A Spatiotemporal Examination of Crime Site Selection for Commercial Burglary and Street Robbery

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A SPATIOTEMPORAL EXAMINATION OF CRIME SITE SELECTION FOR STREET ROBBERY AND COMMERCIAL BURGLARY

by

DEVIN CHRISTIAN COWAN
M.S. University of Central Florida, 2016

A dissertation submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy in the Department of Criminal Justice in the College of Community Innovation and Education at the University of Central Florida Orlando, Florida

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Major Professors: William Moreto & Matt Nobles
The overall goal of this dissertation is to examine how the built and natural environment influences how potential criminals identify crime sites to offend within. Guided by the theoretical principles of crime site selection and crime pattern theory, this study specifically focuses on the crimes of street robbery and commercial burglary in three unique study locations—Atlanta, GA, Fayetteville, NC, and Rochester, NY. The data for this study were collected from multiple publicly available data repositories. Of these repositories, criminal incident data for the dependent variables were gathered from the National Policing Institute’s Police Data Initiative. Data for the independent variables, which are representative of the built and natural environment, were collected from various open-source public and governmental agencies.

To assess the influence of the built and natural environment on crime site selection, several techniques were employed. First, general spatial patterns were mapped using both kernel density estimation (KDE) and directional distribution analysis. Subsequently, temporal trends were identified by separating the data into several temporal units of analysis, including by meteorological season, weekday/weekend, and four-hour block increments. To assess multivariate relationships, two machine learning techniques were used: multivariate clustering and random forest classification.

In alignment with prior literature, findings indicate that criminal incidents for both street robbery and commercial burglary cluster spatially and temporally. Of note, there are seasonal trends identified within the data, as well as trends relating to the time of day. Results from the multivariate clustering analysis reveal several unique spatial
clusters of variables within each study location. The random forest classification and regression analysis rank ordered the importance of independent variables in their relationship to the criminal incidents in question. This ordering varied considerably depending on the temporal unit of analysis in question, which suggests the spatial predictors of street robbery and commercial burglary differ by season, weekday and weekend, and time of day. These results hold theoretical, methodological, and practical implications within the scope of environmental criminology.
ACKNOWLEDGMENTS

To my committee, Drs. William Moreto, Matt Nobles, Erica Fissel, and Grant Drawve, I would first like to thank you for your support and guidance throughout this entire process. I very much appreciate all of the feedback that was provided every step of the way. I’d also like to say a big thank you to Dr. William Moreto for being a big inspiration and mentor throughout my time at UCF. The encouragement and support that you provided during the course of my study at UCF was a tremendous help. I am a better scholar and person because of everything you’ve done for me. I would also like to thank the entire Criminal Justice Department at UCF. In particular, thank you to Elexis Ritz and Toni Rooney for all the help and the many questions that were answered along the way.

To my family: I love you all. Thank you for believing in me. I would not have made it through this without your support. To all my good friends: we made it. I’m truly blessed to have friends that I’ve known for so many years. We’ve made a lot of great memories over the years, and I know we’ll continue making more as time goes on.
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CHAPTER ONE: INTRODUCTION

The field of criminology has a long history that has recognized the role of space and time on crime events, beginning with the early work of Guerry (1833) and Quetelet (1842), who examined the spatial distribution of various crime types. This work is considered to be the first recorded assessments of the relationship between space and crime. The literature base has subsequently expanded in recent decades with research further exploring the spatiotemporal characteristics and relationships of crime. Of particular interest to the current study, research has examined the impact of the built environment on crime (see, for example Connealy, 2021; Eck et al., 2007; Tay et al., 2013).

The built environment refers to man-made structures, such as public transit stops, public housing, commercial establishments, roadways, office buildings, and police stations. These elements of the built environment have been found to influence the occurrence of criminal events. Certain places, such as pawn shops, restaurants, and liquor store, have been found to heighten the risk of a criminal event (Eck et al., 2007), while others, such as police stations, are expected to reduce the likelihood of an offense occurring (Brantingham & Brantingham, 1981). Prior research also suggests that the influence of predictors across space may not be constant (Haberman et al., 2013). Specifically, previous research has found that public housing increases the likelihood of street robberies occurring (Kim & Wo, 2021; Nelson et al., 2001). Haberman and colleagues (2013), however, found results that demonstrate the
influence of public housing on crime is not homogenous across space, suggesting that some public housing developments were criminogenic, while others were not.

While insightful, this research has largely overlooked the potential impact of characteristics of the natural environment, such as tree canopy coverage and slope. Although there is research that examines the influence of parks and urban forests on crime (Anderson et al., 2013; Foster et al., 2013), there is little research dedicated to examining characteristics of the natural environment at micro-units of analysis. Factors related to the natural environment could have potential implications for criminal decision-making that could influence the likelihood of an offense taking place. For instance, elements of the natural environment, such as tree canopy coverage, could provide cover from surveillance mechanisms like CCTV cameras. Another important factor within spatially related inquiries would be that of the temporal dimension.

Inherently, spatial data have a temporal component, even if it is not recorded within the dataset. For example, data representative of the locations of bus stops, ATMs, schools, and commercial establishments, are all subject to change over time.

Geospatial researchers and practitioners have increasingly recognized the importance of the temporal dimension resulting in the use of data collection procedures that involve the collection of various forms of temporal data allowing for more advanced statistical techniques to be applied (Ott & Swiączny, 2001). Using data of this nature, scholars have identified temporal variation relating to criminal offending (He et al., 2015; Kim & Wo, 2021; Nelson et al., 2001; Szkola et al., 2019), where crimes are concentrated within hours of the day (Nelson et al., 2001; Walsh, 2019), on specific
days of the week (Kim & Wo, 2021; Nelson et al., 2001), by month (Hipp & Kim, 2019; Szkola et al., 2019), and within specific seasons (Andresen & Malleson, 2013; Cowan et al., 2020; Haberman et al., 2018).

With relevance to the present study, Nelson and colleagues (2001) found that street robbery incidents tended to cluster on Friday and Saturday nights between the hours of 10pm and 2am. Qualitative research with commercial burglars found that burglars preferred to offend during this exact same time period (Walsh, 2019). Researchers have also found seasonal variation in offending. Specifically, Andresen and Malleson (2013) found that seasonal variation was present for many different crime types, including robbery, burglary, and sexual assault. This means that levels of criminal activity are not constant throughout a year, instead, these levels fluctuate depending on the time of year. Meaning, crimes were more or less likely in certain areas during specific seasons (Andresen & Malleson, 2013). Thus, not only is there temporal variation in that the frequency of crime will increase or decrease depending on the time of year, but also that spatial concentrations of criminal incidents varied by the time of year.

Apart from these various developments within the spatiotemporal literature, there have also been several theoretical developments that seek to explain criminal events. One predominant theoretical framework in the spatial literature for criminology is crime pattern theory (Brantingham & Brantingham, 1978; 1981; 1993; 1995). Brantingham and Brantingham (1978) put forth a theory on offender crime site selection that would ultimately form into modern day crime pattern theory. This theory of offender site
selection outlines seven propositions that explain what might influence an offender to select a specific location to offend within. From this discussion, Brantingham and Brantingham (1978) assert that offenders first select a larger area to operate within. This larger area serves as a hunting ground for potential criminal offenses. Within this larger area, an offender then selects a smaller area, known as the crime site, which is suitable for offending. Modern day crime pattern theory is a combination of this early work of offender site selection, as well as the routine activities approach (Cohen & Felson, 1979), the rational choice perspective (Cornish & Clarke, 1986), and the geometric theory of crime (Brantingham & Brantingham, 1981). Overall, crime pattern theory assists in the prediction of where criminal activity may occur by presenting a logical framework of how human movement patterns and environmental characteristics influence opportunistic offending patterns.

Recent technological advances in computing hardware and software have also led to the development of various techniques that can assist in our understanding of criminal activity. Specifically, the application of machine learning techniques to explain crime-related phenomena has recently picked up steam within the past few years (Alghamdi, 2017; Biswas & Basak, 2019; Lakshan & Weekakoon, 2022; Solomon et al., 2022). These machine learning techniques are particularly useful for model building and the forecasting of event outcomes, including criminal events (Alghamdi, 2017; Biswas & Basak, 2019; Ek et al., 2022; Green, 2021; Solomon et al., 2022; Wheeler & Steenbeek, 2021). One notable machine learning technique is Random Forests. This technique uses an ensemble of decision trees to make predictions from provided data (Breiman, 2001). Apart from forecasting, this technique is also useful for the rank ordering of
variables in terms of their overall informational contributions to the model (Breiman, 2001). The current study seeks to leverage machine learning techniques to better understand the crimes of street robbery and commercial burglary.

**The Current Study**

The current study contributes to the literature by assessing the spatial and temporal variation of predictors within crime sites for two crime types: commercial burglary and street robbery, in three study locations: Atlanta, Georgia; Fayetteville, North Carolina; and Rochester, New York. Commercial burglary and street robbery were chosen for two reasons. First, selecting these two crime types allows for the assessment of offender site selection for one violent and one property crime. Second, these offenses occur in enough frequency across all three study locations to be used for the selected analysis. The three study locations were included because these cities had publicly available crime and other geospatial data that could be used for the dependent and independent variables for the current study.

Guided by several spatiotemporal theories, including crime pattern theory, risky facilities, and temporal constraint theory, and using the Random Forest Classification and Regression tool within ArcGIS Pro, the current study examines the following two research questions that explore offender site selection for both commercial burglary and street robbery:

1. How do spatiotemporal characteristics impact offender site selection for commercial burglary and street robbery?
2. How do environmental characteristics cluster within crime sites for commercial burglary and street robbery?

Data representing the spatial predictors for the study were gathered from multiple open-source geographic information system (GIS) databases. As noted, the literature for the relationship for space, time, and crime, as well as crime pattern theory, helped guide which factors are included in the current study. The dependent variables examined are criminal incident data for street robberies and commercial burglaries between 2012-2018 for each individual study area. This criminal incident data was gathered from the National Police Institute's Police Data Initiative, an open-source police data repository¹.

The outlined research questions will provide several contributions to the body of literature related to inquiries of space, time, and crime. First, the current study seeks to extend this inquiry by examining the spatial variability of multiple variables within crime sites between three unique study locations. Moreover, this study expands on prior research that uses random forests to examine criminal events (Alghamdi, 2017; Biswas & Basak, 2019; Ek et al., 2022; Green, 2021; Solomon et al., 2022; Wheeler & Steenbeek, 2021). The current study also seeks to follow the trend of using statistical and visualization techniques that were developed for the examination of spatial relationships (Brundson et al., 1996; Fotheringham et al., 2000; 2002; Griffith and Amrhein, 1997). Another contribution is the examination of the predictors of crime sites, as well as identifying what factors tend to cluster together within known crime sites.

¹ https://www.policedatainitiative.org/
Additionally, the current study builds off previous literature that suggests the importance of analyzing spatial crime patterning at micro units of analysis (Braga et al., 2011; Weisburd et al., 2004). Apart from spatial patterning, findings from the current study also provide insight into the temporal patterning of spatial predictors within crime sites for both commercial burglary and street robbery. Lastly, the current study provides not only a theoretical contribution in the expansion of the discussion of crime sites, but it also contributes methodologically by identifying how characteristics of the natural environment can be specified within statistical models.

Summary

Inquiries into the relationship between space, time, and crime have been ongoing for nearly two centuries (Guerry, 1833; Quetelet, 1842). From this research, characteristics of the built environment, such as ATMs, bus stops, restaurants, etc., have been found to help predict various types of criminal activity (Brantingham & Brantingham, 1995). Largely absent from this research, however, are examinations into the relationship between the natural environment, such as tree canopy coverage, and crime. One predominant theory used to explain the relationship between space, time, and crime is crime pattern theory. The current study is guided by this theoretical framework to investigate two crime types: street robbery and commercial burglary. To assess these two unique crime types, the current study uses two machine learning techniques, multivariate cluster analysis and Random Forest. Findings from this study will contribute to a large body of literature that examines how the environment influences criminal activity. Additionally, the current study extends discussions of the
temporal variability of the selected crime types. Lastly, the current study explores how
the natural environment influences street robberies and commercial burglaries.
CHAPTER TWO: THEORETICAL FRAMEWORK

Introduction

All types of criminal activity have spatial and temporal characteristics. As an example, every criminal incident occurs at a specific place and time. In terms of spatial characteristics, a place could be in a dense city center, suburban neighborhood, rural countryside, or anywhere in between. Each of these places would be unique in that there are different built elements, such as ATMs, restaurants, schools, etc., as well as different natural elements, such as tree canopy coverage, slope, vegetation, etc. In terms of temporal characteristics, the time that an offense occurs would determine whether it is day or night, whether streetlights are on or off, or whether people are visiting certain establishments. Additionally, this offense occurs within a larger temporal context such as the meteorological season (spring, summer, fall, and winter). To gain insight into the link between spatiotemporal characteristics and crime, the current study is guided by crime pattern theory, temporal constraint theory, and risky facilities. Prior to discussing each of these theories and concepts in detail, a brief overview is provided.

Crime Pattern Theory and Associated Frameworks

As mentioned, the main theoretical framework for the current study is crime pattern theory. This theory is considered a meta-theory as it borrows from several other perspectives to produce a framework that seeks to explain the occurrence of criminal activity based on patterns of human movement and rational decision-making (Brantingham & Brantingham, 1993). Crime pattern theory borrows from a theory of crime site selection (Brantingham & Brantingham, 1978), routine activities (Cohen &
Felson, 1979), rational choice (Cornish & Clarke, 1986), and the geometric theory of
crime (Brantingham & Brantingham, 1981). Each of the concepts and implications
relating to these theories will be presented, followed by an in-depth discussion of crime
pattern theory itself.

The Foundations of Crime Pattern Theory

Theoretical Model of Crime Site Selection

Brantingham and Brantingham (1978) put forth a theory that attempts to explain
the crime site selection process for offenders. As described above, offenders first select
a larger area to operate within, take for example a mall parking lot. Once they are within
this larger area, they then begin to search for a suitable crime site. This crime site is a
small area that is attractive to the offender for any number of reasons, including a lack
of capable guardianship, better or more suitable targets, or higher degree of anonymity
(Brantingham & Brantingham, 1978). Within a mall parking lot, a crime site could be a
small section of the parking lot. Within this general framework, a series of seven
propositions were outlined.

The first proposition of this framework is that some individuals are motivated to
commit specific crimes. The reason for this motivation to offend is not a consideration of
this framework, but it is assumed that this motivation exists, nonetheless. The second
proposition states that the occurrence of a criminal act is the end result of a spatial
filtering process in which potential offenders search within an environment and narrow
down possible crime sites. The more motivated an individual is in committing an
offense, the shorter this filtering process becomes (Brantingham & Brantingham, 1978).
The third proposition from this theory puts forth that “[t]he environment emits many signals, or cues, about its physical, spatial, cultural, legal, and psychological characteristics” (Brantingham & Brantingham, 1978, p. 107). In their discussion of this proposition, Brantingham and Brantingham (1978) make note that “[a] person walking along a street, however, may be aware of pavement texture, store displays, plantings, building architectural features” (p. 111). This suggests the importance of examining elements of both the natural and built environment.

The fourth proposition asserts that potential offenders interpret the cues noted in the third proposition to locate potential targets. Brantingham and Brantingham (1978) further describe this interpretation process as something that offenders update over time. This means that offenders learn from their interactions with the environment around them (Brantingham & Brantingham, 1978). When combined, propositions 3 and 4 from this framework come together to form what is now known as the environmental backcloth, which will be discussed in length through the geometric theory of crime.

The fifth proposition puts forth that offenders, over time, learn what constitutes a potential suitable target from their experience operating within a given environment. This process forms a template for the identification of what a suitable target or victim may be. This proposition would later be expanded into the concept of the “crime template” discussed below. The sixth proposition states that this template is self-reinforcing. Meaning, the template, once established, will help guide future search patterns, thereby reinforcing and refining the template itself (Brantingham & Brantingham, 1978). The final proposition from this theory is that the crime selection
templates for individuals oftentimes overlap. This leads to a series of clusters or patterns that may be apparent during the offending process. A list of the propositions from this framework can be found in Table 1 below.

**Table 1: Propositions from Brantingham and Brantingham (1978) Theory of Crime Site Selection (p. 107-108)**

<table>
<thead>
<tr>
<th>Proposition 1</th>
<th>Individuals exist who are motivated to commit specific offenses.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposition 2</td>
<td>Given the motivation of an individual to commit an offense, the actual commission of an offense is the end result of a multi-staged decision process which seeks out and identifies, within the general environment, a target or victim positioned in time and space.</td>
</tr>
<tr>
<td>Proposition 3</td>
<td>The environment emits many signals, or cues, about its physical, spatial, cultural, legal, and psychological characteristics.</td>
</tr>
<tr>
<td>Proposition 4</td>
<td>An individual motivated to commit a crime uses cues (either learned through experience of learned through social transmission) from the environment to locate and identify targets or victims.</td>
</tr>
<tr>
<td>Proposition 5</td>
<td>As experiential knowledge grows, an individual motivated to commit an offense learns which individual cues, clusters of cues, and sequences of cues are associated with &quot;good&quot; victims or targets. These cues, cue clusters, and cue sequences (spatial, physical, social, temporal, and so on) can be considered a template which is used in victim or target selection. Potential victims or targets are compared to the template and either rejected or accepted, depending on the congruence.</td>
</tr>
<tr>
<td>Proposition 6</td>
<td>Once the template is established, it becomes relatively fixed and influences future searching behavior, thereby becoming self-reinforcing.</td>
</tr>
<tr>
<td>Proposition 7</td>
<td>Because of the multiplicity of targets and victims, many potential crime selection templates could be constructed. But because the spatial and temporal distribution of targets and victims is not regular, but clustered or patterned, and because human environmental perception has some universal properties, individual templates have similarities which can be identified.</td>
</tr>
</tbody>
</table>
Routine Activities Approach

While the routine activities approach (RAA) is often referred to as a theory, the original intent of putting forth this explanation of criminal activity was not to establish a theory that could compete with traditional criminological theory. Rather, the authors of this approach stayed away from this classification because they felt it fell short of being called a theory (Felson, 2000). Specifically, the RAA was originally put forth to explain direct contact predatory offenses. It was not until later years that this framework was expanded to include crimes in which direct contact between offender and target were not necessary or possible, such as the sale of drugs and other contraband (Felson, 2000). Taken together, this approach details how human movement influences crime patterns. This model is important for the current study because it helps explain not only why offenders target specific establishments (Bowers & Johnson, 2013; Clarke & Webb, 1999), but it also helps explain predatory offenses, such as street robbery (Cohen & Felson, 1979). Within this routine activities framework, there are three concepts of interest: motivated offender, suitable target, and a lack of capable guardianship (Cohen & Felson, 1979). While the framework can also be applied to macro-level crime trends, such as why specific locations experience heightened levels of criminal activity over others, the focus of the present study will be on micro-level dynamics.

With the model that routine activities outlined, there are three concepts related to the temporal patterning of human activity that should be noted: rhythm, tempo, and timing (Andresen, 2014). Rhythm is related to the regular interval of specific activities. For example, an individual going to the grocery store every Sunday around 9pm
suggests there is a certain rhythm to their weekly routine. Tempo refers to how often an event occurs given a specific time frame. A common example of this would be how many criminal events occur within a single day at a specific place (Andresen, 2014). Timing refers to the overlap of events that are dependent upon one another. Within the routine activities framework, this can be thought of as the convergence of the motivated offender, suitable target, and a lack of capable guardianship. Without the presence of one of these factors, a criminal event is unlikely to occur. For example, in a given place, there may be a suitable target absent capable guardianship; however, without a motivated offender to take advantage of this opportunity, no criminal event can occur. These concepts are important to consider because they help explain how and why human movement patterns correlate with criminal opportunity.

**Motivated Offender**

The first concept within routine activities is that of the motivated offender (Cohen & Felson, 1979). While many criminological theories attempt to explain motivation for criminal conduct, this concept within routine activities is taken as an assumption. According to Cohen and Felson (1979), the original focus of the routine activity approach is on that of explaining the offense itself; however, these scholars did briefly outline a mechanism for examining criminal motivations in their discussion of future research. For an individual to be considered a motivated offender, they must make the decision to engage in criminal activity (Cohen & Felson, 1979). Apart from this willingness, the individual must also be able to commit whatever criminal act they have decided they will commit. Absent this mental and physical ability to commit crime, they cannot be considered a motivated offender (Cohen & Felson, 1979). Thus, in
summation, for a criminal event to occur, there must be the convergence, in time and space, of a motivated offender, a suitable target, and an absence of capable guardianship. According to this approach, if any of these elements are missing, the criminal event is simply not possible (Cohen & Felson, 1979).

From research that has examined offender motivations, it can be noted that some offenders have an instrumental purpose in committing crime (Brookman et al., 2007; Harding et al., 2019; Wright & Decker, 1997). That is, offenders typically commit crime because they are attempting to reach a specific goal, whether it be monetary or lifestyle related (Brookman et al., 2007). As an example, offenders may be committing crime to obtain resources necessary to sustain a drug habit (Brookman et al., 2007; McLean et al., 2020). Other research in this domain has found that some offenders commit crime because it provides them with a thrill (Brookman et al., 2007; Harding et al., 2019). Thus, there is no instrumental purpose behind the criminal act. After from instrumental purposes or thrill-seeking behavior, another motivation for criminal activity could be inclusion in organized criminal enterprise (Harding et al., 2019). To elaborate, Harding and colleagues (2019) examined the occurrence of street robbery as it relates to organized criminal activity. Findings indicate that some criminal groups would commit street robberies while they were on the hunt for rival groups to victimize (Harding et al., 2019). In other words, these groups originally set out to get into an altercation with a rival gang; however, they ended up committing street robberies on civilians as they pursued their rival gang targets (Harding et al., 2019).
Target Suitability

There are several ways to conceptualize what makes a target suitable. Two models that describe suitable targets are the VIVA and CRAVED models. Cohen and Felson (1979) originally described suitable targets through the VIVA model while Clarke and Webb (1999) extended this into the CRAVED model. The VIVA model was expanded to the CRAVED model to account for limitations revolving around a lack of consideration for the motivations of offenders as well as how an offender might conceal or dispose of a hot product (Clarke & Webb, 1999). The first concept within the CRAVED model is concealability. This refers to whether an offender is able to hide a product on their person (Clarke & Webb, 1999). Smaller objects, such as personal electronics, can easily be hidden on the person, meaning that an offender may have a higher likelihood of getting away with the theft of that item (Bowers & Johnson, 2013).

The second concept within the CRAVED model is the removability of a target (Clarke & Webb, 1999). This concept refers to how easily a targeted product can be removed from the target location. For example, cars and bikes are often frequent targets of theft because they can be moved quite easily from one location to another (Clarke & Webb, 1999). Next within the CRAVED model is availability. If a product is not available, then it is not possible for it to be the target of a theft. Additionally, a product must be valuable in order to be the target of a theft. Value in this context is not restricted to the financial value of a product as sometimes products are stolen for other reasons, such as enjoyment. For example, an individual may steal a car to go on a joy ride. Alternatively, an individual may steal cigarettes or alcohol to enjoy (Clarke & Webb, 1999). Thus, the value of a product is subjective. The concept of value within the CRAVED model has
overlap with the next concept, which is that a product that is enjoyable is more likely to be the target of a theft. For example, a street robber may steal cash not because they need it to buy necessary products, such as food, but because they wish to live a certain lifestyle. The money they steal helps them purchase items that allow them to live this lifestyle, such as expensive clothes, jewelry, or other products (Clarke & Webb, 1999).

Finally, within the CRAVED model, products that are easily disposable are more frequently targeted. For example, a thief might target jewelry or a car that has valuable parts because they can easily be sold once they are obtained. Overall, VIVA and the expansion of this model, CRAVED, help explain why certain products, and subsequently, why some establishments, might be the target of criminal activity.

The above CRAVED model describes why certain products might be targeted over others in the context of a commercial burglary. This model, however, does not help explain why certain individuals may be the target of a street robbery. Some scholars would characterize street robbery as a spontaneous event in which offenders act on an opportunity without much planning (Deakin et al., 2007; Bennett & Brookman, 2008; Jacobs, 2010; Wright & Decker, 1997). Certainly, these individuals had been actively searching for targets, however, street robbery is a crime in which the opportunity to offend can disappear rather quickly as the identified target may be moving (Bennett & Brookman, 2008; Wright & Decker, 1997). Thus, offenders may make a quick decision to commit the offense. In part, offenders are attempting to identify targets that are “soft”. Meaning, they are attempting to select targets based on the perception that the target will not fight back and is not a threat to the offender themselves. Offenders have noted that college students often make good targets for robberies because they do not put up
a fight and are easily intimidated (Deakin et al., 2007). They may also select victims on the basis that specific individuals will not report the offense to police. More specifically, street robbers may target other individuals engaging in criminal activity (Bennett & Brookman, 2008; Deakin et al., 2007; Harding et al., 2019; Jacobs, 2010; Wright & Decker, 1997). This would include drug dealers and users, other robbers, and individual seeking prostitutes. That being said, some robbers have reported that some targets are off-limits, such as women and the elderly (Deakin et al., 2007). The reason behind this is that committing a violent offense against women and the elderly are seen as dishonorable among some offenders (Deakin et al., 2007).

Also of note, in order for a target to be selected, a robber must perceive that they have something of value on them (Brookman et al., 2007; Deakin et al., 2007; McLean et al., 2020; Wright & Decker, 1997). If the potential target is not perceived to have anything valuable, then there is no reason for the offense to take place. In terms of the perception that an individual has something of value, an offender may look at the clothes that the target is wearing, or the offender may take notice that an individual is using their phone in public (Deakin et al., 2007). This could mean that the phone itself is the target or if it is perceived to be an expensive item, it could indicate the individual has other valuable items on their person, whether that be sunglasses, money, among other items (Deakin et al., 2007).

Lastly, target suitability is guided by not only characteristics of a desired product (Bowers & Johnson, 2013; Clarke & Webb, 1999), but also personal characteristics, such as age (Drawve et al., 2014; Miethe et al., 1987; Wright & Decker, 1997), and the
context of the surrounding environment, including the presence of guardianship or the
time of day (Brantingham & Brantingham, 2017; Drawve et al., 2014). Age may play a
role in target suitability in that younger individuals are more likely to travel further
outside of their known environments (Messner & Tardiff, 1985). Drawve and colleagues
(2014) found that the age of targets was positively associated with the likelihood of
arrest for the crime of aggravated assault. Meaning, crimes against individuals aged 15-
55 were more likely to have the offender arrested than attacks against older individuals
(Drawve et al., 2014). The situational context of the environment is influential because
the environment can change depending on the time of day (Brantingham &
Brantingham, 2017; Drawve et al., 2014). For example, a convenience store may have
one or several clerks working at any given time. When only one clerk is present,
offenders may see this target are more suitable (Brantingham & Brantingham, 2017).
Additionally, for a crime like cyberattacks, the operating system of the target server
could make some targets more suitable (Holt et al., 2020). The idea here being that
some open-source operating systems may be more susceptible to attacks because of
the fact that the source code is public (Holt et al., 2020).

**Capable Guardianship**

The next concept within the routine activities approach is capable guardianship
(Cohen & Felson, 1979). The qualifier *capable* for the concept of guardianship means
that an individual or object must have the ability to intervene or prevent the offender
from committing a criminal act (Clarke & Eck, 2005). From this description, capable
guardianship might be a security guard or even a CCTV camera that deters an
individual from offending. From this description, there are two unique forms of
guardianship that can be identified—formal and informal guardianship. Formal guardianship refers to professionals who are tasked with protecting certain establishments, such as police officers, security guards, etc. Informal guardianship would relate to other non-professional forms of guardianship, such as CCTV cameras, motion sensors, and door locks (Clarke & Eck, 2005).

While Cohen and Felson (1979) describe guardianship to some degree, there was a distinct lack of explanation regarding specific forms of guardianship. To address this gap, Clarke and Eck (2005) put forth the problem analysis triangle which describes three forms of guardianship. These forms of guardianship are related to three elements, the target, offender, and place (Clarke & Eck, 2005). In terms of the target, there would be a capable guardian. This would typically be an individual who is responsible for protecting their own property or someone who was hired to protect that property, whether that be a police officer or security guard. Additionally, a guardian could be anyone who might be present around a potential offender and target (Felson & Eckert, 2016). That is, a guardian does not need to be able to physically intervene in order to stop an offense from occurring, sometimes the threat of a report or being able to identify the offender is enough to deter that offense from being committed (Felson & Eckert, 2016). Thus, a capable guardian is someone who has the ability to protect a target against victimization (Clarke & Eck, 2005). See Figure 1 below for a representation of the Problem Analysis Triangle put forth by Clarke and Eck (2005).
From this crime triangle, the concept responsible for guardianship of an offender would be any individual who has the ability to control the offender (Clarke & Eck, 2005). As Clarke and Eck (2005) note, a handler could be a parent, spouse, or sibling. Additionally, within the context of the criminal justice system, a handler could be a probation or parole officer (Clarke & Eck, 2005). These individuals, in particular, have the ability to influence an offender to not act upon criminal opportunities that they may encounter. The reason for this might be a desire not to disappoint family members or friends. Alternatively, a handler, such as a probation officer, might be able to hold the threat of additional legal sanctions over the head of the potential offender. The last concept within the crime triangle is that of place. The specific guardian for this concept would be that of the place manager (Clarke & Eck, 2005). A common example of a
place manager would be that of a bar owner (Madensen & Eck, 2008). The bar owner, and place managers in general, have the unique ability to make decisions about how a specific place will function. If, for example, a bar owner caters to unsavory crowds and overserves alcohol on a regular basis, this might cause crime problems for the bar and the surrounding area (Madensen & Eck, 2008). Another example of a place manager would be an individual who owns an apartment complex. This individual makes decisions on how residents are screened, if at all, how the complex is constructed, and if security is hired for the premises. From this conceptualization of guardianship, we can see that there are many different forms of capable guardianship that might influence criminal activity within a defined place.

Prior research has demonstrated that there many considerations to be made regarding capable guardianship (Hollis-Peel et al., 2011; Reynald, 2011; Reynald et al., 2018; Tewksbury & Mustaine, 2003). For example, in their assessment of guardianship, Reynald (2011) extends the study and understanding of guardianship beyond capability and incorporates the willingness of guardians. Specifically, Reynald (2011) comments that to be a guardian, an individual must be able to surveil the area around them. Additionally, one must be aware they are engaging in an act geared towards the prevention of criminal activity. Lastly, an individual must be willing and able to intervene if a problem is identified. Reynald (2011) also notes that the concept of guardianship is better defined in a more active sense. Meaning, individuals should be taught to actively engage in guardianship. This can be accomplished by encouraging the three characteristics listed above: to learn how to be a guardian, how to be aware of their role, and how to act when a problem is identified (Reynald, 2011). To examine guardianship,
Reynald (2011) conducted a study in The Hague, Netherlands that, in part, assessed the willingness of individuals to intervene when potential outsiders are identified within their neighborhoods. To accomplish this, the research team conducted observations in sampled street segments. One proxy measure of guardianship that was utilized was whether or not residents confronted the research team when they were present. Thus, not only did residents have to be present at the location, but they also had to be aware of the research team. Lastly, they also had to be willing to intervene and confront the research team to inquire what they were doing in this area. The hope was that if residents are willing to confront a team of researchers, they might also be willing to confront other forms of outsiders, such as potential offenders (Reynald, 2011).

Hollis-Peel and colleagues (2011) extends this discussion of guardianship by noting that guardianship can have two purposes. The first being to increase the actual risk of apprehension. The second to increase the perceptual risk of apprehension. In this manner, guardianship can be real or symbolic (Hollis-Peel et al., 2011). Hollis-Peel and colleagues (2011) also identified four different types of guardians that draw from Reynald’s (2011) elaboration of active guardianship, including the intervening, capable, available, and invisible guardians. The intervening guardian is an individual that satisfies all three elements described above by Reynald (2011): they are present, aware, and able to engage in prevention. The capable guardian is an individual or object that is present and aware, but not necessarily able to intervene. The available guardian is present; however, they are not aware, nor are they able to intervene. The invisible guardian is one that is neither present, aware, nor able to engage in prevention (Hollis-Peel et al., 2011). While the above discussion details what exactly makes a capable
guardian, it is equally important to note that this capable guardian, in order to potentially intervene on a criminal act, must converge, in time and space, with a motivated offender and potential target. Further discussions into guardianship make note that there is utility in examining guardianship from both macro- and micro-levels (Tewksbury & Mustaine, 2003; Reynald et al., 2018). Indeed, it has been noted that building guardianship at the micro-level can help enhance guardianship at the aggregate (Reynald et al., 2018). From a micro-level perspective, factors such as exposure to potential offenders and fear of crime, may influence whether an individual adopts certain self-protective strategies (Tewksbury & Mustaine, 2003).

In large part, the routine activities approach details when and where a criminal event, or events, might occur; however, this framework does not consider the thought process that guides this routinized behavior. For that, attention is shifted to the discussion of the rational choice perspective.

**Rational Choice Perspective**

The rational choice perspective developed by Cornish and Clarke’s (1986) is important for the discussion of crime patterns as it provides a basis for the forecasting of criminal activity. Indeed, if we assume that criminal behavior is largely irrational, we would not be able to accurately forecast criminal activity (Andresen, 2014). Thus, understanding the rational basis for criminal activity is paramount to the discussion of crime patterns.

