mile, although this distance may be dependent on the type of neighborhood (i.e. urban, suburban, or rural). As with some of the terms discussed above, this definition is incomplete.

This is best explained with an example, by looking at the facts presented in news articles, with no judgement of innocence or guilt. In August of 2017, Fairfax City Police (not to be confused with Fairfax County Police) arrested a server at a restaurant for pocketing cash used by patrons to pay for meals and then voiding the charges in the point of sale system (Wood, 2017b). This arrested person worked in Fairfax City, Virginia, but resided in Silver Spring, Maryland, about 25 miles away, or about a 45-minute drive, without traffic. With currently accepted definitions, this individual would be classified as a commuter offender. But, without knowing the individual's motive, the basic facts would suggest that the theft was committed because of opportunity at the arrestee's place of employment (local offender) not because the arrestee wanted to across the Washington, DC Metro Area to steal from that specific restaurant (commuter offender).

3.3.4.4. Examples:

- Domestic violence between family members occurring at the offender's residence
- A teenager tagging buildings with graffiti in their own neighborhood
- An employee stealing from an employer in the workplace
- A fight between regular patrons at a bar

3.3.4.5. Comparison to Other Offender Types

Local offenders differ from other offender types because there is generally little to no journey-to-crime. Local offenders commit offenses where they spend most of their times: at their anchor points. This can also include the immediate vicinity of their anchor points, such as in their residential neighborhood. Other offender types have a true journey-to-crime where the offender travels to a location, where they wouldn't be known by the regulars, to commit their offenses.

3.3.4.6. Context in Research

3.3.4.6.1. Regulars vs Strangers:

Locals are direct equivalents to Kelling and Wilson's (1982) discussion of regulars. These are the individuals who are local to the neighborhood. Unlike in Kelling and Wilson's description, today's urban neighborhoods provide more anonymity, thus a local may not be known to the neighborhood but would still be considered a "regular" since the offender is "regularly" present in the neighborhood as part of their routine activities, such as work, shopping, and their personal residence.

3.3.4.6.2. Victim Search Method:

The local offender correlates to the trapper victim search method. A trapper search method will entice victims to a location of choice (Rossmo, 1999), specifically an offender's anchor point. The restaurant server in the above example would be a trapper as victims were enticed to the place of offense by the desire for food and drinks.

3.3.4.6.3. Victim Attack Method:

The local offender also correlates to the raptor and ambusher victim attack methods. A raptor is where an offender attacks the victim upon encounter (Rossmo, 1999), as in the above example where the disorderly individual assaulted the police officers upon encounter. Whereas, an ambusher entices victims to a specific location controlled by the offender (Rossmo, 1999), such as the case with the restaurant server.

3.3.4.6.4. Urban Site:

Research shows that local offenders are present at crime generator sites (Brantingham & Brantingham, 1995: 8). Crime generator neighborhoods are "places with setting conducive to crime where potential offenders notice and exploit opportunities" (Brantingham & Brantingham, 1995: 7-8). Basically, a potential offender is already at the target location and the opportunity for a crime presents itself. This also supports earlier research showing that high rates of homicide, assaults, and residential burglary occur in neighborhoods where many offenders reside (Boggs, 1965: 907). Specifically, serial burglary is believed to be a localized crime, with the offender's age, available transportation, and the value of target being important factors in the distance traveled (Snook, 2004: 63). This further suggests familiarity between offenders and targets, resulting in a set of offenses committed by local offenders.

In the above example, looking through Fairfax County, VA news reports, two incidents occurred at the same restaurant, an assault in front of the restaurant in February of 2017 (Wood, 2017a) and a disorderly (i.e. drunk) individual assaulting a police officer (Wood, 2016). These news reports suggest the possibility of a crime generator site where local offenders (e.g. employees, regular patrons) may be prone to committing crimes, as suggested by the arrested server. This can also be articulated as neighborhoods with the best targets also attracting local offenders (Rhodes & Conly, 1981: 170), thus leading to the need to properly define this class of offenders and including them in the body of research instead of excluding offenses from research when committed within "buffer zones" or "safety zones".

Crime neutral areas are also of interest to local offenders. Because these sites do not typically provide opportunities for crimes and thus attract offenders, then, by definition, majority of offenses will be committed by local offenders (Brantingham & Brantingham, 1995: 9).

3.3.4.6.5. Geometry Case:

When looking at basic search areas, the local offender directly correlates to Case 1, defined by Brantingham & Brantingham (1981b: 31). The case defines a basic search area for an individual offender, acknowledging that it requires resources (e.g. time, money, effort) to overcome distance. If resources are constrained, then closer locations have distinct advantages over distant locations. Summarized: it is quicker and easier for a potential offender to commit a criminal offense close to an anchor point. Granted, this increases the likelihood of an offender being known and increases the risk of being caught (Brantingham & Brantingham, 1981b: 32), but punishment may be handled more informally, possibly extralegally, if the offender is known as a local (Kelling & Wilson, 1982).

3.3.4.7. Purpose of Journey-to-Crime

Essentially, a local offender has no journey-to-crime. The crime occurs where the offender is at the time. For example, in the case of a domestic dispute at home, the offender (and victim) live where the crime is committed, thus, from a geographic viewpoint, there is no journey.

3.3.4.8. Anchor Points

The anchor point, or very close to it, is the location of the offense. Whether the anchor point is the offender's residence, place of work, or a favorite entertainment spot, a local offender is defined as committing an offense at, or in proximity, to the anchor point. Part of defining a local offender is that an anchor point is the focus of the location of the offense.

3.3.4.9. Awareness Space

A local offender's awareness space compared to the commission of a criminal offense is the area of or within proximity to their anchor points, such the offense is committed within the offender's activity space. This is the space where a person's daily routine activities occur and thus where a local offender will commit an offense. This is a key component of the local offender. Further since the offense committed by a local offender occurs within proximity to their anchor points, there is a complete overlap between a local offender's criminal range and home range.

3.3.4.10. Directionality

Because there is no geographical journey-to-crime and a local offender's home range and criminal range are the same, directionality has no bearing on a local offender's offenses. There is not enough travel or distance with which to assess directionality from an anchor point to the site of a criminal offense. As with no journey-to-crime, this is a key component is the characteristics of a local offender.

3.3.4.11. Summary

This spatial type of offender has not previously been fully and clearly defined. Without a clear definition and understanding of this offender's characteristics, knowing the full extent of local offenders is mere guesswork. As such, offenders classified as locals may be mistakenly classified as another spatial type of offender and vice versa. To successfully develop the science of geographic profiling and thus conduct geographic profiles, it is critical to properly classify offenders by spatial type. This section is intended to be the next step in the process of clarifying, and eventually geographically profiling, this offender type.

3.3.5. Drifter Offender

Drifter offenders are often mentioned in research literature, but typically as a side note with no formal definition. This type of offender is generally described as having no fixed anchor point (Canter & Larkin, 1993: 63; Kocsis & Irwin, 1997: 197; Laukkanen & Santtila, 2006: 80: Van der Kemp & Van Koppen, 2008: 349). It is believed that without fixed anchor points a geographic profile is not possible. Even if true, this spatial classification of criminal offender needs to be included to properly classify offenders to ensure geographic profiles on not attempted in vain. It is critical to determine the type of offender prior to conducting a geographic profile. Thus, it is necessary to have a full and complete understanding of each spatial classification of offender, especially those for which profiling is not possible. This way an offender can be properly classified at the beginning of a profile and thus ensuring that valuable profiling time isn't wasted on the wrong type of offender.

3.3.5.1. Existing Definitions:

Geographically transient serial killer - travels continually through his (sic) killing career (Holmes & DeBurger, 1985: 31)

Traveling serial murderers - distinguished by their acts of homicide while traveling through or relocating to other areas (Hickey, 1991: 78, 80)

Drifter - no fixed abode (Canter & Larkin, 1993: 63)

Drifter - no fixed address (Kocsis & Irwin, 1997: 197)

Geographically transient - nomadic murderers kill people while they travel from one area to another. ((Holmes & Holmes, 2001: 24)

Drifter - without a permanent residence (Laukkanen & Santtila, 2006: 80)

Drifter - offender operating without a fixed home base (Van der Kamp & Van Koppen, 2008: 349)

3.3.5.2. Updated Definition:

Drifter - a serial offender who has no fixed anchor points over their series of offenses

3.3.5.3. Why the Change?

In the other spatial classifications of serial offenders, the definition of the term is usually unstable. For this term, it is the term itself that is not stable. The use of "transient" (Holmes & DeBurger, 1985: 31), "traveling" (Hickey, 1991: 78, 80), and "drifting" (Van der Kamp & Van Koppen, 2008: 349) are all prevalent throughout the literature, but all mean essentially the same thing. The decision to use "drifter" versus "transient" or "traveling" was a matter of semantics and clarity. For example, "transient" is defined by Merriam-Webster (2019d) as "passing especially quickly into and out of existence" and as "passing through or by a place with only a brief stay". Thus, the use of "transient" implies speed and disappearance. In the case of criminal acts, the results can be long lasting to the victims, especially in the case of violent crimes which makes "transient" feels like an unfair characterization of this type of offender. In the case of "traveling" Merriam-Webster (2019e) defines the root word "travel" as "to go on or as if on a trip or tour". This definition gives more of an impression of an extended journey-to-crime between two anchor points, thus only changing from a routine activities offender in distance and not purpose or intent. In the case of "drifter", Merriam-Webster (2019a) provides "one that travels or moves about aimlessly". This definition moves more to the heart of the intent of this spatial classification of offenders: an offender with no anchor point whose journey-to-crime seemingly has no purpose but is the journey itself.

As can be seen, although used for essentially the same purpose "transient", "traveling", and "drifter" have different implications and create confusion when used interchangeably.

3.3.5.4. Examples:

- A homeless offender who moves around and breaks into vacant buildings seeking shelter
- Washington, DC area sniper attacks in October 2002

3.3.5.5. Comparison to Other Offender Types

A drifter is closest to a marauder (see Section 3.3.2, Marauder Offender) with the difference being a lack of fixed anchor point. Both drifters and marauders seemingly have no pattern to the offense locations, but marauders have a fixed anchor point (e.g. their residence) that they return to after committing an offense. Drifters also share characteristics with commuters in that they may go to a specific location to commit a criminal offense, but again, the difference being that a drifter has no anchor point to start from and return to. Routine activities (see Section 3.3.3, Routine Activities Offender) and local (see Section 3.3.4, Local Offender) offenders have little similarities to drifters. Routine activities and drifters are practically opposite offender types as a routine activities offender relies on traveling between fixed anchor points to find targets and a drifter specifically has no fixed anchor points to travel between. The offenses of local offenders are focused around their fixed anchor points, thus also being very similar to the opposite of a drifter who has no fixed anchor point around which to commit an offense.

3.3.5.6. Context in Research

3.3.5.6.1. Regular vs Stranger:

Drifters are likened to strangers, as they have no fixed anchor point around which to become known as a regular. Within an urban context, a drifter may be recognized by locals, but not to the point of being considered a regular or a member of the community. Thus, for the most part a drifter will be considered a stranger in locations where criminal offenses are committed.

3.3.5.6.2. Victim Search Method:

A drifter is missing from Rossmo's (1999) victim search method classification. A hunter, poacher, and trapper all rely on fixed anchor points and a troller uses routine activities to seek victims. As a result, there is no clear victim search method that can be assigned to a drifter. But, characteristics of each victim search method can be taken and used to describe a drifter's search method. For a hunter or poacher, the offender's journey-to-crime is for the purpose of finding a victim, but for a drifter this search is not based from a fixed residence (i.e. hunter) or another anchor point (i.e. poacher). Trollers specifically find victims while engaged in non-criminal activities is furthest from a drifter, but like a troller a drifter can opportunistically encounter victims. A trapper is the furthest from a drifter as a trapper requires a location to which to entice a victim. Since drifters have no fixed anchor point, trapping a victim is not a clear option.

3.3.5.6.3. Victim Attack Method:

Drifters are most closely associated with the raptor and stalker attach methods (Rossmo, 1999). Both methods can be used when opportunistically encountering a victim and either attack upon encounter (i.e. raptor) or following a victim prior to attack (i.e. stalker). A drifter is less associated with an ambusher because this method of attack requires a specific location to be controller by the attacker. In a drifter's case the lack of fixed anchor points reduces the ability for a drifter to have a location to which to entice a victim and conduct an ambush.

3.3.5.6.4. Urban Site:

Crime generator sites are places that produce crime due to the confluence of time, place, and availability of targets (Brantingham & Brantingham, 1995: 7-8). These areas are where opportunistic crimes occur most often. Drifters in these areas will likely see opportunities and commit a criminal offense. Less likely for drifters are crime neutral areas as these are generally areas where local offenders commit offenses (Brantingham & Brantingham: 1995: 9) and crime attractor areas which require offenders to know about the target opportunities (Brantingham & Brantingham, 1995: 8). Because drifters are less likely to be familiar with a given area, crime neutral and crime attractor sites are less likely to be where a drifter commits an offense.

3.3.5.6.5. Geometry Case:

Since drifters have no starting point, Case 6 best applies to this offender type (Brantingham & Brantingham, 1981b: 42-44). Unlike the other cases, this case does not specifically require a fixed location for the offender. Case 6 allows for offenses to be committed in the subset of awareness space and areas with targets. In the case of a drifter awareness space will be the area immediately surrounding their current location and when this area includes targets, the opportunity for a criminal offense is present.

Furthermore, Case 6 specifically includes offenses occurring near areas of activity (i.e. the drifter's present location) and along transportation paths (i.e. where the drifter is present).

3.3.5.7. Purpose of Journey-to-Crime

The best explanation of a drifter's journey-to-crime may be the unscientific method of quoting theologian Lynn H. Hough "life is a journey, not a destination" (Quote Investigator, 2012). A drifter's journey-to-crime has no purpose except for the journey itself, and possibly the seeking of targets. With no fixed anchor points a drifter's journey is just that: drifting. As stated in the Merriam-Webster (2019a) definition of a drifter, the journey is aimless, thus having no purpose. This is the key component to defining a drifter and separating this offender type from other spatial classifications of criminal offenders.

3.3.5.8. Anchor Points

A drifter simply has no anchor points. As in the discussion above on purpose of journey-to-crime this lack of anchor is what defines a drifter. A drifter may have locations where they stop for the purposes of eating and resting, but none of these locations would be consider a true anchor point as with other spatial classifications of criminal offenders.

3.3.5.9. Awareness Space

The awareness space of a drifter will greatly depend on if the drifter is moving through a single area, such as specific city or moving from area-to-area. In the case of a single city, a drifter may have a very large awareness space because of continuously drifting in known and unknown areas. If a drifter is continuously moving to unknown areas, then the awareness space may be limited to the immediate area surrounding the drifter and the areas previously traveled through. This would be most analogous to a hiker who is only familiar with the woods immediately surrounding their current location but is not familiar with what is beyond the linear trail. This may be best described by journalist and humorist Edgar Nye's explanation of the Platte River: "a mile wide but an inch deep" (Bugden, 2018).

3.3.5.10. Directionality

As in the discussion on awareness space, a drifter's directionality could appear either linear in nature or seemingly random. As mentioned earlier in the Merriam-Webster (2019a) definition, a drifter's movements are aimless, thus giving the appearance of randomness. Without a fixed anchor point, determining or understanding a drifter's directionality may be near impossible.

3.3.5.11. Summary

This section is intended to bring together a mosaic of terms and create a clear definition of a drifter offender where previously this term was used in an ad hoc manner to offenders with no fixed anchor point. With an initial definition, further research, and hopefully modeling, can be conducted to better understand this spatial type of criminal offender.

4. OBJECTIVE 2 – AGENT-BASED MODEL

The second objective of this thesis is to build an initial agent-based model representing the updated spatial classification of criminal offenders (see Section 3, Objective 1 – Expanding Commuters and Marauders). This agent-based model uses the foundational knowledge presented in the Literature Review (see Section 2, Literature Review) with the expanded spatial offender classification to observe the emergent behavior of criminal offenders.

Agent-based modeling has been proven to capture the emergence of crime patterns, resulting in a more predictive approach to law enforcement (Malleson & Evans, 2014). This thesis uses stylized facts generated from U.S. Census Bureau commute data (American Community Survey, 2013a, American Community Survey, 2013b) to build an initial agent-based model representing the developed spatial classification of criminal offender types. To address gaps in previous crime agent-based models (see Section 2.11, Agent-Based Modeling), this model will not be limited to a subset of crime types (Paulsen, 2007) and will incorporate realistic geographic backdrops (Devia & Weber, 2013) with jurisdictional boundaries. These boundaries will simulate reality by not being respected by offender agents. In consideration of the rise of work-related mega commuting (Rapino & Fields, 2013), this initial spatial offender agent-based model will take the next steps in understanding the spatial classification of criminal offenders and move towards modeling testing of police strategies (Devia & Weber, 2013) to address any resulting spatial patterns in criminal offenders.

Generally, the intended role of this model is explanatory: to assess the theories and hypothesis presented in the realignment of definitions for geographic offender types. This thesis is looking to break the deadlock of analyzing the initial Circle Theory efforts (Canter & Larkin, 1993) and produce mindsets that can move research, and eventually policy, forward.

The following three sections use the Overview, Design concepts, and Details (ODD) protocol (Grimm, et al., 2006) to describe this model (see Sections 4.1, ODD: Overview, 4.2 ODD: Design Concepts, and 4.3 ODD: Details). After the ODD description of this model, the model validation efforts are described (see Section 4.4, Model Verification), followed by a description of the execution of the model (see Section 4.5, Model Execution) and a discussion on the model validation efforts (see Section 4.6, Model Validation).

4.1. ODD: Overview

4.1.1. Purpose

The initial burglary model developed by Malleson, et al. (2010) integrated abstract environment and behavior into predicting where burglaries would occur in a fictional world. Devia and Weber (2013) took another important step forward by incorporating real world geographic backgrounds into crime modeling and modeling crime at-large, regardless of specific types of crime. But both models gave all offenders the same spatial behavior and constricted criminal offenders and police to the same geographic boundaries. The model described in this thesis advances the work of Malleson, et al. (2010), Devia and Weber (2013), and many others by incorporating real world GIS data, modeling crime at-large regardless of type, adding different spatial behaviors to criminal offenders, and allowing criminal offenders to move beyond a specific political boundary to which law enforcement would normally be restricted. Each of the five spatial offender types described (see Section 3.3, Spatial Classification of Criminal Offenders) are modeled in the ABM described in this section and are given different spatial behaviors based on the previously discussed definitions. This effort acknowledges that not all criminal offenders look at the world with the same perspective when searching for suitable targets and attempts to produce the emergence of different spatial behaviors from criminal offenders who differ in their spatial behaviors and decision making that results in the acquisition of a suitable target.

4.1.2. State Variables and Scales

This model focuses specifically on the movement of criminal offenders through Fairfax County, VA. To understand how different spatial types of criminal offenders move when committing crimes, an offender agent's daily work-related commute is incorporated into the model. The environment of Fairfax County, VA and surrounding jurisdictions, is incorporated into this model using geo-referenced spatial data to include jurisdiction boundary, road network, and land use data.

4.1.2.1. Offender Agents

In this model, a single offender agent is used to model all five spatial offender types. This offender agent is assigned variables to designate its offender type, as well as residential and work anchor points; origination, destination, and travel path during movement; offense target locations; and details such as departure and arrival times. Each agent is assigned a spatial offender type (see Section 3.3, Spatial Classification of Criminal Offenders) and makes decisions and has specific behaviors based on the agent's offender type, thus modeling the proposed definitions of the different spatial offender types. Apart from the specific offender type behavior, all other decisions and behaviors are common across all offender agents. For example, each agent is assigned a residential and work anchor point (see Section 2.3, Anchor Points) to guide traditional work commute behavior. The agent deviates from this based on the assigned spatial offender type only when committing an offense. The sole exception to this is an agent assign as a drifter because, by definition, that type of offender has no anchor points (see Section 3.3.5, Drifter Offender).

4.1.2.2. Environment

The agent-based model created for this thesis incorporates real-world geography through the inclusion of political boundaries of Fairfax County, VA and surrounding jurisdictions (Fairfax County Government, 2015), the road network within Fairfax County, VA (Fairfax County Government, 2016), and available Fairfax County, VA land use data (Fairfax County Government, 2018). This provides a realistic backdrop to affect the movement and function of agents within the model and to more closely simulate the real-world behavior and decisions of these same agents. Specifically, agents are generated without respect to the borders of the model but based on commuter flow data and/or inputs assigned by the model's user. These same agents then move in and out of these jurisdictions, simulating work commute behavior in the real-world. This respect to the existing geography outside of the model is a key component to advancing the understanding of how different types of criminal offenders move through space.

4.1.2.3. Extent of the Model World

Fairfax County, VA is approximately 27 miles north to south and 30 miles east to west. This is represented in the model as a grid of 180 by 200 cells (i.e. patches), thus each cell represents 0.15 square miles or 792 feet directly across. If traveling 30 miles per hour, a vehicle will cover 44 feet per second. With each cell being 792 feet directly across and a vehicle traveling 44 feet per second, this means that an agent will travel directly across one cell in 18 seconds.

4.1.2.4. Time Representation

In this model, time is represented by measurement of seconds, minutes, hours, and days. During each step (i.e. tick) of the model a moving agent will travel one cell. Since each cell represents 18 seconds of travel time, each step in the model represents 18 seconds.

4.1.3. Process Overview and Scheduling

Processes in this model repeats on a daily time frame (Figure 2). Each day an agent commutes from residence to work and back again. For the residence to work leg of the commute, the agent is assigned a commute time. The agent then leaves their

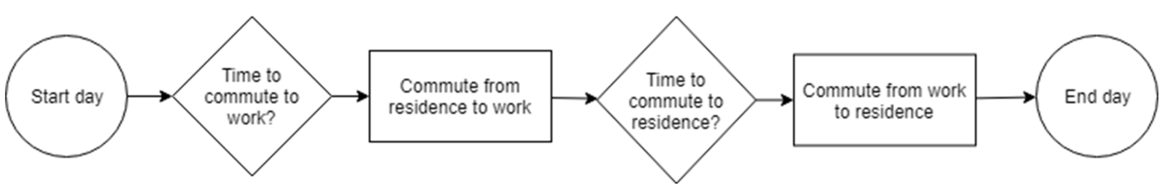

Figure 2: Agent's daily commute process

residence at the assigned time and begins their commute to work. Upon arrival at work, the agent is assigned a random time to leave work between six and ten hours from their arrival at work, simulating a day at work. The agent then leaves work at this scheduled time to return to their residence. This process is repeated each day in which the model is run. Within this daily commute process, an agent will begin the process to commit an offense. This process is different for each type of spatial offender and is discussed in detail below (see Section 4.3.3, Submodels).