The first point of interest within the rational choice model is that of rationality. In the context of criminology, rationality can refer to the decision-making process in which
individuals balance the cost-benefit of committing a specific act. It is this cost-benefit analysis that infers rationality. With a pure form of rationality, it is assumed that an individual would attempt to maximize the benefit of an action while minimizing the cost. In terms of explaining human behavior, this pure form of rationality oftentimes falls short (Andresen, 2014; Cornish & Clarke, 1986). If one were to assume a pure form of rationality for explaining human behavior, many criminal incidents would appear irrational. Thus, it is beneficial to adopt a bounded sense of rationality (Andresen, 2014; Cornish & Clarke, 1986). This bounded, or limited, conceptualization of rationality assumes that decision-making for an individual event is best categorized as acting as rational as possible, given what we know at that specific time.

This highlights the subjective reality of human decision-making; that what is rational to one may not be rational to another. For example, qualitative research examining target selection for robbers (Bennett & Brookman, 2008, 2009; Brookman et al., 2007; Deakin et al., 2007; Harding et al., 2019; McLean et al., 2020; Wright & Decker, 1997) and commercial burglars (Walsh, 2019) identified many different factors that offenders look out for when selecting a target. In general, offenders typically try to seek out targets that offer the path of least resistance; however, the determination of what offers this path of least resistance is entirely subjective. For example, with reference to street robbery, some offenders preferred to rob other individuals engaged in criminal activity, such as drug dealers or users, while others preferred targets they perceived to be less of a threat, such as non-criminals (Brookman et al., 2007; Deakin et al., 2007; McLean et al., 2020; Wright & Decker, 1997). A perceived non-criminal is considered less of a threat due to the assumption that these individuals are not willing to
fight back (Brookman et al., 2007; Deakin et al., 2007; McLean et al., 2020; Wright & Decker, 1997). In terms of commercial burglary, some offenders prefer to target smaller businesses because of the perception that small businesses may not be able to spend as much money on target hardening as a larger business (Walsh, 2019). Other offenders may prefer to target larger businesses because of the increase in patronage to these businesses, which could provide cover for the offender (Walsh, 2019). This highlights the inherent subjectivity in what factors might be deemed to be important to one, may be less or completely unimportant to another.

In terms of offending, there are three primary decisions to be made by an individual: the decision to offend in general, the decision to commit an individual act, and the decision to desist (Andresen, 2014; Cornish & Clarke, 1986). Regarding the initial decision to offend, there are many background factors that might play into propensities to offend, including, but not limited to, intelligence, impulsivity, upbringing, and education (Andresen, 2014; Cornish & Clarke, 1986). From these background factors, an individual may have direct or vicarious experiences with criminal activity. Additionally, their sense of morality or self-judgment may have been impacted which predisposes that individual to see crime as an acceptable solution to their perceived problems in life. These experiences, in combination with some generalized needs, such as money, friendship, or status, lead the individual to weigh both legitimate and illegitimate methods of resolving these needs. Within this, they might balance the cost-benefit of these legitimate and illegitimate activities. If the individual develops a sense of readiness to commit crime, in conjunction with a reaction to a chance event, such as peer pressure or intoxication, they may finally make the decision to offend (Andresen,
This is representative of the initial decision to offend. The individual would then progress into the decision-making process for committing a specific criminal act.

After the decision to offend, an individual must select potential locations for the criminal act. For this discussion, the criminal act will be a commercial burglary. The offender will exclude some locations due to an unfamiliarity with those areas (Bowers & Johnson, 2013). Additional areas may be excluded due to inaccessibility. This inaccessibility may be due to a lack of transportation or due to the area having strict access control (Brantingham & Brantingham, 2008). In terms of a commercial burglary, this would be an establishment that has hired security for when the place is closed for business. The selection of a specific location to offend might be based on a perceived lack of security, ease of access, and a desired product within that establishment (Andresen, 2014; Cornish & Clarke, 1986). When an offender is deciding whether to act at a specific time, they will look for situational cues, such as whether employees are still present at the establishment or if their chosen access point is visible to people who might be able to intervene in the criminal act. If these situational cues are acceptable to the offender, then they will commit the criminal act. The evaluation of each subsequent criminal act will follow this same process (Andresen, 2014; Cornish & Clarke, 1986).

The final decision that an individual makes regarding criminal activity is the decision to desist (Andresen, 2014; Cornish & Clarke, 1986). After each criminal act that is undertaken, an individual goes through a decision-making process in which they evaluate whether to continue offending or not. Some external events may influence this
decision, such as the individual getting married or being confronted while committing a
criminal act (Cornish & Clarke, 1986). For an example related to commercial burglary,
consider the offender is chased away by security. They might make the decision that
the risk outweighs any potential benefit from committing these acts (Andresen, 2014).
After this re-evaluation of their decision to engage in commercial burglaries and
accepting desistance, the offender has two options: to move on to legitimate
opportunities to satisfy their needs or move on to other forms of criminal activity
(Andresen, 2014; Cornish & Clarke, 1986). The discussions of the routine activities
approach and rational choice theory brought up some important considerations, such as
how these two approaches might be combined. To explore this combination of routine
activities and rational choice, we turn to the geometric theory of crime.

**Geometric Theory of Crime**

The geometric theory of crime explains the relationship between space and time
with that of the three concepts of routine activities: the suitable target, motivated
offender, and capable guardian (Andresen, 2014). Indeed, the convergence of a
suitable target, motivated offender, and a lack of capable guardianship exist within a
very complex and dynamic environment (Brantingham & Brantingham, 1981; 1993). All
three of these routine activity components interact with their environments in various
ways, which ultimately impacts the types of crime patterns observed. Within the
geometric theory of crime, there are six noteworthy elements: the environmental
backcloth, activity space, awareness space, pathways, activity nodes, and edges
(Brantingham & Brantingham, 1981; 1993). Each of these elements are extensions of
the seven propositions outlined earlier from the theory of crime site selection put forth
by Brantingham and Brantingham (1978). All six of these elements will be outlined, but first there needs to be a brief discussion on the difference between space and place.

Space can be defined in a geographic sense as referring to objective criteria, such as distance and direction (Andresen, 2014). Place takes on a more subjective interpretation being the specific context of a space. Thus, place provides the overall context of a given location (Andresen, 2014). This difference is important to understand because it is this sense of place which provides the individual interpretation of ones surrounding which ultimately influences behavior in this given location. This sense of place was extended by Brantingham and Brantingham (1981; 1993) to include concepts like movement and change. The additions of movement and change to this sense of place has been referred to as the environmental backcloth (Brantingham & Brantingham, 1981; 1993). That is, as an individual moves throughout a place, there is a unique spatial and temporal context of that location. For example, if we imagine an individual walking along a street segment, the feeling of that location might vary depending on the time of day. This individual may feel comfortable walking along this segment during the day, but uncomfortable at night. Likewise, perhaps one side of this street segment is well-lit while the other is not. Perhaps an individual would feel more comfortable walking at night only on the well-lit side of this segment. Not only would there be temporal variation in how individuals perceive this environment, but there is also a spatial component as well. The environmental backcloth, then, accounts for how individuals perceive place as they move through this environment (Brantingham & Brantingham, 1981). This interpretive aspect of the environmental backcloth is said to occur through a series of infinite feedback loops (Brantingham & Brantingham, 1981).
The environment is giving off certain cues to the individual, such as the presence of lighting or other individuals who are present, and these cues are used to guide behavior through this environment. It would be this aspect that relates to the rational decision-making of both would-be offenders and their targets.

As noted, the geometric theory of crime could be said to be a spatiotemporal extension of the early theory on offender crime site selection, routine activities, and rational choice approaches. The above example of an individual walking along a street segment might be interpreted as an individual who might be perceived as a suitable target. This could also be applied to a potential motivated offender. While the individual noted above was more comfortable walking during the daytime and on well-lit sides of a street segment, the opposite could be true for a potential offender. For example, a robber that is on a search for potential targets on a particular street segment, may feel more comfortable operating at night (Nelson et al., 2001; Wright & Decker, 1997). Additionally, they may feel more at ease on a less lit section of that street segment. The reason for this is that the cover of darkness provides extra protection of being identified by potential victims (Wright & Decker, 1997). Additionally, it may allow an offender to lie in wait without being noticed. This is demonstrative of the subjective, complex, and dynamic relationship between individuals and the environment that they routinely move throughout.

Within this environmental backcloth, there are several concepts to make note of, including pathways, activity nodes, and edges (Brantingham & Brantingham, 1981; 1993). Pathways refer to the routes that an individual may take while going throughout
their daily routine. This could include any type of route, whether that be a foot path, paved roadway, or unpaved path (Brantingham & Brantingham, 1981; 1993). In terms of pathways, research has shown that pathways with more passers-by are less likely to experience criminal activity, at least to a certain degree (Kim, 2018). This would be representative of a curvilinear relationship between pathway passers-by and criminal activity. This suggests that crowd provide a certain level of guardianship up to a certain degree, then beyond that point, the crowd can present a breakdown of guardianship by an excess of potential opportunities and a lack of surveillance (Kim, 2018). Activity nodes refer to places that are frequently visited by both the individual and the aggregate, groups of people. These could include any number of places, including, but not limited to, shopping malls, grocery stores, or banks. These activity nodes are connected by pathways. These connections lead to the emergence of crime patterns whereby individuals frequent specific pathways and activity nodes, which leads to the formation of opportunity for criminal offending (Brantingham & Brantingham, 1981; 1993). One commonly identified problematic activity node is hospitals (Kim, 2018). From a spatial standpoint, these facilities have been found to have a crime enhancing effect (Kim, 2018). In particular, the crime types of assault and theft are prevalent in and around these facilities. In terms of characteristics of activity nodes, the age of the facility was found to have a curvilinear relationship with the overall crime count of that facility. Kim (2018) put forth that possible heightened foot traffic and local unfamiliarity with the facility contributed to the increase at the onset of a facilities life. Later in the life of this facility, crime is thought to decrease because of relationships formed with local residents and a decrease in foot traffic (Kim, 2018).
The next concept within the geometric theory of crime is edges. An edge refers to any type of boundary, whether that be real or perceived, between places (Brantingham & Brantingham, 1981; 1993). An edge, for example, might be the area between specific land uses, such as commercial and residential or industrial and commercial. An edge could also be socially based, such as where two neighborhoods meet (Andresen, 2014). Within a specific place, there is a certain expectation of who might belong to that area. This could influence the ability of individuals within this place to identify would-be offenders. Edges, on the other hand, are the meeting points between two different places. This leads to a distinct uncertainty of who might belong to that area. It might then be more difficult for individuals to identify who belongs and who does not belong in these areas. This provides a certain level of anonymity for potential offenders (Andresen, 2014). This also could have implications for specific crime patterns in these areas. To elaborate, prior research has found that there are elevated levels of criminal activity at edges (Kim & Hipp, 2017; Song et al., 2017). Song and colleagues (2017) defined edges as intersections of land use zones, while Kim and Hipp (2017) examined both physical and non-physical edges, such as highways, parks, and rivers (physical), and city boundaries (non-physical). From these studies, it was found that both property and violent crime were elevated near edges (Kim & Hipp, 2017; Song et al., 2017); however, drug crimes were not found to be impacted by edges (Song et al., 2017).

Next, activity spaces refer to the area in which an individual frequently moves throughout during their daily routine (Brantingham & Brantingham, 1981). This area would be the activity nodes that they frequent as well as the pathways that they take to reach these nodes. For a potential offender, this is the area that they more than likely
offend within or around. Research in this domain has attempted to predict known offender behavior by modeling their activity spaces (Tayebi et al., 2014). This is accomplished through the creation of a probability-based model that assumes individuals will offend in areas that should be known to them. The model calculates the probability that a known offender will visit and subsequently commit a criminal offense on any given street segment within the study area. In other words, the model assumes potential offenders prefer to operate within their activity spaces and attempts to predict crime patterns on this assumption. Results from this study would indicate the selected model outperforms traditional prediction techniques grounded in hot spot identification (Tayebi et al., 2014).

To understand why an offender might choose this area to offend within, it is important to make note of what is commonly referred to as the awareness space. This concept refers to the notion that as an individual moves throughout their environment during their daily routine, they are establishing a sense of familiarity with this area (Brantingham & Brantingham, 1981). In terms of offending, an individual will want to commit crime in this area because they know it best. This means that they potentially have a greater chance of evading detection because they know the escape routes and they know the area in which they plan on offending within. For example, because an offender, throughout their daily routine, frequents certain activity nodes, along certain pathways, they might make note of specific security features of this environment.

These features are considered forms of guardianship and could include people, such as security guards, or structural characteristics, such as the presence of CCTV
cameras. Knowledge of this environment helps the offender make a rational decision about whether to commit the criminal act (Andresen, 2014; Brantingham & Brantingham, 1981; 1993). It also helps potential targets of crime make better decisions about how to protect themselves from victimization. Thus, not only does the geometry of crime help explain offending, but it can also be useful for protecting against victimization. As a demonstration of the environmental backdrop, Bernasco and Block (2009) put forth a model to explain why certain areas might be selected by robbers. Overall, it was found that offenders selected areas that had crime generators and attractors present. Of these crime generators and attractors, Bernasco and Block (2009) used drug and prostitution markets, high schools, and retail businesses. One other factor found to influence where robberies were occurring was gang territoriality. Specifically, it was found that offenders typically committed robberies within census tracts that had the same gang affiliation, which suggests robbers avoid rival territory for this selection process (Bernasco & Block, 2009). For a conceptual model of the geometric theory of crime, please see Figure 2 below.
In years past, there have been attempts to extend the concept of the awareness space (Curtis-ham et al., 2020). Within this extension, two primary characteristics are identified: reliability and relevance. Reliability relates to how trustworthy the information that an offender holds regarding potential offense locations. How often an individual offends and the duration of time they spend within this area will ultimately influence how reliable this information is (Curtis-Ham et al., 2020). In terms of relevance, this term refers to the knowledge of specific criminal opportunities that may be present as a specific location. The guiding elements of this term is the type of location in question and when the offender last operated within this location (Curtis-Ham et al., 2020). With an understanding of how rational individuals move throughout their daily routines and
the surrounding environment, attention can now be shifted to how the aggregate of these actions manifest into crime patterns.

**Crime Pattern Theory**

As noted above, crime pattern theory is a meta-theory that combines routine activities, rational choice, and geometric theory of crime to put forth several rules relating to human movement patterning (Andresen, 2014; Brantingham & Brantingham, 2008). A compilation of these rules can be found in Table 2 below. The first rule establishes that, as individuals go through their daily routine, a series of decisions are made. This series of decisions routinizes a specific process for regulating behavior, both criminal and otherwise. For criminal behavior, this repetition of behavior leads to the creation of a crime template (Andresen, 2014; Brantingham & Brantingham, 2008). This concept refers to a mental checklist of what factors must be present for an individual to make the decision to commit a criminal act. These factors could be relating to specific absences of guardianship, what time of day it is, or any other type of environmentally related factor. As discussed within the context of rational choice theory, each commission of a criminal act, whether successful or not, and no matter if the act is fully committed, leads to the reassessment of whether an individual will continue to commit this type of crime (Cornish & Clarke, 1986). The crime template is similar in that the template is updated based on the experiences of the individual (Brantingham & Brantingham, 2008). If an individual experiences failure in the commission of a criminal act, for example, they might update their crime template to reflect this new factor. The realization of this new factor could mean the risk of offending in this particular area is too costly, thus they no longer see it as a viable offending location. Walsh (2019), in a
qualitative examination of commercial burglary and robbery, found that several offenders made note of their prior experiences and how these experiences guided their current pursuits. Specifically, it was noted that burglars might avoid establishments in which they have had previous issues in the attempted commission of an offense.

**Table 2: Rules of Crime Pattern Theory Adapted from Brantingham & Brantingham (2008)**

| Rule 1 | The repetition of criminal and non-criminal activities causes a regularization process for individuals. This creates what is known as the crime template. This template helps guide the decision of whether to commit an offense. |
| Rule 2 | Individuals often have social circles which assist in the formation of the individual crime template. The sharing of personal experiences leads to crime templates being altered. |
| Rule 3 | Combining the crime templates of individuals can help identify typical crime patterns. |
| Rule 4 | A criminal action is committed when a triggering event occurs, and when there is the convergence of a suitable target(s) and motivated offender(s). The identified target of the criminal action must fit a crime template. The success or failure of the criminal act will update the crime template. |
| Rule 5 | Individuals follow a routine schedule. This schedule takes them to many potential activity nodes, which are connected by pathways. |
| Rule 6 | Criminals follow a normal, routine schedule, just like non-offenders. Criminal actions will take place within the awareness and activity spaces of offenders. |
| Rule 7 | Potential targets or victims have activity spaces that intersect with that of potential offenders. |
| Rule 8 | A high amount of traffic in and around activity nodes creates crime generators. An area that has a concentration of individuals who are motivated to commit crime and has potential targets is referred to as a crime attractor. |

The next rule from crime pattern theory is that there is a social aspect of offending and non-offending (Brantingham & Brantingham, 2008). Specifically, offenders typically operate based off a network of other individuals. These networks of individuals could be loosely organized, such as with gangs, or based on similar offending propensities, such as a burglar and a fence. These networks could influence
likelihoods of offending. For example, a lone individual may not be willing to offend unless they are around others that are willing to do so. With non-offenders, there are networks that work to enhance guardianship or place management in all types of locations (Brantingham & Brantingham, 2008). These networks may help facilitate crime reductions in that the lone individual may not be able to act as a capable guardian, but when they are grouped up, they have a better ability to interrupt offending. An example of this might be a neighborhood watch group. With a network of individuals operating to enhance the surveillance of a place, there is an increased chance of success with neighborhood watch programs (Lab, 2019).

The third rule from crime pattern theory is that crime templates from individuals are likely not independent (Brantingham & Brantingham, 2008). This leads to the belief that one can assess crime patterns by examining the aggregate of individual crime templates. Indeed, as discussed with the second rule, offenders typically operate within a network of individuals. These individuals can share successes and failures of criminal activity, leading to the altering of individual crime templates.

The fourth rule generated from crime pattern theory is that an individual or group of individuals commit an offense when a triggering event occurs and a suitable target is identified (Brantingham & Brantingham, 2008). A trigger event would be the recognition that there is a criminal opportunity present (Andresen, 2014). In terms of commercial burglary, a triggering event might be noticing that a door to an establishment is left unlocked or ajar. In terms of a street robbery, this might be the recognition that a suitable target is near and there is an absence of capable guardianship in the area. As
hinted at above, a triggering event would feed back into the crime template and the offender would adjust this template depending on the circumstances of the event (Brantingham & Brantingham, 2008). Prior qualitative research has found that offenders do commit crime in such an opportunistic manner (Walsh, 2019; Wright & Decker, 1997). For example, with reference to robbery, Wright and Decker (1997) discuss how offenders might act on impulse if an opportunity presents itself at the right moment. This would be a recognition of a triggering event on the part of the offender.

The fifth rule stemming from crime pattern theory relates to the movement patterns of the individual. To elaborate, individuals have a daily routine that takes them to various activity nodes, along specific pathways (Brantingham & Brantingham, 2008). These activities are also temporally based, meaning they occur at specific times according to a routine schedule. As an extension of this rule, the sixth rule asserts that offenders also have normal, daily routines and typically offend within this schedule (Brantingham & Brantingham, 2008). With regard to crime patterns, we can see the influence of these rules in the presence of hot spots (Sherman et al., 1989; Sherman, 1995). Specifically, the overlapping routines of individuals lead to heightened levels of criminal opportunity. Thus, the locations for criminal activity lie within the individual’s activity and awareness space. As noted, the activity space is the area that an individual routinely travels. This includes the typical paths and activity nodes that are frequented. The awareness space is an expansion of this which includes the areas that they can see from this activity space (Brantingham & Brantingham, 2008). Additionally, these would be the areas that they become familiar with as they go throughout their daily routine (Andresen, 2014).
The seventh rule of crime pattern theory relates to potential target movement patterns. That is, as dictated by the routine activities framework, the activity spaces of target and offender overlap, which, if the offender recognizes the opportunity and their crime template is satisfied, then an offense may occur (Brantingham & Brantingham, 2008). As noted, there is a distinct spatiotemporal relationship to these interactions, whereby the offender and target must meet in time and space. Oftentimes, these intersections will occur at activity nodes within a defined place (Brantingham & Brantingham, 2008). This leads to crime clustering around specific activity nodes and around certain pathways. The eighth and final rule stemming from crime pattern theory dictates that certain activity nodes act as crime generators and crime attractors (Brantingham & Brantingham, 2008). As will be discussed in more detail later, a crime generator refers to an activity node that experiences a large volume of individuals, which creates higher levels of criminal opportunity at that place (Brantingham & Brantingham, 1995; 2008). A common example of a crime generator would be a shopping mall (Brantingham & Brantingham, 1995). A crime attractor is a location that has potential criminal targets with a high concentration of individuals that are willing to commit crime (Brantingham & Brantingham, 1995). The literature surrounding crime generators and attractors provides insight into how singular locations might influence crime; however, this does not help explain why some types of places, or facilities, typically account for a large proportion of criminal activity in a given area (Eck et al., 2007).

Although not explicitly stated within the framework of crime pattern theory, Ratcliffe’s (2006) temporal constraint theory is important for the overall understanding of
crime pattern theory. Ratcliffe’s (2006) theory puts forth that human movement is largely regulated by time. That is, there are certain temporal constraints that exist with human movement patterns. For example, as humans, we are limited in how far we can travel within specific time frames. It is, thus, in many situations not possible for an individual to travel large-scale distances in short time periods. These constraints ultimately influence the area that a potential offender becomes familiar with. In relation to crime pattern theory, this holds specific implications for the formation of an awareness space (Brantingham & Brantingham, 1993). According to temporal constraint theory, individuals can only move so far in a single day. This movement is restricted in that individuals cannot travel too far away from their residence if they wish to return at the end of the day. This also influences which activity nodes an individual has access to. Thus, constraints relating to time and space ultimately influence what an individual's awareness space will be (Ratcliffe, 2006). As we know from crime pattern theory, the development of the awareness space and activity space relates to where an offender may choose to offend. This results in specific spatiotemporal patterns of criminal activity to develop (Ratcliffe, 2006). One noted pattern of criminal activity is that crime often clusters around specific types of places. To extend this discussion, the risky facilities literature is leveraged.

**Risky Facilities**

One extension of the crime pattern theory literature base is the formation of the concept of risky facilities. This premise refers to the notion that crime tends to cluster in and around certain establishments within any given area (Clarke & Eck, 2007; Eck et al., 2007). This concentration follows the 80/20 rule, or Pareto Principle, in that a large
majority of criminal events will concentrate around a small percentage of facilities (Clarke & Eck, 2007; Eck et al., 2007). A risky facility refers to a broad range of possible establishments, including bus stops, ATMs, hospitals, shopping malls, restaurants, and bars (Clarke & Eck, 2007). For these risky facilities, there are a wide variety of different crime concentrations that might be present, depending on what type of facility is under examination. For example, it was noted by Clarke and Eck (2007) that hospitals can be a risky facility, and while this might seem odd at first glance, there is certainly crime that occurs in and around these establishments. In terms of crime present at these types of facilities, a hospital might have theft where medication or other medical equipment is the desired product (Clarke & Eck, 2007). Additionally, a bar that is identified as a risky facility might have an elevated number of assaults (Clarke & Eck, 2007; Eck et al., 2007).

One noted method of identifying a risky facility would be to aggregate crime incidents to known facilities and examine whether there is a concentration of incidents at a select few establishments. This could be represented graphically or otherwise (Eck et al., 2007). One must first graph the frequency of incidents for each facility in descending order. When this is accomplished, one would look for what is referred to as an inverted j-curve. Thus, one would notice a large clustering of incidents with a steep drop off as you move to the right of the graph (Clarke & Eck, 2007; Eck et al., 2007). One can also look to the percentage of incidents that each individual facility accounts for. Additionally, one could cumulate these percentages to examine whether a majority of incidents are contained within a select percentage of facilities (Clarke & Eck, 2007; Eck et al., 2007). One example of a relationship of this nature would be bars and calls
for service relating to assaults (Eck et al., 2007). In fact, one bar was responsible for approximately 25% of all assault calls for service. To add to this, 30% of bars were responsible for 85% of assault calls for service in Shawnee, Kansas (Eck et al., 2007). Another example would be stores and shoplifting (Eck et al., 2007). Specifically, it was found that one store accounted for approximately 26% of all shoplifting incidents. Moreover, 5% of all stores accounted for nearly 55% of all shoplifting incidents in Danvers, Massachusetts (Eck et al., 2007). This type of relationship is important to consider because it is representative of variation between facilities of the same type. Indeed, these facilities might often be frequently identified when conducting hot spot analyses; however, this does not mean that all facilities of that type are necessarily risky (Clarke & Eck, 2007).

In terms of this variation between facilities of the same type, there are several variables that might account for this, including size, products offered, location, repeat victims, crime generators and attractors, poor design, and poor place management (Clarke & Eck, 2007). Size would refer to how large the facility is and thus, how many people might frequent this establishment (Clarke & Eck, 2007). This refers to whether the establishment acts as a crime generator, which as noted above is when a place creates a large volume of criminal opportunity due to the number of individuals present (Brantingham & Brantingham, 1995). A facility might also be particularly risky because it offers a highly desirable product (Clarke & Eck, 2007). This could be an establishment that sells electronics, alcohol, tobacco, or other CRAVED products (Clarke, 1999).
Another influential factor of a risky facility would be whether the place is located near potential offenders (Clarke & Eck, 2007). Additionally, a facility might itself be a crime attractor (Clarke & Eck 2007), meaning it attracts a high volume or high frequency of offenders (Brantingham & Brantingham, 1995). An example of this could be a gas station that is frequently used by individuals for drug sales. This could lead to the patrons of the gas station or the gas station itself being the target for victimization. Another example of a crime attractor would be an open-air drug market. This type of place is considered a crime attractor because of the large number of individuals engaging in criminal activity, which predisposes the area to other crime activity. For example, a street robber might be drawn to this type of area because there are many potential targets, whether those targets be dealers themselves or the individuals going to this location to purchase drugs (Brantingham & Brantingham, 1995). A facility also has the potential to function as a crime generator. This concept refers to facilities that have a high volume of non-offending patrons. This high volume of patrons presents itself as a high level of opportunity for potential offenders (Brantingham & Brantingham, 1995).

Previously, there has been an extension to the risky facilities literature base, with specific reference to crime generators and attractors. Specifically, Bower (2014) put forth an explanation for the relationship between crime in and around risky facilities. Within this explanation, there are two primary concepts: crime radiators and crime absorbers (Bowers, 2014). The first concept, a crime radiator, would refer to a facility that exports criminogenic risk to its surrounding area. This reflects the possibility that crime outside of a facility is, in part, influenced by offending within the crime radiator
A crime absorber, on the other hand, would be a facility that imports criminogenic risk from the outside environment. As noted within the discussion of crime pattern theory, offenders make decisions about where to search for criminal opportunities as they move through their daily routine. It is possible, then, that during this search, they are brought to an area which holds criminal opportunities outside of any facility. While in this area, the potential offender then identifies opportunity within the local facilities, which leads to heightened levels of criminal activity in these facilities. Support for the concept of crime radiators was found in this study for the crime of theft; however, research is still limited on other crime types and in different study locations (Bowers, 2014).

In terms of location, elevated levels of criminal activity at one facility might not necessarily be due to the facility itself, but due to the environment surrounding it (Bowers, 2014). Specifically, the concept of crime absorbers is based on the notion that the outside environment of a facility bleeds into the facility, thereby elevating levels of criminal conduct within (Bowers, 2014). Two final considerations for risky facilities would be poor design and place management (Clarke & Eck, 2007). In terms of poor design, the physical layout or structure might make criminal activity more common. For example, a retail establishment that has high shelves that obstruct the view of employees might experience heightened levels of theft because employees are not able to identify potential criminal activity. In reference to poor place management, this concept refers to the ability of individuals with oversight over a place to influence criminal conduct (Madensen & Eck, 2008). An example of a place manager would be
bar staff who might be responsible for increased levels of assaults or other violent activity if they frequently allow the over serving of alcohol (Madensen & Eck, 2008).

In terms of place management, there are many considerations to be made that might influence criminal activity in and around the facility (Madensen & Eck, 2008). One important characteristic of place management is the compounding effect that is present during the entire life cycle of a facility. Indeed, even if ownership changes at an establishment, the prior decisions could impact present criminogenic risk at a facility (Madensen & Eck, 2008). Through their study, Madensen and Eck (2008) identified several themes that influence criminal activity at bars, including structural characteristics, staffing, marketing, activities, theme, and location. In terms of structural characteristics, any factor that increased congestion within a bar, such as restrictive access to the bar itself, was thought to increase propensities for violence within these facilities. Additionally, a larger facility was able to carry more patrons, but this also necessitated the hiring of more staff and security (Madensen & Eck, 2008). Apart from structural characteristics, the staff hired and how they are trained could influence potential violence within the facility. The hiring of the adequate security or bouncers could influence propensities for violence. Moreover, if employees are not adequately trained to manage de-escalation, they might inadvertently increase incidents within the bar (Madensen & Eck, 2008).

Some scholarly attention has also been given to identifying how concepts from the risky facilities literature base might interact with concepts from crime pattern theory (Kim, 2018; Song et al., 2017). More specifically, scholars have attempted to assess
how crime generators and attractors that exist on edges might differ from those towards the center of a defined area (Song et al., 2017). For example, Song and colleagues (2017) mapped out crime rates for property, violent, and drug-based offenses in relation to their distance to edges. For this study, an edge was defined as the meeting of different types of land use. Additionally, they also examined how the presence of crime generators and crime attractors might be influencing these relationships. For all crime types, in the aggregate and when broken down into individual crime type, the edge effect was present (Song et al., 2017). Meaning, as dictated by crime pattern theory, crime was at heightened levels around edges. Kim (2018) found similar results relating to the edge effect around land use edges for both property and violent crime. Results from Song and colleagues (2017) would also indicate that there are stronger relationships between property and violent criminal incidents and crime generators and attractors when they are proximally close to edges (Song et al., 2017). As described above, edges are places that have an extra layer of anonymity due to an inability of individuals to differentiate who does and who does not belong in these areas (Andresen, 2014; Brantingham & Brantingham, 1981; 1993). This could be one explanation as to why there exists an increased edge effect in these areas.

**Natural and Built Environment**

In large part, research using a framework of crime pattern theory have been reliant on characteristics of the built environment. The literature base that examines characteristics of the natural environment, such as tree canopy coverage or slope at the micro spatial unit of analysis, is limited (see Haberman & Kelsay, 2020; Kim & Wo, 2021 for notable exceptions). The concept of the environmental backcloth describes a series
of infinite feedback loops between an individual and the physical environment (Brantingham & Brantingham, 1981). It would make sense, then, that both characteristics of the built and natural environment have the potential to influence offender decision-making. In relation to the current study, tree canopy coverage and slope could have implications for offending when discussing street robbery and commercial burglary. For street robbery, canopy coverage could provide protection from CCTV cameras in the area. Additionally, it could provide a spot in which offenders can hide from potential targets of their offense. This could apply both during the daytime and nighttime. During the daytime, canopy coverage would provide shade from the sun itself, while at nighttime, canopy coverage might block lighting in the area. If lighting is theoretically supposed to increase the potential guardianship of an area (Cornish & Clarke, 2003), then an absence or blockage of this element could heighten the risk of criminal conduct in the area.

From a temporal standpoint, there is also fluctuation in canopy coverage throughout the year as the natural environment typically follows seasonal patterns. If the canopy coverage of a place at the micro unit of analysis is less during winter months, this might reduce the likelihood that this coverage impacts the surveilability of CCTV cameras or other guardians in the area. Additionally, it would also provide less shade, both during the daytime and nighttime. In terms of the slope of the environment, slope could influence offender decision-making by making it more difficult to commit the offense and to get away in a timely manner. Take, for example, the streets of San Francisco, which is known for its hilly terrain. This type of physical environment could present many difficulties for offending. Offenders may choose to offend in areas that
have flat land as this is the easiest terrain to navigate. Even when navigating this terrain in a vehicle, if you go too fast up or down a hill, you run the risk of damaging your vehicle. This holds implications for offenders traveling to and from criminal events. Indeed, the limited research that has been conducted in this domain has found that areas with higher degrees in slope do experience lower levels of street robbery (Haberman & Kelsay, 2020; Kim & Wo, 2021). Additionally, research also demonstrates that elevation could have a similar effect on burglary (Breetzke, 2012). It should be noted, however, that this study did not find higher degrees of slope to be predictive of lower levels of burglary (Breetzke, 2012).

With reference to commercial burglary, the theoretical explanation is largely the same. Offenders may prefer to offend in sites that have a higher degree of canopy coverage, both during the day and night, as this could block potential guardians from viewing the commission of a criminal act. Additionally, this could impact the likelihood the offender is recognized before, during, or after the offense. In terms of slope, a commercial burglar may prefer to offend in areas with a flat terrain as this impacts their ability to gain entrance to an establishment and to remove products from a place after the commission of the offense. If an offender decides to target a specific product which is heavy, they may not want or be able to carry it up or down a steep hill. This poses a risk to not only being apprehended, but also could raise the likelihood the offender is hurt in the process of the offense. Thus, these elements of the natural environment could have an impact on the formation of an offender’s crime template by making the commission of a burglary in these areas too risky.
Summary

As noted, the theoretical framework for the current study is that of crime pattern theory, risky facilities, and temporal constraint theory. To elaborate, one primary concept within crime pattern theory is that of the environmental backcloth (Brantingham & Brantingham, 2008). This concept refers to the real and perceptual environment that individuals interact with as they go throughout their daily routine. This backcloth is made up of activity nodes, pathways, and edges (Brantingham & Brantingham, 1993). These concepts provide us with some of the risk factors that will be utilized in the current study.

Specifically, with reference to activity nodes, there are several places that might be influential in explaining the occurrence of a commercial burglary and street robbery. In brief, several activity nodes that have been identified empirically to have a relationship with street robberies would be bars, retail establishments, and banks (Nelson et al., 2001). In terms of commercial burglaries, research would indicate retail establishments (Hakim & Shachmurove, 1996; Mawby, 2014), food stores, automotive retail, bars, and restaurants (Yu & Maxfield, 2014) as having a relationship with commercial burglaries. The research from Kim (2018) suggests characteristics of pathways could be important for both property and violent offenses. Specifically, the number of passers-by on a pathway in front of a business could impact the amount of criminal activity in that area. Additionally, going back to activity nodes, Kim (2018) put forth findings that suggest the age of the establishment holds a curvilinear relationship with the amount of crime that location experiences. Research also suggests a relationship between crime generators and attractors and edges (Song et al., 2017).
Specifically, crime generators and attractors that exist along edges had an increased level of criminal activity when compared with generators and attractors not on proximally close to an edge (Song et al., 2017). The risky facilities literature also informs us on what type of risk factors to include when modeling these types of criminal behavior, including ATMs, banks, shopping malls, restaurants, and bars (Clarke & Eck, 2007). This cumulation of findings highlights many different predictors that could help explain why some crime sites might be targeted.

Crime pattern theory also highlights the hierarchical nature of expected relationships. Recent literature has demonstrated the utility of examining the geography of crime in a hierarchical manner (Hart, 2021; He et al., 2015; Hipp et al., 2020). This literature makes note that the social environment that the physical environment exists within is equally important when attempting to explain criminal conduct. Crime pattern theory, due to the inclusion of the environmental backcloth, accounts for this notion (Brantingham & Brantingham, 2008). Specifically, crime pattern theory assumes there is a social aspect of offending, which in part can help control the presence of offending in an area. Thus, it would be important to consider how the social environment might impact offending in conjunction with the situational characteristics of an environment.

The most common application of hierarchical modeling in reference to the geography of crime comes in the form of nesting individual incidents within the social context in which they occurred. Oftentimes, this results in a study that pulls from the individual unit of analysis, perhaps using the criminal incident, which would be nested within a neighborhood (Hart, 2021; He et al., 2015; Hipp et al., 2020). Data collected at the neighborhood-level would be related to the overall neighborhood context. An example of
this might involve the collection of census data, such as measures assessing the socioeconomic status, homeownership, and demographics. Each of these measures help contextualize what is occurring at the larger unit of analysis, whether that be block-level, census tract, or neighborhood-level. With this theoretical framework in mind, the following chapter is dedicated to a discussion of the prior literature that provides the foundation for the current study.
CHAPTER THREE: LITERATURE REVIEW

Introduction

The study of the geography of crime relates to the examination of how space and time interact to impact crime patterns (Andresen, 2014). This field of study can be traced back to the work of Quetelet (1842) and Guerry (1833). These two European scholars separately published work that examined crime as it relates to spatial and temporal variability. To elaborate on some of these findings, Guerry (1833) found that there was an element of seasonality when it came to certain offenses, such as crimes against people and property. Property crimes were more common during the summer, while crimes against persons were more common during the winter (Guerry, 1833). Both scholars also examined how the social context of an area might influence criminal activity (Guerry, 1833; Quetelet, 1842). For example, both scholars sought to understand how poverty and education impact crime patterning. Specifically, it was found that crime rates were lowest in areas with high poverty and low education rates (Guerry, 1833; Quetelet, 1842). These early studies formed the foundation for scholarly attention examining the physical and social environments that impact criminal activity.

With the foundation laid by Gerry (1833) and Quetelet (1842), scholars soon began further researching the possible influence of the physical (e.g., man-made structures such as ATMs, restaurants, and bars) and social (e.g., percent poverty and education) environments on crime. This work began with the conceptualization of the concentric zone model by Park and Burgess (1925). This model explained spatial crime trends within the urban context. These scholars discussed the social context of specific
locations within the city which they believe to ultimately be responsible for the increased rates of offending in these areas. It should be noted that these crime rates were stable regardless of the overall demographics of the area (Park & Burgess, 1925). Shaw and McKay (1942) expanded on this research by establishing a framework that would later be known as social disorganization theory. In short, social disorganization theory puts forth that poor economic conditions lead to high population turnover and a lack of social cohesion. With high levels of population turnover and a lack of social cohesion, it is harder for residents of an area to form a sense of community and be able to identify who belongs within a certain area. This creates an environment that is susceptible to elevated levels of criminal activity (Shaw & McKay, 1942).

To further the discussion on human ecology, Park (1952) described cities as superorganisms, which implies that these entities have a life cycle and that they have a relationship with their inhabitants. This concept of superorganisms helps explains the population instability and shift noted within the concentric zone model. The stages of a city’s life cycle mirror that of an individual: juvenile, adult, and senile (Park, 1952). Additionally, there is a noted sense of interdependence within a city. For example, a seaside restaurant industry is reliant on local commercial fishing. Likewise, small businesses are reliant on other local businesses to help drive consistent patronage within the area. Apart from this interdependence, cities also have a cycle of population change that involves the competition, dominance, and succession of one group over another (Park, 1952). This early scholarly attention to elaborating on the connection between the physical and social environment and crime led the way for modern explorations of geography and crime.
The exploration of the geography of crime was continued with the work of Sherman and colleagues (1989) and Sherman (1995). Specifically, the introduction of hot spots (Sherman, 1993) and the criminal careers of places (Sherman, 1995). The premise of hot spots is that specific geographic locations oftentimes contained clusters of criminal offenses. The reason for this geographic clustering was attributed to the unique environmental context that exists within that given location (Sherman et al., 1989). The body of literature related to criminal careers of places suggests that places, much like people, had a criminal career. Meaning, the criminal careers of a place could be characterized by several factors—onset, recurrence, frequency, career length, intermittency, and specialization (Sherman, 1995). Onset is the date at which criminal activity begins. Recurrence refers to the odds of subsequent criminal offending given prior offending within the area. Frequency is how often crimes occur in this area. Career length represents how long criminal activity existed at a specific place. Intermittency is the time period between offenses. Lastly, specialization refers to the different types of crime that may be committed (Sherman, 1995).

Apart from important conceptual contributions to the place and crime literature base, the hot spots and criminal careers of places literature provide important methodological considerations as well, including a better understanding of spatial units of analysis. For example, this research highlighted the utility of using smaller units of analysis for the study of crime and place. The utility of smaller spatial units of analysis is that one is able to capture more variation than if one used a larger spatial unit of analysis. Indeed, subsequent literature (Braga et al., 2011; Groff et al., 2010; Weisburd...
et al., 2004) would echo this notion by highlighting the temporal and spatial stability of hot spots at the micro-unit of analysis, such as the street segment.

Apart from the methodological considerations relating to micro spatial units of analysis, many spatiotemporal characteristics of crime have been theoretically discussed, and subsequently, empirically validated. Of those, a few of these characteristics include public transit nodes and routes (Brantingham & Brantingham, 1981, 1993; Caplan et al., 2020; Gallison, 2017; Hart, 2021; Qin & Liu, 2016), land use (Kinney et al., 2008; Song et al., 2015; Tarkhanyan, 2015; Quick, 2019; Wo, 2019), and seasonality (Andresen & Malleson, 2013; Cowan et al., 2020; Kim & Wo, 2021; Kurland & Hill, 2021; Kurland et al., 2014; Szkola et al., 2019). Additionally, research has explored the hierarchical nature of spatial relationships, where one set of variables are nested within a higher order unit of analysis (Hart, 2021; He et al., 2015; Hipp et al., 2020; Quick, 2019). For example, one common hierarchical spatial ordering is street segments nested within census tracts (He et al., 2015). With specific reference to the current study, two crimes are of interest—street robbery and commercial burglary. The crime and place literature has given much attention to the crime of street robbery, while giving less attention to the crime of commercial burglary. Nonetheless, for both crime types, there is a basis of literature that originates from qualitatively based research that gradually advanced into quantitative examinations. In large part, the results generated from the quantitatively based studies aligns with the qualitative research that came before it.
Space, Time, and Crime: An Overview

Research that examines the intersection of space, time, and crime is often referred to as the study of the geography of crime. This area of research explores how the characteristics of space, at specific times, influence levels of criminal activity within a defined area (Andresen, 2014). Although more modern research is typically focused around using computerized software to study these phenomena, early research relied solely on hand-drawn maps to assess geographic distributions of crime. These early inquiries into the geography of crime began with the work of two European scholars—Quetelet (1842) and Guerry (1833). In particular, Guerry, (1833) examined many different geographic relationships, including that between poverty and crime, as well as seasonal variations in criminal activity. To elaborate, this early research found temporal variations in the crimes committed within France, depending on which season it was at the time. Specifically, crimes against property were more common during the summer, while crimes against persons were more common during the winter (Guerry, 1833). Additionally, Guerry (1833) compared maps of various types of distributions to that of crimes against persons and property, including the percent of individuals that can read and write, suicide rates, illegitimate births, and donations to the poor. Quetelet (1842) followed a similar path for his research by comparing crime distributions within Belgium to distributions of social phenomena, such as education and poverty. Findings from Quetelet’s (1842) study demonstrated that areas with high levels of poverty and low education had the lowest levels of criminal activity.

After the work of Quetelet (1842) and Guerry (1833), another significant contribution to the exploration of the geography of crime comes from the work of Park
and Burgess (1925) and Shaw and McKay (1942). Park and Burgess (1925) put forth the concentric zone model which describes the outward expansion of a major city. This outward expansion, as per Park and Burgess (1925) is characterized by a series of circular rings that envelope the city center. The main contribution to the geography of crime is that crime is expected to concentrate within specific areas of the urban environment. According to this theoretical perspective, this area would be referred to as the zone of transition (Park & Burgess, 1925). The naming of this zone comes from the transitory nature of the overall population of this area. Because this zone has a mix of residential and commercial property, this area has constant fluctuations of the populations that reside in this zone.

An extension of the concentric zone model comes from Hoyt’s Sector Model (1939). Instead of a set of concentric zones originating from a city center, the sector model divides a city into a pie shape, with the center of a city still being the central business district. The divisions within a city are largely related to the socio-economic status of the residents living within that area. Thus, several of the noted sectors would be the low class, middle class, and high-class residential areas (Hoyt, 1939). Apart from these sectors, there also exists the industrial sector which largely exists within the low-class residential area. This industrial sector may exist along railways, which is one reason why this sector extends from the central district out to the edges of the city (Hoyt, 1939).

Another extension of the concentric zone model attempted to take into account expanded levels of mobility for residents due to the automobile revolution (Harris &
Ullman, 1945). This new range of movement for residents created several new central business district areas throughout a city. These new central areas within a city were referred to as nuclei (Harris & Ullman, 1945). Within this model, there were several divisions within a city, including the central business district, outlying business district, light manufacturing, heavy manufacturing, residential suburb, industrial suburb, and the low, medium, and high residential areas (Harris & Ullman, 1945).

Shaw and McKay (1942) also expanded upon the concentric zone model by examining the relationship between juvenile delinquency in Chicago with independent variables such as residential mobility, poverty, and ethnic heterogeneity. This framework for studying the neighborhood effects on crime became known as social disorganization theory (Shaw & McKay, 1942). The early work of Guerry (1833), Quetelet (1842), Park and Burgess (1925), and Shaw and McKay (1942) ultimately set the stage for contemporary explorations of the geography of crime.

The crime and place literature was further expanded upon with the work of Sherman and colleagues (1993) and Sherman (1995). This research put forth the concept known as hot spots, or a defined geographic area where crime tends to concentrate (Sherman et al., 1989; Sherman, 1995). These crime concentrations are often quite large, with, for example, twenty-four retail establishments accounting for a total of 68% of all shoplifting calls for service within the study area (Sherman et al., 1989). Hot spots have been found to exist for both property and violent crimes (Braga et al., 1999; Kooi, 2015; Loukaitou-Sideris, 1999; Sherman et al., 1989; Sherman, 1995). Sherman (1995) compared the trends of crime concentrations at places with those of
the criminal careers of people. Indeed, the crime patterns of places mirror those of people, with places also having specific phases of criminality. These phases of criminality include onset, recurrence, frequency, career length, intermittency, and specialization (Sherman, 1995). Onset refers to when crime begins to occur at a place. Recurrence would be whether the crime continues to occur after the initial offenses. Frequency is how often crimes are committed. Career length refers to how many years from the first to last crime committed in this area. Intermittency would be the period of time between criminal offenses at a particular location. Lastly, specialization would be what types of offenses are committed (Sherman, 1995).

As an extension of the above literature, Brantingham and colleagues (2020) put forth an explanation of hot spot generation. Within this model, it was noted that hot spots are most likely to appear in areas with low social efficacy, near and around major traffic arteries, and around certain crime generators and attractors (Brantingham et al., 2020). In terms of low social efficacy, this would be areas in which local communities are unable to control the behavior of individuals within these communities. Hot spots also typically occur around or along major traffic arteries because these movement paths are what individuals frequently use throughout their routine schedules. Lastly, hot spots are more likely to occur in or around crime generators and attractors. These areas, in particular, have high levels of potential criminal opportunity. Thus, because of the low social efficacy of an area and an offender's activity and awareness space, there may be crime concentrations in areas where these factors overlap (Brantingham et al., 2020).
The previously discussed research surrounding the criminal careers of places represents a shift from larger units of analysis, such as the city, neighborhood (Park & Burgess, 1925; Shaw & McKay, 1942), and department-levels (Guerry, 1933; Quetelet, 1942), to smaller units of analysis, such as the place (Sherman et al., 1989; Sherman, 1995). This shift was aided by the advent of more sophisticated mapping technology that allows for the collection, storage, and analysis of many different types of geographic data. This trend towards smaller units of analysis continued, with research now focusing on units of analysis such as the street segment (Braga et al., 2011; Groff et al., 2010; Weisburd et al., 2004). In terms of overall classification of spatial units of analysis, they can be divided into three primary categories—micro, meso, and macro (Schweingruber & McPhail, 1999). A micro spatial unit of analysis would be the street segment or a similarly sized grid cell. A meso spatial unit of analysis would be that of a block-group or census tract. Lastly, a macro spatial unit of analysis would be a city or nation (Schweingruber & McPhail, 1999).

Very similar to the research conducted on the criminality of places (Sherman et al., 1989; Sherman, 1995), when examining crime at the micro unit of analysis, such as the street segment, there is a large degree of variation with the distributions of criminal activity. At the street segment unit of analysis, these distributions often follow what is referred to as the Pareto Principle, or the 80/20 rule. Meaning, a large majority of crime will often cluster within a small percentage of street segments (Braga et al., 2011; Groff et al., 2010; Weisburd et al., 2004). In fact, these crime concentrations often far exceed this Pareto Principle, with most crime clustering within a percentage of street segments much smaller than 20%. For example, Weisburd and colleagues (2004) found that
between 47 and 52% of all street segments experienced no criminal incidents on a year-to-year basis, over the entire 14-year study period. Throughout each of the 14 years examined, approximately 34 to 35% of street segments experienced between one and four criminal incidents. Continuing this trend, less than 1% of street segments experienced over fifty criminal incidents within a given year. When examining the trajectories of crime at the micro-unit of analysis, Weisburd and colleagues (2004) found that these trajectories were stable over time. Meaning, a street segment that had an increasing, decreasing, or stable trajectory at the beginning of the study period was likely to have a similar trajectory at the end of the 14-year study period. These results point towards not only extreme geographic concentrations of criminal offenses, but also stability of temporal trends as well.

Groff and colleagues (2010) took a similar approach by examining crime trajectories for all reported criminal incidents over a period of 16 years in Seattle, Washington. Like Weisburd and colleagues (2004), Groff and colleagues (2010) found stable crime concentrations over the entire 16-year study period. Specifically, just under 50% of street segments were classified as crime free for the entire duration of the study period. In terms of the spatial trajectories of crime, their findings indicated a high degree of heterogeneity between the identified trajectories. To elaborate on this finding, these results suggested that the trajectories of street segments are largely unaffected by the surrounding street segments (Groff et al., 2010). As an extension of the two previously discussed studies, in Boston, MA, Braga and colleagues (2011) found that approximately 66% of all street robbery incidents were clustered between 1-8% of all street segments over the course of 28 years. This represents a high degree of spatial
stability over time, which suggests there is something about these places that perpetuates these crime trends. Together, these results point towards the overall stability of crime trends within micro-units of spatial analysis. This characteristic of crime trends helps inform policing practice in that it highlights the utility of enforcement strategies that target specific hot spots (Braga et al., 2011; Groff et al., 2010; Weisburd et al., 2004).

While much of the literature discussed up to this point has focused on hot spots or places where crime clusters, there is certainly much discussion to be had around the temporal characteristics of crime. Indeed, the temporal component of hot spots is critical in understanding and subsequently developing enforcement tactics (He et al., 2015; Ratcliffe, 2004). To empirically support this notion, Schnell & McManus (2020) discuss the importance of temporal specification when attempting to identify hot spots. They discuss that, while most street segments with elevated levels of criminal activity remained hot spots regardless of temporal specification, there was still significant variation in how well these specifications improved prediction results (Schnell & McManus, 2020). In other words, temporal specification can impact how accurate prediction models are, with a temporal specification of three to five years providing the best estimates (Schnell & McManus, 2020).

Further evidence that demonstrates this need for taking consideration of temporal characteristics comes in the form of the temporal stability of crime. Above, it was noted that crime trends at micro-spatial units of analysis are temporally consistent through time in a longitudinal manner (Braga et al., 2011; Groff et al., 2010; Weisburd et
al., 2004). Beyond this, there is also significant temporal stability of crime trends at various temporal units of analysis (He et al., 2015; Nelson et al., 2001; Tompson & Townsley, 2009). These temporal units of analysis can be classified much like spatial units of analysis into three categories, the macro-, meso-, and micro-level units of analysis (Schweingruber & McPhail, 1999). A temporally based macro-level unit of analysis would be a longitudinal analysis of crime trends (see Braga et al., 2011; Groff et al., 2010; Weisburd et al., 2004). A meso-level analysis might include months as the unit of analysis. This might include examinations of the seasonality of crime, or how crime might vary over the course of a calendar year (see Cowan et al., 2020; Szkola et al., 2019). In terms of seasonality, Cowan and colleagues (2020) examined differences in predictors of poaching activity within two protected areas in Cambodia. Utilizing risk terrain modeling (RTM), these scholars found that there was seasonal variation among the selected risk factors for poaching activities relating to both flora and fauna. In terms of fauna-related poaching activity, proximity to roadways was identified as a statistically significant predictor during the wet season and not the dry season. The explanation provided for this occurrence is that established roadways are more important during the wet season when some of the land may be inaccessible due to flooding (Cowan et al., 2020). Also using RTM, Szkola and colleagues (2019) found similar results relating to crimes involving firearms. Specifically, the risk factors identified for this crime type varied by month. In total, the models that were estimated on each month of the year identified a mixture of four risk factors, namely bus stops, off site alcohol establishments, restaurants, and pawnbrokers (Szkola et al., 2019).
One step further at the micro-level unit of analysis would include studies that examine crime incidents by the hour, day, or week (see Caplan et al., 2020; Hart, 2021; Nelson et al., 2001). When examining temporal trends, several studies have identified variation existing at these micro units of analysis. In particular, Nelson and colleagues (2001), as well as Caplan and colleagues (2020), found that robberies clustered heavily between the hours of 10pm and 2am. Additionally, this clustering was more prevalent on Friday and Saturday nights (Nelson et al., 2001). Research has also found that the temporal stability of hot spots for various crime types, including robbery, larceny, and aggravated assault, varies by location (Hart, 2021).

With the above temporal units of analysis in mind, it is always important to be aware of how model parameters influence the results of the analysis in question. For example, in relation to hot spot identification, Schnell & McManus (2020) tested several macro-level units of analysis to see how these specifications would impact hot spot stability over time. The analysis began with the temporal specifications provided by previous empirical literature, which was a one-year period (Sherman et al., 1989; Sherman, 1995). They continued this process with temporal bandwidths ranging from 2 through 15 years. Findings from this study align with previous literature (Braga et al., 2011; Groff et al., 2010; Weisburd et al., 2004) that described the stability of hot spots in a longitudinal manner at the street segment unit of analysis. The best temporal bandwidth identified by these scholars was between three to five years of incident data in order to examine the stability of hot spots at the micro-level unit of analysis (Schnell & McManus, 2020).
While Schnell & McManus’s (2020) discussion was based around hot spot identification, the results certainly ring true when applied to spatiotemporal analyses in general: the specifications of the units of analysis will have a large influence on the results of said analysis (Eck, 1997; Openshaw, 1984). This leads to an important question: how does one determine which spatial and temporal units of analysis are best for the study at hand? Eck (1997) proposed that the specifications for hot spot analyses, much like justifications for any model parameters, should be theoretically based. The attachment of a theoretical framework to an analysis allows for the researcher to identify expected and unexpected relationships that can be assessed at the completion of the analysis.

Moreover, a theoretical framework provides for the possibility of examining how policy and practice might be influenced by the identified relationships, or lack thereof (Eck, 1997). This issue has been termed the “modifiable areal unit problem”, or MAUP for short (Openshaw, 1984). Specifically, Openshaw (1984) noted that researcher specifications of spatial units were oftentimes arbitrary and not based on theoretical guidelines. This inherently influences the outcome of the analysis being performed. Thus, much like Eck (1997), Openshaw (1984) stated that the way to overcome this issue is to contextualize the analysis with a theoretical framework. This provides a basis for the selected spatial unit of analysis (Openshaw, 1984). The justification for a temporal unit of analysis is very much the same as the justification for the spatial unit of analysis; there must be some theoretical explanation for why this unit of analysis was selected. The decision on which time period to examine inherently contextualizes the space under study.
With the basis for spatiotemporal research outlined, there are many different previously identified relationships relating to criminal activity. Of note, research has found that public transit is important for explaining the occurrence of criminal activity (Caplan et al., 2020; Hart, 2021; Qin & Liu, 2016), that land use is oftentimes a significant explanatory power for several types of criminal activity (Caplan et al., 2020; Hipp & Kim, 2019; Kurland & Hill, 2021; Nelson et al., 2001; Quick, 2019), that seasonality plays a role in explaining criminal activity (Cowan et al., 2020; Kurland & Hill, 2021), and lastly, that there is a hierarchical nature of spatial relationships (Duru & Kim, 2021; Gilchrist et al., 2019; Hipp & Williams, 2020; Jones & Pridemore, 2019; Tillyer et al., 2021).

**Public Transit Nodes**

Scholars have long studied the relationship between public forms of transit and criminal activity (Qin & Liu, 2016). One reason for this connection comes from opportunity-based theories in which public transit helps facilitate the movement of offenders as they search for potential opportunities to offend (Qin & Liu, 2016). Additionally, public transit nodes, such as bus stops or train stations, may attract potential targets for offenders (Brantingham & Brantingham, 1981; 1993). Block and Block (1995) discuss that the transit node itself is not the only consideration when examining local crime problems, but the characteristics of the surrounding environment of that transit node are equally important. In later studies, it was also found that street robberies most frequently occurred several hundred feet away from transit nodes (Block & Block, 2000; Block & Davis, 1996). This demonstrates that offenders use public transit
to extend their activity and awareness space to reach potential targets (Block & Block, 2000).

To extend the discussion of the influence of public transit on street robbery, and as noted above, Caplan and colleagues (2020) found that bus stops were the most common statistically significant risk factor among the thirteen analyses that were conducted. Additional research has demonstrated a spatial relationship between public transit nodes and both off-street and on-street robbery (Qin & Liu, 2016). Off-street robbery refers to a robbery that occurs within an establishment, as opposed to on the street. Overall, for both on- and off-street robbery, proximity to bus stops increased the numbers of criminal incidents that occurred (Qin & Liu, 2016). When examining these crimes separately, Qin & Liu (2016) found that on-street robberies typically occurred on streets that were not directly on the bus routes but were simply near the bus stops. This could suggest that offenders purposely chose these areas because of a perceived decrease in guardianship from the lesser traveled street segment.

As for off-street robbery, these incidents typically clustered on street segments that contained clustering of residential and/or commercial establishments (Qin & Liu, 2016). These results suggest that offenders use the public transit as a means of reaching a suitable target area, such as a less traveled road or a street lined with potential targets. Another reason why an offender might choose a location near a bus stop to offend is drug-related activity. Specifically, a drug dealer may prefer an area that has high foot traffic. This high foot traffic leads to more potential customers for the dealer. Through the employment of systematic social observation of CCTV footage in
Baltimore, Maryland, Olaghere (2015) noted that drug-related offenses were more likely than property or violent crimes to have a bus stop within view of the CCTV cameras.

Additionally, research has made note that factors such as public transit accessibility and use may contribute to the stability of crime hot spots (Hart, 2021). This result in particular comes from a study that, in part, compared hot spot stability in several different study areas. These hot spots, depending on the city, were either relatively stable or fluid. It was thought that the reason for this variability was potentially related to differences in overall population and density, as well factors such as road network complexity and public transit accessibility (Hart, 2021). Apart from bus stops, train stations have also been examined for their potential influence on criminal activity (Gallison, 2017; Tay et al., 2013). While the presence of an individual train station did not increase reported crime, the presence of multiple stations did (Gallison, 2017). The finding that concentrations of bus stops or public transit terminals influence criminal offending is supported in other studies as well (Gallison & Andresen, 2017; Kooi, 2013; Quick, 2019). Specifically, Kooi (2013), utilizing a quasi-experimental design, found that block-groups with high concentrations of bus stops had elevated levels of criminal activity, including armed robbery, disorderly conduct, weapons violations, and narcotics possession. Another important factor along with the presence of multiple stations was whether the observed census tract was considered socially disorganized (Gallison, 2017; Kooi, 2013).
Land Use

One important relationship in the crime and place literature is that of land use and crime. Land use has long been known to influence various types of criminal activity, including drug crime (Tarkhanyan, 2015), property crime (Kinney et al., 2008; Song et al., 2015; Quick, 2019; Wo, 2019), and violent crime (Browning et al., 2010; Caplan et al., 2020; Kinney et al., 2008; Song et al., 2015; Stucky & Ottensmann, 2009; Twinam, 2017; Wo, 2019). In terms of the impact of land use on property crime, research has found that certain land use types may function as crime generators and crime attractors (Kinney et al., 2008; Wo, 2019). A crime generator refers to a place that has a large number of individuals frequenting due to their routine activities (Brantingham & Brantingham, 1995). A crime attractor is a place that has a large number of motivated offenders and potential targets (Brantingham & Brantingham, 1995). Specifically, areas classified for commercial use often experience heightened levels of criminal activity due to the large number of individuals that routinely visit these areas, thereby acting as a crime generator (Kinney et al., 2008; Wo, 2019). Wo (2019) would add to this literature base by examining how areas of mixed land use (e.g., a mix of commercial and residential) use impact criminal activity. Areas of mixed land use, it was found, contained higher levels of both burglaries and robberies in Los Angeles (Wo, 2019). One example that was provided entails the building of a retail establishment within a once predominantly residential area.

This new activity node, or a place that is frequented by individuals or groups of individuals, invites a substantial number of individuals into the surrounding area, which leads to increases in the number of criminal opportunities present in these areas (Wo,
2019). Likewise, Nelson and colleagues (2001) found that robberies clustered spatially around retail establishments in Cardiff, UK and Worcester, UK, with a majority of incidents occurring during normal hours of operation. Additionally, several other studies have found retail establishments to exhibit heightened levels of criminal activity (Browning et al., 2010; Stucky & Ottensmann, 2009; Twinam, 2017). To continue the discussion of the relationship between mixed land use and crime, Stucky and Ottensmann (2009) investigated the relationship between land use and violent criminal activity in Indianapolis, IN. Much like the results put forth by Wo (2019), these scholars found that high density residential areas with elevated levels of commercial activity contained higher levels of criminal activity. This highlights the importance of exploring areas with heterogenous land uses.

While many studies, have found relationships with land use and crime, a critical extension of this literature comes from the establishment that there are also important considerations to be made about the edges of these land use zones (Song et al., 2017). Edges would refer to the outer boundaries of these zones (Brantingham & Brantingham, 1981). According to Brantingham and Brantingham (1993), an edge can fall under many classifications, including physical and perceptual. A physical edge might be some form of a barrier, including a river, fence, wall, etc. A perceptual edge can be some perceived boundary, such as the extent to which an individual is comfortable or known gang territory (Brantingham & Brantingham, 1993).

One unique aspect of edges is that it is difficult for potential guardians to identify who does and does not belong in these areas. This leads to the possibility of increased
offending in these areas (Brantingham & Brantingham, 1981; 1993). In order to test this proposition, Song and colleagues (2017) examined the impact of edges on drug, property, and violent crime in several Canadian cities. Overall, it was found that edges did experience heightened levels of both property and violent crime. Additionally, results show that there is a strong relationship between crime generators and attractors in relation to crime around edges (Song et al., 2017). To further the literature that discusses the impact of edges on criminal activity, Kim and Hipp (2017) set out to analyze the impact of both physical and non-physical edges, including highways, parks, and rivers (physical), and city boundaries (non-physical). Overall, it was found that there was an increase in crime around edges, including two crime types relevant to the current study—robbery and burglary. Most notably, it was found that edges that enhance the ability of potential offenders to enter or exit an area, such as a highway, had the strongest impact on offending patterns (Kim & Hipp, 2017).

Taken together, the literature on land use demonstrates that types of land use function as crime generators and attractors (Kinney et al., 2008; Wo, 2019). Areas designated for commercial land use often experience heightened levels of criminal activity due to the increased number of individuals that frequent these locations as part of their daily routine (Kinney et al., 2008; Wo, 2019). Within these areas designated for commercial land use, specific activity nodes, such as retail establishments, are responsible for an increase in the number of criminal opportunities present (Browning et al., 2010; Nelson et al., 2001; Stucky & Ottensmann, 2009; Twinam, 2017; Wo, 2019). Additionally, prior research has found that the edges of land use areas have elevated levels of robberies and burglaries (Hipp & Kim, 2017; Song et al., 2017). The theoretical
reason for heightened criminal activity near edges and within areas of mixed land use would be that individuals are less able to identify who belongs to these areas and who does not (Brantingham & Brantingham, 1995). This inability to decipher potential offenders hinders the ability of potential guardians to surveil their communities in an effort to identify and intervene on potential criminal activity (Brantingham & Brantingham, 1995; Song et al., 2017). While land use helps explain part of the spatial dimension of crime, there is still much to be said of the temporal element of crime.

**Seasonality**

Seasonality is one temporal characteristic of crime and highlights how specific time periods throughout a calendar year are more prone to criminal activity than other time periods. One explanation for these fluctuations in offending is that seasonal variation has an impact on aggregate movement patterns of individuals over time. Seasonality can be conceptualized in several different manners, depending on the place being examined. This references a specific contextual dependency of the inquiries into the geography of crime. For example, season can refer to time periods such as fall, winter, spring, and summer. This is representative of variation occurring during specific months or weeks out of a calendar year. In terms of this interpretation, research has found that crime does, indeed, vary spatially depending on the season of the year (Andresen & Malleson, 2013; Kim & Wo, 2021; Szkola et al., 2019). To expand on this, Andresen and Malleson (2013) found significant variation for multiple crime types throughout the year in Vancouver, Canada, including assault, burglary, robbery, sexual assault, theft, thefts from vehicles, and motor vehicle theft.
Overall, results indicate that crime, in the aggregate, is highest during the spring and summer months, with noticeable drops occurring during the fall and winter months (Andresen & Malleson, 2013). When broken down by specific crime types, these fluctuations are less noticeable. Of note, the strongest seasonal variation occurred for the following crime types: assault, theft, motor vehicle theft, and theft from a vehicle. These crime types followed the general aggregate pattern of peaking during the summer with a lesser number of incidents in the other seasons, with winter being the least active in terms of offending. Seasonal variation was found to be least apparent for sexual assault, burglary, and robbery (Andresen & Malleson, 2013). From the results of this study, it can be noted that seasonal variation was strongest for primarily crimes relating to theft. One theoretical reason for this variation is that individuals’ routine activities are likely to be impacted by seasonal variation. Extreme temperatures, whether they be hot or cold, may force individuals to remain home. This means potential offenders are not only staying at home more often, but potential targets are as well. Moreover, if individuals are staying home more often, crimes like residential burglary may be less frequent due to an increase in guardianship in and around potential targets.