4.2. ODD: Design Concepts

4.2.1. Emergence

Locations of offenses committed emerges from the behavior of each offender agent. By running this model with different parameters (e.g. combination and number of offender types and location of residence and work anchor points), different spatial patterns will emerge. These patterns can then be used to understand how each spatial type of offender behaves and how a resulting set of criminal offense locations can be used to determine a serial offender's spatial type and possibly the location of their anchor points or future offenses.

4.2.2. Objectives

Each agent in this model has two objectives during each day represented in the model: (1) commute to and from their residence and work and (2) commit a criminal offense. The only exception to these objectives is an agent assigned the drifter spatial type (see Section 3.3.5, Drifter Offender), which will commute between different locations in lieu of a fixed residence and/or work anchor point.

4.2.3. Sensing

Agents are assumed to know their residence and work anchor point locations, the entirety of the road network (and thus, the most logical path between two points), and the land use types throughout the county. Additionally, each agent is assumed to know the rules that govern their spatial offender type and exhibit behavior within the bounds of these rules.

4.2.4. Interaction

Agents in this model interact with the environment, but not with other agents. Agents will travel to and from their residence and work locations, travel across the road network, and query land use types when searching for offense locations (i.e. suitable targets). Agents are not aware of each other or if an anchor point belongs to another agent. This creates the potential of two agents independently, simultaneously committing offenses at the same location or committing an offense against another agent's anchor point. This was done purely for simplification in the model as adding agent interaction would have increased the complexity with no major benefit to the initial goal of demonstrating spatial offender types.

4.2.5. Stochasticity

Randomness was utilized at several moments in model development either due to a lack of data, the need for more specific data to simulate reality, or to maintain a reasonable scope of this model. It is expected by the author that each of these random aspects in this model are eventually replaced with known data.

During model initialization, agents are assigned anchor points randomly within the parameters of their assigned jurisdiction. For example, an agent with a work location within Fairfax County, VA will be assigned a random location within Fairfax County, VA, but to a land use type that matches a typical work location (i.e. commercial or mixed use and not recreational). Agents are initially assigned work commute time blocks as defined in the ACS data (American Community Survey, 2013a), not exact times. The model then assigns the agent an exact work commute time randomly within this time block. For example, an agent may be assigned a work commute time block of 7:00 am to 7:29 am and randomly given the exact work commute time of 7:02 am.

Upon arrival at work, each agent is assigned a random time to leave work to return to their residence. This random time is between six and ten hours, simulating a typical workday of eight hours, but factoring in leaving early (e.g. doctor's appointment) or work late (e.g. overtime). The length of time between six and ten hours is random and assigned each time an agent arrives at work (i.e. different each day). Drifter offenders (who don't have anchor points), are assigned a random length of time up to 18 hours in which they remain at their destination location. (This is truly random as the author knows of no data on how long drifter offenders remain in any one location.)

Offense locations are assigned randomly, but within the parameters of the agent's spatial offender type. For example, a local offender type will commit an offense within the local range of their anchor point, but at a random exact location within this range. On the extreme opposite of the local, a commuter offender will be assigned a random offense location anywhere within Fairfax County, VA, per the parameters of this offender type.

Specifically, each offender type is given a subset of locations within the model where they could commit an offense. The model then picks randomly from this subset of locations for the exact offense location.

An agent could commit an offense from either their residence or work location. This is determined randomly (a 50/50 chance) at the beginning of each day. For example, a routine activities offender may randomly be assigned to commit an offense with their residence as the start location. During that day, this spatial offender type will commit an offense on their routine commute from their residence to work. If the random assignment was to commit an offense with their work as the start location, then the offense would be committed on their routine commute from work to their residence.

For marauder offenders, an initial offense location is assigned. When this offender type arrives at this initial location a random one-in-four chance is given for the offense to be committed. If the offense is not committed (a three-in-four chance), then the agent is assigned a new offense location. This is repeated until the agent "decides" to commit an offense or is forced to return to their anchor point to resume normal work commuting behavior.

When committing an offense at an offense location, agents are assigned a random departure time of up to 30 minutes. This simulates the length of time to commit an offense and allows for a range of offenses from a purse snatch to burglarizing a house.

4.3. ODD: Details

A geographic backdrop is drawn to incorporate the jurisdictional boundaries and road network. Pieces of this geographic backdrop can be turned on and off for model verification and to suit the needs of the model's user, a time of day is selected from which the model starts, and the number of days is selected to be simulated while running the model (see Section 4.3.1, Initialization). Parameters are set to determine how many offenders of each spatial offender type will be generated and in which jurisdictions these offenders will reside and work (see Section 4.3.2, Input Data). The offenders are then generated (see Section 4.3.3 Submodels). . The model is then started (see Section 4.5, Model Execution). When finished running, the resulting anchor points and offense locations can be outputted to an ASCII file for geospatial analysis (see Section 4.3.4, Model Outputs).

4.3.1. Initialization

At the initialization, or setup, of the model the user can affect the environment, the agents, and temporal aspects.

4.3.1.1. Environment

The model's environment is initialized with geospatial data representing the boundaries of Fairfax County, Falls Church, and the City of Fairfax as well as the road networks in these jurisdictions. Fairfax County land use is also incorporated into the model during initialization. Both the jurisdictions and the road types can be turned on or off at initialization, affecting how the model's agents use those components for navigation in the model.

4.3.1.1.1. Jurisdiction Boundaries

Within the United States, the U.S. Census Bureau delineates regions as Metropolitan Statistical Areas (MSAs) (OMB, 2018), which largely ignore state borders to focus on incorporating the county and city jurisdictions within an urbanized area. Specifically, an MSA is defined as "at least one urbanized area of 50,000 or more population, plus adjacent territory that has a high degree of social and economic integration with the core as measured by commuting ties" (OMB, 2018: 2). Fairfax County, VA and surrounding counties and cities are included within the Washington, DC MSA (OMB, 2018: 74-75). Although not displayed in model, the jurisdictions in the Washington, DC MSA are used as the basis for this model in large part because an MSA is delineated based on "commuting ties" (OMB, 2018: 6) between jurisdictions.

The ABM in this thesis displays Fairfax County, VA as well as the City of Fairfax, VA and Falls Church, VA. These two cities are unique geographic oddities. The City of Fairfax is wholly contained within and surrounded by Fairfax County, but is a separate jurisdiction with a separate police force. Falls Church is similar, sharing all but one border with Fairfax County. Additionally, the towns of Vienna, VA and Herndon, VA are also geographically contained within Fairfax County, but unlike the City of Fairfax, they are considered a part of Fairfax County. Thus, a few geographical oddities complicate modeling Fairfax County and routing of agents through the model's street network without the inclusion of the City of Fairfax and Falls Church would become programmatically overly complicated. To circumvent these complications, the City of Fairfax and Falls Church have been included in the model and are defined by a white boundary line. Controls were added to turn each jurisdiction on and off for testing purposes (Figure 3), but all three jurisdictions were

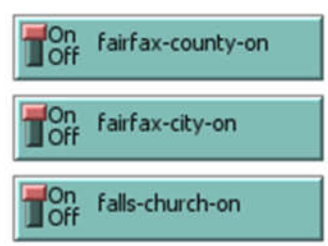

Figure 3: Jurisdiction switches

turned on for the analysis performed in this thesis because of the navigation problems that occur when not including roads that transit through these areas.

In Figure 4, the City of Fairfax (Figure 4, pink circle) and Falls Church (Figure 4, purple circle) are turned off to show the resulting gaps in the road network if these two jurisdictions were not included in the model.

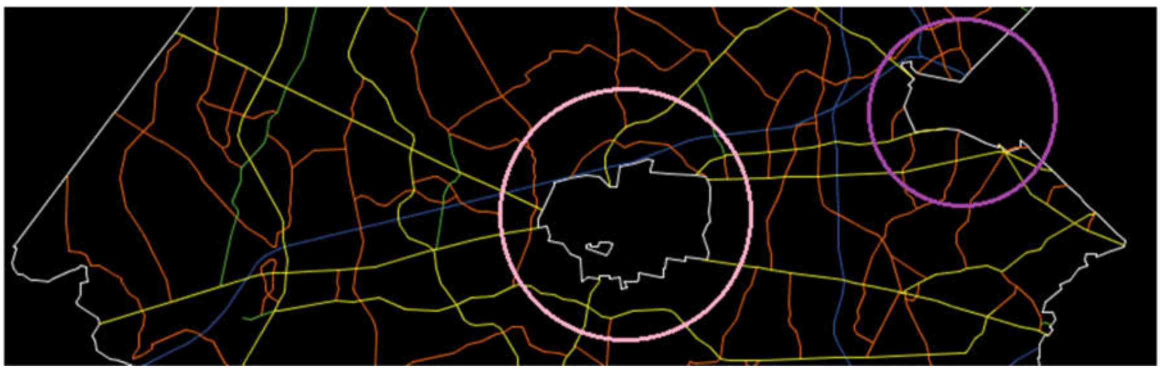

Figure 4: City of Fairfax and Falls Church turned off in the agent-based model.

4.3.1.1.2. Road Network

Figure 5: Road types and colors

Fairfax County defines and classifies five types of roads: interstates, primary, secondary, tertiary, and local. The road network in this model includes the interstates, primary, secondary, and tertiary roads (Figure 5) within Fairfax County, the City of Fairfax, and Falls Church (Fairfax County, VA, 2016). Due to the small scale of the representative map in this model, local roads (colloquially called "side streets") were not included in this model. This was done for the purpose of simplification both in viewing the model and of routing agents through the road network. Including local roads would have severely debilitated the model by radically increasing the load and run times. The four remaining road types were included, and the model's user was given the ability to turn each road type on and off (Figure 6) to analyze how offense locations would change if potential offenders only used certain road types to navigate. All four road types were turned on for the analysis performed in this thesis. In the model, interstates were represented by blue lines, primary roads by yellow lines, secondary roads by green lines, and tertiary roads by red lines. (These colors are entirely arbitrary and chosen purely for visual clarification.)

Figure 6: Road type switches

4.3.1.1.3. Land Use

Land use data from Fairfax County (Fairfax County, VA, 2018) was incorporated into this model to properly assign agents to residences and work locations. Although not displayed to the model's user, the land use data was added as a property to each cell (i.e. patch) during model initialization. The land use types provided by Fairfax County were reduced to basic land use types such as residential, commercial, and mixed use (see Section, 4.3.2, Input Data). Because this data was retrieved from Fairfax County, land use data for the City of Fairfax, Falls Church, Herndon, and Vienna were unavailable and not included with this model. This resulted in gaps of land use and precluded the ability to include these cities in the offender logic for committing offenses. Furthermore, offender agents were not able to be assigned to Herndon and Vienna for work or residence locations. This gap in land use data did not affect the ability to route agents through the road network of these cities, but may have affected resulted spatial offense patterns

4.3.1.2. Agents

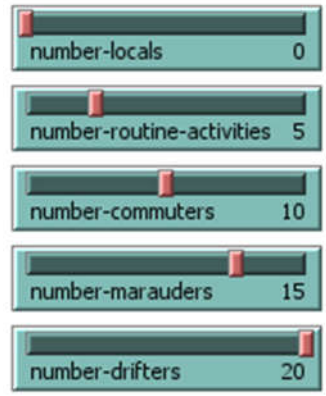

Figure 7: Offender agent sliders

To allow for easy representations of percentages, the model can be initialized with zero to twenty of each spatial type of offender (Figure 7). The model's user can model a single offender of a single offender type or twenty offenders each of all five offender types. This allows for analyzing the resulting offenses and anchor points from a single offender in a vacuum, but also the ability to analyze the resulting offenses and anchor points from a closer representation of offenders acting concurrently, but independently in a real-world environment. This provides the model's user with the ability to adjust the number of each offender type to determine what rate of offenders will result in a close representation of actual crime rates and locations. For the analysis performed in this thesis, the model was run ten times with a single offender for each spatial type, resulting in fifty sets of anchor points and offenses.

All offender agents are initialized with basic properties. Specifically, each offender is assigned a residence and work anchor point and a commute time for when to begin their residence to work commute. Properties related to offense locations are assigned throughout the running of the model and discussed in detail in Section 4.3.3, Submodels.

4.3.1.3. Representation of Time

Although largely a spatial model, temporal aspects were required to simulate an agent's typical day and to provide the model's user with a familiarity with the real world. Specifically, time of day is represented (Figure 8), but days are simply incremented with each day assumed to be a "work" day. (See Section 4.1.2.4, Time Representation).

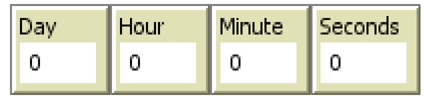

Figure 8: Representation of time

4.3.1.3.1. Representation of Days

This model provides the ability to set the numbers of days to be simulated (Figure 9). A single day in the life of the model's offenders includes the offender leaving their residence, commuting to work, working, and then commuting back to their residence where the offender remains until the next day's work commute. During each day, offenders will attempt to commit a criminal offense. The model is keyed towards all offenders successfully committing a crime during each day simulated. The purpose of this is to generate offense locations with the understanding that this may not accurately model an offender's rate of committing offenses. Thus, if the model is set to run for one day, each offender agent will likely commit one offense. If set to run for thirty days, each offender agent will likely commit thirty offenses. The exception to this is the marauder and drifter, as these offender types seek an offense to commit, but may not find a suitable target in the time allotted.

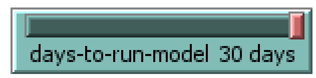

Figure 9: Slider to set the number of days for the model to simulate

4.3.1.3.2. Representation of Time of Day

As with days, time of day is represented in this model. The inclusion of time of day in this model creates a closer representation of the real-world and leads to next steps for analyzing the temporal aspects of spatial offender types. For the purposes of this thesis, the time of day aspect is used as a control designator and largely irrelevant to the analysis performed in this thesis as only the spatial aspect of offenses was analyzed.

4.3.2. Input Data

To model the routine behavior of offender agents, data was required to best model the real world. This data allowed for creating an ideal model based on known facts to help ensure that the criminal aspect of offender behavior was isolated for confidence in the resulting data.

4.3.2.1. Offender Anchor Points

The U.S. Census Bureau provides a set of data quantifying how many people commute to and from work, specifically including data on the origination and destination county or city (American Community Survey, 2013a). To fully understand the spatial behavior of criminal offenders, it is important to understand where people reside and work and the commute flows between these anchor points. To incorporate this into the model, the ability to set percentages of agents residing or working in Fairfax County, VA and surrounding counties and cities is crucial to accurately model how an offender transits through Fairfax County and where an offense would be committed.

The Washington, DC MSA data was extracted from the ACS data set and reviewed for commute flows that include Fairfax County or would result in an individual traveling through Fairfax County. For example: Prince William County is on the southern border of Fairfax County and Arlington County is on the north eastern border of Fairfax County. If an individual resides in Prince William and works in Arlington, then this individual must travel through Fairfax County to minimize their commute distance and time. Thus, commute flows from Prince William to Arlington were included in the extracted data. As a counter example, residences of Prince George's County in Maryland who work in Washington, DC would not realistically travel through Fairfax County on their work commute. These commute flows were removed from the data set. In some situations, travel through Fairfax County could be optional. For example, residents of Falls Church, VA who work in Montgomery County, MD could choose to travel through Fairfax County (west) or Washington, DC (east) for their work commute. In these situations, a weighted factor of 50% was assigned (they either do or they don't), thus half of these individuals were included, and half were not included in the extracted data.

The resulting data set was then stylized for use within the model (see Appendix A, Work Commuting Flow Data). Percentages were derived for both residence and work locations. These percentages resulted in the total number of individuals residing or working in a specific jurisdiction. Each jurisdiction was then calculated to determine its percentage of the total number of residents and workers. For example, the results showed that 13,812 residents of Washington, DC commuted to or through Fairfax County. For all jurisdictions, a total of 981,688 residents commuted to or through Fairfax County. Thus, Washington, DC includes a rounded 1% (13,812 divided by 981,688 equals 1.407%) of all residents in the model. The same method was used for work destinations.

In the example of Washington, DC, this resulted in 136,051 individuals who commuted from or through Fairfax County worked in Washington, DC out of the same total of 981,688 work commuters. Thus, Washington, DC was assigned a rounded 14% (136,051 divided by 981,688 equals 13.859%) of offenders in the model to work in Washington, DC.

When generating offenders, these percentages were used to assign residence and work locations to agents. Since most commuting to, from, and, through Fairfax County includes Fairfax County residents (59%) and Fairfax County workers (56%), when small numbers of offenders were generated (e.g. one offender), Fairfax County would invariably be both the residence and work location of the offenders generated. Logically, this makes sense as the model is centered around Fairfax County.

A set of sliders (Figure 10) was created for offender residences and work locations, each set including one slider for each jurisdiction in the central Washington, DC MSA. These sliders are initially set by the model to the percentages of work commuters based on the U.S. Census Bureau data (American Community Survey, 2013a). These sliders can be adjusted and are intended to be modified using data that specifically reflects the anchor points of known criminal offenders in Fairfax County. This can be done with arrest, charging, and/or conviction data to analyze varying results. The initial efforts in this thesis utilized the U.S. Census Bureau data of people at-large: both law-abiding citizens and criminal offenders. The next step is to analyze arrested records to produce stylized data of where individuals arrested by Fairfax County reside and work. Theoretically, this will move the model closer to a representation of reality by excluding law abiding citizens, but these efforts are currently beyond the scope of this thesis.

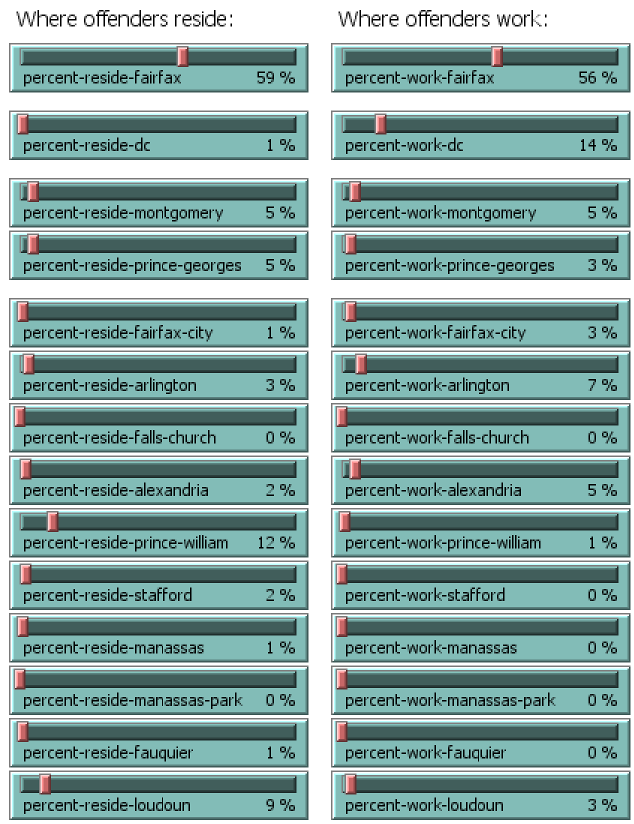

Figure 10: Offender residence and work location sliders

For this thesis, it was originally intended to use Fairfax County arrest records to model the residence locations of offenders within the model. When an individual is arrested by Fairfax County (as in most police jurisdictions), one of the points of information captured is the arrestee's residence address. This information is public record in Fairfax County and provided via the Fairfax County Police Department's website (Fairfax County Government, Virginia)[4]. This data can be imported and stylized into percentages of residence locations for use within the model. (Typically, the arrestee's work location is not captured.) Originally, it was the intent of this thesis to model both routine work commute flows as provided in the ACS data set for comparison against arrest records from Fairfax County, but time and scope constraints persisted, and

[4] Note that the FCPD website has since been updated and this data is now available in comma separated value format at a different address: https://www.fairfaxcounty.gov/police/downloadcenter.

this is now intended as a next step to move this model forward. But the model sliders allow for easy incorporation once stylized data about criminal offenders in Fairfax County can be gleaned from available data. (The same could also be accomplished with charged and convicted individuals for further analysis.)

4.3.2.2. Work Commute Times

Data on work commute times was used from the U.S. Census Bureau (American Community Survey, 2013b) that splits work commute times into blocks of time. These percentages were used to randomly assign the offenders generated by the model to a likely work commute time. This results in most work commuting occurring during traditional rush hour times, but also results in representing offenders who may have second or third shift employment. As with the sliders representing residence and work anchor points, sliders could be added to the model to allow for a better representation of when criminal offenders commute to and from work, but this is currently hard coded into the model.

The U.S. Census Bureau's American Community Survey (ACS) data includes data showing when work commuters leave home going to work (American Community Survey, 2013b) as not everyone conducts their commutes at the same time of day. The data for the Washington, DC MSA was extracted from the larger set of ACS data for review and the stylized data for commute times was used in the model as a percentage to assign work commute departure times. For example, the ACS shows that in the Washington, DC region, 3.8% of work commuters leave home between 12:00 am and 4:59 am. The model uses this data to ensure that 3.8% of offender agents also begin their work commute during this time range. Within each time range, a random time is given to the offenders. Thus, if 100 offenders are generated, three or four of those offenders are assigned to commute between 12:00 am and 4:59 am. Each of these offenders is assigned a random commute time within that range.

4.3.3. Submodels

This section discusses the implementation in the model of each spatial offender type as defined in Section 3.3, Spatial Classification of Criminal Offenders.