Following the same approach with the month as the temporal unit of analysis, Szkola and colleagues (2019), used risk terrain modeling (RTM) and found that spatial risk factors of crimes involving firearms varied by month. From the findings of the yearly model run, there were five risk factors that were identified as statistically significant—bus stops, restaurants, convenience stores, schools, and establishments that sell alcohol for off-site consumption (Szkola et al., 2019). In the month of October, three risk factors were identified as statistically significant: pawnbrokers, off site alcohol
establishments, and restaurants. Pawnbrokers were the only risk factor in the monthly breakdowns that was identified a statistically significant risk factor that was not found within the aggregate yearly model. For the month of May, only bus stops were found to be a statistically significant predictor of gun violence incidents (Szkola et al., 2019). When comparing January to July, there is variability in the ordering of the relative risk values (RRVs). These values are indicative of the risk attributed to the predictor relative to other areas that do not have this feature present. For the month of January, the most significant risk factors, or the factor with the highest RRV, was bus stops, restaurants, and off-site alcohol establishments. Beyond October, January, and July, the only other month that found three significant risk factors was December. Every other month had a variation of one or two risk factors found to be statistically significant predictors of gun violence. The results of this study demonstrate a moderate amount of variation existing between months of the year concerning predictors for gun violence.

Kim and Wo (2021) would extend the two previous studies by examining crime occurrences at the block-level in Orlando, Florida, using the week as their temporal unit of analysis. Results from this study were in line with the previously discussed studies (Andresen & Malleson, 2013; Szkola et al., 2019) in that crime peaked in the summer weeks and there was variation in how much impact land use had on criminal activity throughout the year (Kim & Wo, 2021). Additionally, results are favorable in terms of the applicability of a routine activities framework. To elaborate, three crime types—aggravated assault, robbery, and larceny—exhibited a heightened risk of occurrence during the summer month of June, which is when individuals may be more likely to schedule vacations (Kim & Wo, 2021). Taken together, the results from these studies
(Andresen & Malleson, 2013; Kim & Wo, 2021; Szkola et al., 2019) show that there is utility in research examining temporal variation of various types of criminal activity.

Season, in other parts of the world, may refer to a wet and dry season (Cowan et al., 2020; Kyando et al., 2017; Rashidi et al., 2017). For this conceptualization of season, research has found that the spatial risk factors for animal poaching differ between the wet and dry season in Cambodia. Specifically, proximity to roads was identified as a statistically significant predictor for animal poaching during the wet season and not the dry season. This suggests a heightened importance of man-made roadways during the wet season when specific locations within the protected area are inaccessible due to rainfall (Cowan et al., 2020). Apart from differing spatial risk factors, research has also found that elephant poaching is more common during the wet season in Tanzania (Kyando et al., 2017). As noted, the wet season in many countries causes some terrain to be inaccessible, which has implications for those attempting to poach in these areas. This also has notable implications for law enforcement personnel (e.g., rangers), who are tasked with patrolling these areas. Specifically, the challenges of the wet season often mean that rangers must restrict their patrolling efforts to areas they can easily reach (Kyando et al., 2017). Another important factor is related to the visibility of protected areas during the wet season. Apart from the obvious implication of rain causing issues with visibility, there is also an increase in vegetation during the wet season. This presents difficulties for rangers in their attempt to visually identify potential offenders within these areas (Kyando et al., 2017).
Another less common interpretation may be that of a *sporting* season. Indeed, there are also crime patterns that are influenced, in part, by the activity created by sporting events (Breetzke & Cohn, 2013; Baumann et al., 2012; Kurland & Hill, 2021; Kurland et al., 2014). Baumann and colleagues (2012) tested whether major league sporting events increased the incidence of criminal activity throughout a city. In their analysis, Baumann and colleagues (2012) included all metropolitan areas that hosted a team from one of the four major sporting leagues in the US: National Hockey League (NHL), National Basketball Association (NBA), National Football League (NFL), and Major League Baseball (MLB). They also examined cities that hosted either the World Cup or the Olympics. Findings indicate that sporting events, except for the Olympics and Super Bowl, did not increase the incidence of violent or property offenses in the identified cities (Baumann et al., 2012). Other research, however, has found a relationship between sporting events and criminal activity (Breetzke & Cohn, 2013; Kurland & Hill, 2021; Kurland et al., 2014). This relationship is noted in the area immediately surrounding the stadium or area where the sporting event is taking place, as opposed to the entire city as tested by Baumann and colleagues (2012).

Breetzke and Cohn (2012) found that there was an increase in criminal activity, including assault and drunk and disorderly behavior, within a half mile buffer around the stadium on game days. Much like Baumann and colleagues (2012), Breetzke and Cohn (2012) did not find support for the notion that sporting events increase crime at the city-level. As a continuation of these studies, Kurland and Hill (2021) examined baseball sporting events and assault and found that assault incidents were influenced by the routine activities of fans in the stadium and surrounding regions on gameday (Kurland &
Hill, 2021). Overall, it was found that gamedays did present an increase in criminal assault around the two selected sporting venues. This increase in assault occurred not only in neighborhoods where the stadium itself was located, but also in some surrounding areas as well (Kurland & Hill, 2021).

From a routine activities perspective, the increase of assaults during gameday is explained due to an increased number of potential offenders and targets, there is a higher number of criminal opportunities. For the surrounding areas, the explanation is the same. During a gameday, people are converging in the surrounding area for pre-, mid-, and post-game festivities (Kurland & Hill, 2021). For example, an individual may decide to visit a nearby bar pre-game or even to watch the game itself. Another factor for the increase in assaults in surrounding neighborhoods is that guardianship itself was shifted from these areas to the stadium to account for the increased number of individuals at the stadium (Kurland & Hill, 2021).

**Hierarchical Relationships**

One other consideration for spatiotemporal research relates to hierarchical relationships, or relationships between lower- and higher-order units of analysis. More specifically, research has found that characteristics of a specific jurisdiction may impact the spatiotemporal relationships identified in these areas (Hart, 2021; He et al., 2015; Hipp et al., 2020; Quick, 2019). One such characteristic is whether there are on-going construction projects that ultimately end up changing the physical environment of a neighborhood (Kurland & Hill, 2021). In this instance, two baseball stadiums were being constructed in separate locations, and there were lower levels of assault in surrounding
areas when construction began on these projects. In the years following construction of these stadiums, there was still a noticeable lag in the number of assaults occurring (Kurland & Hill, 2021). To explain the lower levels of assault during construction, the authors noted that the increased number of potential guardians, whether that be construction works, security, or other industry personnel, could have led to these lower sustained levels of criminal activity. For the lag in the number of assaults after construction, it was put forth that offenders, due to the changes in the physical environment, may have had to readjust their awareness space (Kurland & Hill, 2021). The concept of the awareness space was presented by Brantingham and Brantingham (1993) in their description of what is generally referred to as crime pattern theory. The awareness space refers to the notion that an individual establishes a sense of familiarity within the space that they routinely move throughout.

This familiarity of the environment is created through a series of infinite feedback loops between the individual and their environment (Brantingham & Brantingham, 1993). This concept highlights the linkage between the routine activities perspective (Cohen & Felson, 1979) and rational choice theory (Cornish & Clarke, 1986). It is this familiarity with one’s environment that allows an individual to make rational decisions regarding whether to offend in a specific scenario. Thus, as Kurland and Hill (2021) discuss, changes in the physical environment alter an offender’s awareness space, and this familiarity with the environment takes time to rebuild, hence the lag in criminal assaults. In terms of the hierarchical nature of these relationships, the presence of spatial relationships identified at many different units of analysis suggest that there is a possible hierarchical nature to these phenomena.
The most common approach to spatially based multi-level modeling comes in the form of integrating opportunity and social disorganization theories (Duru & Kim, 2021; Gilchrist et al., 2019; Hipp & Williams, 2020; Jones & Pridemore, 2019; Tillyer et al., 2021). Overall, these studies attempt to identify how the micro-place fits into the larger neighborhood context (Duru & Kim, 2021; Tillyer et al., 2021). Research in this domain has identified multi-level relationships for several categories of crime types, including drug, property, and violent offenses (Tillyer et al., 2021). For the relationship between crime generators, which would be places that typically draw in a large number of individuals for routine activities (Brantingham and Brantingham, 1995), and crime, it was found that neighborhood context does help predict all three selected crime types—drug, property, and violent crime (Tillyer et al., 2021). To expand on this, Tillyer and colleagues (2021) utilized blocks nested within block groups as their units of analysis for their multi-level model. It was found that areas with higher levels of concentrated disadvantage had more pronounced relationships between generators and criminal activity at the block level (Tillyer et al., 2021). Theoretically speaking, these findings demonstrate that neighborhoods with lower levels of concentrated disadvantage are more able protect against the influence of crime generators and attractors. More specifically, neighborhood characteristics, such as traffic activity, civic engagement, residential stability, population density, and population heterogeneity, impact the ability of an area to enact collective guardianship, thereby aggravating crime problems in the area (Tillyer et al., 2021).

Extending this idea of place within neighborhoods, Gilchrist and colleagues (2019) took a novel approach of assessing place management decisions for apartment
property managers that are nested within a larger neighborhood context. A place manager would refer to an individual, or group of individuals, who are responsible for decision-making of a specific property. These place managers, overall, have an impact on the amount of crime that occurs in and around the establishment (Madensen & Eck, 2013). For example, a bar manager that refuses to hire an adequate amount of security for the establishment may experience a heightened level of assaults or similar crimes. In terms of apartment place managers, these individuals are tasked with hiring security and maintenance, advertising, and conducting criminal background checks on potential residents. Gilchrist and colleagues (2019) found that neighborhood (dis)advantage does impact place manager decision-making. More specifically, areas of concentrated disadvantage may be less likely to overcome the excess number of criminal opportunities present in these areas. This suggests that place manager decision-making is contextually dependent on the overall neighborhood context (Gilchrist et al., 2019).

Jones and Pridemore (2019) proposed an explicit framework for examining multi-level relationships by nesting street segments within a larger neighborhood context. As described above, the framework is an integration of routine activities and social disorganization to individually explain the occurrence of four crime types: robbery, assault, burglary, and theft. For the micro-level variables, Jones and Pridemore (2019) operationalized several classifications of variables, including suitable targets, local guardianship, and local social disorganization. Suitable targets would include crime generators, such as hotels and motels, restaurants, bars and liquor stores, retail establishments, and convenience stores (Jones & Pridemore, 2019). Another classification within suitable targets includes public places, such as hospitals, libraries,
parks, schools, and bus stops. In terms of local guardianship, there are four items of interest—police and fire stations, security alarms, and CCTV cameras. Local social disorganization would also include several items, such as local SES, a disorder index, a housing assistance index, owner occupied housing, mixed land use, and suburbanization (Jones & Pridemore, 2019).

For the neighborhood-level variables, Jones and Pridemore (2019) relied on two indexes, one assessing neighborhood stability and the other concentrated disadvantage. For the neighborhood stability index, items included the percent of those in college, percent of residential mobility, percent of those in college, and the population density. The concentrated disadvantage index contained five items: percent poverty, percent unemployment, percent of female-headed households, median family income, and the percent of African American or Hispanic (Jones & Pridemore, 2019). The analysis described above by Jones and Pridemore (2019) align with a wealth of literature that identified a relationship between crime and place at the micro- (Braga et al., 2011; Groff et al., 2010; Weisburd et al., 2004) and neighborhood-level individually (Kim & Wo, 2021; Kurland & Hill, 2021). Additional results from Jones and Pridemore (2019) indicate that for both the violent and property crimes assessed, the addition of level-2 indicators improved model fit and produced a model that is more explanatory than the individual micro- and neighborhood-level models (Jones and Pridemore, 2019). These results highlight the utility of hierarchical modeling strategies in understanding how geography impacts criminal activity. From a theoretical standpoint, understanding these hierarchical relationships is important because the individual-level findings could be dependent on a larger neighborhood context.
Spatiotemporal Characteristics and Patterns of Commercial Burglary and Street Robbery

Commercial Burglary

The above section outlines the general spatiotemporal characteristics of crime. The following section is dedicated towards examining the spatiotemporal characteristics of the two crime types that will be examined in the current study: commercial burglary and street robbery.

Overall, within the spatiotemporal literature base, commercial burglary remains an understudied crime type, with much attention being given to residential burglary (Carter et al., 2020; Groff & Taniguchi, 2019; Hodgkinson & Andresen, 2019; Martin, 2002; Moreto et al., 2014; Piza & Carter, 2018). To differentiate these crime types, as the names imply, one of the primary differences between a commercial and residential burglary would be the land uses that these offenses occur within. Considering the established relationship between land use and criminal activity (Tarkhanyan, 2015; Browning et al., 2010; Caplan et al., 2020; Kinney et al., 2008; Song et al., 2015; Stucky & Ottensmann, 2009; Twinam, 2017; Wo, 2019), it would make sense that these crime types might have different predictors. Thus, if factors predicting a commercial burglary differ from those predicting a residential burglary, this would hold implications for prevention strategies.

In terms of the spatiotemporal literature base, we first turn towards qualitative research that provide an initial basis for our understanding of how space and time might impact criminal activity. In their study of residential burglary, Wright and Decker (1996)
discussed how offenders will often probe potential guardianship of targets. This would be accomplished by an offender ringing a doorbell or knocking on a door (Wright & Decker, 1996). In a commercial setting this might be accomplished in the same manner, by probing an access point to see if any alarms or security are present at the establishment. Additionally, residential burglars prefer to target standalone buildings (Felson & Eckert, 2016; Wright & Decker, 1996). The reason for this is that high density apartments or townhomes may provide more guardianship due to the increased number of individuals within an area (Wright & Decker, 1996). This factor may not be applicable to commercial burglary because most offenders prefer to commit their burglaries between the hours of 10pm and 2am (Jenion, 2003; Yu & Maxfield, 2014; Walsh, 2019), as well as clustering around 4am for repeat and non-repeat offenses (Rothstein, 2020), when most businesses will be closed for the night. Research also shows that this temporal clustering may be related to whether the establishment has an alarm installed or not, with more business being victimized at night if they do not have a burglar alarm installed (Hakim & Shachmurove, 1996). Another temporal pattern identified within this research is that commercial burglaries, for both repeat and non-repeat offenses, are most frequent on Sunday and Monday morning (Rothstein, 2020).

In terms of more environmentally related influences of target selection, studies assessing both residential burglary (Wright & Decker, 1996) and commercial burglary (Butler, 2005; Bichler-Robertson & Potchak, 2002; Byun & Ha, 2016; Walsh, 2019) have found that offenders prefer premises that have street-level access points. This would allow for an easier entrance and exit of the offender. Offenders also prefer to target establishments that are not well-lit (Byun & Ha, 2016). Lower levels of lighting would
enhance the ability of the offender to escape without being noticed or identified. Offenders may also be drawn to specific areas due to factors that increase their mobility, such as public transit terminals or nodes (Gallison, 2017; Gallison & Andresen, 2017; Yu & Maxfield, 2014). Because these public transit nodes are often placed near places of interest, such as commercial land uses, the proximity and density of these terminals may help explain the occurrence of criminal activity in these areas. Spatially based research would confirm that bus stops and public transit nodes are an important predictor of commercial burglaries (Gallison, 2017; Yu & Maxfield, 2014).

Another important consideration for commercial burglary are the type of products are being sold or kept by the establishment. As most burglaries are committed with the intention of theft in mind (Butler, 2005; Walsh, 2019), it is important to consider what products might be targeted for theft. For this, attention should be paid to what commercial establishments would have what are considered hot product (Clarke & Webb, 1999). Clarke and Webb (1999) put forth an explanation of hot products through the CRAVED model. CRAVED is an acronym that describes hot products. Specifically, hot products are concealable, removable, available, valuable, enjoyable, and disposable (Clarke & Webb, 1999). Concealability refers to how easy it is for an offender to conceal a product once it is stolen. This refers not only to the size of a product itself but also to the uniqueness of that item. For example, as Felson and Eckert (2016) describe, it is easier to conceal a common car than it would be an expensive car, such as a Rolls-Royce. Additionally, a hot product must be removable. If an offender wishes to target a very valuable classic car that is displayed for show, it may not have a workable engine. This may be the case if the car does not have any gas or liquids to make the engine
run. Thus, this car may not be removable. Another example would be an air compressor for air conditioning units. These are oftentimes placed outdoors, as their functionality demands, so they have the potential to be targeted for parts. If this item is bolted into the ground, it makes it quite difficult to remove.

The next component of the CRAVED model would be availability (Clarke & Webb, 1999). If a product is desirable, it must also be available for an offender to target that product. If, for example, it is commonplace for a shop owner to clear out their register every night before closing up, it would not make sense for a thief to target this establishment for cash. This product would simply not be available. Another component of this model would be the inherent value of a product. If a product is valuable, then it is more desirable by an offender. This value can come from monetary or even the subjective value attributed to this item by the offender (Clarke & Webb, 1999; Felson & Eckert, 2016). Even if an item does not hold a large monetary value, it can still be pursued by an offender because of some perceived aspect of enjoyment. This would include items such as drugs, alcohol, or tobacco (Butler, 2005; Felson & Eckert, 2016).

The final component of the CRAVED model would be whether the product is disposable. This refers to how easily a thief can get rid of an item that they stole, whether this be selling to a fence, which would be an individual who buys and sells stolen goods, or how easily an item that is of no use to the offender can be traced back to this individual. For example, if an individual steals a vehicle for a joyride, they must consider how to dispose of that vehicle when they have had their enjoyment with it. This must be done in a manner that does not draw unwanted attention back to them.
This CRAVED model has specific implications for policy and practice. Each component of this model can be focused on to reduce the likelihood of hot products being targeted (Clarke & Webb, 1999). This follows the same pattern of situational crime prevention (SCP) in that it includes target hardening, reduction of reward, and increasing risk of apprehension (Cornish & Clarke, 2003). As discussed by Clarke and Webb (1999), in order to make a product, like cash, less concealable, a bank might place dye-packs within a bag of money in order to make it so the offender is easily noticed by law enforcement. This would also inherently reduce the value of the stolen cash as it would be useless in any legitimate business. In order to make a product less removable, one might secure it in a way that make it extremely difficult to remove. The example of bolting down an air compressor is applicable here. To make a product less available, one would simply have to remove the product from a vulnerable location (Clarke & Webb, 1999). This might, for example, entail moving a trailer containing power tools into a garage overnight.

The concept of value was discussed above with the dye pack making stolen cash untransferable. In order to make a product less enjoyable, we can look to the example of individuals inhaling computer duster. To combat this, companies producing this product added in a bitterant to make the inhalant of this product less enjoyable. The bitterant would slightly irritate the individual's airways in order to deter usage (Clarke & Webb, 1999). The last aspect of the CRAVED model is harder to target (Clarke & Webb, 1999). Nonetheless, in order to make a product less disposable, one might have to focus on the illicit markets that buy, sell, and trade these products. For example,
having law enforcement work with pawn shops in order to identify and prevent the transfer of stolen products would help reduce means of disposal for potential thieves.

Scholars have also found empirical support for the use of the CRAVED model to explain theft in several contexts (Price et al., 2014; Smith & Clarke, 2015; Smith, 2018). To elaborate, offenders looking to shoplift (Smith & Clarke, 2015; Smith, 2018) or steal from churches (Price et al., 2014) will target items that follow the CRAVED model. Specifically, some offenders are targeting items that are used for drug use (Smith & Clarke, 2015), while others are simply looking for items to fence (Price et al., 2014; Smith, 2018). In their analysis of shoplifting within the US, Smith (2018) found that products that were more concealable, less available, more valuable, more enjoyable, and more disposable were more likely to be stolen. These items frequently included beauty products and small electronics, which are not only valuable, but also highly concealable (Smith, 2018).

From this model, we can assume that offenders will target commercial establishments that have desirable products. That being said, the most common target of any burglary would be cash (Butler, 2005; Felson & Eckert, 2016; Walsh, 2019; Wright & Decker, 1996). Beyond that, from this model, we can make assumptions about specific products that may be desirable, such as smaller electronics, jewelry, or even firearms. Apart from items that are inherently valuable, as noted above, thieves also prefer to target products that are enjoyable, which could include items such as alcohol, drug, tobacco, or expensive clothes (Felson & Eckert, 2016). In relation to the spatial literature base on commercial burglary, this might provide that specific establishments
are at a heightened risk of burglary, such as pawn shops, retail establishments, or convenience stores. Indeed, spatiotemporal literature on this subject would back up these assumptions with studies highlighting empirically driven spatial relationships between commercial burglary and these types of establishments, including food stores and automotive retail (Yu & Maxfield, 2014), retail establishments (Hakim & Shachmurove, 1996; Mawby, 2014), personal services (Hakim & Shachmurove, 1996; Yu & Maxfield, 2014), and bars and restaurants (Yu & Maxfield, 2014). Much like the general spatiotemporal crime literature has shown crimes to cluster spatially (Braga et al., 2011; Groff et al., 2010; Weisburd et al., 2004), commercial burglary also follows this same pattern (Amemiya & Ohyama, 2019; Andresen et al., 2017; Hakim & Shachmurove, 1996). It should be noted, however that this clustering could be a factor of the classification of the crime type itself. Due to the fact that this crime type, by definition, can only occur within commercial or mixed land use areas, it will inherently be clustered within these areas (Andresen et al., 2017).

**Street Robbery**

Robbery has received much attention from a spatiotemporal standpoint (Barnum et al., 2017; Browning et al., 2010; Caplan et al., 2020; Connealy, 2021; Haberman et al., 2018; Hipp, 2016; Nelson et al., 2001; Norton et al., 2018). It is also important to point out that street robbery is a crime that has a person victim, as opposed to a place victim, as is the case with commercial burglary. This, in part, leads to different characteristics being predictive of these criminal acts, but it also holds an implication for the explanation of these offenses. Specifically, place victims are largely stationary, while person victims are mobile, just like potential offenders. For the current study, street
robbery, or a robbery that occurs outdoors, is the focus; thus, this review of the literature will focus on this subset of robbery. Much like the previous section, the review of the robbery literature will first make note of the qualitative studies that have sought to explain the occurrence of robbery. Following that, an in-depth discussion of the quantitatively based spatiotemporal literature will be put forth.

The qualitative research on street robbery, unlike the qualitative research of commercial burglary, is quite abundant (Bennett & Brookman, 2008, 2009; Brookman et al., 2007; Deakin et al., 2007; Harding et al., 2019; McLean et al., 2020; Wright & Decker, 1997). Nonetheless, this qualitative research provides some important considerations for how offenders select targets. To start, robbers prefer to offend in locations that are not near police stations (Wright & Decker, 1997). This provides a potential protective factor of robbery, which would be a factor that has the potential to reduce criminal activity. Additionally, most robbers prefer to commit their crimes at night when they have the cover of darkness (Wright & Decker, 1997). For the offenders that chose to rob during the daytime, they still preferred to hide in shadows as a means of protecting against being identified. Studies have also found that robbers preferred to select targets who themselves were engaged in criminal activity, whether that be prostitution, the sale or use of drugs, or otherwise (Brookman et al., 2007; Harding et al., 2019; McLean et al., 2020; Wright & Decker, 1997). Apart from individuals involved in criminal activity, robbers also made note that they tend to target individuals who are intoxicated.
The qualitative literature on street robbery has also discussed the various motivations for committing these offenses (Bennett & Brookman, 2008; Brookman et al., 2007; Deakin et al., 2007; Wright & Decker, 1997). In part, some robbers have an instrumental motive for committing this offense. More specifically, some offenders commit this offense to sustain their own drug habits (Bennett & Brookman, 2008; Brookman et al., 2007; McLean et al., 2020; Wright & Decker, 1997). Other individuals committed robbery to sustain a lavish lifestyle (Bennett & Brookman, 2008; McLean et al., 2020). While some offenders were motivated by instrumental means, others were motivated by the perceived status that came along with robbing (Bennett & Brookman, 2008, 2009). To some offenders, this perceived status would offer protection because they were known to use violence and may even be affiliated with a gang or other organized group (Bennett & Brookman, 2009; Harding et al., 2019). Additionally, the robbers within Wright and Decker’s (1997) study were predominantly Black. They specifically chose areas to offend in which they could blend in, which meant they had to stay in mostly Black neighborhoods. Robbers also preferred to select locations that were near highways or major thoroughfares in order to have easy access to an escape route (Wright & Decker, 1997). Apart from locations of target selection, robbers also prefer to target individuals who might be holding cash or drugs (Bennett & Brookman, 2008, 2009; Brookman et al., 2007; Deakin et al., 2007; Harding et al., 2019; McLean et al., 2020; Wright & Decker, 1997).

These findings hold specific implications for spatiotemporal examinations into robbery. First, it might be expected that robberies will temporally cluster at night. Indeed, prior literature on street robbery supports this notion, with street robbery
typically clustering at night on the weekends (Andresen & Malleson, 2013; Kim & Wo, 2021; Nelson et al., 2001). Second, because robbers typically target individuals who are criminals themselves and that robbers oftentimes commit crime to sustain a drug habit, we might expect robberies to cluster in areas such as open-air drug markets or known prostitution areas. This expectation comes from discussions of crime attractors (Brantingham & Brantingham, 1995). Specifically, areas known for prostitution or drug sales contain not only individuals that are motivated to commit criminal acts, but also potential targets. These areas are rife for criminal activity because potential offenders can target individuals who are themselves engaged in criminal activity, such as Johns or drug buyers (Brantingham & Brantingham, 1993; 1995). If individuals are engaged in criminal activity themselves, they may be less likely to report when they have been victimized.

Third, because robbers often target individuals who are intoxicated (Deaking et al., 2007; Wright & Decker, 1997), this could mean there will be clusters within areas that sell alcohol, whether that be a liquor store, bar, sporting venue, or similar establishment. Findings from previous research would support this notion with street robberies tending to cluster around nightclubs, liquor stores, restaurants, and bars (Caplan et al., 2020; Caplan & Kennedy, 2016; Connealy, 2021; Nelson et al., 2001). Fourth, because robbers target individuals that are likely to be holding cash (Brookman et al., 2007; Deakin et al., 2007; Wright & Decker, 1997), we might expect to find clustering around pawnshops, ATMs, banks, malls, or check cashing establishments. As will be further discussed below, spatiotemporal research has also identified many of these places as predictors of street robbery incidents (Clarke & Eck, 2007; Connealy,
Fifth, due to robbers preferring to offend near places that provide an easy exit (Wright & Decker, 1997), we might find clustering near entrances to highways. As noted above, prior research by Song and colleagues (2017) does find an increase in street robberies around edges, including entrances and exits to highways. Lastly, because robbers wish to offend in areas where they can easily blend in (Brantingham & Brantingham, 1993; Wright & Decker, 1997), there may be an elevated number of robbery incidents within areas that are racially or ethnically heterogenous.

Quantitative research has also explored the different types of spatial characteristics that have been found to predict the occurrence of street robbery incidents, including foreclosures, schools, banks, nightclubs, grocery stores, liquor stores, restaurants (both sit-down and take-out), and hotels (Caplan et al., 2020; Caplan & Kennedy, 2016). Research has also shown that apartment buildings (Connealy, 2021) and public housing (Kim & Wo, 2021) increase the likelihood of a robbery occurring. Additionally, similar to the results of Caplan and Kennedy (2016), Connealy (2021), through a comparison of hot spots with Google Street View, found that hot spots of robbery were more likely to contain small retail stores, money institutions, and alcohol establishments. In support of the findings presented by Caplan and Kennedy (2016) and Connealy (2021), Nelson and colleagues (2001) found that a majority of robbery incidents were near nightclubs, public housing, restaurants, and bus stops. Connealy (2021) also found that signs of decay were more common in hot spots than control areas. Within this context, decay would refer to sidewalk, street, and garden deterioration, as well as vacant spaces and structural dilapidation (Connealy, 2021).
Much like the general spatiotemporal literature demonstrated (Groff et al., 2010; Kurland & Hill, 2021; Weisburd et al., 2004), there is utility in examining robbery from many different spatial units of analysis, such as the street segment (Braga et al., 2011; Nelson et al., 2001), grid cells (Caplan et al., 2020), or neighborhood-level (Hart, 2021; He et al., 2015; Kim & Wo, 2021). With the spatial stability of micro-level hot spots noted (Braga et al., 2011; Nelson et al., 2001), there also exists variation within the neighborhood level (Hart, 2021; He et al., 2015; Kim & Wo, 2021). Factors such as percent unemployment, residential mobility, and percent of single-family homes have been shown to be important predictors of violent crime, including robbery (He et al., 2015). To add to this, these factors are temporally stable, meaning they consistently predict violent crime incidents through a given year (He et al., 2015; Kim & Wo, 2021). While there is some temporal stability in a single spatial unit of analysis, it has been found that these predictors vary depending on the neighborhood context under study (Kim & Wo, 2021). Factors such as overall population, urban density, street network design, and availability of public transit may influence these patterns (Hart, 2021).

Each of these factors align with the expectations of opportunity theories in that they either increase overall opportunity of criminal activity, like with overall population or density, or they help facilitate offender movement, such as street network design or availability of public transit. While there is certainly some recent scholarly attention dedicated to the place in neighborhoods literature base (see Duru & Kim, 2021; Gilchrist et al., 2019; Hipp & Williams, 2020; Jones & Pridemore, 2019; Tillyer et al., 2021), there is still a sizeable gap in assessing these relationships within many diverse contexts. Replication of these studies and extending them to a variety of neighborhood contexts
and places would be very beneficial for the crime and place literature base. This is increasingly more important when research suggests that there is significant variability in how these crime patterns present, depending on neighborhood context (Gilchrist et al., 2019; Jones & Pridemore, 2019).

While the above denotes some spatial trends relating to robbery, it is equally important to consider the temporal characteristics of this offense. In relation to aggregation of violent crimes, including robbery, it has been found that there is temporal stability of these offenses when examined at the block-group level (He et al., 2015). Temporal stability, in this instance, means that areas that experience heightened levels of criminal activity typically experience heightened levels over a period of time. For robbery specifically, this temporal stability is also found at the street segment unit of analysis (Braga et al., 2011; Nelson et al., 2001) as well as micro-scale grids (Hart, 2021). As discussed above, Braga and colleagues (2011) examined the longitudinal stability of robbery hot spots at the street segment unit of analysis. Apart from longitudinal examinations of robbery, scholars have also studied temporal trends seasonally (Andresen & Malleson, 2013; Haberman et al., 2018; Kim & Wo, 2021), over the course of weeks (Kim & Wo, 2021), and daily (Caplan et al., 2020; Grubesic & Mack, 2008; Hart, 2021; Nelson et al., 2001).

In terms of seasonality, research has demonstrated that robbery incident counts do fluctuate over the course of a calendar year (Andresen & Malleson, 2013; Haberman et al., 2018; Kim & Wo, 2021). As with most spatiotemporal examinations, these patterns can be explained by differences in human movement depending on the season
of the year. Typically, depending on the geographic location, people are most active during the summer months and least active during the winter months. This might have less of an impact in more temperate climates that experience decent weather year-round. Even in areas with significant variation in terms of seasonal temperate averages, we would not expect variation in levels of criminal activity if the patterning of human movement throughout these regions is unaltered. Empirical research supports this notion (Haberman et al., 2018). So, while some research has found seasonal variation present (Andresen & Malleson, 2013), others have made note that this seasonal variation is dependent on the context of the area under study (Haberman et al., 2018; Kim & Wo, 2021).

While there is some commonality among the clustering by day of the week, research also suggests that these patterns could vary spatially (Kim & Wo, 2021; Nelson et al., 2001). At the aggregate, it does appear that robberies tend to cluster temporally on late Friday and Saturday nights (Nelson et al., 2001); however, when looking at individual hot spots, temporal variation exists. Nelson and colleagues (2001), when comparing specific street hot spots, found that different days of the week experienced higher levels of offending. This suggests a contextual dependency for this crime type where variation exists spatially, depending on the time of day. These daily trends can also be broken down into smaller units of analysis by examining how robbery trends throughout the course of a single day (Caplan et al., 2020; Nelson et al., 2001). The theoretical basis for these intra-day crime patterns would come primarily from theories such as routine activities, rational choice, and crime pattern theory (Wheeler & Haberman, 2018). As people move throughout an environment during their daily routine
activities, there exist many clusters of individuals through time and space. These clusters provide opportunity for would-be offenders, such as robbers. In support of Wright and Decker’s (1997) notion that robbers prefer to offend at night, these studies have found that most robberies within Cardiff, UK and Worcester, UK occur between the hours of 2:00-4:00am on Friday and Saturday, with most offenses also clustering spatially near pedestrian nodes (Nelson et al., 2001). Additionally, Caplan and colleagues (2020) found that the spatial risk factors of robbery vary depending on the time of day. Specifically, the most amount of risk factors found to be statistically significant were during the hours of 10:01pm -12:00am as well as between 2:00 -4:00am (Caplan et al., 2020).

The noted concentrations of robbery within specific places and at specific times has been referred to as confluence flashpoints (Nelson et al., 2001). These flashpoints are representative of an increased number of criminal opportunities due to an influx of people at specific places and times. An example of a confluence flashpoint would be an entertainment district at around 2am on either Saturday or Sunday, when most bars and nightclubs might be closing for the night (Nelson et al., 2001). Within this example, we can make note that there is a spatial clustering that exists within the entertainment district of a city. Additionally, there is a temporal pattern existing in the early morning of Saturday and Sunday because entertainment districts are often most visited on Friday and Saturday night, with this activity leading into the early morning of the subsequent day. The concept of a confluence flashpoint is especially applicable to the crime of robbery because this crime targets people, as opposed to structures or products. Additionally, we know that offenders often target individuals who are intoxicated (Wright
& Decker, 1997); thus, it is important to understand how confluence flashpoints might influence the robbery patterns that are identified within a study area. Going back briefly to commercial burglary, the target is obviously an establishment that is not subject to any type of mobility; thus, the conceptual connection with confluence flashpoints is not clear.