4.3.3.1. Local Offenders

Local offenders (see Section 3.3.4, Local Offender) commute between residence and work anchor points on regular schedules. While at either their residence or work location, a local offender will commit an offense at a random location within 1.5 miles of this anchor point. After committing this offense, the local offender will return to same anchor point from which they departed to commit the offense. The local offender will then remain at this anchor point until the time of their regular work commute. (Figure 12)

4.3.3.2. Commuter Offenders

Commuter offenders (see Section 3.3.1, Commuter Offender) travel between residence and work anchor points on a regular schedule. Not to be confused with traditional work commuters, while at either their residence or work location, a commuter offender will randomly pick a suitable target farther than 1.5 miles from their anchor point to travel to for the specific purpose of committing a criminal offense. (The offense location is random and, in the future, can be replaced by known commuter offender behavior characteristics, but at this time this behavior is largely unknown for this specific offender type.) This offender type will then commute to this suitable target and commit a criminal offense. After committing this offense, the commuter offender will return to the anchor point from which they departed prior to committing their offense. The commuter offender will then remain at this anchor point until the time of their regular work commute. (Figure 11)

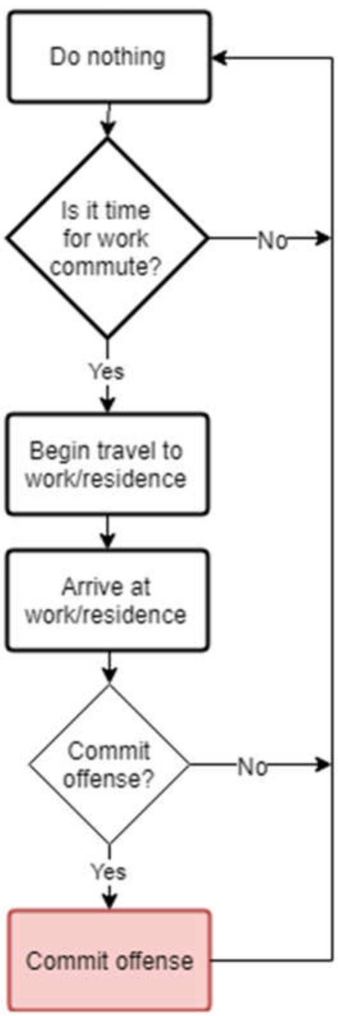

Figure 12: Local offenders decision tree

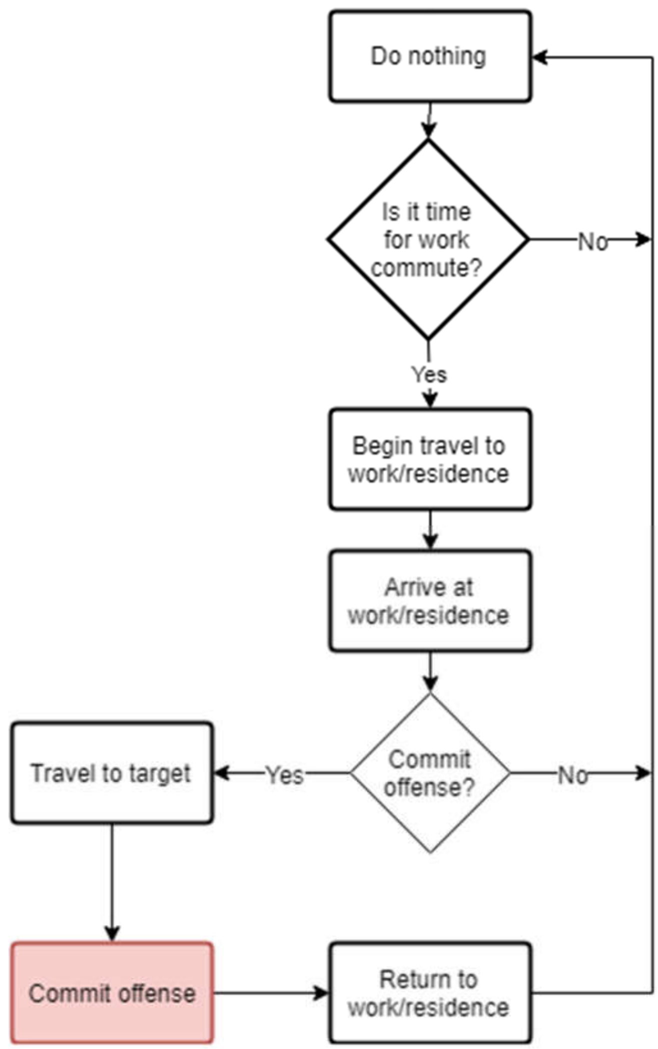

Figure 11: Commuter offenders decision tree

4.3.3.3. *Marauder Offenders*

Marauder offenders (see Section 3.3.2, Marauder Offender) commute between residence and work anchor points on a regular schedule. While at either their residence or work location, a marauder offender will leave their anchor point and travel in a random direction in search of a suitable target. The marauder continues this search until a random decision results in a crime being committed, or until such time when the marauder must return to their anchor point in order to conduct their regular work commute. (This "random decision" is a placeholder and in future research should be replaced with a marauder specific behavioral decision model for finding a suitable target.) The marauder then returns to the same anchor point from which they departed prior to searching for a

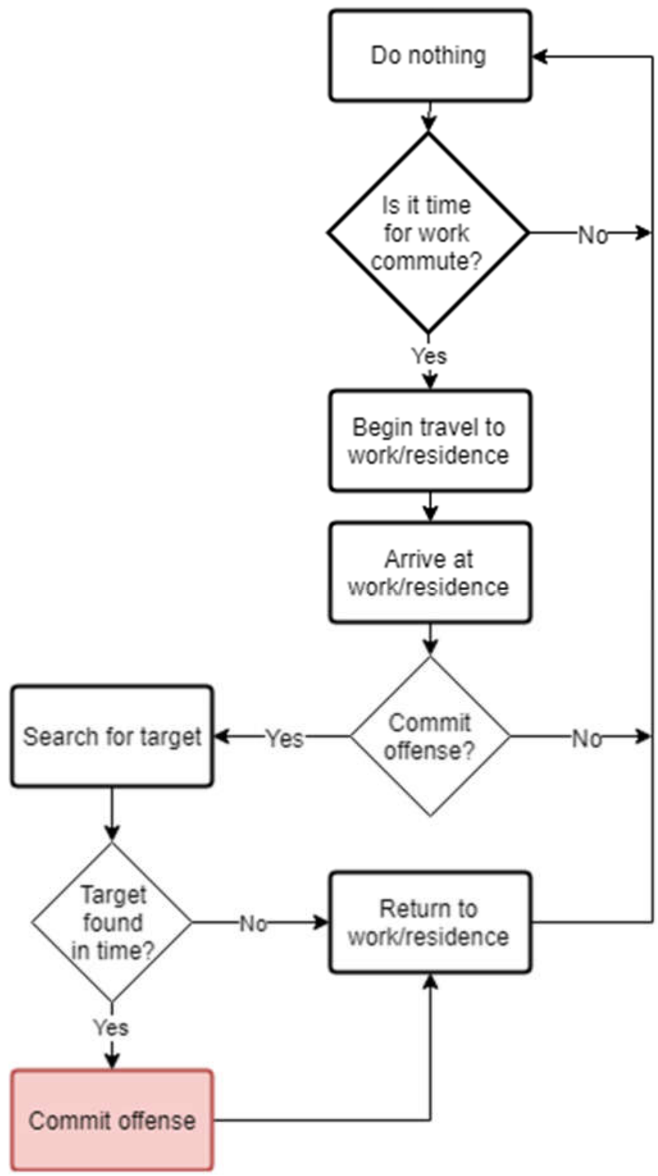

Figure 13: Marauder offender decision tree

suitable target. The marauder offender will then remain at this anchor point until the time of their regular work commute. (Figure 13)

4.3.3.4. Routine Activities Offenders

Routine activities offenders (see Section 3.3.3, Routine Activities Offender) commute between residence and work anchor points on a regular schedule. While at their residence and work locations, a routine activities offender does not commit a criminal offense but remains at the anchor point until the time of their regular work commute. During a routine activities offender's regular work commute, a random location within 1.5 miles of their work commute path is picked as a suitable target. (As this offender type is newly defined, there is no data showing how far this offender will travel from their work commute path to commit an offense. If this data were to become available, then this variable in the model would need to be adjusted.) This offender type

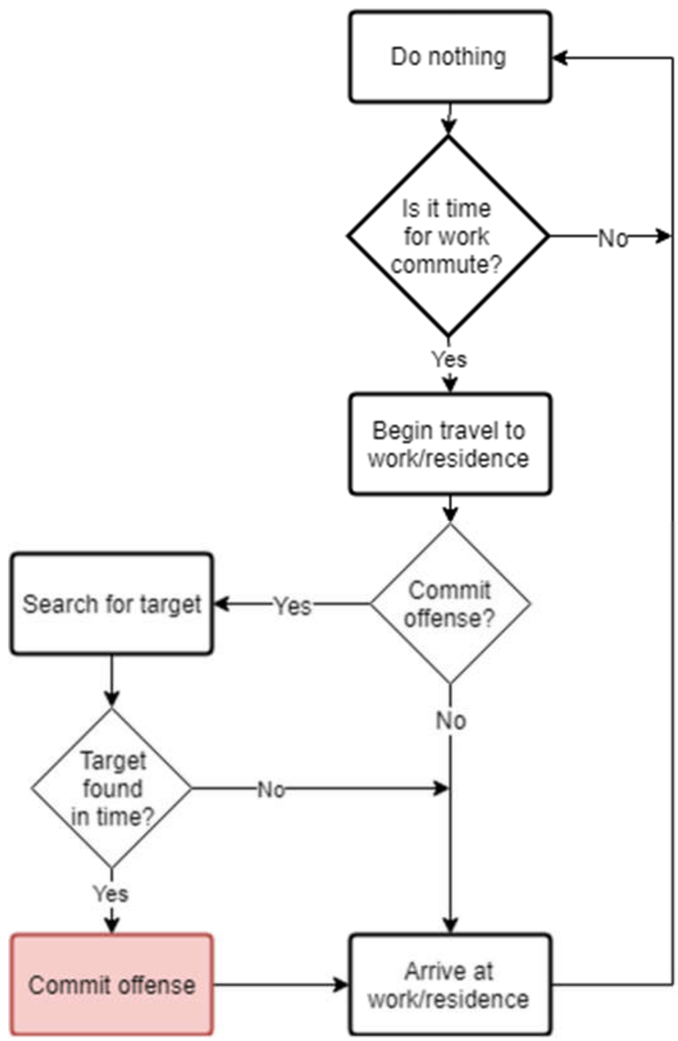

Figure 14: Routine activities offender decision tree

deviates from their routine work commute to this location to commit an offense. After the offense is committed, the routine activities offender continues along their normal work commute to their destination anchor point. (Figure 14)

4.3.3.5. Drifter Offenders

Drifter offenders (see Section 3.3.5, Drifter Offender) have no regular anchor points, thus don't have a regular work commute. Instead, the drifter offender is initially assigned a random starting location. The drifter offender remains at this location for a similar amount of time as other offenders remain at their residence or work locations. The drifter offender picks a random location and travels to that location. Once at the new location the drifter offender "decides" whether the location is a suitable target (i.e. checks if an offense has not been committed that day) and, if so, commits a criminal offense. If a criminal offense is committed, the drifter moves to another random location. Otherwise the drifter remains at the current location for an amount of time as done at the first location. The drifter continues in this fashion throughout the

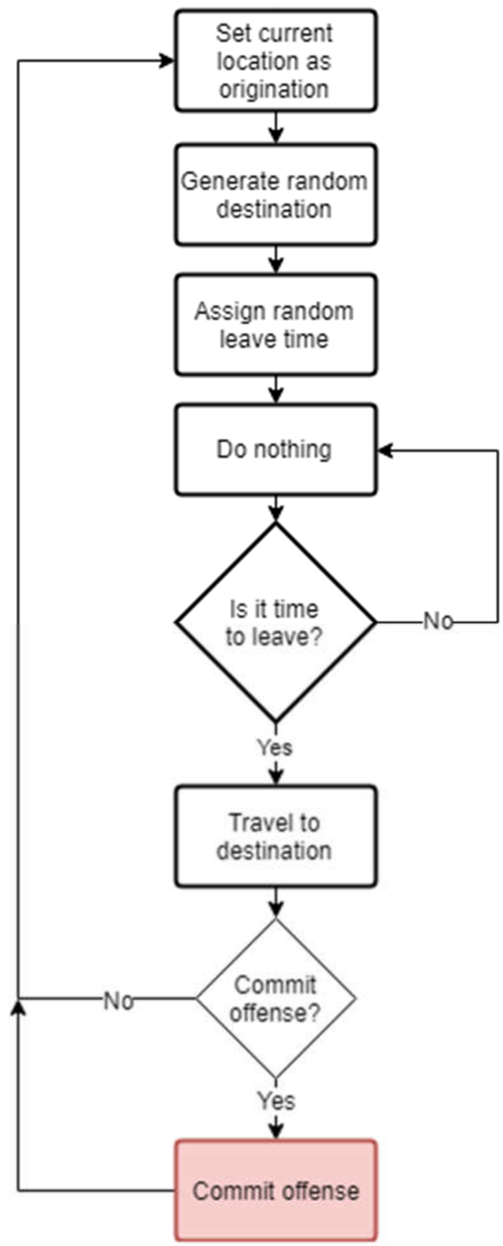

Figure 15: Drifter offender decision tree

running of the model picking new random locations for each movement, with no regard for anchor points or a local 1.5-mile radius. (Figure 15)

Drifter offenders have largely not been researched, thus no data is available for how and when they travel or the likelihood that they will commit offenses at any given location. Therefore, the use of eighteen hours or less at a single location and a fifty-fifty chance of committing offenses is randomly chosen for this model. Once further research provides data, then the model can be updated to better reflect reality. But these numbers were selected to result in offenses being committed by drifter offenders for the purpose of analyzing movement patterns. Additionally, drifter offenders in this model are bound to Fairfax County. Otherwise the modeling could result in drifters drifting infinite distances, thus losing the ability to analyze offenses committed with Fairfax County by this offender type.

4.3.4. Model Outputs

To conduct analysis of the model results, cells (i.e. patches) are turned different colors to represent different locations from each offender's actions. These cells can be exported into an ASCII file for importing into spatial analysis tools. (The colors used were selected for visual representation only and the color's resulting number representation in the ASCII has no specific meaning to the analysis except to differentiate between the different locations.)

4.3.4.1. Anchor Points

When offenders are generated at the beginning of the model, anchor points are assigned that remain the same for each offender throughout the running of the model. Residence anchor points for each offender generator are represented by a green cell (55 in the ASCII export) and work anchor points are represented by a blue cell (105 in the ASCII export). The exception is the drifter offender who does not have traditional anchor points (see Section 4.3.3.5, Drifter Offenders).

4.3.4.2. Offense Locations

When offenders commit an offense at a specific location, that location's cell is turned red (15 in the ASCII export). The choice of red is a cultural choice, because in Western society red typical represents something negative (versus green represents something positive) and generally people can agree that a criminal act is a bad thing to occur.

4.3.4.3. Results Export

After the model is run, the cell colors can be exported to an ASCII file. This results in all the cells being exported, not just the anchor points and offense locations. For analysis purpose, the black cells (nothing occurred here) can be discarded (0 in the ASCII export). The exported ASCII can then be imported into a spatial analysis tool and converted to x, y coordinates for analysis. In this thesis, this is done using the Esri suite of tools including ArcMap and ArcGIS Pro. Initially, some validation was done using QGIS to ensure that the exported ASCII file resulted in the same data across multiple spatial analysis tools.

4.3.4.4. Model Statistics

Displayed in the model are two graphs representing (1) crimes committed by offender type and (2) crimes committed by land use type (Figure 16). Included with these graphs are counters showing the same data, broken down by each offender type and

Figure 16: Model output graphs and statistics

land use type. These are representative of the current state of the model and largely used for testing purposes.

4.4. <u>Model Verification</u>

Although a basic model in principle, multiple facets were required to build this model. The finalized model is essentially a work commuting model with the addition of criminal aspects. Thus, the aspects of time, transportation, and criminal offense behavior all needed to be verified to ensure that the model behaved as intended.

4.4.1. Offender Agent Generation

This model can generate between zero and twenty offender agents of each of the five spatial offender types. Each iteration of zero through twenty for each offender type was tested. These tests successfully resulted in the expected offender types and the expected number of agents being generated.

4.4.2. Assignment of Anchor Points

Offender agents are assigned residence and work locations based on the percentages of where offenders reside and work across the various jurisdictions within the Washington, DC MSA. Additionally, offender residence and work anchor points were programmed to be assigned to appropriate land use types. The cells representing the residence and work anchor points were also turned green and blue, respectively.

The maximum number of offender agents were generated for each offender type and then the properties and location of each agent were checked to ensure that each agent resided in the expected jurisdiction and that the total percentages were the same as the actual percentages. This was done for both the residence and work anchor points. The land use types of these anchor points were then verified to ensure that residence and work locations were on representative land use locations. Each agent's assigned anchor points were then verified to the corresponding color cell to ensure proper assignment and proper color representation. Agents where then commanded to move directly to and from their residence and work anchor points to ensure proper assignment among all generated agents.

4.4.3. Building of Road Network

To represent travel throughout Fairfax County, geospatial data of the county's road network was simplified and imported into the model for display. The model generated agents representing road intersections throughout the county's road network to be used by offender agents navigating between anchor points and offense locations.

Once polyline shapefiles were imported into the model, the data was verified by visual comparison between the original data and the model's representation of the road network. Road segments were randomly selected and ensured that the segment's location in the model represented the segment's location in the original data as well as the segment's meta data (i.e. route number and road type).

Where road segments shared common points, intersections agents were generated to allow for offender agents to navigate turns through the model. The exception to this is where streets crossed interstates at bridges without interchanges. This was handled by ensuring that these segments crossed mid-segment and did not share common points that would be turned into intersections. The model's inter-connectivity was then verified by cross-checking with the original data to ensure a realistic representation of the Fairfax County road network. This was done manually by reviewing all road segments in the simplified data against the roads in the original data set. Due to the importance of offenders navigating through the model, a substantial amount of time was taken to manually verify the road network.

The road network connectivity of the model was verified to ensure that offender agents properly traveled throughout the model's road network. This was done with each road type individually and then with all road types operating in unison. Offender agents were generated with anchor points and individually followed as they navigated the road network between anchor points. The routes taken were then compared to routes recommended by navigation software (i.e. Google Maps) to ensure that the routes were relatively similar. At times it was found that agents would travel unexpected paths between anchor points. In all instances it was found that through the process of simplifying the original road data, road segments had become orphaned and were disconnected from the broader road network. A manual review of all road segments was conducted, and orphaned roads were removed, and disconnected road segments were reconnected to the network. Final testing resulted in expected agent navigation throughout the model.

4.4.4. Movement Along Road Network

To program movement of agents along an imported spatial road network, agents were told to follow a given path. Agents were generated and reviewed during navigation to ensure that the agent adhered to the road segments, adhered to the expected path of travel, moved through the network in a logical manner, and maintained consistent and realistic speeds expected of motor vehicle travel. Tests resulted in successful travel being residence and work locations using logical paths of travel.

4.4.5. Movement Between Anchor Points

Once generated and assigned anchor points, offender agents are assigned commute departure times based on U.S. Census Bureau worker commute data (American Community Survey, 2013b). This data was stylized to determine what percentage of commuters in the Washington, DC MSA began their work commutes at what time of day. Offender agents were then assigned a work commute time based on these percentages. Thus, 9.3% of workers started their commutes between 6:00 am and 6:29 am (American Community Survey, 2013b), 9.3% of offender agents (rounded) would be assigned a work commute start time between 6:00 am and 6:29 am. Offender agents were generated multiples times and the assigned work commute times were calculated to ensure that the percentages match as expected.

Single offender agents were generated with assigned anchor points. The model was executed, and the movement of each offender agent was followed to ensure that the agent moved along the road network toward the destination anchor point and destination offense location. It was also verified that once the offender agent reached the destination location that the offender agent stops and remained at this location until the assigned departure time. The travel time between anchor points and offense locations was calculated to ensure that this matched realistic travel times. (An average of 30-40 MPH was used as a rough estimate of realistic travel time throughout Fairfax County.)

4.4.6. Commission of Offenses

Once an offender reached a destination offense location, an offense must be committed and reflected in the model. This was done by turning the destination cell red in color and increasing the offense counters by one for both that specific offender type and for the total number of offenses committed. Single and multiple offender models were run, and messages were printed to the model's output to verify when an offense was committed within the model's code. This information was then compared to the number of red cells and the counters. This was largely verified, but in a few cases two offenses were committed in the same location, thus increasing the counters, but not resulting in an additional red cell on the model.

For each specific offender type tests were run with only those offender agents to verify that offenses were committed in expected locations based on the definition of that offender type.

4.4.6.1. Local Offenders

It was verified that local offenders (see Section 3.3.4, Local Offender) committed offenses within the local range of their anchor points and while at their anchor points outside of a work commute.

4.4.6.2. Commuter Offenders

Verification ensured that commuter offenders (see Section 3.3.1, Commuter Offender) were assigned a specific offense location, traveled to that location, committed an offense, and returned to their origination anchor point. It was also verified that this activity occurred outside of the offender's work commute.

4.4.6.3. Marauder Offenders

Marauder offenders (see Section 3.3.2, Marauder Offender) were verified to have a destination location assigned within the range parameters, traveled to that destination, and decided whether to commit an offense. It was verified that if an offense was committed, then the marauder returned to their origination anchor point and if not, then another destination within the parameters was assigned and traveled to, thus repeating the offense decision process. Lastly, the marauder offender was verified to return to the origination anchor point if an offense was not committed within a specified amount of time to ensure that the offender was at their anchor point in time to conduct their regularly scheduled work commute.

4.4.6.4. Routine Activities Offenders

These offenders were verified to decide on which leg of their commute to use for committing their daily offense (see Section 3.3.3, Routine Activities Offender). It was then verified that this specific leg of the work commute began routinely, but that the offender was assigned a target offense location. Verification then ensured that the offender traveled to the assigned offense location, committed an offense, and then continued traveling towards the original destination anchor point.

4.4.6.5. Drifter Offenders

It was verified that drifter offenders (see Section 3.3.5, Drifter Offender) were assigned random locations within Fairfax County, traveled to that location, made an offense decision, waited a specified period of time, and then repeated the process throughout the running of the model.