A noted gap in this literature base is that most studies are focused on examining how aspects of the built environment, like risky facilities, influence criminal activity. Missing from this literature would be examinations of how the natural environment influences this activity. By natural environment, this would refer to characteristics of the physical environment, such as tree coverage, land elevation, and slope. Indeed, there is spatially based research that examines the impact of the natural environment, such as parks and urban forests (Anderson et al., 2013; Foster et al., 2013); however, little research has examined how characteristics of the natural environment might play out at the micro unit of analysis, such as the street segment (see Haberman & Kelsay, 2020; Kim & Wo, 2021). If offenders’ decision-making is, in part, guided by their own perceptions of the environment as a whole (Brantingham & Brantingham, 1993), then it would make sense to also include characteristics of the natural environment. For example, if tree coverage on a specific street segment impacts the surveillance capabilities of potential guardians, whether these be people or CCTV cameras, then this could create a situation where an offender is more comfortable committing a crime. The research by Wright and Decker (1997) also suggests that robbers, if they offend during the day, prefer to operate in shaded areas to avoid detection. This could provide some support for evaluating the influence of tree coverage at the micro-place unit of analysis.
Alternatively, areas that are sloped, meaning they are on an incline or decline, may present difficulties for an offender committing the initial offense and subsequently getting away in a timely manner. Thus, it would be useful to examine characteristics of both the built and natural environment in relation to criminal activity. With the literature relating to the linkage between space, time, and crime as well as specific spatiotemporal characteristics of street robbery and commercial burglary outlined, the next focus will be discussing the methods of the current study.

**Summary**

The study of the environment and its relationship to crime has been in progress for nearly two centuries. Early research identified spatial and temporal distributions of criminal activity. This work was subsequently expanded upon with elaborations of the relationship of not only the physical environment, but the social environment as well. Contemporary research has found that criminal activity is heavily spatially concentrated, and that these concentrations are longitudinally stable. In relation to the current study, research has found several elements of the built environment that help predict either commercial burglaries or street robberies. Additionally, prior research has made note of some temporal trends relating to these crime types. With the theoretical framework and foundational literature outlined, attention is now shifted to a presentation of the methods for the current study.
CHAPTER FOUR: METHODS

Overview

The current study uses publicly available crime incident and GIS data to explore how spatial and temporal factors impact offender site selection for commercial burglary and street robbery in three different US cities: Atlanta, Georgia; Rochester, New York; and Fayetteville, North Carolina. To examine the spatial variability of predictors for both crime types, the Random Forest Classification and Regression tool is employed. As an extension of the model, a temporal component will be assessed on four-hour block increments, providing a total of six blocks throughout the day. Additionally, the data will be split by weekdays and weekends, and finally, into seasons of the year. This will provide for a robust assessment of how time may impact offender site selection. Lastly, an assessment of how spatial factors cluster within crime sites will be performed.

Gaps in the Existing Literature and Justification for the Present Study

Several identified gaps within the literature will first be discussed. First, as noted in previous chapters, the process of an offense begins with the offender first selecting a large area to operate within. This individual then selects a smaller location that might be more desirable for offending (Brantingham & Brantingham, 1978). While there are studies examining site selection for serial sex offending (Deslauriers-Varin & Beauregard, 2014), body disposal (Beauregard & Field, 2008), and facilities (Kennedy, 1990), little research has been dedicated to examining offender site selection for both street robbery and commercial burglary. Thus, the current study will extend the theoretical discussion of offender site selection by examining this process for the two
noted crime types. As an extension of this, the current study will also seek to identify common clusters of predictors that present as unique crime sites within each study location. This will provide insight into the unique combinations of predictors that might be present in various types of identified crime sites.

Second, few studies have explored how characteristics of the natural environment can be measured as it relates to crime event forecasting (Haberman & Kelsay, 2020; Kim & Wo, 2021). Thus, it is important to explore the impact of the natural environment on criminal activity. While crime pattern theory provides a justification for the inclusion of the natural environment in the explanation of criminal behavior, little is known about how this plays out practically. Moreover, the natural environment itself might be more susceptible to seasonal changes throughout a year due to a change in weather patterns. This provides an avenue for exploration in relation to this classification.

Third, the current study also helps expand the discussion of how time influences the identified spatial relationships. The temporal dimension of crime is a topic that has received much attention in years past (Andresen & Malleson, 2013; Chen et al., 2020; Schnell & McManus, 2020; Tompson & Townsley, 2009). One noted area of interest with the temporal dimension is how spatial predictors vary temporally (Ott & Swiaczny, 2001). Thus, the current study seeks to address this need by examining the spatial non-stationarity of many predictors across several temporal units of analysis. Taken together, the current study seeks to contribute to the methodology and theory surrounding spatiotemporal inquiries of criminal behavior within crime sites. With the
inclusion of three unique study areas, the current study will be able to compare the spatiotemporal patterning of predictors for various types of analyses that are outlined below.

Research Questions

For the current study, two research questions will be examined:

1. How do spatiotemporal characteristics impact offender site selection for commercial burglary and street robbery?

2. How do environmental characteristics cluster within crime sites for commercial burglary and street robbery?

Study Locations and Description

Study locations for the current study were selected by the size and demographic makeup of each study location, then on a basis of availability of open-source outcome and predictor data. The first step of this selection process was to identify two large and two medium-sized cities for comparison. The reason for this selection is to be able to identify whether spatial and temporal factors vary depending on the size of the city in question. The chosen metric for identifying large and medium-sized cities comes from the National Center for Education Statistics (NCES). This metric classifies city size based on the total population of that city. According to the NCES, a large city is classified as having a population that exceeds 250,000. A midsized, or medium-sized, city is equal to or greater than 100,000 inhabitants, but less than 250,000. Lastly, a small-sized city is classified as having a population of less than 100,000.
Due to limitations in the availability of predictor data for small-sized cities, the current study focuses on large and medium-sized cities. This ensures that all study locations have a congruent set of predictor variables that allows for model comparison between these locations. Another selection basis was to identify cities that were demographically diverse from each other. Atlanta, while having a similar poverty rate, percent of individuals over the age of 65, and percent female, are diverse in the race/ethnicities of inhabitants and median income for each city. The small cities, while having similar populations for White and Black residents, have differing populations for Hispanics and median income levels. Thus, the one large city selected for the current study is Atlanta, Georgia. The medium-sized cities selected for the current study are Fayetteville, North Carolina and Rochester, New York. Demographic information from the US Census (2020) for each study is listed below within Table 3. A table that displays the violent and property crime rates for each of the included study locations is also shown below (see Table 4). Table 5 displays the size of each study location, in square miles.

<table>
<thead>
<tr>
<th>City</th>
<th>Population</th>
<th>% White</th>
<th>% Black</th>
<th>% Hispanic</th>
<th>% Asian</th>
<th>% Female</th>
<th>% Under 18</th>
<th>% 65 and over</th>
<th>25+ with BA/BS</th>
<th>Median Income ($)</th>
<th>% Poverty</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atlanta</td>
<td>498,715</td>
<td>39.8</td>
<td>47.2</td>
<td>6.0</td>
<td>4.2</td>
<td>51.3</td>
<td>17.6</td>
<td>11.6</td>
<td>53.4</td>
<td>64,179</td>
<td>19.2</td>
</tr>
<tr>
<td>Rochester</td>
<td>211,328</td>
<td>37.6</td>
<td>41.7</td>
<td>16.4</td>
<td>3.1</td>
<td>51.6</td>
<td>22.5</td>
<td>11.6</td>
<td>27.1</td>
<td>37,395</td>
<td>30.4</td>
</tr>
<tr>
<td>Fayetteville</td>
<td>208,501</td>
<td>34.5</td>
<td>41.8</td>
<td>12.6</td>
<td>3.1</td>
<td>49.6</td>
<td>23.5</td>
<td>12.0</td>
<td>27.3</td>
<td>46,321</td>
<td>19.9</td>
</tr>
</tbody>
</table>
Table 4: Crime Rate by City 2018, Per 100,000

<table>
<thead>
<tr>
<th>City</th>
<th>Violent Crime Rate</th>
<th>Property Crime Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atlanta</td>
<td>435.7</td>
<td>392.6</td>
</tr>
<tr>
<td>Rochester</td>
<td>441.3</td>
<td>282.0</td>
</tr>
<tr>
<td>Fayetteville</td>
<td>482.8</td>
<td>292.3</td>
</tr>
</tbody>
</table>

Table 5: Size of Study Locations

<table>
<thead>
<tr>
<th>City</th>
<th>Area (mi²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atlanta</td>
<td>136.3</td>
</tr>
<tr>
<td>Rochester</td>
<td>150.1</td>
</tr>
<tr>
<td>Fayetteville</td>
<td>37.17</td>
</tr>
</tbody>
</table>

Data Sources

Study Boundaries and Map Specifications

The study boundaries used for this study include shapefiles gathered from online publicly accessible local or county GIS clearinghouses. The maps for each study location were created using ArcGIS Pro v2.8.3. All data used within the current study were placed on localized projected coordinate systems for each respective study area. The projected coordinate system assigned to each study area is listed below in Table 6. The projected coordinate system for each map was identified by the data collection process. The GIS clearinghouses contained GIS resources that were managed by the municipality, county, or state itself (see Table 7). This means that most of the data
collected for each study location already had a common projected coordinate system. For consistency, these were the projected coordinate systems used for each map of the study locations. Additionally, some of the data were collected by the government entities themselves, thus, to ensure the integrity of the data, each shapefile was projected in the same coordinate system in which the data were presumably collected within. For a list relating to the origins of the data, please refer to Table 7 below.

**Table 6: Projected Coordinate Systems**

<table>
<thead>
<tr>
<th>City</th>
<th>Projected Coordinate System</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atlanta</td>
<td>NAD 1983 (2011) StatePlane Georgia West FIPS 1002 (US Feet)</td>
</tr>
<tr>
<td>Rochester</td>
<td>NAD 1983 StatePlane New York West FIPS 3103 (US Feet)</td>
</tr>
<tr>
<td>Fayetteville</td>
<td>NAD 1983 StatePlane North Carolina FIPS 3200 (US Feet)</td>
</tr>
</tbody>
</table>

**Table 7: Origins of Ready-to-Use Collected Data**

<table>
<thead>
<tr>
<th>City</th>
<th>Data Sources Utilized</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atlanta</td>
<td>Department of City Planning GIS – City of Atlanta</td>
</tr>
<tr>
<td></td>
<td>Georgia State University (GSU) – GIS Resources</td>
</tr>
<tr>
<td></td>
<td>Fulton County, Georgia Open Data</td>
</tr>
<tr>
<td>Rochester</td>
<td>City of Rochester GIS Maps</td>
</tr>
<tr>
<td></td>
<td>GIS Data – Monroe County</td>
</tr>
<tr>
<td></td>
<td>New York State (NYS) GIS Clearinghouse</td>
</tr>
<tr>
<td>Fayetteville</td>
<td>City of Fayetteville Open Data Portal</td>
</tr>
<tr>
<td></td>
<td>Cumberland County GIS Maps and Apps</td>
</tr>
<tr>
<td></td>
<td>North Carolina County GIS Data</td>
</tr>
</tbody>
</table>
**Outcome Event Data**

All outcome event data used for the current study were gathered from the Police Data Initiative, which is managed by the National Police Institute\(^2\). This initiative collects data from law enforcement agencies around the US with the aim of providing transparency for policing practice. Within this compilation of data, one can find datasets on traffic accidents, assaults on officers, calls for service, incidents, community engagement, complaints, hate crimes, officer involved shootings, citations and arrests, and use of force. These data were downloaded as comma separated value (.csv) files and subsequently imported into ArcGIS Pro using the XY Table to Point Geoprocessing tool. With this tool, each shapefile generated from this process were displayed using the projections listed above in Table 6. Once the full datasets were imported into ArcGIS Pro, individual shape files for each crime type for the years 2012-2018 were exported. A multi-year time period was selected to ensure there are sufficient data points for the subsequent analyses. This time period also aligns with when a majority of the predictor data were captured. Descriptive information for the crime incident data for each study location are displayed below in Table 8.

\(^2\) See [https://www.policedatainitiative.org/](https://www.policedatainitiative.org/)
Table 8: Variable Descriptive Information

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Atlanta (n)</th>
<th>Rochester (n)</th>
<th>Fayetteville (n)</th>
<th>Data Type</th>
<th>Which model?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Street Robbery Incidents</td>
<td>3,425</td>
<td>1,053</td>
<td>661</td>
<td>Point</td>
<td>-</td>
</tr>
<tr>
<td>Commercial Burglary Incidents</td>
<td>2,543</td>
<td>805</td>
<td>962</td>
<td>Point</td>
<td>-</td>
</tr>
<tr>
<td>Bus Stops</td>
<td>3,999</td>
<td>2,848</td>
<td>962</td>
<td>Point</td>
<td>Both</td>
</tr>
<tr>
<td>Vacant Properties and Lots</td>
<td>358</td>
<td>1,453</td>
<td>10,634</td>
<td>Polygon</td>
<td>Both</td>
</tr>
<tr>
<td>Colleges and Universities</td>
<td>72</td>
<td>3</td>
<td>7</td>
<td>Polygon</td>
<td>Both</td>
</tr>
<tr>
<td>Schools (K-12)</td>
<td>94</td>
<td>100</td>
<td>68</td>
<td>Point</td>
<td>Both</td>
</tr>
<tr>
<td>Police Departments</td>
<td>15</td>
<td>6</td>
<td>3</td>
<td>Point</td>
<td>Both</td>
</tr>
<tr>
<td>Greenways and Paths</td>
<td>207</td>
<td>43</td>
<td>17</td>
<td>Polyline</td>
<td>Both</td>
</tr>
<tr>
<td>Parks</td>
<td>105</td>
<td>91</td>
<td>72</td>
<td>Polygon</td>
<td>Both</td>
</tr>
<tr>
<td>Restaurants</td>
<td>2,974</td>
<td>661</td>
<td>2,539</td>
<td>Point</td>
<td>Both</td>
</tr>
<tr>
<td>At-Risk Housing</td>
<td>241</td>
<td>143</td>
<td>61</td>
<td>Point</td>
<td>Both</td>
</tr>
<tr>
<td>Gas Stations</td>
<td>1,488</td>
<td>374</td>
<td>331</td>
<td>Point</td>
<td>Both</td>
</tr>
<tr>
<td>Liquor Stores</td>
<td>300</td>
<td>115</td>
<td>16</td>
<td>Point</td>
<td>Both</td>
</tr>
<tr>
<td>Grocery Stores</td>
<td>1,034</td>
<td>252</td>
<td>135</td>
<td>Point</td>
<td>Both</td>
</tr>
<tr>
<td>Tree Canopy Coverage</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Raster</td>
<td>Both</td>
</tr>
<tr>
<td>LandScan Day</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Raster</td>
<td>Both</td>
</tr>
<tr>
<td>LandScan Night</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Raster</td>
<td>Both</td>
</tr>
</tbody>
</table>

**Predictor Variables**

**Built Environment**

Brantingham and Brantingham (1981) put forth that characteristics of the environment influence the individual perception of place. This perceptive environment is referred to as the environmental backcloth (Brantingham & Brantingham, 1981). The built environment, or man-made structures and infrastructure, are part of this
environmental backcloth, and therefore, have the potential to influence both offender and victim decision making. For example, individuals may perceive areas with vacant properties or lots to be lacking in guardianship. This could lead to an offender choosing this area to commit an offense, whether that be a robbery or commercial burglary. Offenders, on the other hand, might avoid areas immediately surrounding police departments. To elaborate, police stations may act as a deterrent for criminal activity because of the heightened levels of police activity and surveillance (Jones & Pridemore, 2019). Because of this, it would be expected that the area immediately surrounding a police station would have decreased levels of criminal activity. Greenways and paths could be used by offenders to escape detection or generally as a path of travel. Some variables are also representative of areas where potential victims may be targeted, such as colleges and universities. As discussed in previous chapters, some offenders made note that they target college students (Deakin et al., 2007). Parks within cities could also facilitate target selection for robbers (Jones & Pridemore, 2019). For example, if the park is public, an offender would have an excuse to loiter while looking for a potential target. Additionally, if a park is near a commercial establishment, it can provide an avenue for escape for a would-be burglar.

Additional predictor variables (see Table 8), such as bus stops, vacant properties and lots, schools (K-12), restaurants, at-risk housing, gas stations, liquor stores, and grocery stores, fall in line with the concepts of risky facilities, crime generators, and crime attractors. Specifically, bus stops, not only help facilitate offender movement, but they are also considered risky facilities (Hart & Miethe, 2021). Because bus stops facilitate offender travel, they have the potential to influence both commercial burglaries
and street robberies. For one, bus stops can attract groups of individuals. This could provide a potential offender with an opportunity to commit a robbery. Indeed, previous research supports this notion, with findings that demonstrate bus stops are a statistically significant predictor of street robbery incidents (Nelson et al., 2001). Also, potential commercial burglars could use public transit to reach their targets (Walsh, 2019). For the current study, it would be expected that bus stops have elevated levels of criminal activity surrounding them, for both street robberies and commercial burglaries.

Previous research has found that vacant properties and lots are a risk factor for street robberies (Connealy, 2021). In terms of commercial burglary, qualitative research has put forth that vacant properties may provide cover for a would-be burglar that may be attempting to break into an adjacent building (Nasar, 1981; Walsh, 2019). For the variable capturing vacant properties and lots, it is expected that these places will increase the number of both commercial burglaries and street robberies. For K-12 schools, prior research has shown that street robberies are more likely to occur around these places (Caplan & Kennedy, 2016; Caplan et al., 2020). Prior literature also demonstrates that burglaries are more likely to occur at or around schools (Jones & Pridemore, 2019). The reason for the heightened occurrence of these offenses could be due to the offenders being students at these respective schools. Within the current study, it is anticipated that schools will elevate the occurrences of both street robberies and commercial burglaries. Another place that could help predict the occurrence of street robberies and commercial burglaries would be restaurants. Specifically, prior literature suggests that restaurants are considered a suitable target for burglaries (Jones & Pridemore, 2019; Yu & Maxfield, 2014). The reason for these burglaries could
be that restaurants have the potential to have money present. Similarly, restaurants are thought to increase the occurrences of street robberies since servers often leave with cash from tips, which would be an ideal target for robbers (Jones & Pridemore, 2019; Nelson et al., 2001). Several scholars, using risk terrain modeling (RTM), have found restaurants to be a statistically significant risk factor of street robberies (Caplan & Kennedy, 2016; Caplan et al., 2020). For the current study, it is anticipated that restaurants will coincide with elevated levels of both commercial burglaries and street robberies.

One variable that will only be used within the models for street robbery is at-risk, or public, housing. This type of place has been found to generally increase the occurrence of street robberies (Kim & Wo, 2021; Nelson et al., 2001), however, research also demonstrates that the heightened risk of robberies is not consistent between all public housing areas (Haberman et al., 2013). The last three remaining variables—gas stations, liquor stores, and grocery stores—will also only be utilized within the models examining street robbery. Each of these variables has been found in prior research to be a significant predictor of street robbery incidents (Caplan & Kennedy, 2016; Caplan et al., 2020; Nelson et al., 2001). For the current study, it is expected that each of these variables will follow that same relationship. More specifically, it is expected that gas stations, liquor stores, and grocery stores will all increase the likelihood of a street robbery incident occurring.

The data for several variables, including bus stops, vacant properties and lots, colleges and universities, schools (K-12), police departments, greenways and paths,
and parks, were downloaded from online, open-source data repositories from multiple levels of government. Specifically, these data were pulled from local, county, state, and/or federal government open-source GIS clearinghouses for each of the noted study areas. For these data sources, preference was given to local or county data sources because, as noted above, these resources were often managed by local or county governmental authorities. Thus, these sources should have the most up-to-date data on these places. Four of the previously noted variables, including bus stops, colleges and universities, schools (K-12), and police departments, are displayed as points within ArcGIS Pro. One of the variables are line data, which includes greenways or paths. The remaining two variables are displayed as polygons: vacant properties and lots and parks. The data for the remaining variables, including gas stations, restaurants, liquor stores, at-risk housing, and grocery stores, were captured using an open-source web crawler that combed online Yellow Pages databases for the relevant place locations. The web crawler used was Web Scraper: Free Web Scraping. Once this data was exported to an Excel CSV file, it was then geocoded into ArcGIS Pro as point shapefiles to be used in subsequent analyses. As noted above, the data for each study location was displayed using localized projected coordinate systems which are highlighted within Table 6 above. Table 9 below summarizes the justification for each variable that captures elements of the built environment.

---

https://chrome.google.com/webstore/detail/web-scraper-free-web-scra/jnhgonknheijnehehlklliplmblh?hl=en
### Table 9: Characteristics of the Built Environment

<table>
<thead>
<tr>
<th>Predictor Variable</th>
<th>Model</th>
<th>Conceptualization and Rationale</th>
<th>Operationalization</th>
<th>Sources/References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bus Stops</td>
<td>Both</td>
<td>Bus stops provide a method of travel for offenders. Additionally, opportunity for specific crimes might be elevated around bus stops.</td>
<td>Count of bus stops within grid cell</td>
<td>Brantingham &amp; Brantingham (1981; 1993); Caplan et al. (2020); Yu &amp; Maxfield (2014)</td>
</tr>
<tr>
<td>Vacant Properties and Lots</td>
<td>Both</td>
<td>Vacant properties and lots provide an area for offenders to loiter. Lack of guardianship likely around areas with vacant properties.</td>
<td>Count of vacant properties within grid cell</td>
<td>Connealy (2021)</td>
</tr>
<tr>
<td>Colleges and Universities</td>
<td>Both</td>
<td>Represent locations where offenders may find targets (street robbery). Offenders may visit these places as part of their routine (both crime types).</td>
<td>Count of colleges and universities in grid cell</td>
<td>Deakin et al. (2007); Wright &amp; Decker (1997); Walsh (2019)</td>
</tr>
<tr>
<td>Schools (K-12)</td>
<td>Both</td>
<td>Represent locations where offenders may find targets (street robbery). Offenders may visit these places as part of their routine (both crime types).</td>
<td>Count of schools in grid cell</td>
<td>Wright &amp; Decker (1997); Walsh (2019)</td>
</tr>
<tr>
<td>Police Departments</td>
<td>Both</td>
<td>Police departments should act as a protective factor for both crime types.</td>
<td>Count of police departments in grid cell</td>
<td>Jones &amp; Pridemore (2019)</td>
</tr>
<tr>
<td>Greenways and Paths</td>
<td>Both</td>
<td>Greenways and paths provide a means of escape for potential offenders.</td>
<td>Dichotomous; presence of greenway or path in grid cell (0/1)</td>
<td>Andresen (2014); Brantingham &amp; Brantingham (1981; 1993); Cohen &amp; Felson (1979)</td>
</tr>
<tr>
<td>Parks</td>
<td>Both</td>
<td>Parks may provide robbers with potential targets. Additionally, parks can provide cover for offenders loitering while searching for opportunity.</td>
<td>Count of parks in grid cell</td>
<td>Anderson et al., 2013; Foster et al., 2013; Hipp (2017); Jones &amp; Pridemore (2019)</td>
</tr>
<tr>
<td>Restaurants</td>
<td>Both</td>
<td>Restaurants provide robbers with potential targets. Restaurants may also be part of an offender’s awareness space.</td>
<td>Count of restaurants in grid cell</td>
<td>Brantingham &amp; Brantingham (1981; 1993); Jones &amp; Pridemore (2019); Szkola et al. (2019); Yu &amp; Maxfield</td>
</tr>
<tr>
<td>Predictor Variable</td>
<td>Model</td>
<td>Conceptualization and Rationale</td>
<td>Operationalization</td>
<td>Sources/References</td>
</tr>
<tr>
<td>--------------------</td>
<td>-------</td>
<td>---------------------------------</td>
<td>--------------------</td>
<td>-------------------</td>
</tr>
<tr>
<td>At-Risk Housing</td>
<td>Both</td>
<td>Has been found to be associated with elevated levels of street robberies and commercial burglaries.</td>
<td>Count of at-risk housing developments in grid cell</td>
<td>Haberman et al. (2013); Kim &amp; Wo (2021)</td>
</tr>
<tr>
<td>Gas Stations</td>
<td>Both</td>
<td>Robbers may use these establishments to identify potential targets.</td>
<td>Count of gas stations in grid cell</td>
<td>Brantingham &amp; Brantingham (1995); Caplan et al. (2021); Kim (2018)</td>
</tr>
<tr>
<td>Liquor Stores</td>
<td>Both</td>
<td>Robbers may use these establishments to identify potential targets.</td>
<td>Count of liquor stores in grid cell</td>
<td>Brantingham &amp; Brantingham (1995); Caplan et al. (2021); Kim (2018)</td>
</tr>
<tr>
<td>Grocery Stores</td>
<td>Both</td>
<td>Robbers may use these establishments to identify potential targets.</td>
<td>Count of grocery stores in grid cell</td>
<td>Brantingham &amp; Brantingham (1981; 1995); Caplan et al. (2021); Kim (2018)</td>
</tr>
</tbody>
</table>

**Natural Environment**

There is one predictor variable related to the natural environment—tree canopy coverage. The justification for this variable would be that it is considered an element of the environmental backcloth (Brantingham & Brantingham, 1978, 1981, 1995). As discussed in previous chapters, tree canopy coverage has the potential to block sightlines for would-be guardians, like CCTV cameras and individuals. Additionally, tree canopy coverage can provide shade during the day for a would-be offender to scope out potential targets for a street robbery or commercial burglary. Canopy coverage also has the potential to block out light at night. This has the potential to undermine the ability of targets to evade being victimized by a street robber. This could also provide cover for a commercial burglar looking to break into a property at night. From these theoretical explanations, the expected relationship would be as follows. For tree canopy coverage, a higher percentage of tree canopy coverage should correspond with elevated levels of criminal activity. This relationship should be similar for both selected crime types—commercial burglary and street robbery.
The data for this variable undergoes a collection process involving a Lidar system that is attached to a plane. The data for canopy coverage were collected using a 30m resolution. A 30m resolution equates to each pixel on the raster image to be representative of a 30m x 30m piece of land. Each raster cell is assigned a value that equates to the average percent of canopy coverage in that cell. Once the value for each individual raster cell is identified, 2x2 squares of these raster cells will be combined into grid cells equal to the 2x2 raster cells. For the tree canopy coverage variable, an average will be taken of the four included raster cell values. This will provide a single measure for that 2x2 square, which would be representative of the average % of tree canopy coverage for that defined space. Table 10, shown below, displays a summary of the justifications for the inclusion of this variable.

<table>
<thead>
<tr>
<th>Predictor Variable</th>
<th>Model Conceptualization and Rationale</th>
<th>Operationalization</th>
<th>Sources/References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tree Canopy Coverage</td>
<td>Both</td>
<td>Tree canopy coverage is how much of an area is covered by tree canopy; may provide cover from potential guardians</td>
<td>Average percentage of tree canopy coverage across individual grid cell</td>
</tr>
</tbody>
</table>

**Population Metrics**

For the current study, there are two variables relating to population metrics, LandScan day and LandScan night. These variables come from the Oak Ridge National Laboratory (ORNL) LandScan USA dataset. This dataset is publicly available and is
measured at a 3-arc-second resolution. This resolution produces a 90 m raster surface which displays the ambient population across a geographic landscape. ORNL also offers LandScan Global, which is an international dataset for ambient population that is captured at a 30-arc-second resolution. This resolution equates to 1 km raster cells. While LandScan data have been used for several criminological and criminal justice oriented studies (see Andresen, 2006, 2010, 2011; Andresen et al., 2012; Ristea et al., 2018; Schaefer, 2021), these studies were all using the LandScan Global dataset. The utility of using the LandScan USA dataset lies not only with the much finer resolution, but also with a temporal split of the data. Specifically, LandScan USA data are captured for both day and night. Thus, the LandScan USA data provide a measure for the average ambient population for a study area during the daytime and nighttime. Thus, because of the finer resolution, the current study can assess the impact of ambient population at a micro-spatial unit of analysis. Additionally, the current study can explore the impact of ambient population at differing temporal units of analysis. In terms of the justification for using a measure for ambient population, crime pattern theory dictates that crime patterns are the product of an intersection, in time and space, of motivated offenders and suitable targets. A measure for ambient population provides a proxy measure for criminal opportunity present within a given area. A more densely population area is thought to be at higher risk for criminal activity (Brantingham & Brantingham, 2017). A summary of the conceptualization and operationalization of these variables is listed below in Table 11.
Table 11: Population Metrics

<table>
<thead>
<tr>
<th>Predictor Variable</th>
<th>Model Conceptualization and Rationale</th>
<th>Operationalization</th>
<th>Sources/References</th>
</tr>
</thead>
<tbody>
<tr>
<td>LandScan Day &amp; Night</td>
<td>Both</td>
<td>These variables are measures of the ambient population during the day and nighttime.</td>
<td>Average number of individuals thought to be within an area during the day or night.</td>
</tr>
</tbody>
</table>

Analytic Strategy

Data Visualizations

The first analytic step of the current study is to create visualizations of the dependent variables. This includes kernel density estimation (KDE) and standard deviational ellipses for each of the three study locations. The utility of KDE is that it helps identify where events are clustering across space. This would be a preliminary investigation into the spatial patterning of the dependent variables. This initial analysis would be completed using the Kernel Density geoprocessing tool within ArcGIS Pro. For the KDE, an output cell size of 200 ft will be used. Additionally, a default search radius is selected, along with the output cell values being calculated as a density. Within ArcGIS Pro, the default search radius for KDE is calculated using Silverman’s Rule of Thumb formula for bandwidth selection. This method is particularly resistant to the impact of outliers within the dataset; thus, it provides a robust estimate for a bandwidth that accounts for the spatial dispersion of the data (ESRI). Lastly, the method of calculation for the KDE would be Planar.
Apart from KDE, the current study will also include a standard deviational ellipses analysis for each of the study locations. Within ArcGIS Pro, there is a geoprocessing tool called the Directional Distribution (DD) tool which allows for the use of X and Y coordinates to produce standard deviational ellipses. The produced ellipse is useful for identifying the directionality of the distributions. The parameters for this visualization would be an ellipse size of one standard deviation. This means that the created ellipse will contain all data that lie within one standard deviation of the identified mean center.

**Random Forest Classification and Regression**

To answer the first research question, the Random Forest Classification and Regression tool is used. This tool relies on the random forest algorithm to classify data and make predictions. Random forests is a machine learning technique that relies on an ensemble of decision trees to classify data (Breiman, 2001; Credit, 2022; Hartshorn, 2016). Decision trees are a process by which categorizations are made based on the values of identified variables. As noted, random forest uses an ensemble of these decision trees, meaning each random forest model contains a user-defined number of individual decision trees that are used to make predictions. The random forest algorithm leverages this ensemble of decision trees to make votes about predictions. Thus, the random forest algorithm is a learning process in which data are sampled and used in each decision tree to identify variation within the dataset. This is referred to as the training process because the algorithm creates a model for prediction based on the variation that is picked up from the decision tree process (Breiman, 2001; Hartshorn, 2016). The model created through the training process can then be used to make predictions outside of the data provided (Breiman, 2001).
As noted, the Random Forest Classification and Regression tool within ArcGIS Pro is used for the current study. For this tool, there are several parameters that need to be set. First, ArcGIS Pro has two parameter settings for the prediction type of the model: train only and predict to features. The prediction type for the current study is predict to features, which means the program will not only train the model, but also use the trained model to predict values of the dependent variable within the identified spatial unit of analysis. A feature class of the grid cells was utilized for the input training features. Data for the full dataset and many temporal units of analysis are used as the variable to predict. The Random Forest Classification and Regression tool allows for three different variable operationalizations, density, distance, and rasters. Only the density and distance operationalizations are used for the current study. Five variables are operationalized as density and ten as distance measures. Density variables are count variables that are aggregated into the spatial unit of analysis, which would be 1000x1000ft grid cells. Distance variables, on the other hand, are given a value by the Random Forest Classification and Regression tool relating to the distance to the nearest data point from the variable to predict, which would be the dependent variable under study. The five density variables are bus stops, LandScan day, LandScan night, tree canopy coverage, and vacant properties. The ten distance measures include trails, colleges, schools (K-12), gas stations, grocery stores, liquor stores, parks, police stations, public housing, and restaurants. The input predicted features would be the same feature class used for the training model. This allows for the program to predict using the same unit of analysis and variables specified for the training model.
The number of decision trees for all models is 1000. Ideally, it is recommended that the highest number of decision trees possible be used, with regard to hardware limitations (Breiman, 2001). For the current study, initial tests found that going larger than 1000 decision trees did not yield much overall improvement within the models. The Random Forest Classification and Regression tool also allows for the specification of leaf size, tree depth, and number of random sampled variables. Unless one is familiar with the data, it is recommended to allow the random forest model to explore various settings to maximize the explanatory power of the model (Breiman, 2001; Hartshorn, 2016). The data available per tree is set at 100%, which is the default. This means that, during the training process, the individual decision trees will use 100% of the data available from the sample pulled for that tree. Lastly, the value for the amount of training data excluded for validation is set at 15%. This means that 15% of the overall dataset will be withheld from the random forest training process to validate the created model. This allows for predictions to be made on data that the model was not trained with (Breiman, 2001). This validation process helps evaluate how well the model can be used to make predictions with new data.

The Random Forest Classification and Regression tool provides several outputs that are of use to the current study. First, this tool produces two model fit statistics: $r^2$ and out of bag (OOB) error rate. These model fit statistics are outlined below within the following chapter. Another output from this process would be the variable importance lists. This list details the overall importance of a variable throughout the training process (Breiman, 2001; Hartshorn, 2016). As each decision tree is tested individually, variables are assigned a score that relates to the amount of information that the variable is adding
to the model. This is calculated using Gini coefficients, which are a measure of the variability explained by an individual variable. Thus, the variable importance lists provide a ranking of how influential a variable is in explaining the outcome of interest, which would be commercial burglary and street robbery incidents for the current study.

**Temporal Analysis**

To examine the temporal variability of the predictors, the data will be split up into multiple temporal units of analysis. Specifically, the data will be split into four-hour block increments to examine temporal variability throughout the day. Past research shows that commercial burglaries (Jenion, 2003; Yu & Maxfield, 2014; Walsh, 2019) and street robberies (Nelson et al., 2001) tend to be most frequent during the hours of 10pm and 2am, thus, the four-hour blocks will start off with this temporal bandwidth. This will provide a total of six block periods to compare. The data will also be split by weekdays and weekends to examine any variability occurring within these time frames. Previous research demonstrates that both commercial burglaries (Jenion, 2003; Yu & Maxfield, 2014; Walsh, 2019) and street robberies (Nelson et al., 2001) are more common on weekends. Lastly, the data will be split by meteorological seasons to assess any seasonal variation that might be present (winter: December – February; spring: March – May; summer: June – August; fall: September – November). With these temporal bandwidths specified, the Random Forest Classification and Regression tool will be run to compare the spatial and temporal variability present. This part of the analysis will help answer the temporal component of Research Question 1, which seeks to evaluate how temporal characteristics might influence offender site selection.
**Multivariate Cluster Analysis**

To answer Research Question 2, a cluster analysis was performed. The purpose of this phase of the analysis is to identify common environmental factors within specific crime sites within each study location. To accomplish this, the Multivariate Clustering tool with ArcGIS Pro will be used. This tool can be used to identify specific clusters of crime sites that have a common set of unique environmental factors. This analysis will be performed for all four of the study locations and with each of the noted crime types: street robbery and commercial burglary. The results from this analysis will be used to compare the identified clusters across the study areas. In terms of the parameters for the tool, the criminal incidents for street robbery and commercial burglary would be the dependent variables of interest. Likewise, the noted environmental factors of both the built and natural contexts, will be used as the common characteristics for each cluster. The clustering method selected for this portion of the analysis would be k-means clustering. K-means clustering works by attempting to minimize the differences within clusters (Fotheringham et al., 2000). For the initialization method, the optimized seed location option will be selected. This allows for the software to automatically select the initial data point (seed) that is used for the analysis. Lastly, one must specify the number of clusters that will be identified from the analysis. Within ArcGIS Pro, leaving this field of the input parameters blank will allow the software to automatically identify the appropriate number of clusters for your dataset. For this software, the number of clusters is restricted to between 2 and 30.
Limitations

There are several limitations that warrant careful consideration. First, this study, as with many forms of spatial research, are susceptible to what is known as the modifiable areal unit problem (MAUP) (Openshaw, 1984). This problem occurs when an individual attempts to aggregate spatial data for use in analyses. The issue being that these aggregate units of analysis are oftentimes not inherently related to the data being aggregated. This causes issues when an individual conducts analyses at different units of analysis. For example, a hot spot map that uses census tracts and one that uses micro-grid cells will yield quite different results. The reason for this difference, however, is attributed to the decision of the researcher, not as a function of the spatial unit of analysis. In the current study, criminal incidents and other environmental data are aggregated into grid cells that are 1000x1000ft, thus MAUP is something to be considered. Openshaw (1984) put forth that one way to protect against the introduction of bias through MAUP would be to use spatial units of analysis that are theoretically guided. For the current study, the 1000x1000ft grid cell was selected, in part, because it aligned well with the notion of a possible site for criminal activity. Brantingham and Brantingham (1978) discuss that offenders first selected a large area to operate within, then they subsequently choose a smaller area, the crime site, to commit the offense within. Thus, the spatial unit of analysis used for the current study is representative of the crime site itself. In further support of this micro-unit of analysis, previous studies have used a similar cell size for studies using risk terrain modeling (for example, Caplan et al., 2017).
Much like there are considerations of MAUP with space, there are also considerations to be made with reference to time. Specifically, attention must be given to the modifiable temporal unit problem (MTUP) (Cöltekin et al., 2011; de Jong & de Bruin, 2012; Hunt, 2016). Indeed, just like with spatial units of analysis, the selection of specific temporal units of analysis will ultimately impact the results that are obtained (de Jong & de Bruin, 2012; Hunt, 2016). Thus, if one is attempting to aggregate data temporally and conduct an analysis using these aggregations, it is recommended that the selected temporal unit of analysis theoretically corresponds to the dependent variable (de Jong & de Bruin, 2012). For example, when analyzing trends in seasonal vegetation, it would be best to aggregate to a calendar year, as opposed to any unit of analysis smaller or larger than this (de Jong & de Bruin, 2012). By aggregating any larger than a calendar year, one runs the risk of washing out within season variation that might exist (de Jong & de Bruin, 2012). The same could be applied to a criminal justice setting (Hunt, 2016). To elaborate, in an analysis of MAUP and MTUP on hot spot stability, Hunt (2016) found that increasing the temporal bandwidth being utilized only brought marginal increases in predictive efficiency. Additionally, as anticipated by the conceptual discussion by Cöltekin and colleagues (2011), Hunt (2016) found that using larger temporal units of analysis tends to wash out variation that could be identified at smaller units of analysis.

Another common issue within spatial research is related to spatial autocorrelation. This concept follows Tobler’s first law of geography, which states that “everything is related to everything else, but near things are more related than distant things” (Tobler, 1970, p. 236). Thus, within spatial research, we run into the statistical
problem that our data points may not be independent of each other (Fotheringham et al., 2000). The presence of positive spatial autocorrelation is that high values tend to cluster around other observations with high values. Conversely, negative spatial autocorrelation is when high values tend to cluster with low values. A lack of any relationship would be indicated by the presence of no spatial autocorrelation (Fotheringham et al., 2000; 2002). The violation of this assumption in statistics would call into question any hypothesis testing done with this data because of the impact on the produced standard errors. The impact on standard errors comes into play from the correlation of error terms.

This is primarily what separates spatial autocorrelation from that of multicollinearity. With multicollinearity, there is also a correlation present, but instead of with the error terms, the correlation is between two or more independent predictors within a model (Fotheringham et al., 2000). The issue of multicollinearity is important to consider because of the impact on the variance of the standard errors. Typically, the variance of the standard errors is inflated which leads to issues with hypothesis testing (Fotheringham & Oshan, 2016).

Another potential issue with spatial data, primarily that of openly sourced datasets, is that the data collected are from different temporal periods. For example, some data may have been collected and be of reference for the year 2018, while some may be of reference for 2012. To minimize the possibility of this occurring, the data for the predictor variables were collected as close to the time period selected for the dependent variables of interest (2012-2018). One other potential limitation is that of
omitted variable bias. This problem occurs when influential variables are left out of the model. This raises the possibility that the model is missing out on some explanatory power. To protect against this issue, an in-depth literature review was conducted to identify predictor variables that have been previously utilized within studies and shown to be important in explaining the outcomes of interest.

Lastly, because the current study uses criminal incident data, this means that the only data represented within this study are crimes that are formally reported to police. This leaves open the possibility that the datasets being used for the current study are not truly representative of the crime problems within each study location. Criminal incidents that are not reported to police are often referred to as the “dark figure of crime” (Lab, 2019).

Summary

The current study seeks to assess offender site selection across three study areas: Atlanta, Rochester, and Fayetteville. The data for the study boundaries, dependent variables, and predictors were gathered from online publicly available data clearinghouses. To assess offender site selection, a variety of visualization and analytic techniques will be utilized, including KDE, Directional Distribution, Random Forest Classification and Regression, and multivariate cluster analysis. These analyses will help expand the discussion of offender site selection by identifying how predictors vary spatially and temporally. Apart from these theoretical contributions, the current study will expand the literature that assesses the impact of the natural environment on offender site selection. More specifically, due to a limited number of studies incorporating these
characteristics into statistical models, the current study will identify model specifications for characteristics of the natural environment. Lastly, the current study seeks to assess how characteristics of both the built and natural environment cluster within specific crime sites in the identified study areas.
CHAPTER FIVE: RESULTS

Overview

As noted within the previous chapter, the overall analysis for the current study has several steps. First, an examination of the spatial and temporal distributions will be presented. This will include two main techniques, including kernel density estimation (KDE) and directional distribution (DD). Additionally, frequencies of dependent variables across temporal units of analysis will be presented. This will help identify any temporal variation across the selected units of analysis. Secondly, the results of the Random Forest Classification and Regression tool will be put forth. This tool will help answer the first research question, which asks, “how do spatiotemporal characteristics impact offender site selection for commercial burglary and street robbery?” Lastly, the findings of the Multivariate Clustering tool will be described. The findings outlined by this tool will help answer the second research question, “How do environmental characteristics cluster within crime sites for commercial burglary and street robbery?”

Spatial and Temporal Distributions

To get an idea of how commercial burglaries and street robberies are distributed, both spatially and temporally, several methods are employed. To identify the spatial distributions for the dependent variables, both Kernel Density Estimation (KDE) and Directional Distribution (DD) are utilized. The results of the KDE tool within ArcGIS Pro will create a hot spot map for the selected variable of interest. For the current study, the variables of interest would be commercial burglaries and street robberies. For each hot spot map that is produced, dark purple areas are indicative of a concentration of
offenses. The results of the DD tool will help provide details about the directionality of the criminal activity in each respective study location. After describing the spatial distribution of offending for each study location, the temporal distributions will be assessed through a comparison of event frequency by various temporal units of analysis.

**Figure 3: Atlanta Commercial Burglary Kernel Density Estimation and Direction Distribution Results**

Figures 3-8 above displays the results of Kernel Density Estimation (KDE) and Directional Distribution (DD) tools from within ArcGIS Pro. For ease of interpretation, the
ellipse output from the DD tool is overlayed the KDE for each of the study locations. With reference to Figure 3, which displays the results of the KDE and DD for commercial burglaries in Atlanta, there are several noted concentrations of offenses throughout the study area. Several of these concentrations are in the northeast portion of the city. Additionally, these are several other concentrations within the central location of the city, slightly offset to the eastern boundaries of the study location. Lastly, there are a couple concentration within the southern portion of the city, with two of them being offset to the southwestern boundaries. The ellipse provided by the DD analysis demonstrates the directionality of the distribution. Specifically, there is a noted northeast and southwest pull to the ellipse. Moreover, the central location of the ellipse is right over the concentration of offenses that are centralized, but slightly offset to the eastern boundary. This ellipse can be used to highlight specific locations of the study area that are influencing the identified trends.
Figure 4 displays the results of the KDE and DD for street robberies within Atlanta. The KDE for street robberies shows a much less dispersed concentration of offenses than the KDE for commercial burglaries. Overall, the concentrations of street robbery are near the central area of the city, with a slight offset to the eastern boundary. The ellipse output from the DD analysis is slightly less elongated than the ellipse shown for commercial burglaries, although there is still a pull towards the northeast and southwest of the city. This is because the concentration of offenses for street robberies
is pulled further south than the main concentration of offenses for commercial burglaries.

![Figure 5: Fayetteville Commercial Burglary Kernel Density Estimation and Direction Distribution Results](image)

The results of the KDE and DD for commercial burglaries in Fayetteville is displayed in Figure 5. Overall, with reference to the results of the KDE, there is a strong concentration of offenses within the southeast corner of the city, with several smaller concentrations existing in the south, southeast quadrant of the city. The ellipse from the DD analysis is overlayed these south, southeastern concentrations of offenses, with the ellipse being elongated towards the east and west boundaries of the city.
The findings of the KDE for street robberies in Fayetteville differ from the identified concentrations of offenses for commercial burglary. While there is still a large concentration of street robberies in the southeastern corner of the city, there are two other notable concentrations. One of those concentrations is within the central location of the city, while the other is off to the west. The ellipse for street robbery is like that of the commercial burglary ellipse for Fayetteville in that it is elongated towards the east and west boundary; however, the mean center is slightly shifted west, relative to the mean center of the ellipse for commercial burglary.
Figure 7 displays the results of the KDE and DD for commercial burglaries in Rochester. With reference to the results of the KDE, there is a string of concentrations going from west to east within the central location of the city center. There are also several other noted concentrations immediately surrounding this identified string. Thus, for the DD analysis, there is not much elongation of the ellipse. Instead, the ellipse more
closely resembles a circle, with a very slight elongation towards the northwest and southeast boundaries of the city.

Figure 8: Rochester Street Robbery Kernel Density Estimation and Direction Distribution Results

The findings of the KDE and DD for street robberies in Rochester is contained within Figure 8. Much like with commercial burglaries, there is not much dispersion with reference to the concentrations of street robberies in Rochester. The KDE identified several concentrations, with most of these being contained within the northeast portion
of the city center. There is also another concentration of offenses south of this main concentration. Additionally, there is another smaller concentration off to the west of both aforementioned concentrations. As noted, because there is less dispersion of street robberies within this city, the ellipse provided by the DD analysis is quite small. Additionally, because of the main concentration of offenses within the northeast portion of the city center, the ellipse is slightly elongated within this direction.

### Table 12: Temporal Unit of Analysis Data Description for Dependent Variables

<table>
<thead>
<tr>
<th>Seasonal (n)</th>
<th>Day of Week (n)</th>
<th>Time of Day (n)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CB</td>
<td>SR</td>
</tr>
<tr>
<td>Atlanta</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spring</td>
<td>1,466</td>
<td>2,593</td>
</tr>
<tr>
<td>Summer</td>
<td>1,711</td>
<td>2,893</td>
</tr>
<tr>
<td>Fall</td>
<td>1,455</td>
<td>2,873</td>
</tr>
<tr>
<td>Winter</td>
<td>1,596</td>
<td>2,464</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fayetteville</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spring</td>
<td>562</td>
<td>499</td>
</tr>
<tr>
<td>Summer</td>
<td>671</td>
<td>652</td>
</tr>
<tr>
<td>Fall</td>
<td>645</td>
<td>607</td>
</tr>
<tr>
<td>Winter</td>
<td>543</td>
<td>538</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rochester</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spring</td>
<td>436</td>
<td>731</td>
</tr>
<tr>
<td>Summer</td>
<td>695</td>
<td>930</td>
</tr>
<tr>
<td>Fall</td>
<td>527</td>
<td>876</td>
</tr>
<tr>
<td>Winter</td>
<td>392</td>
<td>724</td>
</tr>
</tbody>
</table>
Table 12 above displays the temporal distributions of the two relevant dependent variables of interest. In terms of seasons, all of the three study locations have a similar distribution, with commercial burglaries and street robberies peaking during the summer months. Following this peak of criminal activity during summer, commercial burglaries and street robberies then decline during fall. This decline in activity continues into the winter months, which account for the least amount of criminal activity throughout the year.

Much like there is consistency between the study locations with reference to seasonal trends, there is also considerable consistency with distributions of criminal activity during the weekdays and weekends. For all study locations and both crime types, commercial burglaries and street robberies are more frequent during the weekdays. This finding can be expected simply because there are more days of the week encompassing the weekday versus the weekend (5 vs 2). To compare the levels of criminal activity across study locations, one can calculate ratios of the criminal activity occurring during weekdays to weekends (see Table 13 below). From these ratios, each
study location is experiencing about the same level of criminal activity between weekdays and weekends.

Table 13: Ratio of Weekday to Weekend Criminal Activity

<table>
<thead>
<tr>
<th></th>
<th>CB</th>
<th>SR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atlanta</td>
<td>2.47</td>
<td>2.20</td>
</tr>
<tr>
<td>Fayetteville</td>
<td>2.57</td>
<td>2.30</td>
</tr>
<tr>
<td>Rochester</td>
<td>2.52</td>
<td>2.60</td>
</tr>
</tbody>
</table>

The distributions of criminal activity for the four-hour block increments of each study location show differing temporal patterns. With reference to commercial burglaries in Atlanta, these offenses are most common during the third time block (T3), which is representative of the hours 6:00am to 9:59am. The second largest temporal concentration for Atlanta is during the hours of 2:00am and 5:59am (T2), followed by the 10:00am to 1:59pm time block (T4). Thus, for commercial burglaries in Atlanta, the most common time period for these offenses is between 2:00am and 1:59pm. For commercial burglaries in Fayetteville, the sixth time block (T6), which is between 6:00pm and 9:59pm, contains the greatest number of offenses. This time block is followed by the first time block (T1), which is between 10:00pm and 1:59am. The time block with the third highest concentration of offenses is the second time block (T2; 2:00am – 5:59am). Overall, in Fayetteville, commercial burglaries are most common between the hours of 6:00pm and 5:59am.
For commercial burglaries in Rochester, the time block with the highest concentration of offenses is the second time block (T2; 2:00am – 5:59am). The second highest concentration is within the first time block (T1; 10:00pm – 1:59am), followed by the sixth time block (T6; 6:00pm – 9:59pm). While the ordering of the time blocks in terms of the concentration of offenses differs between Fayetteville and Rochester, both have the same overall range of heightened levels of commercial burglaries between the hours of 6:00pm and 5:59am.

For street robberies, all three study locations share the same ordering of the highest (T1; 10:00pm – 1:59am) and second highest (T6; 6:00pm – 9:59pm) concentrations of offenses. Thus, for all three study locations, there is a peak in offending between the hours of 6:00pm and 1:59am. The time block with the third highest concentration of street robberies differs for each study location. For Atlanta, this is the third time block (T3; 6:00am – 9:59am). For Fayetteville, this is the second time block (T2; 2:00am – 5:59am). This would mean Fayetteville has heightened levels of street robberies between the hours of 6:00pm and 5:59am. Lastly, for Rochester, the third highest concentration of street robberies is within the fifth time block (T5; 2:00pm – 5:59pm). This means that Rochester has elevated levels of offenses between the hours of 2:00pm and 1:59am.

**Multivariate Clustering Tool**

To answer the second research question, which states “how do environmental characteristics cluster within crime sites for commercial burglary and street robbery?”, the Multivariate Clustering tool within ArcGIS Pro was used. As noted in the previous
chapter, this tool identifies unique clusters of variables across a given study location.

Figures 9-14 display the results of the Multivariate Clustering tool. These results include both a map that displays where the identified clusters are occurring spatially, as well as a figure that shows the values of the variables within each identified cluster. To facilitate the following discussion, variables will be grouped into classifications (see Table 14).

**Table 14: Classification of Independent Variables**

<table>
<thead>
<tr>
<th>At-Risk Properties</th>
<th>Vacant Properties &amp; Public Housing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Places of Business</td>
<td>Restaurants, Gas Stations, Liquor Stores, Grocery Stores</td>
</tr>
<tr>
<td>Population</td>
<td>LandScan Day &amp; LandScan Night</td>
</tr>
<tr>
<td>Schools</td>
<td>Colleges &amp; Schools (K-12)</td>
</tr>
<tr>
<td>Transit and Recreation</td>
<td>Bus Stops, Trails, and Parks</td>
</tr>
<tr>
<td>Natural Environment</td>
<td>Tree Canopy Coverage</td>
</tr>
<tr>
<td>Protective Factor</td>
<td>Police Stations</td>
</tr>
</tbody>
</table>
Figure 9: Map of Clusters from the Multivariate Clustering Tool for Atlanta
For the results of the Multivariate Cluster tool for Atlanta, five unique clusters were identified. The map shown in Figure 9 displays where the identified clusters are occurring spatially. Below this map, Figure 10 displays the values of the variables for each identified cluster. Overall, each identified cluster within the Atlanta dataset was quite unique, especially when compared to the other study locations to be discussed. Cluster One for Atlanta contains high levels of both commercial burglaries and street robberies, as well as several classifications of variables, including Places of Business, Population Metrics, and Transit and Recreational areas. In terms of the clusters of Places of Business, this cluster contains mid-range values for gas stations, grocery stores, and liquor stores. For Population Metrics, this cluster contains mid-range values for LandScan day and high values for LandScan night. The identified variables under the classification of Transit and Recreation would be trails and bus stops.

Cluster Two for Atlanta contains low levels of both commercial burglaries and street robberies. This cluster is predominantly made up of Schools and Places of Business. Within Schools, both colleges and schools (K-12) were identified within this cluster as having high values. This cluster also contains the highest values out of any
cluster for gas stations, grocery stores, liquor stores, and restaurants. Cluster Three for Atlanta contains mid-range values for commercial burglary and low levels of street robbery incidents. Additionally, this cluster contains variables within the classifications of Schools, Population Metrics, and Transit and Recreation. This cluster contained the highest ranking for colleges within the Schools classification. This cluster also contained the highest values for both Population Metric variables, LandScan day and LandScan night. Lastly, Cluster three contained the highest value of all clusters for the variable trails, which falls under the Transit and Recreation classification.

Cluster Four for Atlanta contains the lowest values for both commercial burglary and street robbery. This cluster only contained elevated values for two variables. One variable would be tree canopy coverage, which falls under the Natural Environment variable classification, and vacant properties, which falls under the At-Risk classification. Lastly, Cluster Five contains high levels of both commercial burglaries and street robberies, as well as variables from the Transit and Recreation, Protective Factors, Places of Business, and At-Risk variable classifications. This cluster contained the highest values for both bus stops and parks, which are Transit and Recreation variables. The variable police, which is the only variable within the Protective Factors classification, also contained the highest values of any other identified cluster. This cluster also contained mid-range values for several Places of Business, including gas stations, grocery stores, and restaurants. The At-Risk variable, public housing, was also identified within this cluster. The values for this variable in this cluster are the highest of any previously identified cluster.
Figure 11: Map of Clusters from the Multivariate Clustering Tool for Fayetteville

Figure 12: Cluster Values from the Multivariate Clustering Tool for Fayetteville
The results of the Multivariate Clustering tool for Fayetteville are displayed in both Figures 11 and 12. As can be seen from Figure 12, there are five identified clusters of variables within Fayetteville. Overall, these clusters contain less variability than what was seen with the results from the Atlanta dataset. For example, Cluster One is ranked low in every included variable. As can be seen within Figure 11, this is the most common cluster across Fayetteville. Thus, most of Fayetteville’s landscape does not contain a clustering of the included variables. In terms of Cluster Two for Fayetteville, this cluster contains the highest levels of commercial burglary incidents and a low amount of street robbery incidents. Additionally, this cluster has several Places of Business variables, including the highest values for gas stations and grocery stores. Also, from within this cluster, there are elements of Population Metrics, including LandScan night.

Cluster Three contains mid-range levels of commercial burglary and high levels of street robbery incidents. In terms of the present variable classifications, this cluster contains Places of Business, Population Metrics, and At-Risk variables. For Places of Business, this Cluster contains mid-range values for gas stations and grocery stores. Additionally, this cluster contains the highest values for liquor stores. The identified Population Metric would be LandScan day, which contained mid-range values. The At-Risk variable that was present within Cluster Three is public housing. Overall, this cluster contained the highest values for the variable public housing.

Cluster Four for Fayetteville contains low values of both commercial burglaries and street robberies. This cluster predominantly contains variables from within the
Transit and Recreation and School classifications. Specifically, from the Transit and Recreation classification, both parks and trails have the highest values when compared to other clusters. The school variable makes up the other identified variable of interest from within Cluster Four. Within this cluster, schools contain the highest values of any other cluster. The last cluster, Cluster Five, contains high levels of both commercial burglaries and street robberies. This cluster had the highest values for street robbery incidents. There were several identified variables of high value within this cluster, each of which come from a different variable classification. The noted variables include bus stops (Transit and Recreation), LandScan day (Population Metric), and police stations (Protective Factors).
Figure 13: Map of Clusters from the Multivariate Clustering Tool for Rochester

Figure 14: Cluster Values from the Multivariate Clustering Tool for Rochester
Rochester, unlike the two previous study locations, only contained two unique clusters (see Figures 13 and 14). Cluster One for Rochester contained high values of both commercial burglaries and street robberies. Additionally, this cluster contained elevated values for Places of Business, Population Metrics, Transit and Recreation, and At-Risk Properties. For Places of Business, this would include gas stations, grocery stores, liquor stores. From Population Metrics, both LandScan day and LandScan night were identified within this cluster. From within the Transit and Recreation classification, the variables bus stops and parks are present. Lastly, for At-Risk Properties, both public housing and vacant properties were identified. Cluster Two only contains elevated values for two variables, tree canopy coverage (Natural Environment) and trails (Transit and Recreation). This cluster does not contain values for both commercial burglary and street robbery incidents. Thus, Cluster One identifies variables that generally cluster with criminal activity, while Cluster Two identifies variables that cluster in areas absent criminal activity. While the Multivariate Clustering tool is useful for identifying how factors cluster together spatially, it has less utility in identifying which of those factors are most influential in explaining certain phenomena. To identify what specific factors might be influential in explaining the occurrence of street robbery and commercial burglary incidents within the identified spatial unit of analysis, attention is turned to the results of the Random Forest Classification and Regression tool.

**Random Forest Classification and Regression Tool Results**

The Random Forest Classification and Regression tool within ArcGIS Pro uses an adaption of the random forest algorithm to create a predictive model using regression techniques. This tool provides several outputs that can be used to assess
model fit as well as the overall importance of each included independent variable. As noted above, the Random Forest Classification and Regression tool provides a ranked list of variables that order variables based on their overall contribution to the model building process. The results of these analyses are highlighted below.

Table 15: Model Fit of Training Datasets (r2)

<table>
<thead>
<tr>
<th></th>
<th>Full</th>
<th>Seasonal</th>
<th>Day of Week</th>
<th>Time of Day</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CB</td>
<td>SR</td>
<td>CB</td>
<td>SR</td>
<td>CB</td>
</tr>
<tr>
<td>Atlanta</td>
<td>0.910</td>
<td>0.926</td>
<td>Spring 0.910 0.913</td>
<td>Weekday 0.908 0.924</td>
<td>T1 0.913</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Summer 0.908 0.920</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Fall 0.913 0.918</td>
<td>Weekend 0.910 0.920</td>
<td>T3 0.907</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Winter 0.905 0.919</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>T5 0.932</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>T6 0.929</td>
</tr>
<tr>
<td>Fayetteville</td>
<td>0.923</td>
<td>0.918</td>
<td>Spring 0.909 0.912</td>
<td>Weekday 0.919 0.917</td>
<td>T1 0.910</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Summer 0.914 0.909</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Fall 0.915 0.913</td>
<td>Weekend 0.918 0.911</td>
<td>T3 -</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Winter 0.909 0.911</td>
<td></td>
<td></td>
</tr>
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<td></td>
<td></td>
<td></td>
<td>T5 0.909</td>
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<td></td>
<td></td>
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<td></td>
<td>T6 0.913</td>
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<tr>
<td>Rochester</td>
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<td>0.944</td>
<td>Spring 0.905 0.923</td>
<td>Weekday 0.917 0.937</td>
<td>T1 0.914</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Summer 0.914 0.930</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td>Fall 0.911 0.926</td>
<td>Weekend 0.916 0.930</td>
<td>T3 -</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Winter 0.915 0.924</td>
<td></td>
<td></td>
</tr>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>T5 0.909</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>T6 0.916</td>
</tr>
</tbody>
</table>

Table 15 above displays part of the model fit statistics for the training datasets. Specifically, this table displays the $r^2$ of each model. This model fit statistic details the percent of variation explained from the in sample obtained from bootstrapping. This can
be compared with the out of sample percent of variation explained, which is referred to as the out-of-bag (OOB) error rates, discussed below. From Table 15, every $r^2$ value is above 0.900, which means that the models can explain over 90% of the in-sample variation.

Table 16: Model Fit of Training Datasets (Out of Bag Error Rate)

<table>
<thead>
<tr>
<th></th>
<th>Full (%)</th>
<th>Seasonal (%)</th>
<th>Day of Week (%)</th>
<th>Time of Day (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CB</td>
<td>SR</td>
<td>CB</td>
<td>SR</td>
</tr>
<tr>
<td>Atlanta</td>
<td>31.705</td>
<td>42.826</td>
<td>Spring</td>
<td>16.199</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Summer</td>
<td>20.803</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Fall</td>
<td>21.392</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Winter</td>
<td>21.945</td>
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<tr>
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</tr>
<tr>
<td></td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>Fayetteville</td>
<td>42.891</td>
<td>35.703</td>
<td>Spring</td>
<td>23.242</td>
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<td></td>
<td></td>
<td></td>
<td>Summer</td>
<td>28.038</td>
</tr>
<tr>
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<td></td>
<td></td>
<td>Fall</td>
<td>28.171</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Winter</td>
<td>22.115</td>
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</tr>
<tr>
<td></td>
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</tr>
<tr>
<td>Rochester</td>
<td>35.737</td>
<td>58.146</td>
<td>Spring</td>
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<td>Summer</td>
<td>23.696</td>
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<td></td>
<td>Fall</td>
<td>14.054</td>
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<tr>
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<td></td>
<td></td>
<td>Winter</td>
<td>16.063</td>
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</tr>
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<td></td>
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</tr>
</tbody>
</table>

Table 16 above displays the out of bag error rate for the classification process. Because random forest involves bootstrapping to create many small samples, a subset of the data will be excluded from the in sample and subsequently tested for prediction
accuracy from the identified model. The OOB error rate is interpreted as the percent of correctly predicted rows from the out of bag sample that is created during the model training process. This would also be the percent of variation explained by the created model when it is tested against data not used for the training procedure. As can be expected, when examining the models for the temporal units of analysis, there is a drop in the OOB prediction rate. This is expected because many machine learning techniques, including random forest, are reliant on the amount of data that are included. Thus, reducing the amount of data available for classification will inherently reduce the predictive accuracy of the identified models. This can be seen by comparing Table 12 to Table 16. Specifically, the models experience higher drops in the OOB error rate when there is less data within the dependent variables available for the training process.

From the comparison of Tables 15 and 16, which is a comparison of the in bag and out of bag errors, it can be said that the models created by the random forest algorithm predict in-sample variation quite well; however, they struggle to predict outside of the data used for the creation of the models. While a common goal and application of the random forest algorithm is to predict outside of the input data, the current study is focused on understanding the variation that is present within the input data. To gain insight into what factors are responsible for the identified variation in the datasets, the outputs of the variable importance lists are compared. As noted within the previous chapter, the variable importance lists identify which variables are most meaningful in the explanation of the occurrences of the dependent variable. Tables 17 – 22 contain a summary of the outputs from the variable importance lists. The
independent variables from each model are rank ordered in their individual contributions to the identified models.

**Atlanta Random Forest Results – Commercial Burglary**

**Full Model**

A compilation of the results from the Random Forest Classification and Regression tool for commercial burglaries within Atlanta are compiled within Table 17. For the random forest of the full dataset, which includes all commercial burglaries in Atlanta from the years 2012 – 2018, the three most important variables identified were restaurants, LandScan day, and schools. The least influential variables for this model were public housing, trails, and vacant properties, with vacant properties being the least influential overall. Also of note, the fourth, fifth, and sixth most influential variable in the prediction of commercial burglary incidents is grocery stores, tree canopy coverage, and bus stops, in that order.
<table>
<thead>
<tr>
<th></th>
<th>Seasonal</th>
<th>Days of Week</th>
<th>Four Hour Time Blocks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full</td>
<td>Spring</td>
<td>Summer</td>
</tr>
<tr>
<td>Bus Stops</td>
<td>6</td>
<td>13</td>
<td>11</td>
</tr>
<tr>
<td>Vacant Properties</td>
<td>15</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td>Colleges</td>
<td>9</td>
<td>9</td>
<td>12</td>
</tr>
<tr>
<td>Schools</td>
<td>3*</td>
<td>2**</td>
<td>4</td>
</tr>
<tr>
<td>Police</td>
<td>10</td>
<td>8</td>
<td>10</td>
</tr>
<tr>
<td>Trails</td>
<td>14</td>
<td>14</td>
<td>14</td>
</tr>
<tr>
<td>Parks</td>
<td>12</td>
<td>12</td>
<td>13</td>
</tr>
<tr>
<td>Restaurants</td>
<td>1***</td>
<td>1***</td>
<td>1***</td>
</tr>
<tr>
<td>Public Housing</td>
<td>13</td>
<td>11</td>
<td>6</td>
</tr>
<tr>
<td>Gas Stations</td>
<td>8</td>
<td>7</td>
<td>7</td>
</tr>
<tr>
<td>Liquor Stores</td>
<td>11</td>
<td>10</td>
<td>9</td>
</tr>
<tr>
<td>Grocery Store</td>
<td>4</td>
<td>4</td>
<td>3*</td>
</tr>
<tr>
<td>Tree Canopy Coverage</td>
<td>5</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>LandScan Day</td>
<td>2**</td>
<td>3*</td>
<td>2**</td>
</tr>
<tr>
<td></td>
<td>Seasonal</td>
<td>Days of Week</td>
<td>Four Hour Time Blocks</td>
</tr>
<tr>
<td>----------------</td>
<td>----------</td>
<td>--------------</td>
<td>-----------------------</td>
</tr>
<tr>
<td></td>
<td>Full</td>
<td>Spring</td>
<td>Summer</td>
</tr>
<tr>
<td>LandScan Night</td>
<td></td>
<td>7</td>
<td>6</td>
</tr>
</tbody>
</table>

*Note: *** = 1*st in the importance list; ** = 2*nd in the importance list; * = 3*rd in the importance list*
Seasonal Models

Within the seasonal temporal units of analysis, there are some noted similarities to the Full model previously discussed, as well as some variation from that model. With reference to the Spring model, the top three most influential variables are the same as the Full model; however, there is a slightly different ordering to them. Specifically, the ordering of the Spring variables of importance is with restaurants, LandScan Day, and schools. This is contrasted with the Full model rank order of restaurants, schools, and LandScan Day. Thus, schools and LandScan day have switched positions within the Spring model. The least influential variables within the Spring model are bus stops, trails, and vacant properties. In comparison, within the Full model, bus stops were identified as the sixth most influential variable in the model. Additionally, police stations were slightly more influential in the Spring model (8th place) when compared with the Full model (10th place). Beyond these identified differences, the Full and Spring models are quite similar in their ranking of the independent variables.