4.5. Model Execution

Once the model inputs are set and the model is run, a basic cycle happens. During each day represented in the model, offender agents start at their residence and wait until their assigned work commute time. At their assigned work commute time, the offender agent calculates an efficient commute path and begins traveling from their residence to their work. The offender agent arrives at work and remains there for a random time between six and ten hours. At the end of this time (i.e. the end of the workday), the offender agent calculates an efficient commute path and begins traveling back to their residence. When the offender agent arrives at their residence, they remain there until their assigned work commute time the next day. This process is repeated for each offender agent, for each day represented in the model and largely simulates the working commute flow of a law-abiding citizen.

Interjected into this routine, law abiding commute between residence and work is the criminal offense aspect of an offender's behavior. How, when, and where criminal offenses are interjected depends on the type of spatial offender.

4.5.1. Locals Offenders

Local offenders will commit offenses while at their residence or work, outside of their work commute. Which anchor point is chosen is determined randomly within the model, but parameters are set to help ensure that local offenders generally commit one offense per day the model is run. When the local offender commits an offense, a location within 1.5 miles of their current anchor point is chosen for the offense. The key is that the local offender commits offenses while at their anchor point, or relatively close in their anchor point's immediate neighborhood.

4.5.2. Commuter Offenders

While at their residence or work, commuter offenders will select a random location within the model and travel to that location in the same manner as they would commute to and from their residence or work. For example, a commuter offender will commute to work as expected, but then in the middle of the workday leave work, commit an offense at a specific location, return to work, finish the workday, and then conduct a routine commute to their residence. During each day represented in model, a new random location is selected for the commuter offender to travel to and commit an offense. This results in the commuter offender traveling to and from their residence and work, interjected with a travel to a random location to commit an offense.

4.5.3. Marauder Offenders

Like a commuter offender, the marauder offender interjects a journey-to-crime into their day while at their residence or work. The difference being that a marauder offender does not have a pre-determined location to commit an offense but travels randomly seeking a suitable target. While at either their residence or work, a marauder offender is randomly assigned a location greater than 1.5 miles from their current location (i.e. outside of local range), but within three miles of their current location. The marauder then travels to that location and has a 25% chance of committing an offense. If an offense is committed the marauder returns to their origination anchor point and remains until their next assigned work commute time. If an offense is not committed, then the marauder is assigned another random location between 1.5 and three miles away and travels to that location with another 25% chance of committing an offense. This process is repeated until the marauder commits an offense or needs to return to their anchor point to simulate regular work commuting behavior.

4.5.4. Routine Activities Offenders

This offender type differs from the previous offender types as it is the work commute path that determines the offense locations and not the anchor points. A routine activities offender will commit an offense while traveling either to work or their residence as a part of their work commute. The work or residence leg of the commute is selected at random in the model as no information is available as to which leg of the commute is more likely to result in this offender type committing an offense. The model picks a random location that is within 1.5 miles (local range) of a random intersection on their daily work commute path, if that intersection is not with local range of the offender's anchor points. This location then becomes the routine activities offender's initial destination for their work commute. This offender type travels to that location, commits an offense, and then resumes their work commute by traveling a direct path to their residence or work. The result is an offense being committed within local range of their commute path, but not within local range of their anchor points.

4.5.5. Drifter Offenders

Due to their unique nature, drifter offenders are modeled very differently from other offender types. Specifically, since drifters have no anchor points, there is no work commute to model. To fill this gap, drifter offenders are initially assigned a random start location in the model, equivalent to the residence location of other offender types. When the model is run, the drifter offender is assigned another random location within the model and travels to that location, equivalent to the work location of other offender types. The drifter offender then remains at that location for a random time up to eighteen hours and is then assigned another random location to which the offender travels. This is repeated throughout the running of the model. At each location, the drifter offender is given a 50% chance of committing an offense (they either do or don't).

4.6. <u>Model Validation</u>

Validation is a key challenge in agent-based model development and thus it is important to compare model output with real-world statistics or at least acknowledge that the model is theoretical (Crooks, et. al, 2008). For agent-based model validation, models are split into four definitions based on two parameters: whether the agents and environment are designed (i.e. theoretical/abstract) or analyzed (i.e. empirical) (Parker, et al, 2002). Additionally, models can be assigned one of four levels classifying the model performance and analysis showing whether there is qualitative or quantitative agreement with macro- or micro-structures (Axtel & Epstein, 1994). This section classifies this model using these frameworks and then articulates the validation for the model.

4.6.1. Designed Agents

The agents in this model represent a new, largely theoretical (i.e. designed), spatial classification of offender that is based on a scattered collection of research literature. This literature is being brought together for the first time in this thesis, thus the agents in this model are designed to operate in the pre-existing environment of road networks, land use designations, and jurisdictional boundaries. These agents are representative of behavior, but this behavior is abstract (i.e. designed) and will remain so until these theoretical concepts can be review, tested, and confirmed by further research. As a result, the only validation of the agents that occurred in this initial effort is ensuring that the agent behavior functions as designed based on the proposed definitions. Next steps include moving these agents from designed to analyzed. Improved validation would include moving from ACS data on traditional commute flows and times to crime and arrest data that can be used to calibrate the model parameters and produce criminal offenses that more closely represent known crime locations and statistics.

4.6.2. Analyzed Environment

The environment used in this model is a representation of the real-world location of Fairfax County, VA and surrounding jurisdictions (i.e. analyzed). This was done by using geospatial data for the jurisdictional boundaries, road network, and land use. (Figure 17 shows side-by-side comparison of the model's road network with Google Maps and OpenStreetMap.) Additional data was used to create a real-world representation for where the model's agents reside and work, thus creating a representation of actual work commute flows. A temporal aspect was added to further model the timing of real-world work commutes. This resulted in the model's agent being intricately linked with real geospatial data and work commuting flow locations for residences and work. This real-world representation was validated through model runs to ensure that commute flows generated were representative of the ACS work commute

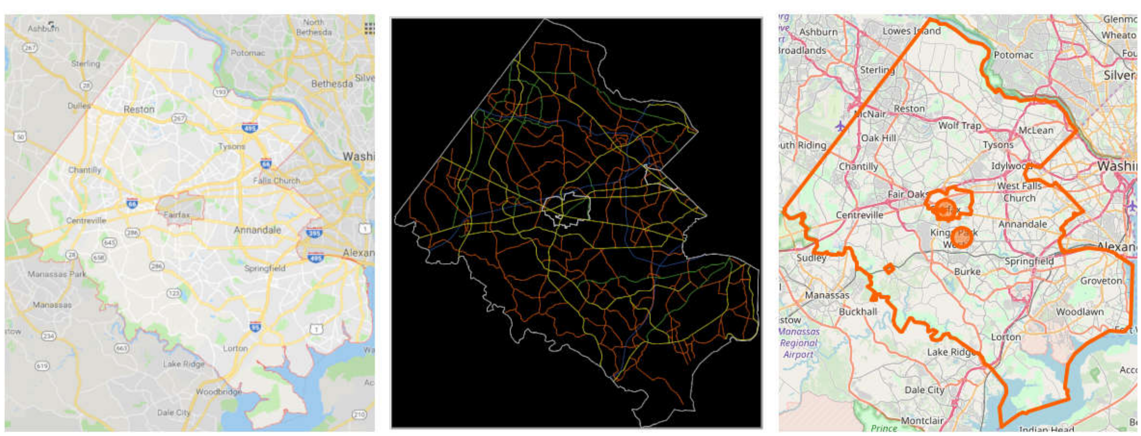

Figure 17: Comparisons of Google Maps, the model, and OpenStreetMap

flow and time data and that the geospatial components were representative of the real-world.

This real-world representation was created to offset the designed aspect of the agent's behavior with the intent of producing criminal offense locations that can be validated against actual crime statistics in future work.

4.6.3. Agreement with Empirical Structures

There are some aspects of this model that can be classified as Level 1 as these aspects are in qualitative agreement with empirical macro-structures (Axtel & Epstein, 1994: 28). Specifically, the flow of criminal offenders through commuting and offending behaviors are in qualitative agreement with the empirical macro-structures of the Fairfax County environment. This agreement is more in-line with the designed nature of the agents and is rooted in the theory developed for spatially classifying offender types. Other aspects of this model can be classified as Level 2 as these agent properties are in quantitative agreement with empirical macro-structures (Axtel & Epstein, 1994: 28). The use of commuter flow data to model the residence and work locations of offender agents creates this quantitative agreement with actual commuters within the empirical macro-structures of the Fairfax County environment.

5. OBJECTIVE 3 – ANALYSIS OF ABM RESULTS

The third objective of this thesis is to conduct spatial analysis on the ABM results to move towards a method of classifying spatial offender types from a series of offenses. This is possible through the export of emergent offense locations (see Section 4.3.4, Model Outputs) to be imported into a traditional spatial analysis tool.

Previous analysis of commuter and marauder offenders looked at a limited number of offense types (Kocsis & Irwin, 1997; Meany, 2004) and had utilized conviction records as the foundation set of data (Paulsen, 2007). Further research has shown that all offense types should be used in analysis of commuter and marauder offender types (Paulsen, 2007; Leitner & Kent, 2009) and that not all crimes committed result in clear convictions (Paulsen, 2007). Thus, this analysis will look at all theoretical offenses committed in a single police jurisdiction based on ABM output, instead of conviction records. This approach across all crime types will provide new insight into the extent and spatial patterns of commuting and marauding offenders, as well as other spatial offender types.

After the model was completed, spatial data incorporated, stylized data assembled, and the model was verified, offense data from different spatial offender types could be produced for analysis.

5.1. Running the Model

The following setup was conducted individually for each offender type. A single offender of one spatial offender type was generated and the model was set to start at midnight and run for thirty days. This captured up to thirty committed offenses from a single offender, for the best possible spatial analysis. Understanding that this may not reflect an offender's realistic crime patterns, the intent was to capture the spatial aspect of offense locations without regard to the true temporal aspect of committing offenses.

With these parameters set, the model was initiated (see Figure 18). This resulted in a residence location being set, the model cell turned green and a work location being set, the model cell turned blue. The offender agent was then placed at the residence cell. An ASCII file was exported to capture the offender's anchor points separately from their eventual offense locations. (This was done for all offender types, except for drifters, as the initial anchor points were only starting points for the first day and were changed each day to model a drifter offender's defined behavior of no fixed anchor point.)

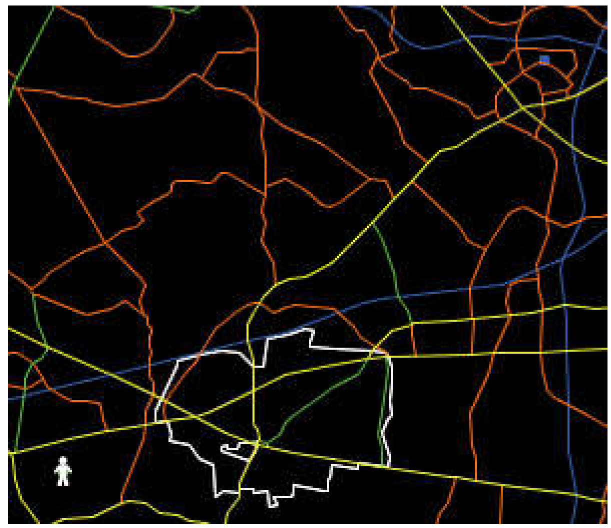

Figure 18: Initial model setup with offender and work anchor point (blue cell in upper right corner) visible

Next, the model was run, resulting in a single offender of a specific spatial type committing up to thirty offenses per the behavioral definition of that offender type (Figure 19). The resulting offense locations were exported to an ASCII file that converts the color of each cell in the model to a number. Lastly, the model was reset for the next running, which reset all cell colors and removed the offender agent from the model. (Technically, agents are "killed" in an agent-based model, but since this is a crime model using that term seems insensitive.)

Figure 19: Model after local offender commits offenses (red cells in upper right and lower left corners)

This same process was conducted ten times for each spatial offender type. This produced 100 exported ASCII files: two for each running of the model (one for the anchor points and one for the offense locations), and twenty for each spatial offender type. Each of these files were imported into spatial analysis software (i.e. ArcGIS Pro version 2.3.x) and the ASCII data converted to real world geographic coordinates (Figure 20). This import and conversion allowed for the application of Circle Theory (Canter & Larkin, 1993) analysis (see Section 5.2, Circle Theory Analysis) and to use spatial analysis to work towards classifying a set of offenses to a spatial offender type (see Section 5.3, Spatially Classifying a Set of Offenses).

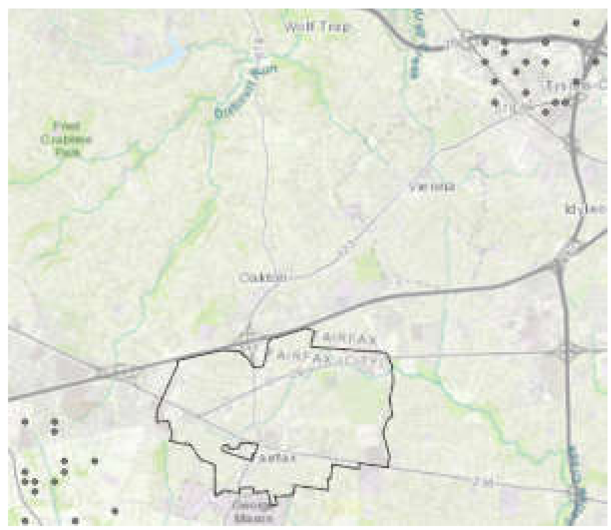

Figure 20: Offenses imported into ArcGIS Pro

5.2. Circle Theory Analysis

Currently, the predominate spatial offender theory is Circle Theory: the separation of offenders into commuters and marauders (Canter & Larking, 1993: 65, Canter & Gregory, 1994: 171) (see Section 2.6, Commuters vs. Marauders). By incorporating additional literature, this thesis expanded the types of spatial offenders by adding locals, routine activities, and drifters to Circle Theory's commuters and marauders (see 3.3 Spatial Classification of Criminal Offenders). Thus, the first analysis step is to use Circle Theory to determine how the model results from all five spatial offender types would be classified by conventional methods.

5.2.1. Separating Offenses into Clusters

Because the model uses two anchor points as an offender's potential starting point for committing offenses, it is reasonable to think that two distinct clusters of offenses would be created. One cluster associated with the residence anchor point and one cluster with the work anchor point. Additionally, spatial offender literature argues that offense locations are distributed around anchor points (Canter et al., 2000: 458; Bernasco, 2010). This lends towards the use of density-based clustering analysis to look at a series of offenses and divide these offenses into groups, each of which would theoretically be attributed to one of an offender's anchor points.

To separate a full series of offenses into two groups, the density-based clustering tool in ArcGIS Pro version 2.3.x was used with the inputs listed in Table 1.

Option	Setting
Input Point Features	Data set from each ASCII export of offenses
Output Features	Desired file location
Clustering Method	DBSCAN
Minimum Features Per Cluster	3
Search Distance	4 miles (initially)

Table 1: Density-based clustering settings

The DBSCAN method was used to control the search distance of the clustering algorithm. The minimum of 3 features (i.e. offenses) was selected, because this is the minimum number of results in a cluster needed to conduct other analysis, such as standard deviations (see Section 5.3.2, Applying Mean Center and Standard Distance Analysis).[5] The initial search distance of 4 miles was used because this is the shortest distance between an offender's residence and work anchor points with a gap between offense ranges, if the offender were a local offender. (Remembering that locals in this model were program to offend with 1.5 miles of their anchor point. See 4.3.3.1 Local Offenders). If the initial clustering results did not produce two clusters then the search distance was incremented by a quarter mile until at least two clusters were produced. The intent here was to produce the densest two clusters possible for the given series of

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[5] The author fully acknowledges that the choice of 3 features is a line in the sand to start the spatial analysis. After reviewing some results with disparate cluster sizes, it might be worth researching the validity of this setting.

offenses. For some sets of offenses outlier offenses existed and/or a third cluster was unavoidable.

5.2.2. Applying Circle Theory

The application of Circle Theory (Canter & Larkin, 1993: 65, Canter & Gregory, 1994: 171) to the model results was conducted within the spatial analysis software ArcGIS Pro version 2.3.x (Figure 21). No known tools existed to automate Circle Theory analysis, thus the following manual steps were conducted for each series of offenses conducted by a single model running:

1. Using the Measure Distance tool, find the two farthest apart offenses.
2. Using the Create tool, draw a line with the above two offenses as end points.
3. Using the Vertices tool, add a vertex at the midpoint of the line.
4. Using the Create tool, draw circle with the center point at the midpoint of the line and the radius to one of the end points of the line.
5. Determine which anchor points are inside and outside of the drawn circle.

These steps were conducted three times for each series of offenses.

1. For all offenses in the series (Figure 21).
2. For the largest cluster of offenses in the series (i.e. cluster 1) (Figure 22).

3. For the second largest cluster of offenses in the series (i.e. cluster 2) (Figure 22).

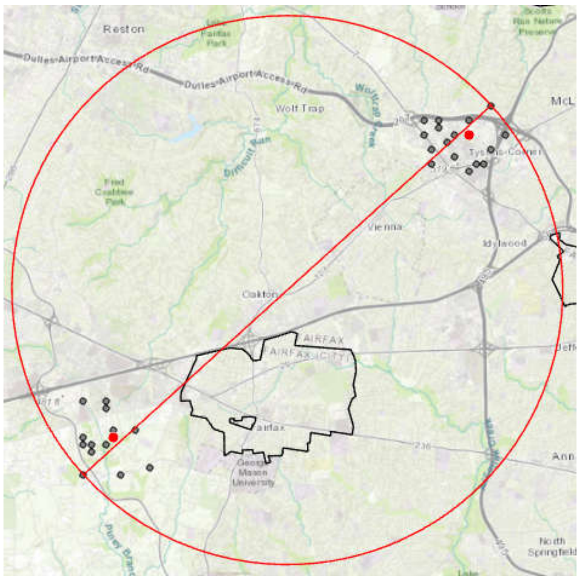

Figure 21: Circle Theory analysis of all offenses

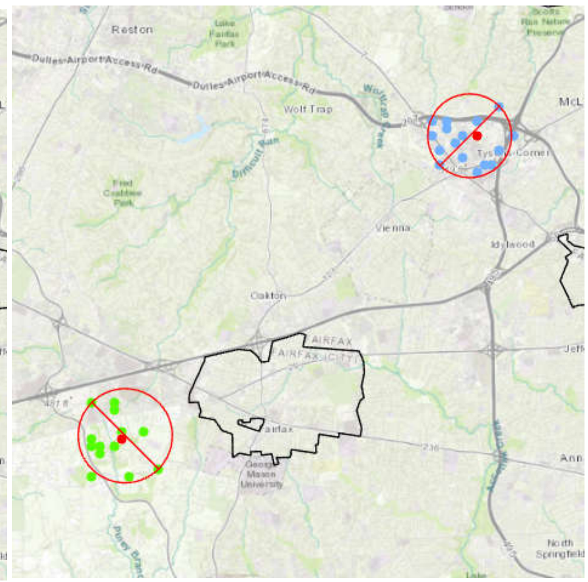

Figure 22: Circle Theory analysis of clustered offenses

5.2.3. Classifying Circle Theory Results

When applying Circle Theory to a set of offenses, only two results are possible: commuter or marauder (Canter & Larkin, 1993: 65). The results in Table 2 show how the modeled offenders would be classified with this approach. (Note: drifters were not included in this analysis because anchor points are required. Thus, any Circle Theory analysis applied to a set of offenses committed by a drifter would be inherently flawed and inaccurate.)

Offender Type	Anchor Point	All Offenses	Cluster 1	Cluster 2
Commuter	Residence	Commuter: 0 Marauder: 10	Commuter: 3 Marauder: 7	Commuter: 8 Marauder: 2
	Work	Commuter: 0 Marauder: 10	Commuter: 5 Marauder: 5	Commuter: 7 Marauder: 3
Marauder	Residence	Commuter: 0 Marauder: 10	Commuter: 3 Marauder: 7	Commuter: 8 Marauder: 2
	Work	Commuter: 1 Marauder: 9	Commuter: 7 Marauder: 3	Commuter: 8 Marauder: 2
Routine Activities	Residence	Commuter: 5 Marauder: 5	Commuter: 9 Marauder: 1	Commuter: 9 Marauder: 1
	Work	Commuter: 7 Marauder: 3	Commuter: 9 Marauder: 0	Commuter: 9 Marauder: 1
Locals	Residence	Commuter: 0 Marauder: 10	Commuter: 4 Marauder: 6	Commuter: 7 Marauder: 3
	Work	Commuter: 0 Marauder: 10	Commuter: 7 Marauder: 3	Commuter: 3 Marauder: 7

Table 2: Circle Theory analysis results

Analyzing an entire series of offenses as one group shows that Circle Theory fails to properly distinguish between commuter and marauder offenders (Table 3). Both commuters and marauders were classified as marauders, with one exception (Figure 23).[6] Local offenders were also classified as marauders, but this would be expected as local

Offender Type	Circle Theory classification results
Commuters	All classified as marauders
Marauders	Largely classified as marauders
Routine Activities	Evenly split between commuters and marauders
Locals	All classified as marauders
Drifter	No anchor – cannot be classified by Circle Theory

Table 3: Single anchor point Circle Theory classification results

[6] Reviewing this one exception, the failure to classify as a marauder was because the anchor was on the border of Fairfax County, thus all known offenses were committed in one cardinal direction. If offenses were analyzed without regard to jurisdictional lines, then it would be reasonable to assume the resulting analysis of this one set would be the same as the other sets.

offenders exhibit the same behavior as marauders only with a limited offending range. Routine activities offenders were almost evenly split as classified between marauders (8 anchor points) and commuters (12 anchor points), being the only offender type to not be primarily classified as marauders.