Within the Summer model, the differences with the Full model are more apparent. These differences, however, mostly lie within the variables ranked within the middle of the pack, as opposed to the most and least influential variables. For example, the first two most influential variables within the Summer model mirror that of the Full model, with restaurants being ranked first and schools second. The third most influential variable, instead of being LandScan day, is grocery stores. Schools, which were within the top three in both the Full and Spring model, have fallen down to fourth place within the summer model. With schools within the United States largely having summer off, the student populations while school is in session could be driving the relationship seen
outside of the Summer months. Within the Summer months, the least influential variables are parks, trails, and vacant properties. In terms of the middle-ranked variables, the influence of public housing rose considerably within the Summer model, from 13\textsuperscript{th} (Full model) and 11\textsuperscript{th} (Spring model) to 6\textsuperscript{th}. Additionally, colleges are less influential in the Summer months, when compared with the Full model and the other seasons.

For the Fall model, there is again some slight variation when compared to the other seasons, as well as the Full model. The three most influential variables within the Fall model are LandScan day, grocery stores, and schools. Restaurants, which were identified as the most influential variable of the three previously discussed models—Full, Spring, and Summer—have decreased to fourth place within the Fall model. The least influential variables in this model are bus stops, trails, and vacant properties. Overall, the least influential variables for the Fall model are quite like Spring and Summer. One variable that rose within the variable importance list within the Fall model is that of parks. Specifically, parks were identified as either 12\textsuperscript{th} or 13\textsuperscript{th} place in previously discussed models but was identified as 9\textsuperscript{th} place for the Fall model.

For the Winter model, there is once again consistency when comparing the top three most influential variables. Specifically, the Winter model identified restaurants, LandScan day, and schools as the most influential variables. The least influential variables within this model are public housing, trails, and vacant housing. Both ordered sets mirror the findings of the Full model. Grocery stores, just like within the Full and Spring models, was ranked as the fourth most influential variable for the Winter months. Bus stops, which were ranked as either 11\textsuperscript{th} or 13\textsuperscript{th} place in the three other seasons,
was identified as the 6th most influential variable. This finding, much like the rank order for the most and least influential variables, mirrors that of the Full model.

**Weekday and Weekend Models**

With reference to the models comparing weekdays to weekends, the overall results are similar to those previously discussed with the Full and seasonal models. To elaborate, in the Weekday model, the three most influential variables is restaurants, LandScan day, and grocery stores. The three least influential variables are parks, trails, and vacant properties. This ranked order for both the most and least influential variables mirrors that of the findings from the Summer model. Schools are ranked as the fourth most influential variable within the Weekday model, which represents a drop in ordering when compared to the fill model which ranked schools as the 3rd most influential variable. Within the Weekday model, bus stops were ranked as the 7th most influential variable.

For the Weekend model, there is again consistency with the top three influential variables. Of note, the rank order for the top three influential variables is LandScan day, grocery stores, and restaurants. This differs from the Weekday model in that both grocery stores and LandScan day were elevated one position in the Weekend model, and restaurants fell from 1st to 3rd overall. The least influential variables within the Weekend model are bus stops, trails, and vacant properties. This represents a fairly large change in the influence of bus stops from weekday to weekend. In the Weekday model, bus stops were ranked 7th overall and they dropped quite significantly to 13th place within the Weekend model. Colleges rose in their influence between the Weekday and Weekend models, from 11th to 7th place. Additionally, parks were more influential on
weekends (9th) compared with weekdays (13th). Lastly, the LandScan night variables was more influential during the weekday (6th) compared with weekends (12th).

**Time Block Models**

When breaking the models into the four-hour block increments, there is a noteworthy amount of variation between the models. To start, for the first time block (T1), which represents the hours of 10:00pm – 1:59am, the three most influential variables are LandScan day, grocery stores, and parks. The least influential variables within T1 are LandScan night, bus stops, and vacant properties. While the first two most influential variables are like the previous models, including the Full, seasonal, and days of week models, the third most influential variable within T1, parks, was not previous identified higher than 9th place within any model. Similarly, trails are ranked 7th overall in the T1 model, while only being ranked 14th in the Full, seasonal, and day of week models. Schools, which were quite influential in previous models, are still ranked quite high at fourth place in overall influence. One very influential variable in previous models which held the most influential position in 5 previously discussed models dropped down to 8th place overall within the first time block (T1).

For the second time block (T2; 2:00am – 5:59am), the three most important variables are restaurants, grocery stores, and LandScan day. With restaurants being ranked #1 overall within this model, this represents a big difference from the model for T1 in which restaurants were ranked 8th overall. The three least important variables from the second time block (T2) are trails, public housing, and vacant properties. As noted above, trails were ranked 7th overall for the T1 model. Within the T2 model, however, trails fell in rank to 13th overall. Parks, which were ranked 3rd within T1, are now ranked
11th within T2. Schools, which were ranked 4th overall in T1 are now ranked 9th within the T2 model. Bus stops, which were ranked quite low in most previously discussed models, are now ranked 8th overall within T2. Bus stops, in particular, were only moderately influential within the Full, Winter, Weekday, and T2 models. Outside of those models, bus stops were ranked between positions 12-15.

For the model of the third time block (T3; 6:00am – 9:59pm), the three most important variables are LandScan day, restaurants, and grocery stores. This has similarities to the model for the second time block (T2), which had these same three variables within the top three. The least important variables within this time block are trails, parks, and vacant properties. When compared with the models for T1 and T2, gas stations rose quite significantly within the ranked ordering. Specifically, gas stations were ranked 12th (T1) and 10th (T2) but are now ranked 7th overall within the model for T3. A similar level of importance will continue to be seen for gas stations for the last remaining models to be discussed (T4 – T6).

The findings of the fourth time block show a developing trend in which schools are the number one variable of importance for T4 – T6. Within T4 (10:00am – 1:59pm), the second most influential variable is grocery stores, followed by LandScan day. The least influential variables for T4 are bus stops, trails, and vacant properties. This grouping of the least influential variables is similar to the findings from models T1 & T3. In comparison to T1 (6th) & T2 (5th), the model for T4 has colleges ranked much lower in terms of overall importance (12th). With all prior models, tree canopy coverage was ranked either 4th or 5th. For the T4 model, however, tree canopy coverage drops down to 8th place. This trend continues throughout T5 (10th) & T6 (8th). Another notable trend
is the increase in overall rank for public housing. Specifically, prior models have this variable ranked from 6th – 13th place. Within T4, however, public housing was found to be the fourth most important variable. This variable will hold the fourth overall place of importance for the remaining two models, T5 and T6.

As noted above, the most important variable in the model for T5 (2:00pm – 5:59pm) is that of schools. The second most important variable from this model is LandScan day, with the third most important variable being police stations. The three least important variables for this model are trails, bus stops, and vacant properties. During this time block, liquor stores are found to be the fifth most important variable, which is slightly higher than all other time blocks where liquor stores held the position of 6th, 8th, and 9th place. From the findings of the model for T5, it can also be seen that restaurants, which were ranked in the top three within eight previous models, is now ranked at 12th place overall. Within the next time block, T6, restaurants also hold the same position. Lastly, the model for T6 (6:00pm – 9:59pm) was found to have the same first and second place variables of importance as T5—schools and LandScan day. The third variable of importance was LandScan night. The three least important variables for T6 were paths, vacant properties, and bus stops. It should be noted that vacant properties were found to be the least important variable in all other models than T6, where it now holds the second to last place position.
Atlanta Random Forest Results – Street Robbery

Full Model

For the discussion of the Random Forest Classification and Regression results for street robbery in Atlanta, Table 18 will be referenced. When viewing the findings across all models, it does appear that there is a great deal of consistency between the various temporal units of analysis. For most of the models, the 1st and 2nd place variables are switching back and forth between public housing and bus stops. Likewise, the third and fourth place variables, for the most part, rotate between grocery stores and LandScan day. With specific reference to the Full model for Atlanta street robberies, the top three variables of importance are public housing, bus stops, and grocery stores. The least important variables from this model are gas stations, trails, and vacant properties. It should be noted that vacant properties, similar to the above discussion of the commercial burglary results, are the least influential variable in every single model for Atlanta street robberies. The fourth, fifth, and sixth variables of importance for the Full model are LandScan day, tree canopy coverage, and LandScan night.
### Table 18: Variable Importance Comparison Chart [Atlanta – SR]

<table>
<thead>
<tr>
<th></th>
<th>Full</th>
<th>Spring</th>
<th>Summer</th>
<th>Fall</th>
<th>Winter</th>
<th>Weekday</th>
<th>Weekend</th>
<th>T1</th>
<th>T2</th>
<th>T3</th>
<th>T4</th>
<th>T5</th>
<th>T6</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Bus Stops</strong></td>
<td>2**</td>
<td>2**</td>
<td>2**</td>
<td>1***</td>
<td>2**</td>
<td>1***</td>
<td>2**</td>
<td>2**</td>
<td>7</td>
<td>1***</td>
<td>2**</td>
<td>1***</td>
<td>2**</td>
</tr>
<tr>
<td><strong>Vacant Properties</strong></td>
<td>15</td>
<td>15</td>
<td>15</td>
<td>15</td>
<td>15</td>
<td>15</td>
<td>15</td>
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<td>15</td>
<td>15</td>
<td>15</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td><strong>Colleges</strong></td>
<td>11</td>
<td>10</td>
<td>11</td>
<td>12</td>
<td>10</td>
<td>12</td>
<td>9</td>
<td>11</td>
<td>11</td>
<td>12</td>
<td>8</td>
<td>8</td>
<td>12</td>
</tr>
<tr>
<td><strong>Schools</strong></td>
<td>9</td>
<td>8</td>
<td>9</td>
<td>8</td>
<td>9</td>
<td>10</td>
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Note: *** = 1<sup>st</sup> in the importance list; ** = 2<sup>nd</sup> in the importance list; * = 3<sup>rd</sup> in the importance list
Seasonal Models

Within the seasonal models, the model for the Spring data was quite similar to that of the Full model noted above. Specifically, the top three variables of importance for the Spring model are public housing, bus stops, and LandScan day. Grocery stores, which were ranked as 3\textsuperscript{rd} within the Full model, have dropped down to 5\textsuperscript{th} place within the Spring model. Additionally, police departments rose from 8\textsuperscript{th} place in the Full model to 4\textsuperscript{th} within the Spring model. The least important variables within this model were noted as gas stations, trails, and vacant properties. While tree canopy coverage held the 5\textsuperscript{th} place of importance in the Full model, this variable dropped down to 9\textsuperscript{th} place within the Spring model.

In terms of the model for Summer, public housing, bus stops, and grocery stores make up the top three influential variables. This ordering aligns exactly with that of the Full model. To extend this, the Full and Summer models also share the first six variables of importance. Additionally, the first two influential variables are shared with that of the Spring model. While police departments were fourth overall within the Spring model, they dropped back down to seventh place within the Summer model. Tree canopy coverage, which was ranked at 9\textsuperscript{th} place within the Spring model, was ranked at 5\textsuperscript{th} place within the Summer model. The variable for tree canopy coverage rose back up to fifth place within the Summer model, where it was previously ranked 9\textsuperscript{th} within the Spring model.

The findings from the Fall model indicate that bus stops, public housing, and grocery stores are the most influential variables, with parks, trails, and vacant properties encompassing the least influential variables. The findings of the Fall model have
remarkable similarities to that of the Full and Summer models, with one of the major differences being the ordering of the first two influential variables. The Winter model has slightly more variation when compared to the previous seasonal and Full models. Specifically, the three most important variables for the Winter model are public housing, bus stops, and LandScan day. The least influential variables for this model are restaurants, trails, and vacant properties. With reference to restaurants, this variable was previously ranked 7th and 8th within the other seasonal models. Liquor stores were more influential during the Winter months, with a ranking of 8th, compared with 10th or 11th in other seasons.

**Weekday and Weekend Models**

As noted above, there is more consistency with the street robbery models than with the commercial burglary models. This trend continues into the days of the week temporal unit of analysis which compares weekdays to weekends. For the Weekday model, the three most influential variables are bus stops, public housing, and grocery stores. The Weekend model has a similar top three with public housing, bus stops, and grocery stores. The least influential variables for the Weekday model are parks, trails, and vacant properties. For the Weekend model, the three least important variables are trails, gas stations, and vacant properties. Within the Weekday model, gas stations are ranked 11th overall in their importance. Restaurants, while holding 5th place for the Weekend model, is ranked 8th for the Weekday model. Colleges are also more influential on Weekends (9th) compared with Weekdays (12th). Comparatively, tree canopy coverage is more influential during the week (5th) as opposed to on weekends (7th).
**Time Block Models**

While there is an overall lack of variation between the temporal units of analysis, the most amount of between group variation is seen within the four-hour time block units of analysis. To start, within T1 (10:00pm – 1:59am), the three most important variables follow the same trend already identified within the Full, Summer, and Weekend models, with public housing, bus stops, and grocery stores encompassing the top three. The least important variables for T1 also mirror those of the aforementioned models, with gas stations, trails, and vacant properties being in the bottom three. Within the Full model, restaurants were ranked 7th overall, and within T1, they are ranked 5th overall.

The findings of the second time block (T2; 2:00am – 5:59am) are slightly more varied than that of T1. Specifically, the three most influential variables for T2 are public housing, LandScan day, and restaurants. Within T1, restaurants were at 5th overall place. In the subsequent models within the four-hour time block increments (T3 – T6), restaurants are placed 13th and 14th overall. The least influential variables for the T2 model are the same as the model for T1 (gas stations, trails, and vacant properties). Liquor stores, which were ranked 12th within the T1 model, are now ranked 8th within the model for T2. This ranking for liquor stores would stay quite constant across the several remaining temporal units of analysis with a place of 9th for T3 – T5 and 7th for T6. Grocery stores were also one placement lower within T2 (4th) when compared with the results from T1 (3rd). One important finding from the T2 model would be that bus stops were ranked 7th overall. In every other model, this variable was ranked either 1st or 2nd overall.
The most important variables for T3 (6:00am – 9:59am) mirror those found for the Fall and Weekday models—bus stops, public housing, and grocery stores. This ordering is also found within the model for T5, which also shares the least important variables with T3, including restaurants, trails, and vacant properties. Within T3, LandScan day was ranked the lowest out of all the models at 5th overall. The most influential variables for T4 are also the same for T6, which would include public housing, bus stops, and LandScan day. The least influential variables for T4 and T6 does, however, differ. For T4, the least influential variables are parks, restaurants, and vacant properties. Additionally, for the T4 model, tree canopy coverage was ranked the lowest (10th) when compared to the other temporal units of analysis (6th – 9th place). For T6, the least influential variables are restaurants, trails, and vacant properties. With reference to the model for T5, LandScan night is ranked at the lowest position (11th) when compared with the other temporal units of analysis where it was ranked between 4th and 7th place.

Fayetteville Random Forest Results – Commercial Burglary

Full Model

The findings for the Random Forest Classification and Regression tool for commercial burglary in Fayetteville are displayed in Table 19. As a whole, similar to the results of the random forests for street robbery in Atlanta, there is a lot of consistency in the most and least influential variables across temporal units of analysis. Of note, gas stations, bus stops, LandScan day, and police departments are frequently within the top three most influential variables across all models. Additionally, restaurants, LandScan night, and vacant properties are frequently in the bottom three least influential variables
across all models. Following this trend, the most influential variables identified for the
full model are gas stations, bus stops, and LandScan day. Following the top three
variables, in fourth, fifth, and sixth place, are the variables for police departments,
grocery stores, and public housing. The least influential variables from the full model are
LandScan night, vacant properties, and restaurants.
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Note: *** = 1<sup>st</sup> in the importance list; ** = 2<sup>nd</sup> in the importance list; * = 3<sup>rd</sup> in the importance list
Seasonal Models

Within the seasonal units of analysis, the results of the Spring model were similar to the results of the full model, with several noteworthy distinctions. Gas stations, LandScan day, and bus stops were identified as the three most important variables in the Spring model. When compared to the full model, the ranked order of bus stops and LandScan day were switched. The least influential variables within this model are tree canopy coverage, LandScan night, and vacant properties. Within the full model, tree canopy coverage was ranked 10th overall so this represents a slight drop in the overall importance of this variable within the Spring model. Restaurants, which were ranked as the least influential variable within the full model, are ranked 11th within the Spring model. When looking at the results of all four models, public housing is ranked the lowest within the Spring model (8th), while being ranked 6th in the others.

For the Summer model, the top three variables are once again shifted around in place, with bus stops being ranked 1st overall, LandScan day 2nd, and gas stations 3rd. While LandScan day remained ranked 2nd overall in both the Spring and Summer models, bus stops rose from 3rd to 1st overall and gas stations fell from 1st to 3rd. The least important variables from the Summer model are vacant properties, LandScan night, and restaurants. Within the Summer model, tree canopy coverage was ranked 7th overall. In the previously discussed Spring model, this variable was within the bottom three least important variables (13th). Looking ahead, tree canopy coverage is also ranked 13th within the Fall and Winter models as well. The influence of colleges dropped within the Summer model, when compared to the Spring model. Specifically, colleges were ranked 7th overall in the Spring model and only 10th overall in the Summer model.
For the Fall model, the three most important variables are gas stations, police departments, and LandScan day. From this finding, it can be seen that bus stops dropped out of the top three most important variables. Nonetheless, bus stops were still ranked 4th overall within this model. The three least influential variables for the Fall model are tree canopy coverage, restaurants, and vacant properties. When looking at the results of all four models, LandScan night is ranked slightly higher (12th) in the Fall than all other seasons where this variable was ranked 14th. Grocery stores were ranked 5th overall within the Fall model, which is similar to the placement of this variable in the other seasons (4th and 5th). Colleges, which were ranked 7th overall within the Spring model were ranked 8th overall in both the Fall and Winter model.

For the Winter model, the top three variables of importance are similar to those of the previously discussed model, with a slightly different ordering. Specifically, the top three variables are LandScan day, bus stops, and gas stations. The three least important variables within the Winter model are the same for the Spring model—tree canopy coverage, LandScan night, and vacant properties. From the middle rankings, it can be seen that trails are least important within the Winter model (9th), when compared to the other seasons (6th – 8th). The Spring model is when trails were most influential (6th). Police departments, which were ranked 2nd overall within the Fall model, are back down to the 5th overall ranking for the Winter model. Thus, police departments were most influential during the Fall model, and fairly stable across the other seasons (4th and 5th place). Liquor stores were ranked 9th overall for the Spring, Summer, and Fall models, but they were ranked 7th overall for the Winter model.
**Weekday and Weekend Models**

The Weekday model has the same three most important variables as several previously discussed models, however, there is a unique ordering to these variables. Specifically, bus stops are ranked 1\textsuperscript{st}, gas stations 2\textsuperscript{nd}, and LandScan day 3\textsuperscript{rd}. The variables making up the bottom three least important variables for the Weekday model are LandScan night, vacant properties, and restaurants. For the Weekend model, the three most influential variables are gas stations, bus stops, and LandScan day. Between weekdays and weekends, findings indicate that gas stations are slightly more influential on weekends than weekdays. Additionally, bus stops are less influential over weekends than during weekdays. Public housing is ranked as the 6\textsuperscript{th} overall variable in terms of importance within the Weekday model, but within the Weekend model, this variable was ranked 9\textsuperscript{th} overall. For liquor stores, this relationship is reversed, with liquor stores being ranked higher over the weekend (6\textsuperscript{th}) than weekdays (9\textsuperscript{th}). Between the Weekday and Weekend models, there is a moderate degree of similarity with the rankings of the variables. Some minor differences between the models would include colleges being ranked 8\textsuperscript{th} for the Weekday model, but 7\textsuperscript{th} for the Weekend model. Additionally, trails are ranked 7\textsuperscript{th} for the Weekday model, and 8\textsuperscript{th} for the Weekend model.

**Time Block Models**

As with previously discussed models, the temporal unit of analysis representing four-hour time blocks contained the most amount of variation between the models for commercial burglaries in Fayetteville. For the first time block (T1), the three most important variables are the same as the Spring model—gas stations, LandScan day,
and bus stops. The three least influential variables within this time block are parks, vacant properties, and restaurants. Within the T1 model, colleges are found to be ranked the lowest out of any temporal unit of analysis, including the rest of the four-hour time blocks yet to be discussed. Within the remaining time blocks, colleges are ranked 8\textsuperscript{th} (T2), 7\textsuperscript{th} (T4), 6\textsuperscript{th} (T5), and 10\textsuperscript{th} (T6). Within the models for T1 and T4, schools are ranked the highest of any other models (9\textsuperscript{th}). Grocery stores, within the T1 model, are ranked 4\textsuperscript{th} overall. This aligns with both the Summer and Winter models where this variable was also ranked 4\textsuperscript{th}. Other previously discussed models, not including T2 – T6, have grocery stores ranked 5\textsuperscript{th} overall.

In terms of the model for T2, there is a large deviation in the three most important variables from previous models. Specifically, the ranking of the top three for T2 is gas stations, grocery stores, and police stations. This would be the highest ranking for grocery stores when compared with all other models, including T4 – T6. Within T2, bus stops were ranked 4\textsuperscript{th} overall, which was also seen within the Fall model. This represents a drop in one position from the T1 model. The three least influential variables in the model were similar to that of previous models, with restaurants, vacant properties, and LandScan night. When compared to previous models, this is the lowest LandScan night has been ranked. This low ranking for LandScan night is seen once again within the model for T4. Colleges, which were ranked 11\textsuperscript{th} within T1, are ranked 8\textsuperscript{th} within T2. This increase in the importance of colleges continues with the models for T4 (7\textsuperscript{th}) and T5 (6\textsuperscript{th}). Schools were ranked lower within the T2, T5, and T6 models (12\textsuperscript{th}) when compared with T1 and T4 where schools were ranked 9\textsuperscript{th}. Within the T1 model previously discussed, parks were ranked within the bottom three least influential
variables (13th). Within the T2 model, parks are ranked 9th overall. Between T1 and T2, liquor stores fell in importance from 7th (T1) to 11th (T2). When looking at the results of all four-hour time blocks, tree canopy coverage is most influential during T1 & T2 (10th) and least influential during T4, T5 (13th), and T6 (15th). The model for T2 is also the only model in which LandScan day was ranked outside of the top three most important variables (5th).

Results for the third time block (T3) are not reported because the Random Forest Classification and Regression tool for this time block was unable to run due to a lack of unique values within the dependent variable. This issue also occurred with several other models for the four-hour time blocks in other study locations. The Random Forest Classification and Regression tool within ArcGIS Pro, by default, utilizes random seeds for each of the obtained samples when training the random forest model. This means that it could be possible to obtain results by re-running the tool, which would generate a new sample for the training of the model; however, this would not be good practice. Moreover, when viewing the temporal distribution of this crime type within Fayetteville (see Table 12 above), it can be seen that T3 contains only a total of 156 commercial burglaries. The next lowest time block (T4) contains 227 incidents, while all other time blocks contain over 450 incidents per time block. Thus, the inability of the tool to run the analysis is a representation of a highly decreased amount of activity within this time block. Implications of the missing results for all study locations will be discussed within the Discussion chapter.

Results of the model for the fourth time block (T4) show that the top three most important variables within this model are LandScan day, police stations, and liquor
stores. This high ranking for police stations was also seen within the models for T2 (3rd) and T5 (2nd). Outside of these models, for T1 and T6, police departments are ranked 5th. The model for T4 also ranks liquor stores the highest of any model (3rd). Liquor stores are also ranked high (4th) within the model for T5. The other time blocks rank liquor stores quite low, T1 (7th), T2 (11th), and T6 (9th). The least important variables within T4 are tree canopy coverage, vacant properties, and LandScan night. While there is not much deviation in terms of the least important variables for this model, there is considerably more variation present within the middle rankings for this time block. For example, grocery stores were ranked 2nd overall for T2, but were ranked 6th overall for T4. As noted above, schools are ranked higher in T1 and T4, but lower in the other models (T2, T5, and T6). Out of all four-hour time blocks, T4 contained the highest ranking for the variable representing restaurants (8th). Other time block models had this variable ranked 10th, 13th, and 15th overall.

The top three most important variables for T5 are LandScan day, police departments, and gas stations. Between T4 and T5, the positions of gas stations and liquor stores are switched, with T4 ranking gas stations 4th and T5 ranking them 3rd. Likewise T4 ranked liquor stores 3rd and T5 ranked them 4th. Within T4 and T5, bus stops are ranked quite low, 12th and 8th respectively. Colleges within T5 are ranked 6th overall, which is the highest ranking for this variable within the four-hour time block units of analysis. Within T4 and T5, public housing is ranked 5th overall. In previously discussed models, this variable was consistently ranked 6th, 8th, or 9th overall. The three least important variables within T5 are tree canopy coverage, LandScan night, and vacant properties.
Lastly, for the results of the sixth time block (T6), the three most important variables are bus stops, LandScan day, and grocery stores. The three least important variables for this model are restaurants, LandScan night, and tree canopy coverage. When compared to all other models, T6 is the only model in which vacant properties were not ranked within the bottom three. Additionally, the public housing variable is ranked the lowest (11th) within the model for T6 out of all other models. Within only the four-hour time block units of analysis, the lowest ranking for public housing is 6th overall. Of note, tree canopy coverage also received its lowest score out of all models within T6.
Table 20: Variable Importance Comparison Chart [Fayetteville – SR]

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<tr>
<td>Gas Stations</td>
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<td>14</td>
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</tbody>
</table>

*Note: *** = 1st in the importance list; ** = 2nd in the importance list; * = 3rd in the importance list*
**Fayetteville Random Forest Results – Street Robbery**

**Full Model**

The findings of the Random Forest Classification and Regression tool for street robberies in Fayetteville are displayed in Table 20. As with the previously discussed models, there is a great deal of consistency between the temporal units of analysis in terms of the most and least influential variables within the models. Once again, it can be seen that vacant properties are the least important variable across all models. Apart from vacant properties, LandScan night was also consistently rated low across all models. Additionally, the most common variables ranked within the top three are police stations, gas stations, bus stops, and LandScan day. Thus, most models have a combination of these predictors within the top three. With specific reference to the Full model for Fayetteville street robberies, the top three most important variables are bus stops, police stations, and gas stations. Following the top three most important variables, the fourth, fifth, and sixth most important variables are LandScan day, grocery stores, and liquor stores. Additionally, the lowest ranked variables from the Full model are restaurants, LandScan night, and vacant properties. Trails are ranked the highest within the Full model (7th) when compared to all other models.

**Seasonal Models**

From the seasonal temporal units of analysis, there is a moderate amount of variation with the ranking of the variables in terms of their overall importance within the models. For the Spring model, the three most important variables are police stations, gas stations, and bus stops. The Spring model is the only seasonal model in which bus stops are within the top three variables of importance. After this top three, the next three...
most important variables are LandScan day, grocery stores, and liquor stores. The least important variables for this model are LandScan night, schools, and vacant properties. When compared to the Full model (10th), the Spring model (7th) has colleges, ranked lower overall. Additionally, trails are ranked 12th overall, compared with 7th for the Full model. Within the Spring model, Parks are ranked the highest of any of the seasonal temporal units of analysis (8th).

For the Summer model, the three most influential variables are police stations, LandScan day, and gas stations. As noted, Spring is the only model that has bus stops ranked within the top three. Within the Summer model, bus stops were ranked 4th overall. LandScan day was previously ranked 4th overall within the Spring model and rose in importance within the Summer model to 2nd overall. The least influential variables for the Summer model are restaurants, schools, and vacant properties. When compared to the Spring model, the same bottom two variables are seen, however, restaurants were previously ranked 11th overall. Trails, which were ranked 12th overall for the Spring model, are ranked 8th overall within the Summer model. Tree canopy coverage is ranked the highest during the Summer model (7th) out of any of the seasonal units of analysis. Specifically, tree canopy coverage is ranked 9th (Spring and Fall) and 13th overall (Winter) in the other seasonal models.

The Fall model has a somewhat unique top three, including gas stations, police stations, and colleges. The Fall model is the only seasonal model that has police stations ranked lower than 1st overall. For colleges, this is the highest ranking out of all of the seasonal units of analysis. Other seasons have this variable ranked 7th (Spring), 10th (Winter), and 11th (Summer) overall. The least important variables for the Fall
model are public housing, LandScan night, and vacant properties. For all seasonal models, this is the lowest public housing is ranked. In other seasonal models, this variable is ranked 7th (Winter) and 10th overall (Spring and Summer). Within both the Fall and Winter models, schools are ranked higher (11th) than the two previous models, Spring and Summer (14th). Bus stops, much like the previously discussed Summer model, are ranked 4th overall within the Fall model. While trails were ranked 8th overall within the Summer model, they are now ranked 12th overall within the Fall model. Within the Fall model, liquor stores were ranked the lowest of any seasonal unit of analysis (7th).

In terms of the Winter model, the three most important variables are police stations, gas stations, and LandScan day. The bottom three variables of importance for this model are tree canopy coverage, restaurants, and vacant properties. This would be the lowest ranking identified for tree canopy coverage and restaurants across all seasonal units of analysis. Bus stops are ranked 6th overall for the Winter model, which is the lowest ranking for all seasonal units of analysis for this variable. Much like within the Summer model, trails are ranked 8th overall. Within both the Spring and Fall models, this variable was ranked 12th overall. Public housing, which was ranked 10th and 13th overall in previous seasonal models, is ranked 7th overall within the Winter model.

**Weekday and Weekend Models**

For the Weekday model, the top three variables of importance are police stations, bus stops, and LandScan day. Between the Weekday and Weekend model, it can be seen that bus stops are more influential during the weekdays (2nd), as opposed to over weekends (4th). Making up the bottom three variables in terms of their
importance for the Weekday model would be schools, LandScan night, and vacant properties. Within the Weekend model, the three most influential variables are police stations, gas stations, and LandScan day. Thus, the Weekday and Weekend models share the same 1st and 3rd overall variables, with differing variables occupying the 2nd overall position. The least influential variables from the Weekend model are LandScan night, tree canopy coverage, and vacant properties. While tree canopy coverage is ranked within the bottom three for the Weekend model, it was ranked 7th overall for the Weekday model. Colleges are more influential over the Weekends (6th) than on Weekdays (10th). Likewise, restaurants are more influential on weekends (9th) than weekdays (11th). Additionally, trails are ranked 8th overall within the Weekday model and 10th overall within the Weekend model.

**Time Block Models**

In reference to the first time block (T1), the three most important variables are gas stations, LandScan day, and bus stops. The next most influential variables are police stations (4th), grocery stores (5th), and colleges (6th). In all previously discussed models, police stations were ranked within the top three most important variables. The model for T1 is the first model in which police stations are outside of this top three. Grocery stores have been consistently ranked either 5th or 6th for all previous models.

The least important variables from the first time block (T1) are schools, restaurants, and vacant properties. When comparing the model for T1 to the Full model, there are several noteworthy differences. For example, colleges (10th vs 6th), public housing (11th vs 8th), LandScan day (4th vs 2nd), and LandScan night (14th vs 11th) are all ranked higher in the model for T1 than the Full model.
The second time block (T2) contains a unique ordering for the three most influential variables. Specifically, colleges are ranked 1st overall, followed by police stations (2nd) and gas stations (3rd). For the variable colleges, this is the highest ranking for all models. The model for T2 also has LandScan day ranked the lowest of all models (6th). Within this time block, the least influential variables are LandScan night, tree canopy coverage, and vacant properties. For all included time blocks (T1, T2, and T6), tree canopy coverage is ranked the lowest during the T2 time block (14th). Similarly, grocery stores are ranked the lowest within T2 (9th) out of all other models, not just within the four-hour time block unit of analysis. Within the model for T2, liquor stores are ranked the highest (4th) out of the other time block units of analysis (7th and 10th). Restaurants are ranked 7th overall within T2 while being ranked 14th overall for T1 and T6.