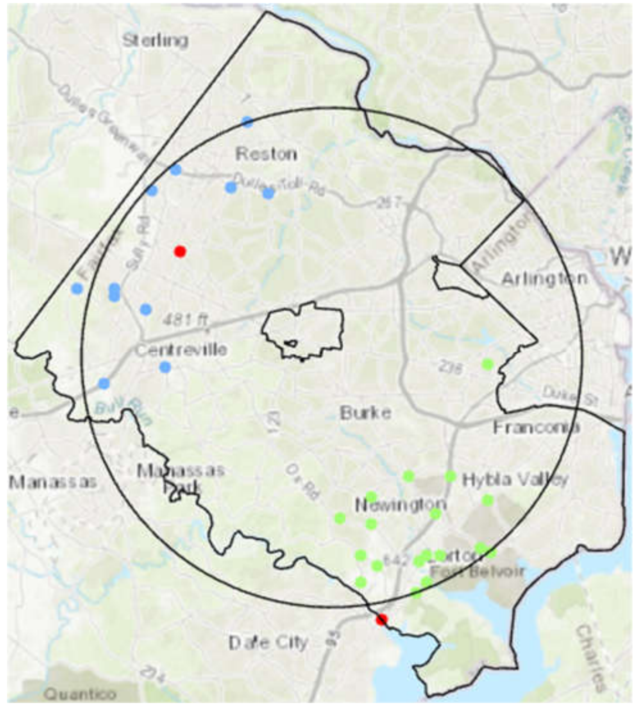

Figure 23: Marauder Series 8 (Circle Theory – All Offenses)

Analyzing a series of offenses based on clustering is a little more complicated than analyzing the series as one group. If density-based clustering produces two distinct clusters each attributed to an anchor point, then a marauder to the first anchor point would be a commuter to the second anchor point. Thus, if cluster 1 is a marauder to the residence anchor point, cluster 2 must be a commuter to the residence anchor point. Conversely, cluster 1 would be a commuter to the work anchor point and cluster 2 would be marauder to the work anchor point. This should hold true for marauders and locals, but not to commuters and routine activities. For commuters, it is possible for the clusters to be any combination of commuter or marauder to either anchor point but should not be evenly split as with marauders. With routine activities, since all offenses are theoretically in between the two anchor points, then Circle Theory should show both clusters as commuters to both anchor points. Most of the results support this theory (Table 4), but there's enough error to make this theory unreliable.

Offender Type	Circle Theory Classification Results
Commuters	9 out of 10 exhibited expected commuter results 1 out of 10 did not exhibit expected commuter results
Marauders	6 out of 10 exhibited expected marauder results 4 out of 10 did not exhibit expected marauder results
Routine Activities	7 out of 10 exhibited expected routine activities results 3 out of 10 did not exhibit expected routine activities results
Locals	9 out of 10 exhibited expected locals results 1 out of 10 did not exhibit expected locals results
Drifters	No anchor point – cannot be classified by Circle Theory

Table 4: Dual anchor point Circle Theory classification results

Analyzing a series of offenses based on clustering, or considering two anchor points, resulted in most commuters being classified as commuters, with one series of offenses being classified as a marauder. These results are expected as commuters can exhibit any combination of commuter/marauder behavior to any anchor point. The concern is when a commuter exhibits marauder behavior, using only traditional Circle Theory analysis, it cannot be determined if the results are true marauder behavior or coincidental commuter behavior.

Two specific sets of behavior were noticed in the four series of offenses that did not exhibit expected marauder analysis results. In one of the series (Marauder Series 8, Figure 24), one of the two anchor points was near (less than one-tenth of a mile) the Fairfax County jurisdictional border. This resulted in offenses clustered near that anchor point being skewed into the county and away from the anchor point. This series provide a clear example of one of the flaws in Circle Theory when utilized in a real-world environment: the need for cross-jurisdictional data to show a full series of offenses.

For the other three series of offenses that did not exhibit expected marauder analysis results, all three (Marauder Series 2, 7, and 9; Figure 25, Figure 26, and Figure 27, respectively) did exhibit diameter ratios between the two resulting circles of .50 or less (0.32, 0.19, and 0.50, respectively). Additionally, two of these series (2 and 9) also exhibited circles with overlapping borders. In the six series that exhibited expected

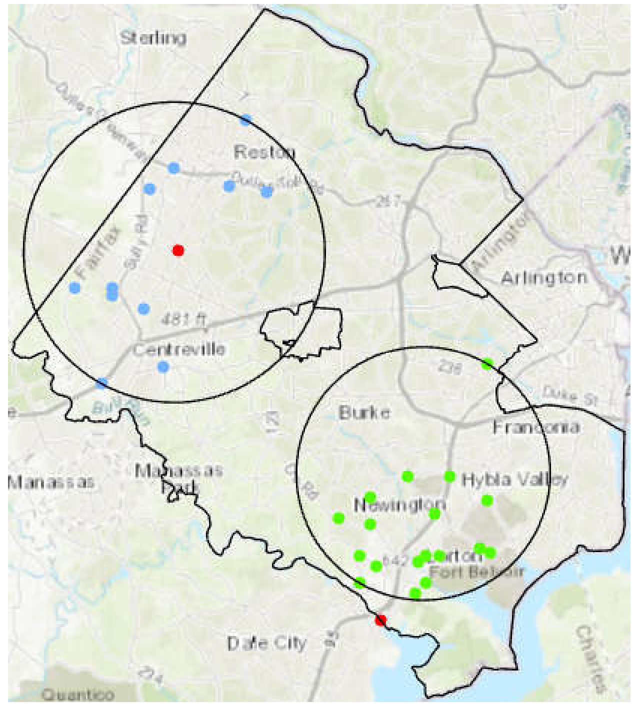

Figure 24: Marauder Series 8 (Circle Theory – Clustered)

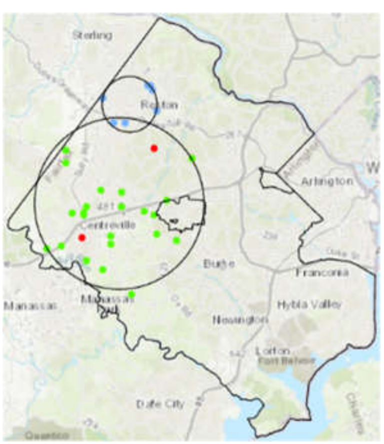

Figure 25: Marauder Series 2

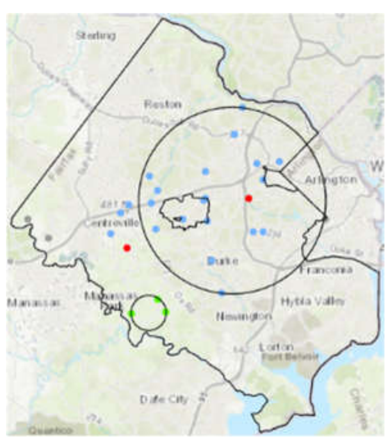

Figure 26: Marauder Series 7

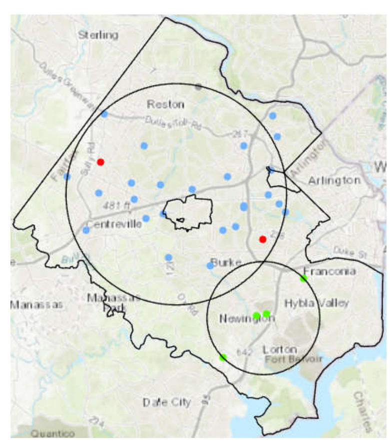

Figure 27: Marauder Series 9

marauder results (and in Marauder Series 8, Figure 24), all circles had ratios greater than 0.50 and none of the circles overlapped. Although not conclusive by analyzing only ten series of offenses, these observations indicate that other characteristics resulting from Circle Theory may be pertinent to the classification of spatial offender types. These observations also highlight the need for a clustering technique that accurately attributes offenses to the correct anchor point for analysis.

All three series of offenses (Routine Activities Series 2, 7, and 10; Figure 28, Figure 29, and Figure 30, respectively) that did not exhibit expected routine activities analysis results, appear to be a result of indirect travel routes between anchor points when compared to the Fairfax County road network.

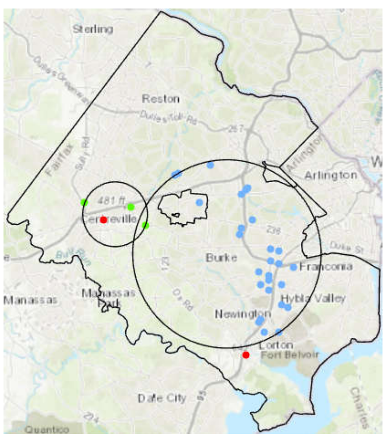

Figure 28: Routine Activities Series 2

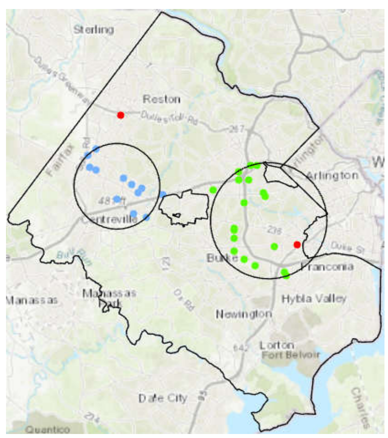

Figure 29: Routine Activities Series 7

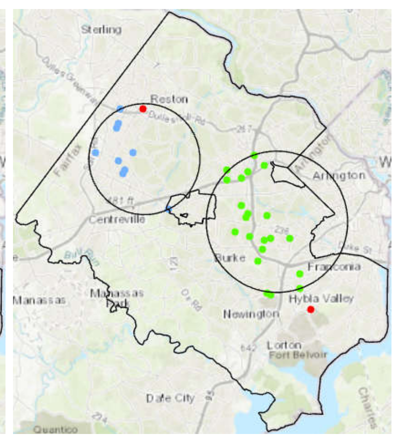

Figure 30: Routine Activities Series 10

For example, the anchor points in Routine Activities Series 2 are on a direct southeast, northwest line, but optimal travel from the residence anchor point in the southeast requires interstate travel in a northeast direction before traveling north and finally due west to reach the work anchor point. In Routine Activities Series 7 (Figure 29), optimal travel from the residence anchor point requires interstate travel to the southwest even though the work anchor point is to the northwest. Routine Activities Series 10 (Figure 30) is similar to Routine Activities Series 7 (Figure 29) in that the optimal route requires the offender to travel west even though the work anchor point is to the southeast.

These real-world oddities in travel result in non-expected results when using Circle Theory to analyze a series of offenses. Direct optimal travel routes existed between residence and work anchor points for the seven series of offenses that exhibited expected routine activities analysis results. Optimal travel can be indirect as the crow flies, thus resulting in offenses that are not in "expected" locations. This analysis demonstrates that consideration of the jurisdiction's specific road network is necessary when classifying a spatial offender type based on a series of offenses.

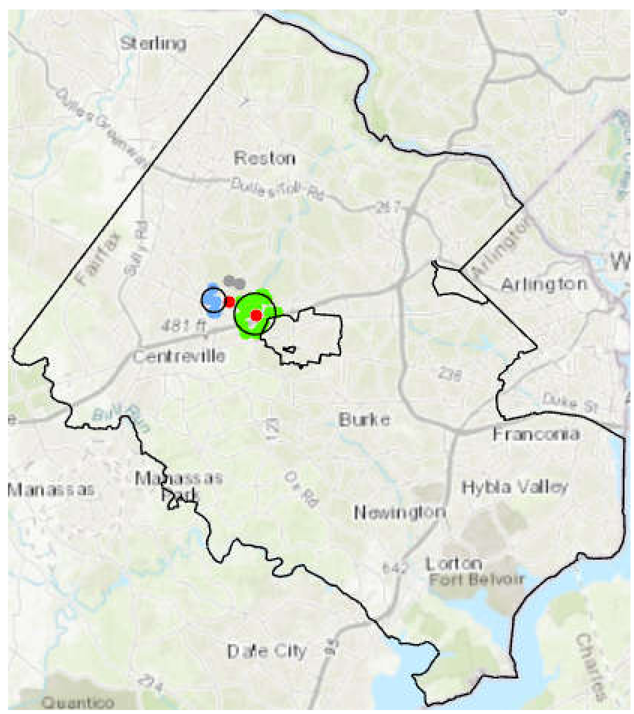

Figure 31: Local Series 8

The single series of offenses (Local Series 8, Figure 31) that did not exhibit expected local analysis results was due to the residence and work anchor points being less than 1.5 miles apart. This resulted in the two anchor points being in the same neighborhood, thus failing to create two distinct clusters of offenses for two different neighborhoods. A review of the model code shows that this potential result in generating two anchor points was not considered. In future work, the model should ensure that anchor points are not generated within local range of each other. The remaining nine series of offenses all support the expected local analysis results.

Although drifters have no anchor points and cannot be classified by Circle Theory, this analysis can be conducted on the series of drifter offenses. After clustering the offenses and drawing circles per Circle Theory, it is not possible to determine whether the non-existent anchor points were within the circles, but it is possible to note the diameter ratio of the circles and whether the circles overlapped. This observation showed that in two of the offense series the circles had a diameter ratio of 0.50 or less (Drifter Series 5 and 8; example in Figure 34), in six of the offense series the circles overlapped (Drifter Series 1, 4, 6, 7, 9, and 10; example in Figure 32), and in the remaining two of the offense series both observations occurred (Drifter Series 2 and 3;

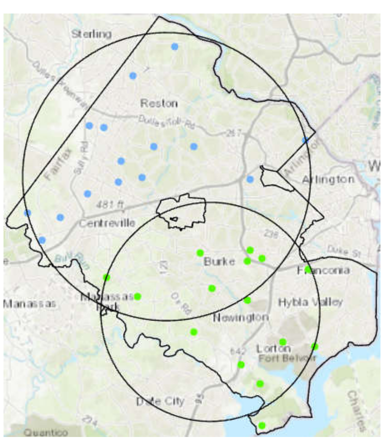

Figure 32: Drifter Series 1

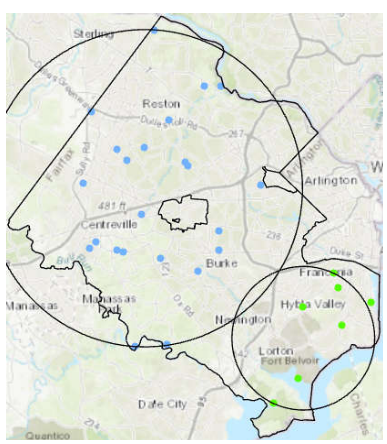

Figure 33: Drifter Series 2

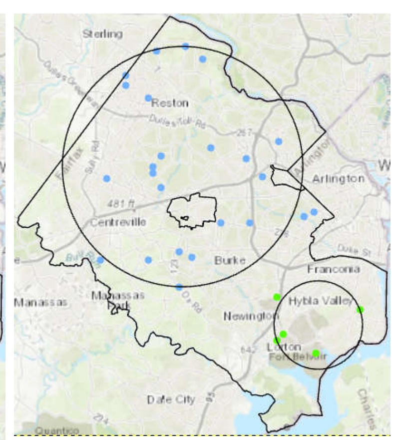

Figure 34: Drifter Series 8

example in Figure 33). The observations of the marauder series indicating that diameter ratios of 0.50 or less or of overlapping circles could indicate that spatial problems also hold true for the series of drifter offenses. In all ten series of drifter offenses one of these two observations held true. As suggested in the analysis of marauders and locals, observations of other characteristics resulting from Circle Theory may be pertinent to the classification of spatial offender types.

5.2.4. Additional Circle Theory Analysis

As indicated in the above analysis of marauders, locals, and drifters, characteristics resulting from Circle Theory may be useful when used with clustering and for multiple anchor points (Table 5).

Offender Type	Observed Patterns
Commuters	All circles overlap or have disparate ratios
Marauders	Incorrectly classified series have overlapping circles or disparate ratios
Routine Activities	Only one circle overlapped; ratios equally likely to be close or disparate
Locals	No circle overlap, all circle ratios are close
Drifters	All circles overlap or have disparate ratios

Table 5: Observed patterns in Circle Theory analysis

Initial observations show that the spatial offender types that commit offenses independent of geography (commuters and drifters) all have overlapping circles or disparate diameter ratios. The correctly classified spatial offender types that make offense decisions geographically (marauders, routine activities, and locals) largely have non-overlapping circles and similar sized circle diameters. Although these observations are interesting, further work with a larger number of series of offenses would be necessary to fully understand these characteristics and the relationship with each type of spatial offender.

5.2.5. Circle Theory Analysis Conclusion

Based on the above analysis, Circle Theory does not reliably distinguish between commuters and marauders but may have value in distinguishing routine activities offenders from all other spatial offender types. An analysis of the spatial relationships between circles created using Circle Theory on clustered offenses may have potential for distinguishing between spatial offender types, but a larger study would need to be conducted before making any definitive conclusions.

As shown by the resulting patterns of routine activities, local, and drifter offender types, there are clear differences in the resulting offense patterns. These differences show that additional spatial offender types exist beyond commuters and marauders. As these offense types are not consider in Circle Theory, applying this theory to a series of offenses is fundamentally flawed in its current state.

Another fundamental flaw is that Circle Theory can only be used if the offender's anchor point is known. Once an anchor point is known, Circle Theory classifies an offender as either a commuter or a marauder. Even if Circle Theory were to be used with the expanded spatial offender types, the theory is only applicable if an offender's anchor point is known. Once the offender's anchor point is known, then the analysis becomes largely moot as the offender can already be found and arrested for their offenses. Knowing the spatial offender type after an arrest may be helpful in attributing additional crimes to a series but serves no purpose in locating an offender.

5.3. Spatially Classifying a Set of Offenses

Circle Theory was found to be unable to successfully classify spatial offender types but was found to show that there are differences between spatial offender types and that potential problems in a series of offenses could be identified that could hinder classification into spatial offender types. Further, Circle Theory is not able to classify a spatial offender type, even in the theory's original form, without knowing the anchor point in advance. This identifies a need to develop spatial analysis that can classify a spatial offender type and to narrow a search area for the anchor point of an offender responsible for a set of offenses. This section begins this needed effort.

5.3.1. Applying Nearest Neighbor Analysis

Nearest neighbor analysis takes a set of features (i.e. offense locations) and calculates the nearest to each feature's nearest neighboring feature. If the average of these distances is less than a hypothetical random distribution, then the features are clustered. If the average is greater than the hypothetical random distribution, then the features are dispersed. If the average distance is as expected, then the features are random (ArcGIS Pro Tool Reference, 2018a).

Based on the proposed definitions in Section 3.3, Spatial Classification of Criminal Offenders, offenses from a local offender should be clustered within the local range of an anchor point. Marauders and routine activities offenders should exhibit either clustered patterns greater than a local range or random patterns contained to specific areas. Commuters and drifters may exhibit any, or no, spatial pattern, but are less likely to be clustered. Therefore, nearest neighbor analysis should help separate local offenders from other spatial offender types by observing which series of offenses are clustered.

The nearest neighbor tool in ArcGIS Pro version 2.3.x was used with the settings listed in Table 6.

Option	**Setting**
Input Feature Class	Data set from each ASCII export of offenses
Distance Method	Euclidean
Generate Report	Checked

Table 6: Nearest neighbor settings

Running nearest neighbor analysis on each series of offenses showed whether the series of offenses was random, dispersed, or clustered (Table 7). This classification resulted in observed patterns within the series of offenses for each spatial offender type (Table 8). These results support the theory that offender types with non-spatial decisions will not be clustered, but other spatial types are also not clustered, thus this spatial analysis test alone is not enough to classify a spatial offender type.

Offender Type	Nearest Neighbor Results
Commuter	Clustered: 0 Dispersed: 5 Random: 5
Marauder	Clustered: 1 (series 3) Dispersed: 1 (series 9) Random: 8
Routine Activities	Clustered: 2 (series 2 and 7) Dispersed: 1 (series 1) Random: 7
Locals	Clustered: 8 Dispersed: 0 Random: 2 (series 5 and 8)
Drifters	Clustered: 0 Dispersed: 2 (series 1 and 5) Random: 8

Note: For nearest neighbor ratios, z-scores, and p-values see Appendix B, Nearest Neighbor Analysis Results.

Table 7: Nearest neighbor analysis results

Offender Type	Observed Patterns
Commuters	Largely not clustered, split between random and dispersed
Marauders	Largely random
Routine Activities	Largely random
Locals	Largely clustered
Drifters	Largely not clustered, largely random

Table 8: Observed patterns in nearest neighbor analysis

5.3.2. Applying Mean Center and Standard Distance Analysis

As with the above Circle Theory analysis (see Section 5.2, Circle Theory Analysis), further attempts to use spatial analysis to classify an offender type required separating a series of offenses into groups (i.e. clusters) that would theoretically be attributed to a specific anchor point. Thus, the same density-based clustering was applied to the series of offenses.

Mean center analysis identifies the geographic center of a set of features (ArcGIS Pro Tool Reference, 2018b). Standard distance analysis measures to what degree that set of features are concentrated about the mean center (ArcGIS Pro Tool Reference, 2018c). These two analyses combined provide the standard distance from which all features in a set are distributed from the mean center of that feature set.

Based on the proposed definition (see Section 3.3.4, Local Offender), a series of local offenses should have a standard distance to the mean center of less than one mile. All other spatial offender types should have a standard distance of greater than one mile. Assuming an offender does not exhibit different offense types from different anchor points, this should be true for all clusters within a series of offenses. Thus, if this analysis shows a standard distance of less than one mile around the mean center, then the feature set would likely be the result of a local offender (see Table 9).

Offender Type	**Standard Distance**
Commuter	Less than 1 mile: 1 (series 3) Anchors inside: 9
Marauder	Less than 1 mile: 0 Anchors inside: 15
Routine Activities	Less than 1 mile: 2 (series 1 and 3) Anchors inside: 1
Local	Less than 1 mile: 20 Anchors inside: 19
Drifter	Less than 1 mile: 0 Anchors inside: no anchors
Note: For full measures of distances see Appendix C, Standard Distance Measurements.	

Table 9: Standard distance analysis results

5.3.3. Spatial Analysis Observations

After conducting nearest neighbor analysis and determining the mean center and standard distance of each cluster of offenses within each series of offenses, observations were made. These observations included noting for each offender type how many series were clustered, dispersed, and random, how many standard distances were within one mile of the mean center, and how many anchor points were found within the standard distance (See Table 10).

Offender Type	Num of Series Clustered	Num of Series Dispersed	Num of Series Random	Num of Mean Centers Less Than 1 Mile from Standard Distance	Num of Anchors Within Standard Distance
Commuters	0 out of 10	5 out of 10	5 out of 10	1 out of 20	9 out of 20
Marauders	1 out of 10	1 out of 10	8 out of 10	0 out of 20	15 out of 20
Routine Activities	2 out of 10	1 out of 10	7 out of 10	2 out of 20	1 out of 20
Locals	8 out of 10	0 out of 10	2 out of 10	20 out of 20	19 out of 20
Drifters	0 out of 10	2 out of 10	8 out of 10	0 out of 20	N/A

Table 10: Spatial Analysis Observations

As expected, commuter offenders were not clustered and nineteen out of twenty standard distance measurements were greater than one mile. In one series (Commuter Series 3, Figure 35) the standard distance for the other cluster in the series was greater than one mile. This observation separates commuting offenders from the expected behavior of local offenders. Additionally, roughly half (45%) of commuting offender anchor points were found to exist within a standard distance circle. This confirms the proposed definition (see Section 3.3.1, Commuter Offender) that commuters do not make offense decisions spatially and thus can exhibit any spatial pattern of offenses.

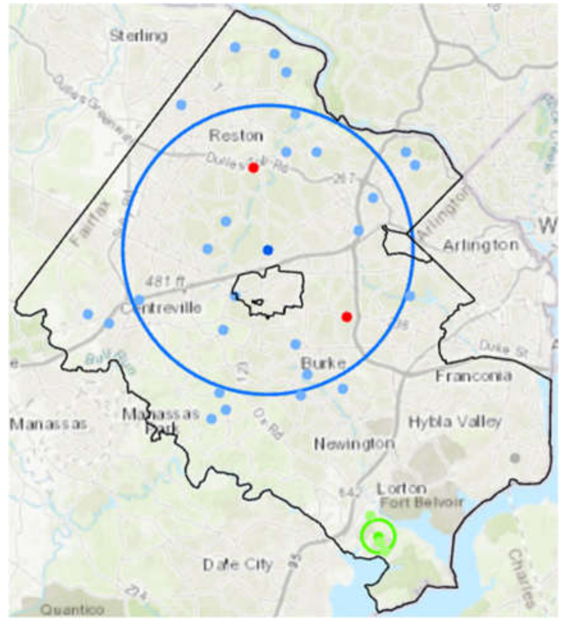

Figure 35: Commuter Series 3

Marauder series of offenses were largely found to be distributed randomly, with two exceptions. The single clustered series (Marauder Series 3, Figure 36) included an anchor point that was positioned near the Fairfax County border, as observed in Marauder Series 8 during the Circle Theory analysis (see Section 5.2.3, Classifying Circle Theory Results). The series that was dispersed (Marauder Series 9, Figure 37) was identified as not exhibiting expected marauder analysis results as described in Section 5.2.3, Classifying Circle Theory Results. Despite these two divergences from expected nearest neighbor analysis, all marauder series of

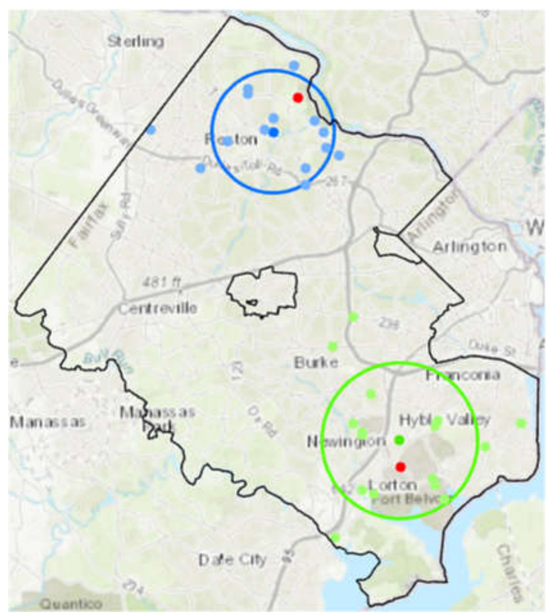

Figure 36: Marauder Series 3

offenses produced the expected result of standard distances being greater than one mile from the mean center. Thus, even in the clustered result, the radius of the standard distance successfully separated all marauder series from the expected results of a local offender. Of the series that did not include an anchor point within the standard distance (Marauder Series 2, 7, 8, and 9, Figure 38, Figure 39, Figure 40, and Figure 37, respectively) all four series were identified during Circle Theory analysis as not exhibiting expected marauder analysis results (see Section 5.2.3, Classifying Circle Theory Results).

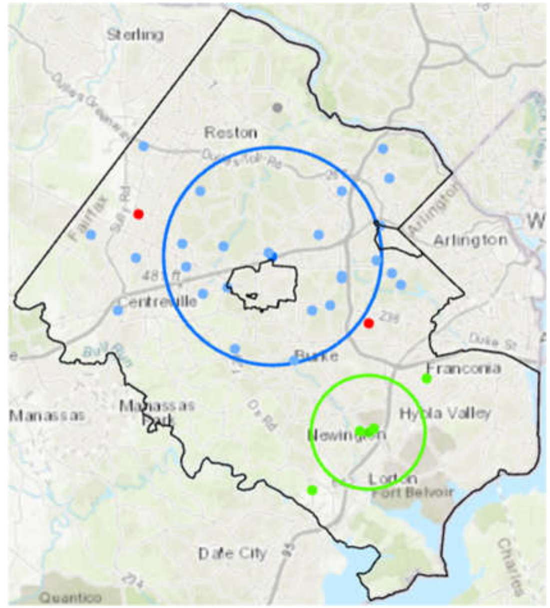

Figure 37: Marauder Series 9

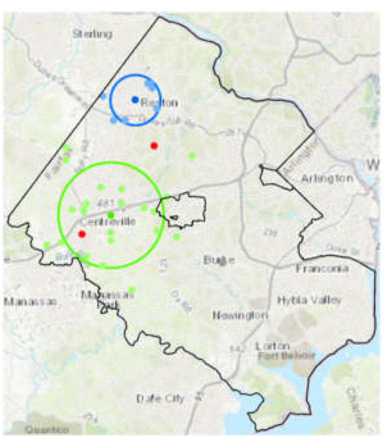
Figure 38: Marauder Series 2

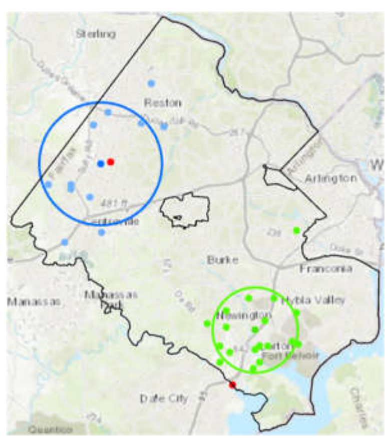
Figure 39: Marauder Series 7

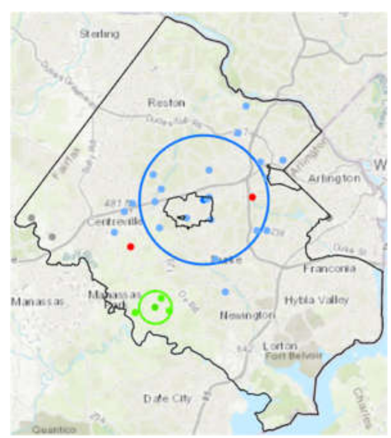
Figure 40: Marauder Series 8

Most routine activities series of offenses were found to be distributed randomly. The two series (Routine Activities Series 2 and 7, Figure 42 and Figure 43, respectively) that were found to be clustered were previously identified during Circle Theory analysis as not exhibiting expected routine activities analysis results due to the indirect route required to travel between residence and work anchor points. The single series (Routine Activities Series 1, Figure 41) found to have a dispersed distribution was previously found to exhibit expected routine activities behavior, but also shows an indirect travel route. But, of the two series that were clustered, neither had standard distances less than one mile. Neither of the two series with standard distances less than one mile were found to have clustered distributions. Thus, all routine activities series of offenses were successfully separated from the expected results of a local offender. The single series (Routine Activities Series 2, Figure 42) found to have an anchor point with the standard distance was previous identified as not exhibiting expected routine activities behavior (see Section 5.2.3, Classifying Circle Theory Results).

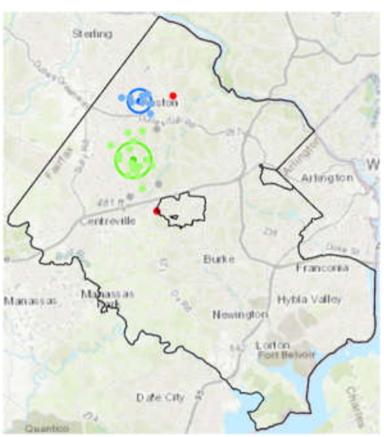

Figure 41: Routine Activities Series 1

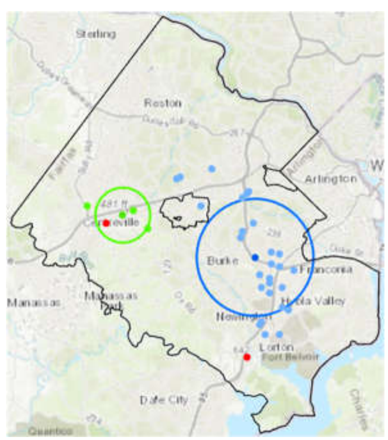

Figure 42: Routine Activities Series 2

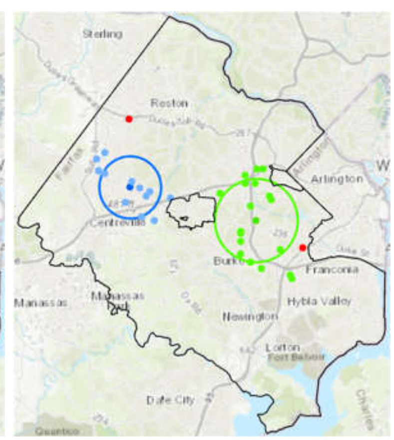

Figure 43: Routine Activities Series 7

Local offenders were found to be largely clustered. The two exceptions (Local Series 5 and 8, Figure 44 and Figure 45) were found to be random. Of these two, one series (Local Series 8, Figure 45) was previously identified (see Section 5.2.3, Classifying Circle Theory Results) as not exhibiting local offender behavior. Both anchor points of the second of the two (Local Series 5, Figure 44) had both anchor points within one mile of a jurisdictional border, thus potential exhibiting the same problems as other series of offenses close to borders (e.g. Marauder Series 8, Figure 40). Even with the two series distributed randomly, all means centers were less than one mile from the standard distance. This indicates that the standard distance to mean center measurement, rather than the distribution of offenses, is the key spatial analysis for classifying a local offender. Additionally,

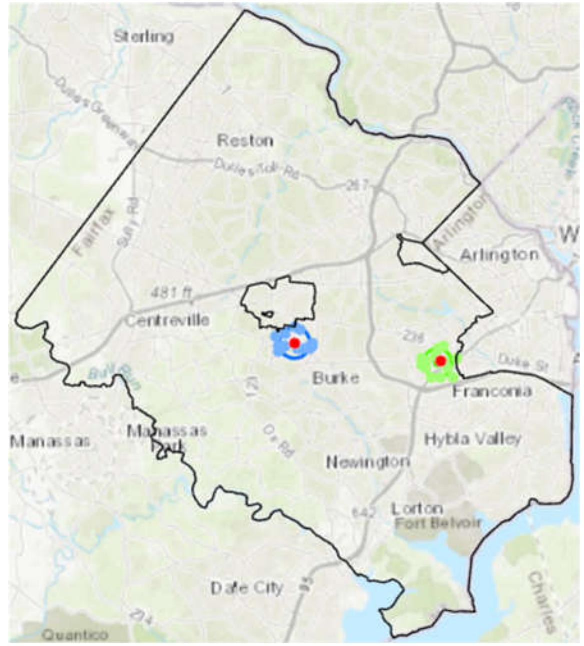

Figure 44: Local Series 5

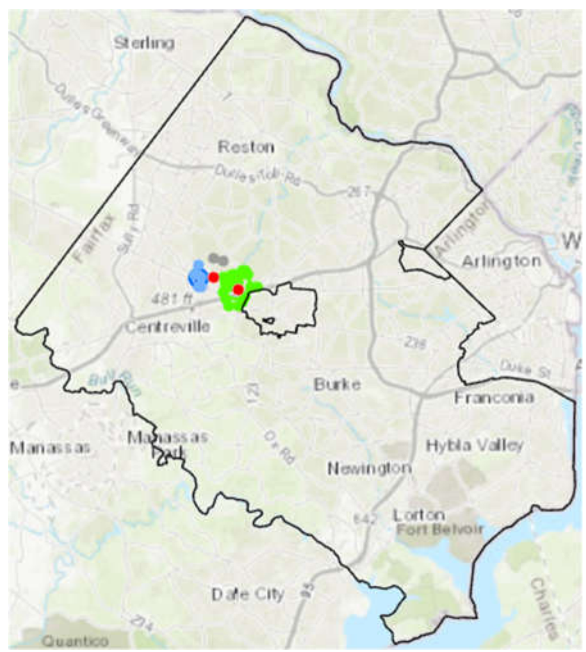

Figure 45: Local Series 8

all but one anchor point (Local Series 8, Figure 45) were found to be within the standard distance. This indicates that the standard distance may be a successful method of determining a search area for a local offender's anchor point. (More than twenty series of offenses should be analyzed before formally making this conclusion.)

With the drifter series of offenses, the distribution of two of the series were found to be dispersed and the remaining eight series were random. Since drifter offenders do not make decisions spatially, any spatial pattern could result. But practically speaking, it makes sense that the spatial pattern would not be clustered. Supporting this, all twenty mean centers were found to be greater than one mile from the standard distance. Thus, all drifter series of offenses were successfully separated from the expected behavior of local offenders. As drifters have no anchor points, no analysis could be conducted on whether anchor points were successfully found to be within the standard distance.

5.3.4. Spatial Analysis Results

Although not complete, this analysis represents the beginnings of creating a spatial analysis decision tree for classifying a series of offenses to a spatial offender type. This analysis successfully showed that a combination of spatial analysis methods can classify a series of offenses to a spatial offender type. Specifically, the combination of density-based clustering, nearest neighbor, mean center, and standard distance can classify a series of offenses as belonging to a local offender type and not belonging to the other spatial types of offenders. Furthermore, it was found that for local offenders, the resulting standard distance can identify a search area that includes a local offender's anchor point. Further work needs to be conducted to apply these results to more than twenty series of offenses conducted by local offenders to further validate this conclusion. Additionally, further analysis of the results needs to be conducted to find additional patterns that can classifying the remaining four spatial offender types and to lead to additional spatial analysis to assist in building a complete classification decision tree of spatial offender types.

5.4. Analysis Results / Conclusions

5.4.1. Ability to Spatially Classify Serial Offenders

Although fundamentally flawed in its current stated, Circle Theory (or a future iteration of the theory) may still have validity in classifying different types of spatial offenders. As highlighted above, when using Circle Theory to analyze a series of offenses committed from multiple anchor points, the relationship between resulting circles may provide insight into which offender type committed the series of offenses. Initial observations noted that overlapping circles and the ratio between circle diameters may have insight into the appropriate spatial offender type. Further analysis would need to be conducted for definitive results, but the initial results appear promising.

As acknowledged by Canter and Larkin in their initial paper, Circle Theory "makes no allowances for variations in local topography, transport routes, and so on" (Canter & Larkin, 1993: 66). This analysis verified this statement, especially with the results from Marauder Series 8 and Routine Activities Series 2, 7, and 10. These results demonstrated the need to pursue expanded spatial analysis techniques (e.g. clustering, nearest neighbor, route analysis) to analyze the resulting series of offenses from the agent-based model developed in this thesis. With the expanded definitions of spatial offender types, this agent-based model, and improved spatial analysis techniques, it should be possible to spatially classify offenders from a series of offenses.

5.4.2. Better Idea of Methods for Locating Serial Offenders

By successfully classifying a serial offender to a spatial offender type, serial offenders can be divided into spatial and non-spatial decision-making behavior. With this division, spatial analysis can be properly conducted on serial offenders who use space as a decision method for committing offenses. This analysis can be further developed into successful techniques for narrowing down potential locations of the offender's anchor points, thus assisting in narrowing down potential suspects for further traditional investigation. Additionally, the division between spatial and non-spatial decision makers can help to ensure that geographic profiling is not conducted when space has no affect over a serial offender's selection of offense locations. This would help to ensure valuable time and investigative resources are not used inappropriately, and traditional, non-spatial police investigative techniques are properly applied when identifying serial offenders.

6. FUTURE WORK / WHAT'S NEXT?

Canter described Circle Theory as "a starting point" (1994: 143). This thesis moves the literature past this "starting point" by updating foundation terms in geographic profiling, expanding spatial offender types beyond commuters and marauders, and using agent-based modeling and spatial analysis to support this expanded spatial classification of offenders.

As shown in this thesis, agent-based modeling can greatly assist in the develop of geographic profiling concepts and theories. With the use of realistic geographic backdrops and modeling crime at-large, the emerging offense locations of serial offenders can provide insight into patterns to assist in spatial analysis and spatial classification of offenders. To counter the argument that agent-based modeling is cyclic logic, it is the logic that is theoretical until the theory can be demonstrated in real-world situations. Does what we expect to happen actually happen in reality? Since it is not possible to conduct these experiments on living criminals and victims, modeling can fill this need and assist in developing the foundation theories of geographic profiling and spatially classifying offenders. Ultimately, this will move geographic profiling to become a common investigative tool and eventually to the point of crime prevention. But there is still more work to be done before these spatial offender types can be utilized in real-world serial offender analysis and investigations.

6.1. Categorizing Serial Offenders into Spatial Offender Types

The first major next step is to develop a decision tree for categorizing spatial offender types. This decision tree would utilize spatial analysis techniques on a series of offenses to separate and categorizing a series into the proper spatial offender type. For example, clustering a series of offenses and then analyzing the randomness of each cluster could potential separate commuters and drifters (non-spatial decision making) from marauder, routine activities, and locals (spatial decision making). From there, the distance between offenses and the spread of offenses from a central point could separate marauders from locals. The clustering of offenses along transportation routes could further help to classify routine activities offenders.

With a proven decision tree for classifying spatial offender types, the results would assist in building a geographic profile of a serial offender. This piece of a geographic profile could then feed into other existing geographic profiling techniques to help better determine approximate locations of offender anchor points. These efforts would ultimately assist in narrowing down potential suspect lists and identifying offenders for further investigation.

6.2. Historical Serial Offenses as Test Cases

To further support and prove the expanded definitions of spatial offender types, historical serial offense cases with known anchor points should be used as test cases. Resulting spatial analysis and spatial offender classification can be applied to these test cases to determine if the results support known facts, specifically the known behavior of the serial offender and the offender's known anchor points.

Test cases can be specifically chosen for cross-jurisdictional offenses to be analyzed both within specific jurisdictions and at-large. This analysis would help demonstrate series of patterns that law enforcement can apply to developing serial crimes for better understanding of cross-jurisdictional offenders. These results would provide law enforcement with a better understanding of when neighboring jurisdictions and potentially which specific jurisdictions should be consulted

6.3. Categorize Investigation Techniques Based on Spatial Offender Types

With a fully vetted spatial offender classification decision tree and historical serial case patterns, the application of investigative techniques need to be attributed to spatial offender types. It is fair to assume that not all investigative techniques should be applied to all spatial offender types. An analysis of investigative techniques and the validity to specific spatial offender types would be necessary to ensure proper application of techniques. Basically, understanding that if a series of offenses is being committed by a specific spatial offender type, what is the next investigative step for law enforcement? For example, investigating a local offender versus a drifter offender would require radically different investigative techniques and law enforcement resources (e.g. community-based policing versus region wide notifications).

6.4. Temporal Components of Spatial Offender Types

The agent-based model built for this thesis factored in the temporal component of serial offenders, but no analysis was conducted. The temporal factor is important and should not be ignored. Once spatial offenders can be properly classified based on a known series of offenses, investigations will need to understand how each spatial type behaviors temporally, if there are even temporal differences between the spatial types. There could potential be an entirely different set of temporal classifications of criminal offenders. The temporal factor was largely ignored in this thesis only due to scope, not importance.

6.5. <u>Compare Model Results to Real-World Offenses</u>

With historical serial offenses compared against spatial classification of offenders, the true test of the validity of this work will be classifying know series of offenses without known offenders and/or anchor points. By analyzing crimes reported, series of offenses can be classified to a spatial offender type and investigative efforts applied as discussed above. Does this result in timely identifying offenders? Can these efforts be automated to identify emerging patterns of serial offenders or even to identify unknown serial offenders?

The reverse is also potentially beneficial: analyzing the arrests of individuals and where they reside. If an individual is arrested for low level offenses, can additional offenses be attributed to that arrested individual based on their known anchor points? Analysis tools can be created to theorize additional offense locations if an individual were of different spatial offender types, based on their known anchor points. For example, if an arrested individual were a local serial offender, where would they commit offenses if they were a routine activities offender or a marauder?

6.6. <u>Expanding the Agent-Based Model</u>

The agent-based model in this thesis utilized a realistic backdrop of Fairfax County, VA to include county borders, road networks, and land use. The agents within this model moved outside of the county, but to simulate typical law enforcement practices only offenses within the county were observed. Temporal aspects were also added, but not for analysis purposes. Data was used to help simulate work commute flows between jurisdictions and to adjust work commute times closer to reality. Model outputs included an offender's anchor points and offense locations, but there was no exported connection between an offense and the associated anchor point. Additionally, no decision behavior models were included to determine whether an agent would offend at any given moment, not to mention the lack of capable guardians to deter agents from committing offenses. These decisions were made either to maintain the scope of the agent-based model or due to lack of available data. Filling these gaps in the agent-based model will help to improve the resulting series of offenses for analysis and to better understand how each spatial offender type behaves under certain circumstances.

The ability to model multiple offenders was built into this model, but the initial spatial analysis in this thesis was conducted solely on the series of offenses resulting from a single offender. The initial intent of this agent-based model was to model crime at-large given a certain percentage of each spatial offender type for comparison to arrest records and known offender residences. Before modeling multiple offenders is possible, the model functionality must include data attributing offenses to a specific offender agent and to each offender agent's residence or work anchor point. Once this functionality is included, it will be possible to model crime patterns at-large and tune the model to known crime data. This will lead towards understanding a jurisdiction's offender break down per spatial offender type, thus allowing for law enforcement resources to be developed and deployed accordingly.

This model helps to understand how a criminal offender from anywhere in the Washington, DC metro area would offender within Fairfax County, VA. But this is limited as the model only shows those offenses that would theoretically be committed within Fairfax County, VA. Further work should be done to open the offender agents to offending anywhere, regardless of a jurisdictional boundary. This would help to eliminate anomalies noted during spatial analysis (see Section 5.2.3, Classifying Circle Theory Results). Specifically, the model could be expanded to include an entire metropolitan region instead of a specific law enforcement jurisdiction and by increasing the distance beyond the Fairfax County, VA border, some of the problems with boundary effects in the spatial analysis could be resolved. This boundary effect is most clearly seen in Figure 23 and Figure 24 where offenses are recorded only in Fairfax County, VA while the offender anchor point is on the border.

Although applied solely to Fairfax County, VA, this model provides the capability to swap out boundaries, road networks, and land use data for any jurisdiction. This is an area of future study that would help determine if the spatial offender behaviors remain true in any given geographic background, whether urban, suburban, or rural. Additionally, other modes of transportation can be added to help determine how spatial offenders interact with mass transportation networks, walking paths, bicycles, ride sharing, or some unknown future method of moving around. This opens the potential to model future transportation projects to assist urban planners in understanding how decisions can affect crime and how law enforcement resources may need to be shifted in preparation for development.

There's an entire temporal aspect to this agent-based model that is underutilized in its current iteration. By fully incorporating temporal aspects, a full spatio-temporal analysis of crime can be conducted. This will help determine when crimes are committed, not just where, thus further assisting in the deployment of law enforcement resources, whether through preventative measures or through investigations.

APPENDIX A. WORK COMMUTING FLOW DATA

The following tables are derived from the American Community Survey (2013a) data set showing county-to-county commuting workflows. The subset of data provided below is for traditional work commutes in the Washington, DC MSA that either start, end, or are likely to traverse through Fairfax County, VA.

With the extracted ACS data, a likelihood of travel through Fairfax County, VA was assessed as either 0% (discarded from the dataset), 50% (work commuters had the option to travel through Fairfax County or not), and 100% (travel through Fairfax County was required). These weights were multiplied against the number of work commuters to derive a weighted number of commuters. The derived numbers were totaled per county and represented as a stylized percentage of the total to represent residence and work anchor points in the agent-based model (see Section 4.3.2.1, Offender Anchor Points).

Note: "County" is used to collectively describe counties and independent cities.

Residence Location	Work Location	Workers in Commuting Flow	Likelihood of traveling through Fairfax County	Weighted Workers	County Totals	County % of Total
Washington, DC	Fairfax city, VA	781	100%	781		
Washington, DC	Fairfax County, VA	11,750	100%	11,750		
Washington, DC	Loudoun County, VA	978	100%	978		
Washington, DC	Manassas city, VA	10	100%	10		
Washington, DC	Manassas Park city, VA	23	100%	23		
Washington, DC	Prince William County, VA	224	100%	224		
Washington, DC	Stafford County, VA	46	100%	46	13,812	1.41%
Montgomery County, MD	Prince George's County, MD	30,717	50%	15,359		
Montgomery County, MD	Alexandria city, VA	3,359	50%	1,680		
Montgomery County, MD	Arlington County, VA	9,823	50%	4,912		
Montgomery County, MD	Fairfax city, VA	817	100%	817		
Montgomery County, MD	Fairfax County, VA	19,736	100%	19,736		
Montgomery County, MD	Falls Church city, VA	260	50%	130		
Montgomery County, MD	Fauquier County, VA	61	100%	61		
Montgomery County, MD	Loudoun County, VA	1,801	50%	901		
Montgomery County, MD	Manassas city, VA	200	100%	200		
Montgomery County, MD	Manassas Park city, VA	17	100%	17		
Montgomery County, MD	Prince William County, VA	451	100%	451		
Montgomery County, MD	Stafford County, VA	72	100%	72	44,334	4.52%
Prince George's County, MD	Montgomery County, MD	45,739	50%	22,870		
Prince George's County, MD	Fairfax city, VA	757	100%	757		
Prince George's County, MD	Fairfax County, VA	17,471	100%	17,471		
Prince George's County, MD	Falls Church city, VA	454	100%	454		
Prince George's County, MD	Fauquier County, VA	62	100%	62		
Prince George's County, MD	Loudoun County, VA	1,799	100%	1,799		
Prince George's County, MD	Manassas city, VA	314	100%	314		
Prince George's County, MD	Manassas Park city, VA	28	100%	28		
Prince George's County, MD	Prince William County, VA	628	100%	628		

Prince George's County, MD	Stafford County, VA	113	100%	113	44,496	4.53%
Arlington County, VA	Montgomery County, MD	4,330	50%	2,165		
Arlington County, VA	Fairfax city, VA	1,025	100%	1,025		
Arlington County, VA	Fairfax County, VA	24,462	100%	24,462		
Arlington County, VA	Fauquier County, VA	16	100%	16		
Arlington County, VA	Loudoun County, VA	1,141	100%	1,141		
Arlington County, VA	Manassas city, VA	208	100%	208		
Arlington County, VA	Manassas Park city, VA	39	100%	39		
Arlington County, VA	Prince William County, VA	903	100%	903		
Arlington County, VA	Stafford County, VA	73	100%	73	30,032	3.06%
Fairfax County, VA	Washington, DC	95,323	100%	95,323		
Fairfax County, VA	Montgomery County, MD	16,252	100%	16,252		
Fairfax County, VA	Prince George's County, MD	10,532	100%	10,532		
Fairfax County, VA	Alexandria city, VA	31,314	100%	31,314		
Fairfax County, VA	Arlington County, VA	50,129	100%	50,129		
Fairfax County, VA	Fairfax city, VA	18,310	100%	18,310		
Fairfax County, VA	Fairfax County, VA	314,595	100%	314,595		
Fairfax County, VA	Falls Church city, VA	4,626	100%	4,626		
Fairfax County, VA	Fauquier County, VA	734	100%	734		
Fairfax County, VA	Loudoun County, VA	23,020	100%	23,020		
Fairfax County, VA	Manassas city, VA	2,392	100%	2,392		
Fairfax County, VA	Manassas Park city, VA	288	100%	288		
Fairfax County, VA	Prince William County, VA	10,155	100%	10,155		
Fairfax County, VA	Stafford County, VA	790	100%	790	578,460	58.93%
Fauquier County, VA	Washington, DC	1,096	100%	1,096		
Fauquier County, VA	Montgomery County, MD	174	100%	174		
Fauquier County, VA	Prince George's County, MD	148	100%	148		
Fauquier County, VA	Alexandria city, VA	272	100%	272		
Fauquier County, VA	Arlington County, VA	580	100%	580		
Fauquier County, VA	Fairfax city, VA	490	100%	490		
Fauquier County, VA	Fairfax County, VA	6,367	100%	6,367		
Fauquier County, VA	Falls Church city, VA	44	100%	44	9,171	0.93%

Loudoun County, VA	Washington, DC	9,841	100%	9,841		
Loudoun County, VA	Montgomery County, MD	3,771	50%	1,886		
Loudoun County, VA	Prince George's County, MD	898	100%	898		
Loudoun County, VA	Alexandria city, VA	1,472	100%	1,472		
Loudoun County, VA	Arlington County, VA	4,535	100%	4,535		
Loudoun County, VA	Fairfax city, VA	1,971	100%	1,971		
Loudoun County, VA	Fairfax County, VA	61,217	100%	61,217		
Loudoun County, VA	Falls Church city, VA	426	100%	426		
Loudoun County, VA	Manassas city, VA	595	50%	298		
Loudoun County, VA	Manassas Park city, VA	89	50%	45		
Loudoun County, VA	Prince William County, VA	1,891	50%	946		
Loudoun County, VA	Stafford County, VA	50	50%	25	83,558	8.51%
Prince William County, VA	Washington, DC	22,033	100%	22,033		
Prince William County, VA	Montgomery County, MD	2,367	100%	2,367		
Prince William County, VA	Prince George's County, MD	3,135	100%	3,135		
Prince William County, VA	Alexandria city, VA	7,419	100%	7,419		
Prince William County, VA	Arlington County, VA	13,166	100%	13,166		
Prince William County, VA	Fairfax city, VA	4,888	100%	4,888		
Prince William County, VA	Fairfax County, VA	58,742	100%	58,742		
Prince William County, VA	Falls Church city, VA	802	100%	802		
Prince William County, VA	Loudoun County, VA	6,696	50%	3,348	115,900	11.81%
Stafford County, VA	Washington, DC	5,108	100%	5,108		
Stafford County, VA	Montgomery County, MD	352	100%	352		
Stafford County, VA	Prince George's County, MD	409	100%	409		
Stafford County, VA	Alexandria city, VA	1,263	100%	1,263		
Stafford County, VA	Arlington County, VA	3,258	100%	3,258		
Stafford County, VA	Fairfax city, VA	692	100%	692		
Stafford County, VA	Fairfax County, VA	7,885	100%	7,885		
Stafford County, VA	Falls Church city, VA	110	100%	110		
Stafford County, VA	Loudoun County, VA	552	50%	276	19,353	1.97%
Alexandria city, VA	Montgomery County, MD	1,748	50%	874		
Alexandria city, VA	Fairfax city, VA	545	100%	545		

Alexandria city, VA	Fairfax County, VA	15,483	100%	15,483		
Alexandria city, VA	Falls Church city, VA	484	50%	242		
Alexandria city, VA	Fauquier County, VA	66	100%	66		
Alexandria city, VA	Loudoun County, VA	545	100%	545		
Alexandria city, VA	Manassas city, VA	45	100%	45		
Alexandria city, VA	Prince William County, VA	977	100%	977		
Alexandria city, VA	Stafford County, VA	60	100%	60	18,837	1.92%
Fairfax city, VA	Washington, DC	1,329	100%	1,329		
Fairfax city, VA	Montgomery County, MD	167	100%	167		
Fairfax city, VA	Prince George's County, MD	182	100%	182		
Fairfax city, VA	Alexandria city, VA	301	100%	301		
Fairfax city, VA	Arlington County, VA	904	100%	904		
Fairfax city, VA	Fairfax County, VA	5,416	100%	5,416		
Fairfax city, VA	Falls Church city, VA	31	100%	31		
Fairfax city, VA	Fauquier County, VA	10	100%	10		
Fairfax city, VA	Loudoun County, VA	339	100%	339		
Fairfax city, VA	Manassas city, VA	53	100%	53		
Fairfax city, VA	Prince William County, VA	256	100%	256	8,988	0.92%
Falls Church city, VA	Montgomery County, MD	258	50%	129		
Falls Church city, VA	Prince George's County, MD	45	100%	45		
Falls Church city, VA	Alexandria city, VA	183	50%	92		
Falls Church city, VA	Fairfax city, VA	46	100%	46		
Falls Church city, VA	Fairfax County, VA	2,166	100%	2,166		
Falls Church city, VA	Fauquier County, VA	41	100%	41		
Falls Church city, VA	Loudoun County, VA	94	100%	94		
Falls Church city, VA	Prince William County, VA	74	100%	74	2,687	0.27%
Manassas city, VA	Washington, DC	906	100%	906		
Manassas city, VA	Montgomery County, MD	213	100%	213		
Manassas city, VA	Prince George's County, MD	29	100%	29		
Manassas city, VA	Alexandria city, VA	277	100%	277		
Manassas city, VA	Arlington County, VA	537	100%	537		
Manassas city, VA	Fairfax city, VA	844	100%	844		

Manassas city, VA	Fairfax County, VA	4,484	100%	4,484		
Manassas city, VA	Falls Church city, VA	39	100%	39		
Manassas city, VA	Loudoun County, VA	972	50%	486	7,815	0.80%
Manassas Park city, VA	Washington, DC	415	100%	415		
Manassas Park city, VA	Montgomery County, MD	163	100%	163		
Manassas Park city, VA	Prince George's County, MD	140	100%	140		
Manassas Park city, VA	Alexandria city, VA	226	100%	226		
Manassas Park city, VA	Arlington County, VA	168	100%	168		
Manassas Park city, VA	Fairfax city, VA	390	100%	390		
Manassas Park city, VA	Fairfax County, VA	2,550	100%	2,550		
Manassas Park city, VA	Falls Church city, VA	14	100%	14		
Manassas Park city, VA	Loudoun County, VA	359	50%	180	4,246	0.43%
Totals		1,038,526		981,688	981,688	100.00%

Table 11: Work commute flows based on residence location

Work Location	Residence Location	Workers in Commuting Flow	Likelihood of traveling through Fairfax County	Weighted Workers	County Totals	County % of Total
Washington, DC	Fairfax County, VA	95,323	100%	95,323		
Washington, DC	Fauquier County, VA	1,096	100%	1,096		
Washington, DC	Loudoun County, VA	9,841	100%	9,841		
Washington, DC	Prince William County, VA	22,033	100%	22,033		
Washington, DC	Stafford County, VA	5,108	100%	5,108		
Washington, DC	Fairfax city, VA	1,329	100%	1,329		
Washington, DC	Manassas city, VA	906	100%	906		
Washington, DC	Manassas Park city, VA	415	100%	415	136,051	13.86%
Montgomery County, MD	Prince George's County, MD	45,739	50%	22,870		
Montgomery County, MD	Arlington County, VA	4,330	50%	2,165		
Montgomery County, MD	Fairfax County, VA	16,252	100%	16,252		
Montgomery County, MD	Fauquier County, VA	174	100%	174		
Montgomery County, MD	Loudoun County, VA	3,771	50%	1,886		
Montgomery County, MD	Prince William County, VA	2,367	100%	2,367		
Montgomery County, MD	Stafford County, VA	352	100%	352		
Montgomery County, MD	Alexandria city, VA	1,748	50%	874		
Montgomery County, MD	Fairfax city, VA	167	100%	167		
Montgomery County, MD	Falls Church city, VA	258	50%	129		
Montgomery County, MD	Manassas city, VA	213	100%	213		
Montgomery County, MD	Manassas Park city, VA	163	100%	163	47,611	4.85%
Prince George's County, MD	Montgomery County, MD	30,717	50%	15,359		
Prince George's County, MD	Fairfax County, VA	10,532	100%	10,532		
Prince George's County, MD	Fauquier County, VA	148	100%	148		
Prince George's County, MD	Loudoun County, VA	898	100%	898		
Prince George's County, MD	Prince William County, VA	3,135	100%	3,135		
Prince George's County, MD	Stafford County, VA	409	100%	409		
Prince George's County, MD	Fairfax city, VA	182	100%	182		
Prince George's County, MD	Falls Church city, VA	45	100%	45		

Prince George's County, MD	Manassas city, VA	29	100%	29		
Prince George's County, MD	Manassas Park city, VA	140	100%	140	30,877	3.15%
Alexandria city, VA	Montgomery County, MD	3,359	50%	1,680		
Alexandria city, VA	Fairfax County, VA	31,314	100%	31,314		
Alexandria city, VA	Fauquier County, VA	272	100%	272		
Alexandria city, VA	Loudoun County, VA	1,472	100%	1,472		
Alexandria city, VA	Prince William County, VA	7,419	100%	7,419		
Alexandria city, VA	Stafford County, VA	1,263	100%	1,263		
Alexandria city, VA	Fairfax city, VA	301	100%	301		
Alexandria city, VA	Falls Church city, VA	183	50%	92		
Alexandria city, VA	Manassas city, VA	277	100%	277		
Alexandria city, VA	Manassas Park city, VA	226	100%	226	44,315	4.51%
Arlington County, VA	Montgomery County, MD	9,823	50%	4,912		
Arlington County, VA	Fairfax County, VA	50,129	100%	50,129		
Arlington County, VA	Fauquier County, VA	580	100%	580		
Arlington County, VA	Loudoun County, VA	4,535	100%	4,535		
Arlington County, VA	Prince William County, VA	13,166	100%	13,166		
Arlington County, VA	Stafford County, VA	3,258	100%	3,258		
Arlington County, VA	Fairfax city, VA	904	100%	904		
Arlington County, VA	Manassas city, VA	537	100%	537		
Arlington County, VA	Manassas Park city, VA	168	100%	168	78,189	7.96%
Fairfax city, VA	Washington, DC	781	100%	781		
Fairfax city, VA	Montgomery County, MD	817	100%	817		
Fairfax city, VA	Prince George's County, MD	757	100%	757		
Fairfax city, VA	Arlington County, VA	1,025	100%	1,025		
Fairfax city, VA	Fairfax County, VA	18,310	100%	18,310		
Fairfax city, VA	Fauquier County, VA	490	100%	490		
Fairfax city, VA	Loudoun County, VA	1,971	100%	1,971		
Fairfax city, VA	Prince William County, VA	4,888	100%	4,888		
Fairfax city, VA	Stafford County, VA	692	100%	692		
Fairfax city, VA	Alexandria city, VA	545	100%	545		
Fairfax city, VA	Falls Church city, VA	46	100%	46		

Fairfax city, VA	Manassas city, VA	844	100%	844		
Fairfax city, VA	Manassas Park city, VA	390	100%	390	31,556	3.21%
Fairfax County, VA	Washington, DC	11,750	100%	11,750		
Fairfax County, VA	Montgomery County, MD	19,736	100%	19,736		
Fairfax County, VA	Prince George's County, MD	17,471	100%	17,471		
Fairfax County, VA	Arlington County, VA	24,462	100%	24,462		
Fairfax County, VA	Fairfax County, VA	314,595	100%	314,595		
Fairfax County, VA	Fauquier County, VA	6,367	100%	6,367		
Fairfax County, VA	Loudoun County, VA	61,217	100%	61,217		
Fairfax County, VA	Prince William County, VA	58,742	100%	58,742		
Fairfax County, VA	Stafford County, VA	7,885	100%	7,885		
Fairfax County, VA	Alexandria city, VA	15,483	100%	15,483		
Fairfax County, VA	Fairfax city, VA	5,416	100%	5,416		
Fairfax County, VA	Falls Church city, VA	2,166	100%	2,166		
Fairfax County, VA	Manassas city, VA	4,484	100%	4,484		
Fairfax County, VA	Manassas Park city, VA	2,550	100%	2,550	552,324	56.26%
Falls Church city, VA	Montgomery County, MD	260	50%	130		
Falls Church city, VA	Prince George's County, MD	454	100%	454		
Falls Church city, VA	Fairfax County, VA	4,626	100%	4,626		
Falls Church city, VA	Fauquier County, VA	44	100%	44		
Falls Church city, VA	Loudoun County, VA	426	100%	426		
Falls Church city, VA	Prince William County, VA	802	100%	802		
Falls Church city, VA	Stafford County, VA	110	100%	110		
Falls Church city, VA	Alexandria city, VA	484	50%	242		
Falls Church city, VA	Fairfax city, VA	31	100%	31		
Falls Church city, VA	Manassas city, VA	39	100%	39		
Falls Church city, VA	Manassas Park city, VA	14	100%	14	6,918	0.70%
Fauquier County, VA	Montgomery County, MD	61	100%	61		
Fauquier County, VA	Prince George's County, MD	62	100%	62		
Fauquier County, VA	Arlington County, VA	16	100%	16		
Fauquier County, VA	Fairfax County, VA	734	100%	734		
Fauquier County, VA	Alexandria city, VA	66	100%	66		

Fauquier County, VA	Fairfax city, VA	10	100%	10		
Fauquier County, VA	Falls Church city, VA	41	100%	41	990	0.10%
Loudoun County, VA	Washington, DC	978	100%	978		
Loudoun County, VA	Montgomery County, MD	1,801	50%	901		
Loudoun County, VA	Prince George's County, MD	1,799	100%	1,799		
Loudoun County, VA	Arlington County, VA	1,141	100%	1,141		
Loudoun County, VA	Fairfax County, VA	23,020	100%	23,020		
Loudoun County, VA	Prince William County, VA	6,696	50%	3,348		
Loudoun County, VA	Stafford County, VA	552	50%	276		
Loudoun County, VA	Alexandria city, VA	545	100%	545		
Loudoun County, VA	Fairfax city, VA	339	100%	339		
Loudoun County, VA	Falls Church city, VA	94	100%	94		
Loudoun County, VA	Manassas city, VA	972	50%	486		
Loudoun County, VA	Manassas Park city, VA	359	50%	180	33,106	3.37%
Manassas city, VA	Washington, DC	10	100%	10		
Manassas city, VA	Montgomery County, MD	200	100%	200		
Manassas city, VA	Prince George's County, MD	314	100%	314		
Manassas city, VA	Arlington County, VA	208	100%	208		
Manassas city, VA	Fairfax County, VA	2,392	100%	2,392		
Manassas city, VA	Loudoun County, VA	595	50%	298		
Manassas city, VA	Alexandria city, VA	45	100%	45		
Manassas city, VA	Fairfax city, VA	53	100%	53	3,520	0.36%
Manassas Park city, VA	Washington, DC	23	100%	23		
Manassas Park city, VA	Montgomery County, MD	17	100%	17		
Manassas Park city, VA	Prince George's County, MD	28	100%	28		
Manassas Park city, VA	Arlington County, VA	39	100%	39		
Manassas Park city, VA	Fairfax County, VA	288	100%	288		
Manassas Park city, VA	Loudoun County, VA	89	50%	45	440	0.04%
Prince William County, VA	Washington, DC	224	100%	224		
Prince William County, VA	Montgomery County, MD	451	100%	451		
Prince William County, VA	Prince George's County, MD	628	100%	628		
Prince William County, VA	Arlington County, VA	903	100%	903		

Prince William County, VA	Fairfax County, VA	10,155	100%	10,155		
Prince William County, VA	Loudoun County, VA	1,891	50%	946		
Prince William County, VA	Alexandria city, VA	977	100%	977		
Prince William County, VA	Fairfax city, VA	256	100%	256		
Prince William County, VA	Falls Church city, VA	74	100%	74	14,614	1.49%
Stafford County, VA	Washington, DC	46	100%	46		
Stafford County, VA	Montgomery County, MD	72	100%	72		
Stafford County, VA	Prince George's County, MD	113	100%	113		
Stafford County, VA	Arlington County, VA	73	100%	73		
Stafford County, VA	Fairfax County, VA	790	100%	790		
Stafford County, VA	Loudoun County, VA	50	50%	25		
Stafford County, VA	Alexandria city, VA	60	100%	60	1,179	0.12%
Totals		1,038,536		981,688	981,688	100.00%

Table 12: Work commute flows based on work location

APPENDIX B. NEAREST NEIGHBOR ANALYSIS RESULTS

The following tables are the analysis results of running the Nearest Neighbor spatial analysis tool in ArcGIS Pro version 2.3.x on each series of spatial offender type outputs from the agent-based model (see Section 5.3.1, Applying Nearest Neighbor Analysis).

Offender Series	Ratio	Z-score	P-value	Result
Commuter 1	1.162925	1.707179	0.087789	Dispersed
Commuter 2	1.154018	1.613845	0.106561	Random
Commuter 3	0.954392	-0.447893	0.632726	Random
Commuter 4	0.919745	-0.840935	0.400384	Random
Commuter 5	1.267404	2.801949	0.005079	Dispersed
Commuter 6	1.072241	0.756965	0.449071	Random
Commuter 7	1.177497	1.859869	0.062904	Dispersed
Commuter 8	1.099316	1.040667	0.298030	Random
Commuter 9	1.215206	2.256994	0.024134	Dispersed
Commuter 10	1.161755	1.694919	0.090091	Dispersed

Table 13: Commuter nearest neighbor results

Offender Series	Ratio	Z-score	P-value	Result
Marauder 1	1.113269	1.125962	0.260181	Random
Marauder 2	0.987193	-0.134196	0.893247	Random
Marauder 3	0.761412	-2.499997	0.012419	Clustered
Marauder 4	1.103389	0.137932	0.890294	Random
Marauder 5	1.052275	0.538547	0.590199	Random
Marauder 6	1.082911	0.854170	0.393011	Random
Marauder 7	1.101778	1.011735	0.311665	Random
Marauder 8	0.921115	-0.812692	0.416395	Random
Marauder 9	1.263732	2.763470	0.005719	Dispersed
Marauder 10	0.891961	-1.132062	0.257609	Random

Table 14: Marauder nearest neighbor results

Offender Series	Ratio	Z-score	P-value	Result
Routine Activities 1	1.243060	2.504049	0.012278	Dispersed
Routine Activities 2	0.926946	-1.813319	0.069783	Clustered
Routine Activities 3	0.936985	-0.649190	0.516216	Random
Routine Activities 4	0.934261	-0.688836	0.490927	Random
Routine Activities 5	1.019204	0.197840	0.843170	Random
Routine Activities 6	0.906186	-0.983016	0.325599	Random
Routine Activities 7	0.795931	-2.138297	0.032493	Clustered
Routine Activities 8	1.008444	0.088483	0.929493	Random
Routine Activities 9	0.900363	-0.830864	0.406050	Random
Routine Activities 10	0.861620	-1.449985	0.147063	Random

Table 15: Routine activities nearest neighbor results

Offender Series	Ratio	Z-score	P-value	Result
Local 1	0.745526	-2.621639	0.008751	Clustered
Local 2	0.808883	-1.899818	0.057457	Clustered
Local 3	0.683270	-3.148484	0.001641	Clustered
Local 4	0.484719	-4.829261	0.000001	Clustered
Local 5	0.839278	-1.626989	0.103740	Random
Local 6	0.809563	-1.927801	0.053880	Clustered
Local 7	0.572741	-4.401707	0.000011	Clustered
Local 8	1.142971	1.472914	0.140774	Random
Local 9	0.623406	-3.879751	0.000105	Clustered
Local 10	0.823825	-1.751286	0.079897	Clustered

Table 16: Local nearest neighbor results

Offender Series	Ratio	Z-score	P-value	Result
Drifter 1	1.290579	3.044783	0.002328	Dispersed
Drifter 2	1.044017	0.461228	0.644635	Random
Drifter 3	1.028869	0.302501	0.762270	Random
Drifter 4	0.978368	-0.226665	0.820685	Random
Drifter 5	1.163885	1.717241	0.085935	Dispersed
Drifter 6	1.034942	0.366133	0.714266	Random
Drifter 7	1.086239	0.903643	0.366185	Random
Drifter 8	1.029628	0.310452	0.756217	Random
Drifter 9	1.118510	1.241783	0.214317	Random
Drifter 10	1.104373	1.093656	0.274106	Random

Table 17: Drifter nearest neighbor results

APPENDIX C. STANDARD DISTANCE MEASUREMENTS

The following tables are the analysis results of running the Density-Based Clustering spatial analysis tool in ArcGIS Pro version 2.3.x on each series of spatial offender type outputs from the agent-based model (see Section 5.3.2, Applying Mean Center and Standard Distance Analysis). After each series of offenses were clustered into groups, the mean center and standard distance of each clustered group were calculated. Next, it was observed whether an anchor point was with the standard distance and how many offenses were within the standard distance. Lastly, measurements were taken to compare the distance between anchor points and mean centers as well as the distance from each mean center to the nearest anchor and the mean center to the standard distance.

Note: All distances are in miles.

Offender Series	Cluster Search Distance	Anchor within Standard Distance?	Offenses within Standard Distance
Commuter 1	4.50	Cluster 1: yes Cluster 2: no	Cluster 1: 12 out of 23 Cluster 2: 3 out of 5 Noise: 2
Commuter 2	4.00	Cluster 1: no Cluster 2: no	Cluster 1: 5 out of 10 Cluster 2: 6 out of 11 Cluster: 3 Noise: 6
Commuter 3	6.25	Cluster 1: yes Cluster 2: no	Cluster 1: 12 out of 26 Cluster 2: 1 out of 3 Noise: 1
Commuter 4	5.25	Cluster 1: yes Cluster 2: no	Cluster 1: 13 out of 19 Cluster 2: 3 out of 6 Noise: 5
Commuter 5	3.50	Cluster 1: yes Cluster 2: no	Cluster 1: 5 out of 12 Cluster 2: 10 out of 15 Noise: 3
Commuter 6	5.50	Cluster 1: yes Cluster 2: no	Cluster 1: 18 out of 27 Cluster 2: 2 out of 3 Noise: 0
Commuter 7	4.75	Cluster 1: yes Cluster 2: no	Cluster 1: 13 out of 25 Cluster 2: 3 out of 5 Noise: 0
Commuter 8	3.75	Cluster 1: yes Cluster 2: no	Cluster 1: 13 out of 20 Cluster 2: 3 out of 4 Cluster 3: 0 out of 3 Noise: 3
Commuter 9	6.25	Cluster 1: yes Cluster 2: no	Cluster 1: 16 out of 25 Cluster 2: 4 out of 5 Noise: 0
Commuter 10	5.75	Cluster 1: no Cluster 2: yes	Cluster 1: 9 out of 14 Cluster 2: 8 out of 14 Noise: 2

Table 18: Commuter standard distance analysis

Offender Series	Cluster Search Distance	Anchor within Standard Distance?	Offenses within Standard Distance
Marauder 1	4.00	Cluster 1: yes Cluster 2: yes	Cluster 1: 7 out of 12 Cluster 2: 8 out of 15 Noise: 0
Marauder 2	3.75	Cluster 1: no Cluster 2: yes	Cluster 1: 5 out of 7 Cluster 2: 14 out of 22 Noise: 1
Marauder 3	7.00	Cluster 1: yes Cluster 2: yes	Cluster 1: 9 out of 14 Cluster 2: 11 out of 16 Noise: 0
Marauder 4	3.25	Cluster 1: yes Cluster 2: yes	Cluster 1: 8 out of 11 Cluster 2: 8 out of 15 Noise: 3
Marauder 5	4.25	Cluster 1: yes Cluster 2: yes	Cluster 1: 12 out of 17 Cluster 2: 7 out of 10 Noise: 2
Marauder 6	4.75	Cluster 1: yes Cluster 2: yes	Cluster 1: 5 out of 7 Cluster 2: 12 out of 20 Noise: 2
Marauder 7	4.25	Cluster 1: yes Cluster 2: no	Cluster 1: 11 out of 21 Cluster 2: 2 out of 3 Noise: 3
Marauder 8	10.0	Cluster 1: yes Cluster 2: no	Cluster 1: 7 out of 11 Cluster 2: 13 out of 18 Noise: 0
Marauder 9	4.75	Cluster 1: no Cluster 2: no	Cluster 1: 16 out of 25 Cluster 2: 2 out of 4 Noise: 1
Marauder 10	3.50	Cluster 1: yes Cluster 2: yes	Cluster 1: 2 out of 5 Cluster 2: 12 out of 20 Cluster 3: 3 Noise: 2

Table 19: Marauder standard distance analysis

Offender Series	Cluster Search Distance	Anchor within Standard Distance?	Offenses within Standard Distance
Routine Activities 1	1.00	Cluster 1: no Cluster 2: no	Cluster 1: 6 out of 8 Cluster 2: 12 out of 18 Noise: 3
Routine Activities 2	3.75	Cluster 1: no Cluster 2: yes	Cluster 1: 15 out of 27 Cluster 2: 1 out of 3 Noise: 0
Routine Activities 3	1.25	Cluster 1: no Cluster 2: no	Cluster 1: 16 out of 25 Cluster 2: 3 out of 4 Noise:
Routine Activities 4	3.25	Cluster 1: no Cluster 2: no	Cluster 1: 7 out of 12 Cluster 2: 10 out of 18 Noise: 0
Routine Activities 5	2.50	Cluster 1: no Cluster 2: no	Cluster 1: 3 out of 5 Cluster 2: 15 out of 24 Noise:0
Routine Activities 6	4.25	Cluster 1: no Cluster 2: no	Cluster 1: 17 out of 25 Cluster 2: 3 out of 5 Noise: 0
Routine Activities 7	3.50	Cluster 1: no Cluster 2: no	Cluster 1: 6 out of 12 Cluster 2: 10 out of 18 Noise: 0
Routine Activities 8	1.75	Cluster 1: no Cluster 2: no	Cluster 1: 8 out of 15 Cluster 2: 8 out of 14 Noise: 1
Routine Activities 9	4.50	Cluster 1: no Cluster 2: no	Cluster 1: 9 out of 14 Cluster 2: 3 out of 5 Noise: 0
Routine Activities 10	4.50	Cluster 1: no Cluster 2: no	Cluster 1: 7 out of 9 Cluster 2: 11 out of 21 Noise: 0

Table 20: Routine Activities standard distance analysis

Offender Series	Cluster Search Distance	Anchor within Standard Distance?	Offenses within Standard Distance
Local 1	4.50	Cluster 1: yes Cluster 2: yes	Cluster 1: 8 out of 16 Cluster 2: 8 out of 13 Noise: 0
Local 2	2.75	Cluster 1: yes Cluster 2: yes	Cluster 1: 8 out of 11 Cluster 2: 9 out of 16 Noise: 0
Local 3	Did not matter	Cluster 1: yes Cluster 2: yes	Cluster 1: 9 out of 16 Cluster 2: 7 out of 11 Noise: 0
Local 4	Did not matter	Cluster 1: yes Cluster 2: yes	Cluster 1: 7 out of 12 Cluster 2: 7 out of 12 Noise: 0
Local 5	5.25	Cluster 1: yes Cluster 2: yes	Cluster 1: 6 out of 14 Cluster 2: 7 out of 14 Noise: 0
Local 6	5.25	Cluster 1: yes Cluster 2: yes	Cluster 1: 9 out of 16 Cluster 2: 7 out of 12 Noise: 0
Local 7	Did not matter	Cluster 1: yes Cluster 2: yes	Cluster 1: 7 out of 15 Cluster 2: 8 out of 14 Noise: 0
Local 8	0.75	Cluster 1: no Cluster 2: yes	Cluster 1: 2 out of 5 Cluster 2: 10 out of 22 Noise: 2
Local 9	Did not matter	Cluster 1: yes Cluster 2: yes	Cluster 1: 6 out of 14 Cluster 2: 9 out of 15 Noise: 0
Local 10	3.25	Cluster 1: yes Cluster 2: yes	Cluster 1: 5 out of 9 Cluster 2: 9 out of 18 Noise: 0

Table 21: Local standard distance analysis

Offender Series	Cluster Search Distance	Anchor within Standard Distance?	Offenses within Standard Distance
Drifter 1	5.00	Cluster 1: N/A Cluster 2: N/A	Cluster 1: 9 out of 15 Cluster 2: 9 out of 15 Noise: 0
Drifter 2	7.25	Cluster 1: N/A Cluster 2: N/A	Cluster 1: 16 out of 23 Cluster 2: 5 out of 7 Noise: 0
Drifter 3	4.50	Cluster 1: N/A Cluster 2: N/A	Cluster 1: 14 out of 22 Cluster 2: 3 out of 6 Noise: 2
Drifter 4	4.75	Cluster 1: N/A Cluster 2: N/A	Cluster 1: 8 out of 15 Cluster 2: 9 out of 14 Noise: 1
Drifter 5	6.75	Cluster 1: N/A Cluster 2: N/A	Cluster 1: 12 out of 22 Cluster 2: 4 out of 8 Noise: 0
Drifter 6	4.25	Cluster 1: N/A Cluster 2: N/A	Cluster 1: 12 out of 19 Cluster 2: 6 out of 10 Noise: 1
Drifter 7	4.50	Cluster 1: N/A Cluster 2: N/A	Cluster 1: 10 out of 14 Cluster 2: 6 out of 10 Noise: 1
Drifter 8	5.75	Cluster 1: N/A Cluster 2: N/A	Cluster 1: 13 out of 24 Cluster 2: 3 out of 5 Noise: 1
Drifter 9	4.50	Cluster 1: N/A Cluster 2: N/A	Cluster 1: 11 out of 17 Cluster 2: 5 out of 8 Noise: 5
Drifter 10	4.75	Cluster 1: N/A Cluster 2: N/A	Cluster 1: 6 out of 9 Cluster 2: 11 out of 21 Noise: 0

Table 22: Drifter standard distance analysis

Offender Series	Distance Between Anchors	Distance Between Mean Centers	Mean Center to Standard Distance	Mean Center to Nearest Anchor
Commuter 1	13.47	14.19	Cluster 1: 6.65 Cluster 2: 3.13	Cluster 1: 5.31 Cluster 2: 4.53
Commuter 2	10.24	10.98	Cluster 1: 5.95 Cluster 2: 5.29	Cluster 1: 9.08 Cluster 2: 5.56
Commuter 3	8.86	15.41	Cluster 1: 7.26 Cluster 2: 0.83	Cluster 1: 4.20 Cluster 2: 11.11
Commuter 4	14.82	9.99	Cluster 1: 6.49 Cluster 2: 1.75	Cluster 1: 2.97 Cluster 2: 6.59
Commuter 5	9.81	9.71	Cluster 1: 3.70 Cluster 2: 4.68	Cluster 1: 3.57 Cluster 2: 8.24
Commuter 6	3.37	13.94	Cluster 1: 8.78 Cluster 2: 1.30	Cluster 1: 5.29 Cluster 2: 13.99
Commuter 7	6.83	14.86	Cluster 1: 6.03 Cluster 2: 2.72	Cluster 1: 4.56 Cluster 2: 15.82
Commuter 8	14.49	8.52	Cluster 1: 5.25 Cluster 2: 1.70	Cluster 1: 4.97 Cluster 2: 3.83
Commuter 9	17.99	14.51	Cluster 1: 7.38 Cluster 2: 3.05	Cluster 1: 6.64 Cluster 2: 7.37
Commuter 10	8.50	12.03	Cluster 1: 4.38 Cluster 2: 5.60	Cluster 1: 9.15 Cluster 2: 2.94

Table 23: Commuter standard distance measurements

Offender Series	Distance Between Anchors	Distance Between Mean Centers	Mean Center to Standard Distance	Mean Center to Nearest Anchor
Marauder 1	18.07	13.48	Cluster 1: 4.17 Cluster 2: 2.87	Cluster 1: 3.22 Cluster 2: 2.44
Marauder 2	8.35	8.57	Cluster 1: 1.83 Cluster 2: 3.85	Cluster 1: 3.59 Cluster 2: 2.53
Marauder 3	19.69	17.12	Cluster 1: 3.14 Cluster 2: 3.99	Cluster 1: 2.16 Cluster 2: 1.36
Marauder 4	11.05	9.87	Cluster 1: 2.47 Cluster 2: 2.78	Cluster 1: 2.39 Cluster 2: 1.94
Marauder 5	12.26	12.37	Cluster 1: 3.46 Cluster 2: 2.57	Cluster 1: 0.40 Cluster 2: 2.46
Marauder 6	17.80	13.67	Cluster 1: 3.19 Cluster 2: 3.66	Cluster 1: 2.54 Cluster 2: 2.54
Marauder 7	9.59	8.60	Cluster 1: 4.70 Cluster 2: 1.19	Cluster 1: 3.54 Cluster 2: 4.47
Marauder 8	18.53	16.55	Cluster 1: 4.47 Cluster 2: 3.11	Cluster 1: 0.72 Cluster 2: 4.35
Marauder 9	13.0	10.25	Cluster 1: 5.57 Cluster 2: 2.91	Cluster 1: 5.95 Cluster 2: 5.61
Marauder 10	9.03	9.65	Cluster 1: 2.24 Cluster 2: 3.22	Cluster 1: 1.34 Cluster 2: 1.19

Table 24: Marauder standard distance measurements

Offender Series	Distance Between Anchors	Distance Between Mean Centers	Mean Center to Standard Distance	Mean Center to Nearest Anchor
Routine Activities 1	8.52	4.35	Cluster 1: 0.85 Cluster 2: 1.30	Cluster 1: 2.48 Cluster 2: 4.09
Routine Activities 2	14.16	10.12	Cluster 1: 4.25 Cluster 2: 2.00	Cluster 1: 7.30 Cluster 2: 1.33
Routine Activities 3	3.54	3.31	Cluster 1: 1.12 Cluster 2: 0.62	Cluster 1: 2.25 Cluster 2: 2.18
Routine Activities 4	15.76	7.36	Cluster 1: 2.53 Cluster 2: 2.66	Cluster 1: 5.65 Cluster 2: 4.81
Routine Activities 5	14.68	6.19	Cluster 1: 1.05 Cluster 2: 2.15	Cluster 1: 3.82 Cluster 2: 4.76
Routine Activities 6	10.67	7.92	Cluster 1: 2.09 Cluster 2: 1.16	Cluster 1: 5.62 Cluster 2: 2.58
Routine Activities 7	15.72	9.52	Cluster 1: 2.26 Cluster 2: 3.03	Cluster 1: 4.96 Cluster 2: 3.91
Routine Activities 8	10.68	5.18	Cluster 1: 1.31 Cluster 2: 1.41	Cluster 1: 3.37 Cluster 2: 2.85
Routine Activities 9	19.82	10.31	Cluster 1: 3.95 Cluster 2: 1.68	Cluster 1: 6.71 Cluster 2: 4.17
Routine Activities 10	18.82	10.98	Cluster 1: 2.45 Cluster 2: 3.39	Cluster 1: 3.48 Cluster 2: 7.17

Table 25: Routine Activities standard distance measurements

Offender Series	Distance Between Anchors	Distance Between Mean Centers	Mean Center to Standard Distance	Mean Center to Nearest Anchor
Local 1	5.86	6.00	Cluster 1: 0.68 Cluster 2: 0.69	Cluster 1: 0.21 Cluster 2: 0.19
Local 2	4.16	4.29	Cluster 1: 0.47 Cluster 2: 0.67	Cluster 1: 0.43 Cluster 2: 0.05
Local 3	7.77	7.85	Cluster 1: 0.68 Cluster 2: 0.52	Cluster 1: 0.12 Cluster 2: 0.14
Local 4	17.84	17.94	Cluster 1: 0.67 Cluster 2: 0.64	Cluster 1: 0.23 Cluster 2: 0.05
Local 5	7.13	6.96	Cluster 1: 0.74 Cluster 2: 0.69	Cluster 1: 0.02 Cluster 2: 0.18
Local 6	7.01	6.90	Cluster 1: 0.68 Cluster 2: 0.68	Cluster 1: 0.22 Cluster 2: 0.19
Local 7	11.86	11.78	Cluster 1: 0.63 Cluster 2: 0.74	Cluster 1: 0.12 Cluster 2: 0.20
Local 8	1.35	1.84	Cluster 1: 0.41 Cluster 2: 0.68	Cluster 1: 0.72 Cluster 2: 0.26
Local 9	11.91	11.73	Cluster 1: 0.65 Cluster 2: 0.62	Cluster 1: 0.15 Cluster 2: 0.18
Local 10	4.60	4.78	Cluster 1: 0.70 Cluster 2: 0.63	Cluster 1: 0.21 Cluster 2: 0.28

Table 26: Local standard distance measurements

Offender Series	Distance Between Anchors	Distance Between Mean Centers	Mean Center to Standard Distance	Mean Center to Nearest Anchor
Drifter 1	N/A	13.20	Cluster 1: 6.40 Cluster 2: 5.48	Cluster 1: N/A Cluster 2: N/A
Drifter 2	N/A	15.16	Cluster 1: 6.62 Cluster 2: 3.88	Cluster 1: N/A Cluster 2: N/A
Drifter 3	N/A	7.44	Cluster 1: 8.84 Cluster 2: 2.62	Cluster 1: N/A Cluster 2: N/A
Drifter 4	N/A	14.53	Cluster 1: 5.66 Cluster 2: 5.73	Cluster 1: N/A Cluster 2: N/A
Drifter 5	N/A	16.51	Cluster 1: 6.83 Cluster 2: 4.12	Cluster 1: N/A Cluster 2: N/A
Drifter 6	N/A	10.68	Cluster 1: 6.55 Cluster 2: 4.72	Cluster 1: N/A Cluster 2: N/A
Drifter 7	N/A	10.31	Cluster 1: 5.07 Cluster 2: 4.12	Cluster 1: N/A Cluster 2: N/A
Drifter 8	N/A	14.00	Cluster 1: 6.65 Cluster 2: 2.77	Cluster 1: N/A Cluster 2: N/A
Drifter 9	N/A	9.87	Cluster 1: 4.25 Cluster 2: 5.30	Cluster 1: N/A Cluster 2: N/A
Drifter 10	N/A	11.59	Cluster 1: 4.41 Cluster 2: 7.48	Cluster 1: N/A Cluster 2: N/A

Table 27: Drifter standard distance measurements

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