As noted above, the Random Forest Classification and Regression tool takes a sample of the data each time this tool is run. In some of the models for the current study, the initial sample did not contain enough unique values within the dependent variable for the analysis to successfully run. For the time blocks T3 – T5, this same issue occurred. Implications for the null results will be discussed within the next chapter.

Much like the model for T2, the model for T6 has a unique top three variables of importance: police stations, LandScan day, and grocery stores. This ranking is the highest position for grocery stores out of any of the previously discussed models for street robberies in Fayetteville. Additionally, out of the models for the four-hour time block units of analysis, police departments were ranked the highest within the model for T6. Also within the model for T6, parks are ranked the highest (9th) out of all other time
blocks (12th). Gas stations, which were within the top three in both T1 and T2, are ranked 6th overall within the model for T6. The bottom three variables within the T6 model are schools, restaurants, and vacant properties.

*Rochester Random Forest Results – Commercial Burglary*

**Full Model**

Table 21 displays the results of the Random Forest Classification and Regression tool for commercial burglaries within Rochester. From the overall results, it can be seen that LandScan day, grocery stores, and liquor stores frequently make up the top three variables of importance across all models. While there exists a certain degree of variability for the least influential variables across all models, bus stops were constantly ranked as one of, if not the least influential variable out of all models. For the Full model, the three most important variables are LandScan day, grocery stores, and liquor stores. After this top three, the next three variables of importance would be tree canopy coverage (4th), public housing (5th), and restaurants (6th). The least influential variables for the Full model are bus stops, vacant properties, and parks.
### Table 21: Variable Importance Comparison Chart [Rochester - CB]

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<th>Summer</th>
<th>Fall</th>
<th>Winter</th>
<th>Weekday</th>
<th>Weekend</th>
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<th>T2</th>
<th>T3</th>
<th>T4</th>
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### Table: Seasonal Days of Week Four Hour Time Blocks

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*Note: *** = 1\textsuperscript{st} in the importance list; ** = 2\textsuperscript{nd} in the importance list; * = 3\textsuperscript{rd} in the importance list*
Seasonal Models

For the Spring model, the most important variables are the same as the Full model: LandScan day, grocery stores, and liquor stores. In fact, LandScan day is the most important variable across all of the seasonal units of analysis. Grocery stores are ranked 2nd overall in three out of four models (Spring, Fall, and Winter) and ranked 3rd overall in the other (Summer). The least impactful variables within the Spring model are gas stations, schools, and bus stops. This bottom grouping is slightly different from the set of variables identified within the Full model. Specifically, only bus stops are shared between the two models within the bottom three. Gas stations, which are in the bottom three for the Spring model (13th), are ranked 12th overall in the Full model. The other variable within the Spring model bottom three, schools (14th), is ranked considerably higher within the Full model (8th). Vacant properties, which were within the bottom three in the Full model (14th), are ranked 11th overall within the Spring model. Parks, which were also within the bottom three for the Full model, are ranked 12th overall for the Spring model. When comparing the four seasonal models, tree canopy coverage is ranked the highest within the Spring model (4th), while being ranked 6th (Summer and Winter) and 10th (Fall) in other models.

For the Summer model, the same group of variables is once again within the top three, with a slight re-ordering. Specifically, LandScan day is ranked 1st overall, followed by liquor stores (2nd) and grocery stores (3rd). The least influential variables for the Summer model are trails, vacant properties, and bus stops. Within the Summer model, and when compared to the other seasonal models (9th and 11th), colleges are ranked the highest (8th). Additionally, trails are ranked the lowest in the Summer model (13th),
while being ranked quite high in other models (Spring, 5\textsuperscript{th}; Fall, 11\textsuperscript{th}; Winter, 8\textsuperscript{th}). Restaurants were ranked a bit higher within the Summer model than other seasons. Specifically, this variable was ranked 4\textsuperscript{th} overall for the Summer model and 7\textsuperscript{th} (Spring and Fall) and 9\textsuperscript{th} (Winter) in others.

The Fall model is the first set of results that has a different top three than the previously discussed models. Specifically, the Fall model has LandScan day ranked 1\textsuperscript{st}, then grocery stores (2\textsuperscript{nd}) and gas stations (3\textsuperscript{rd}). This ranking for gas stations is the highest out of all other seasonal models, where the highest ranking for this variable was 9\textsuperscript{th} overall. Thus, the impact of gas stations within the Fall model is considerably higher than other seasonal units of analysis. Additionally, public housing is also ranked the highest during the Fall model, when compared to the other seasonal units of analysis. As noted above, tree canopy coverage was ranked highest within the Spring model. The lowest ranking for this variable would be within the Fall model where it was ranked 10\textsuperscript{th} overall. Within the Fall model, schools are ranked the highest (8\textsuperscript{th}) out of all other seasonal units of analysis. Making up the bottom three variables of importance for the Fall model are parks, vacant properties, and bus stops. The bottom two variables for the Fall model are the same as the Summer model, with the 13\textsuperscript{th} position being switched between parks and trails.

The Winter model also has a unique top three with LandScan day being ranked 1\textsuperscript{st}, grocery stores 2\textsuperscript{nd}, and police stations 3\textsuperscript{rd}. For all seasonal units of analysis, this represents the highest ranking for police stations. In previous models, this variable was ranked 5\textsuperscript{th} and 6\textsuperscript{th} overall. One variable that is ranked much higher within the Winter model than other models would be vacant properties. This variable is ranked 5\textsuperscript{th} overall.
in the Winter model, while being ranked 11\textsuperscript{th} and 14\textsuperscript{th} overall in others. Another variable that is ranked highest within the Winter model would be LandScan night. This variable is ranked 7\textsuperscript{th} overall in the Winter model and 10\textsuperscript{th} and 12\textsuperscript{th} within the other seasonal units of analysis. Within the Winter model, two variables were ranked the lowest when compared to the other seasonal units of analysis—parks (14\textsuperscript{th}) and public housing (10\textsuperscript{th}). For the bottom three variables of importance within the Winter model, we have schools, parks, and bus stops.

**Weekday and Weekend Models**

Both the Weekday and Weekend models have the same top and bottom three variables of importance. For the top three variables of importance for both models, LandScan day is ranked 1\textsuperscript{st}, followed by grocery stores (2\textsuperscript{nd}), and liquor stores (3\textsuperscript{rd}). The bottom three for both models include vacant properties, parks, and bus stops. While the top and bottom three variables of importance are the same for both models, there is a small degree of variability with reference to the middle-ranked variables. For example, schools are ranked 10\textsuperscript{th} on weekdays and 12\textsuperscript{th} over weekends. Additionally, police stations are ranked 4\textsuperscript{th} overall for the Weekday model and 6\textsuperscript{th} overall for the Weekend model. Trails were ranked 12\textsuperscript{th} overall for the Weekday model and 9\textsuperscript{th} overall for the Weekday model. Both restaurants and public housing were ranked the same within both models, 7\textsuperscript{th} and 5\textsuperscript{th} overall, respectively. Lastly, gas stations were ranked higher within the Weekday model (8\textsuperscript{th}) than the Weekend model (11\textsuperscript{th}).
**Time Block Models**

From within the four-hour time block units of analysis, T1 has grocery stores ranked 1\(^{st}\) overall, LandScan day 2\(^{nd}\), and public housing 3\(^{rd}\). This would be the highest ranking for public housing across all temporal units of analysis\(^4\). Public housing was also ranked the highest out of all four-hour time block units of analysis within the model for T1 (9\(^{th}\)). Other four-hour time block units of analysis had this variable ranked 11\(^{th}\) (T5), 14\(^{th}\) (T2), and 15\(^{th}\) (T6). The time blocks T1 and T2 also had grocery stores ranked higher (1\(^{st}\)) than other previously discussed units of analysis. All previously discussed models also had LandScan day ranked 1\(^{st}\) overall, while T1, T2, and T5 have this variable ranked 2\(^{nd}\) overall. Thus, the influence of LandScan day is slightly less within these units of analysis than others. The variable vacant properties is also ranked the highest within the first time block (T1; 9\(^{th}\)) than other four-hour block units of analysis (11\(^{th}\), 14\(^{th}\), and 15\(^{th}\) overall). Restaurants are also ranked quite low within the model for T1 (10\(^{th}\)) when compared with other time blocks (3\(^{rd}\) and 9\(^{th}\)). The bottom three variables for T1 are the same as they were for the Winter model, with schools, parks, and bus stops.

The model for T2 contains the same top three variables noted within most other models, except in a differing order. Specifically, T2 has grocery stores ranked 1\(^{st}\), then LandScan day (2\(^{nd}\)) and liquor stores (3\(^{rd}\)). The least influential variables for this time block are schools, vacant properties, and parks. The model for T2 is the only model across all temporal units of analysis that has bus stops ranked outside of the bottom

\(^4\) For the models of the third (T3) and fourth (T4) time block, there was an issue with not having enough unique values within the dependent variable for analysis. Because of this, there are no results displayed within Table 21 for these models.
three variables of importance. While bus stops are consistently ranked very low within all models, they are ranked the highest within the T2 time block (12th). Within the T2 time block, public housing is also ranked the lowest (7th) when compared with the other time block units of analysis (3rd, 4th, and 6th). Gas stations were ranked the highest within the second time block (T2), with a ranking of 5th overall, compared with 7th and 10th overall in other models. Within the model for T2, trails are ranked quite high at 4th overall. In other time blocks, this variable is ranked 6th, 12th, and 13th overall.

For the fifth time block (T5), the most important variables are police stations, LandScan day, and restaurants. T5 and T6 are the only temporal units of analysis that contained restaurants within the top three variables of importance. The other four-hour block units of analysis have restaurants ranked 9th and 10th overall. Additionally, T5 is the only four-hour block unit of analysis that contained police stations within the top three variables of importance. Colleges are also ranked higher within T5 when compared with the other four-hour block units of analysis. To elaborate, colleges are ranked 5th overall in T5 and 8th (T2 and T6) and 12th (T1) otherwise. Within both T5 and T6, gas stations are ranked the lowest (10th) between the four-hour block units of analysis (5th and 7th). Liquor stores also received the lowest ranking within T5 (7th) than other time blocks (2nd, 3rd, 4th). The least important variables for T5 are LandScan night, parks, and bus stops. For LandScan night, this represents the lowest ranking across all temporal units of analysis.

The model for the sixth time block (T6) also contains a unique top three variables. Specifically, the three most influential variables ranked within the sixth time block (T6) are LandScan day, liquor stores, and restaurants. This represents the highest
ranking for liquor stores (2nd) out of all other time blocks (3rd, 4th, and 7th). Grocery stores, which were ranked 1st overall within T1 and T2, are ranked 7th overall within the model for T6. This represents the lowest ranking for grocery stores out of all time blocks. Alternatively, tree canopy coverage was ranked the highest within T6 (5th) than within the other time block units of analysis (8th and 10th). The least important variables within T6 are trails, bus stops, and vacant properties. From this bottom three, it can be seen that trails are ranked the lowest within T6 (13th), while being ranked quite high in others, such as T1 (6th) and T2 (4th).
<table>
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<th>Four Hour Time Blocks</th>
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<td>4</td>
</tr>
<tr>
<td>Tree Canopy Coverage</td>
<td>14</td>
<td>14</td>
<td>14</td>
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<tr>
<td>LandScan Day</td>
<td>5</td>
<td>7</td>
<td>5</td>
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<td></td>
<td>Seasonal</td>
<td>Days of Week</td>
<td>Four Hour Time Blocks</td>
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<td></td>
<td>Full</td>
<td>Spring</td>
<td>Summer</td>
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<tr>
<td>LandScan Night</td>
<td>2**</td>
<td>1***</td>
<td>1***</td>
</tr>
</tbody>
</table>

Note: *** = 1<sup>st</sup> in the importance list; ** = 2<sup>nd</sup> in the importance list; * = 3<sup>rd</sup> in the importance list
Rochester Random Forest Results – Street Robbery

Full Model

Table 22 displays the results of the Random Forest Classification and Regression tool for street robberies in Rochester. Overall, the results from this set of analyses vary considerably from the previously discussed models. Most notably, vacant properties, which were constantly ranked as the least important variable in previous models, is ranked within the top three in eleven out of thirteen models. Additionally, LandScan night, which was frequently ranked within the bottom three of the previously discussed models, is also frequently within the top three for street robberies in Rochester. Another noteworthy pattern across all units of analysis would be that tree canopy coverage and bus stops are ranked the same in every single model. More specifically, tree canopy coverage is ranked 14th overall in all models, which means this variable is second to last in terms of importance. Bus stops are ranked 15th overall, which means this variable is the least important variable for every single model for street robberies in Rochester. Because of this noted congruency across all models, only the third from last (13th overall) variable will be reported for each of the models. For the Full model, the top three variables of importance are vacant properties, LandScan night, and police. After this top three would be grocery stores (4th), LandScan day (5th), and schools (6th). As noted, the bottom two variables for all models are tree canopy coverage and bus stops. The 13th overall variable within the Full model, then, would be gas stations.
Seasonal Models

Within the Spring model, the top three variables of influence are LandScan night, vacant properties, and grocery stores. When compared with the Full model, the variables LandScan night and vacant properties have swapped first and second place rankings for the Spring model. LandScan day was found to be less influential (7th) within the Spring model than the Full model. Two other variables, colleges and parks, followed this same trend of being less influential in the Spring model than the Full model. Specifically, colleges are ranked 9th within the Full model and 11th within the Spring model. Likewise, parks are ranked 10th within the Full model and 12th in the Spring model. This represents the lowest ranking that the variables parks would receive within all of the seasonal units of analysis. Restaurants were also ranked the lowest within the Spring and Fall models (8th overall), when compared with the Summer (6th) and Winter (7th) models. Schools, which were ranked 6th overall in the Full model, are ranked 4th overall within the Spring model. For the Spring model, police stations are ranked the lowest (5th) of any seasonal model (3rd and 4th). Taking up the 13th overall ranking for the Spring model would be the variable for gas stations.

The top three variables of importance for the Summer model include LandScan night, vacant properties, and police departments. The noted variables encompassing the top two for this model mirror that of the Spring model. Police departments are also ranked the highest within the Summer and Fall models (3rd overall). In the other two models, this variable was ranked 4th (Winter) and 5th (Spring) overall. Restaurants were ranked 6th overall for the Summer model, which is the highest ranking for this variable across the seasonal units of analysis. Two other variables that are ranked highest within
the Summer model would be that of liquor stores (8th) and LandScan day (5th). The least important variables in the Summer model are colleges, tree canopy coverage, and bus stops.

For the Fall model, LandScan night is ranked 1st overall, followed by vacant properties (2nd) and police stations (3rd). This top three is the same as the previously reported results for the Summer model. For the Fall model, colleges are ranked 7th overall, which, when compared to the other seasonal units of analysis, is the highest ranking for this variable. Schools, which were ranked 9th overall within the Summer model, are ranked 5th overall within the Fall model. While liquor stores and restaurants were ranked the highest in the previously discussed Summer model, within the Fall model, they are ranked the lowest out of the seasonal units of analysis. The variable ranked in the 13th overall position is gas stations. This mirrors the results of both the Spring and Full models.

For the Winter model, the most influential variables differ slightly than the other seasonal models. Specifically, vacant properties are ranked 1st overall, then LandScan night (2nd) and schools (3rd). This represents the highest ranking for both vacant properties and schools across all seasonal units of analysis. Both parks and grocery stores are ranked the lowest within the Winter model when compared to the other seasonal units of analysis. As noted, LandScan day is ranked the highest within the Winter and Summer models at 5th overall. This variable was ranked 6th (Fall) and 7th (Spring) in other models. Encompassing the bottom three variables for the Winter model would be trails, tree canopy coverage, and bus stops.
**Weekday and Weekend Models**

Between the Weekday and Weekend models, there are small differences in the top three variables of importance. For example, the Weekday model has vacant properties, LandScan night, and grocery stores as the top three, while the Weekend model has LandScan night, police stations, and vacant properties. The bottom three variables are also very similar, with tree canopy coverage (14\textsuperscript{th}) and bus stops (15\textsuperscript{th}) taking the least important rankings for both models. For the Weekday model, the 13\textsuperscript{th} overall variable in terms of importance is trails. For the Weekend model, this would be gas stations (13\textsuperscript{th}). When comparing the Weekday and Weekend models, there are a few noteworthy comparisons to be made. To start, trails are ranked higher within the Weekend model (10\textsuperscript{th}) than in the Weekday model (13\textsuperscript{th}). This holds true for liquor stores as well which are ranked 10\textsuperscript{th} in the Weekday model and 8\textsuperscript{th} overall in the Weekend model. Additionally, restaurants follow this same pattern, with this variable being ranked 8\textsuperscript{th} during the weekdays and 5\textsuperscript{th} during the weekends. Conversely, schools are ranked higher during the weekdays (6\textsuperscript{th}) than the weekends (7\textsuperscript{th}).

**Time Block Models**

For the first time block (T1), the three most important variables are LandScan night, vacant properties, and grocery stores. This is the same top three that was found within the Spring model discussed above. The bottom three variables are the same as the previously noted Summer model, with colleges, tree canopy coverage, and bus stops. When compared to the full model, colleges, parks, public housing, and LandScan day are ranked lower in the model for T1 than the Full model. Colleges, in particular, were ranked 9\textsuperscript{th} overall in the Full model, and 13\textsuperscript{th} within the first time block (T1). Parks
only dropped one placement from the Full model to T1, going from 10\textsuperscript{th} to 11\textsuperscript{th} overall. Public housing was ranked 7\textsuperscript{th} overall in the Full model, while being ranked 9\textsuperscript{th} within the first time block (T1). LandScan day, which was ranked 5\textsuperscript{th} overall in the Full model, is ranked 6\textsuperscript{th} overall in T1.

Within the T2 model, the most influential variables are police stations, LandScan night, and restaurants. For both T2 and T3, these are the only models that did not have vacant properties within the top three most important variables. Police stations being ranked 1\textsuperscript{st} overall within T2 begins a trend where this variable is also ranked 1\textsuperscript{st} overall for the next two subsequent models of T3 and T4. The 3\textsuperscript{rd} overall ranking for schools is the highest ranking for this variable across all time block units of analysis. The model for T3 also has restaurants ranked at this position, while other four-hour time blocks have this variable ranked between 5\textsuperscript{th} and 10\textsuperscript{th} overall. Liquor stores were ranked 4\textsuperscript{th} overall for T2, which would be representative of the highest ranking for this variable across the time block units of analysis, which had this variable ranked between 8\textsuperscript{th} and 12\textsuperscript{th} overall.

The least important variables within T2 are schools, tree canopy coverage, and bus stops. This 13\textsuperscript{th} overall ranking for schools represents the lowest ranking for schools across all time block units of analysis. Other models within the four-hour time block unit of analysis had this variable ranked between 3\textsuperscript{rd} and 10\textsuperscript{th} overall.

For the third time block (T3), the most influential variables are police stations, LandScan day, and restaurants. For all time block units of analysis, LandScan day is ranked in the top three in only two models, T3 and T5. Additionally, T3 is the first model in which LandScan night was not ranked within the top three most influential variables. The only other model that this occurs is within T4. Within the model for T3, vacant
properties are ranked the lowest (11th) out of any other the other models. For many of the other models, this variable was consistently ranked within the top three. Thus, this ranking of 11th overall represents a large deviation from the other models. Colleges are ranked the highest within T3 (5th) when compared to the other time block units of analysis, which have this variable ranked between 8th and 13th place overall. The lowest ranking for parks out of all time block units of analysis is also seen within the model for T3 (13th). Other time blocks had this variable ranked between 7th and 11th overall. Two variables, restaurants and public housing, also received the highest ranking within the model for T3 when compared with the other time block units of analysis. The least important variables for the third time block are parks, tree canopy coverage, and bus stops.

Within the fourth time block (T4), the three most influential variables are police stations, vacant properties, and grocery stores. This ranking for grocery stores is the highest among the time block units of analysis, which is a ranking also shared with the model for T1. Trails are ranked the lowest within the model for T4 (13th) when compared to the other time block units of analysis. This means that the least important variables for T4 are trails, tree canopy coverage, and bus stops. For both T4 and T5, liquor stores are ranked the lowest (12th) of the other time block units of analysis (4th – 9th). LandScan day was ranked 6th overall, which is a ranking that is also shared with T1 and T2. This represents the lowest ranking for LandScan day out of the time block units of analysis.

For T5, the three most influential variables in the model are vacant properties, LandScan night, and LandScan day. This would be the only model in which both
LandScan variables are identified within the top three most important variables. The least important variables within this temporal unit of analysis are gas stations, tree canopy coverage, and bus stops. Three variables—restaurants, gas stations, and liquor stores—were ranked the lowest within T5 than all of the other four-hour time block units of analysis. Restaurants were ranked 10th overall within T5 and ranked from 3rd – 9th overall in other models. Gas stations were ranked 13th overall in both T5 and T6. In other time blocks, this variable was ranked between 9th and 12th overall. Liquor stores, as noted above, were ranked the lowest within both T4 and T5.

The top three variables of importance for the sixth time block are somewhat unique when compared to all other models. Specifically, vacant properties are ranked 1st overall, followed by LandScan night (2nd) and schools (3rd). Only one other model, the Winter model, has schools ranked within the top three variables of importance. This represents the highest ranking for this variable across the other time block units of analysis. When compared with the other time block units of analysis, police stations are ranked the lowest with T6. While this ranking was still 6th overall, this variable was ranked 1st overall in three models and 4th overall in the other two. Parks were most influential within T6, with a ranking of 7th overall. In other models, this variable was ranked between 9th and 13th overall. Lastly, the least important variables within the sixth time block are gas stations, tree canopy coverage, and bus stops. This low ranking for gas stations is also shared with the model for T5.

Summary

Several techniques were used to describe the spatial and temporal distributions of the data. Overall, each study location presents a unique spatial and temporal
patterning with respect to the dependent variables under study. Of note, there was considerable variation identified for each study location across the identified temporal units of analysis. Each study location presented a unique seasonal distribution of criminal activity. Additionally, each study location had a unique temporal distribution of offenses across the four-hour time block units of analysis. From the results of the random forest, each study location contained a unique rank ordering of predictors. These predictors also varied within and between the temporal units of analysis for each study location. Lastly, a cluster analysis was performed. The results of these analyses outlined several unique clusters within each study location. The following chapter is dedicated to a discussion of these results.
CHAPTER SIX: DISCUSSION

Overview

This chapter is dedicated to a discussion of the presented results. Below, the results will be compared with prior literature as well as contextualized within the selected theoretical frameworks. Overall, this discussion will be framed around both the Theoretical Model of Crime Site Selection (Brantingham & Brantingham, 1978) and Crime Pattern Theory (Brantingham & Brantingham, 2017). The Theoretical Model of Crime Site Selection puts forth that offenders engage in a spatial filtration process when seeking a location that is suitable for offending. The identified location that is suitable for offending is called a crime site. For the current study, the spatial unit of analysis that is utilized (1000x1000ft grid cells) is representative of crime sites. Crime pattern theory, as the name implies, largely provides the theoretical understanding of the identified crime patterns. Thus, the following discussion is contextualized within crime sites and explanations of patterning are guided by crime pattern theory. The discussion below begins first with a description of the temporal distributions of the dependent variables. After this, the discussion shifts to the noted temporal patterns identified through the Random Forest Classification and Regression and Multivariate Clustering toolsets.

Theoretical, Methodological, and Practical Implications

Temporal Distributions of Dependent Variables

While the prior literature on the temporal variability of commercial burglaries is limited, several noteworthy connections can be made to the findings of the current study. These connections are related to both the seasonal variability of these offenses, as well as the variation that can be identified within specific time blocks throughout the
day. In terms of seasonality, prior research has found that criminal activity, in general, is typically least frequent during the winter months of a year (Andresen & Malleson, 2013; Haberman et al., 2018; Kim & Wo, 2021). While these studies were not examining commercial burglary separate from other crime types, the theoretical explanation levied for the noted seasonal variation is still applicable to the current study. For example, seasonal variation is expected because of the impact of weather on the routinized nature of human movement patterns (Andresen & Malleson, 2013). As the weather shifts throughout the year, this changes the routine behavior of individuals. During winter months, individuals may be less likely to leave their homes. From within a routine activities approach, this would mean that offenders, targets, and guardians may be less likely to be outside of their homes during this time period. This would represent an overall reduction in the amount of criminal opportunity present. Summer months, on the other hand, tend to have more activity. For the most part, the findings of the current study support prior research.

Specifically, in alignment with prior research that discusses the seasonality of crime (Andresen & Malleson, 2013), the current study found that commercial burglaries were less frequent during winter for both Fayetteville and Rochester (see Table 12 in Chapter 5). For Atlanta, fall was the season with the least number of offenses, followed by spring. While this finding does not align with the expectation of criminal activity being less frequent during winter, it does align with prior discussions about the local impact on the seasonality of offending (Haberman et al., 2018; Kim & Wo, 2021). To elaborate, these scholars made note that while there are commonalities to be expected for the seasonality of offending, there is still a local context that must be considered. For
example, some study locations may have a decreased influence of seasonality because the weather does not reach extremes that ultimately change the routine movement patterns of individuals within these locations. Additionally, some locations, like Miami, Florida, may experience an uptick in the number of individuals present during winter. Likewise, as noted, some places may experience a reduction in the number of individuals living in a particular area during winter. Thus, a contextual dependency can be noted for the seasonality of crime (Haberman et al., 2018; Kim & Wo, 2021). This is one explanation for why the study locations in the current study had differing seasonal distributions for commercial burglary.

Apart from the seasonality of crime, there has also been discussions of the temporal variability relating to the time of day for the crime of commercial burglary (Jenion, 2003; Rothstein, 2020; Yu & Maxfield, 2014; Walsh, 2019). Several studies have found that commercial burglaries tend to cluster within the 10:00pm – 2:00am time block within a given day (Jenion, 2003; Yu & Maxfield, 2014; Walsh, 2019). Alternatively, another study has found that both repeat and non-repeat commercial burglaries cluster around 4am (Rothstein, 2020). From the results of the current study, commercial burglaries were found to cluster in different time blocks for each study location. For Atlanta, the time block with the most offenses was T3 (6:00am – 9:59am). The sixth time block (T6; 6:00pm – 9:59pm) contained the greatest number of commercial burglaries for Fayetteville. Lastly, for Rochester, the second time block (T2; 2:00am – 5:59am) had the greatest number of commercial burglaries compared to other time blocks. While the results of the current study do not align with previous literature that found commercial burglaries to cluster within the 10:00pm – 2:00am time block
(Jenion, 2003; Yu & Maxfield, 2014; Walsh, 2019), the findings from Rochester do align with the study by Rothstein (2020) in which commercial burglaries were found to cluster around 4am.

While prior literature has made note of a contextual dependency for the seasonality of crime, it is equally important to consider this for other types of temporal units of analysis, such as with time of day and the aforementioned time blocks. Much like there is variation of human movement patterns by season, there is also variation throughout a given day. Moreover, this variation throughout a given day is also likely to have a local contextual dependency. This local contextual dependency is related to the overall environment that exists within a study location. Even though study locations may share many common types of structures, how these structures are operated may vary greatly between study locations. For example, some cities may have local ordinance that regulates when alcohol may be served, which would impact when certain establishments may be open for business. Through the lens of the crime pattern theory, the routinized movement patterns of humans are what is responsible for the crime patterns that we observe (Brantingham & Brantingham, 1981; Brantingham & Brantingham, 2017). Thus, if the environments of these study locations are different enough, then one might expect the routine activities of individuals operating within these locations to differ as well. This means we can expect the temporal variation of human movement that is occurring throughout a day to vary depending on the location under study. This is one explanation why commercial burglaries are concentrating in differing time blocks across each of the study locations for the current study.
In terms of street robbery, there is more prior literature dedicated to examining the temporal distribution of this offense than that of commercial burglary (see Andresen & Malleson, 2013; Caplan et al., 2020; Haberman et al., 2018; Kim & Wo, 2021; Nelson et al., 2001; Wright & Decker, 1997). Much like with commercial burglary, there is a discussion relating to the seasonality of street robberies (Andresen & Malleson, 2013; Haberman et al., 2018; Kim & Wo, 2021), as well as the time of day (Andresen & Malleson, 2013; Caplan et al., 2020; Haberman et al., 2018; Kim & Wo, 2021; Nelson et al., 2001; Wright & Decker, 1997). For the seasonality of street robbery, prior literature makes note that offenses are least common during the winter months and most frequent during the summer months (Andresen & Malleson, 2013; Haberman et al., 2018; Kim & Wo, 2021). For two of the three study locations in the current study, this holds true. Specifically, Atlanta and Rochester both have a reduction in offenses during winter, but a heightened level of activity during summer. For Fayetteville, the spring months contain the lowest level of street robberies, followed by winter. The season with the most frequency of offenses for Fayetteville is summer. As noted above, scholars have discussed a contextual dependency related to the seasonality of offending, in which the impact of seasons will vary from location to location. Thus, while there might be commonalities of seasonal variation, the local context will determine just how varied this relationship might be (Haberman et al., 2018; Kim & Wo, 2021).

For the temporal distributions relating to the time of day, the results of the current study align with several previous studies. Specifically, the current study found that street robbery incidents tend to cluster during the nighttime. Moreover, for most study locations, there is a trend of street robberies peaking during T1, then reducing in
frequency throughout subsequent time blocks. This trend is seen within all three study locations for the current study. Prior qualitative literature made note that offenders prefer to commit this offense at night (Wright & Decker, 1997). Additionally, several quantitative studies have found this similar pattern with street robberies clustering at night (Andresen & Malleson, 2013; Caplan et al., 2020; Kim & Wo, 2021; Nelson et al., 2001). The current study diverges from prior research when comparing the clustering of offenses within specific time blocks throughout the day. Several studies have found that street robbery incidents cluster within the 2:00am – 4:00am time block (Nelson et al., 2001; Wright & Decker, 1997). The current study found that each study location had the highest concentration of street robberies within the T1 time block, which represents the time period 10:00pm – 1:59am. Only Atlanta has a second peak of street robberies that are within the subsequent time period, T2 (2:00am – 5:59am), which is when prior literature found most street robberies to cluster within (Nelson et al., 2001; Wright & Decker, 1997). Apart from these studies, Caplan and colleagues (2020) found that the 10:00pm to 12:00am time period contains the highest number of statistically significant risk factors. The results of the current study align with this previous study in that all study locations had a concentration of offenses within this time period.

It is also important to note that Atlanta has a tertiary peak of offending within the T4 time block, which represents the 10:00am – 1:59pm time period. While it might seem odd to have a concentration of street robberies during the daytime, Wright and Decker (1997), with their qualitative study of street robbers, made note that some offenders within their sample did actually prefer to commit their offenses during the day, as opposed to at night. One possible explanation for this trend could be that individuals
who are traveling through the city during lunchtime may be the target of street robberies. Alternatively, because this occurs during normal school hours, it is entirely possible that the individuals committing these offenses could be school-aged youth who are skipping school. No matter the explanation, this trend is representative of the contextual dependency noted above. Because of the unique local context of each study location, it can be expected that unique temporal trends might exist between these areas.

While the above results detail general temporal trends within and between the study locations, there is some discussion to be had for the implications relating to crime sites. To elaborate, because there is a noted element of temporal variability relating to general crime trends, it would be a fair assumption to make that there will be variation in the spatial predictors identified within each study location. Additionally, because of the noted temporal variability in the clustering of street robberies and commercial burglaries, we can also expect the predictors to vary between study locations. To examine this variability of spatial predictors within crime sites, attention is now turned to a synthesis of the results of the Multivariate Clustering tool and the Random Forest Classification and Regression tool.

**Discussion of Results Across Study Locations**

As noted, the independent variables used for the current study are grouped into several classifications. Table 14 in Chapter 4 displays these classifications. To start, a comparison of the top and bottom three variables by crime type for each study location will be made. Within this discussion, the results of the cluster analyses will be compared
to the overall results of the random forests. Following this, a discussion of the temporal variation identified within the results of the current study will be presented.

In terms of the overall discussion of the findings from the three study locations, there are some commonalities, and some noted differences that can be identified between the studied crime types. Specifically, for commercial burglary, the variable for LandScan day, which is classified as a population metric for the current study, was frequently within the top three for all study locations, across all temporal units of analysis. This variable represents the ambient daytime population across a study location. Crime pattern theory would dictate that identified crime patterns are largely the result of aggregate human movement patterns (Brantingham & Brantingham, 2017). For the crime of commercial burglary, the noted importance of this LandScan day variable can be interpreted in a few ways. First, the ambient daytime population could be a metric for the number of potential offenders in a given location. Secondly, a higher ambient population could make it easier for an offender to move throughout an area undetected if they are able to blend into a crowd. Through the lens of crime pattern theory, a higher ambient population would also make it more difficult for individuals within a location to identify who belongs and who does not belong to this area (Andresen, 2014; Brantingham & Brantingham, 2017). This can make it difficult for individuals to take action to prevent criminal activity within the area (Brantingham & Brantingham, 2017). Thus, for explaining the criminal event of a commercial burglary, the variable LandScan day appears to be quite influential.

While the other overall top three variables for commercial burglary differ, there are similarities in terms of the classification of these variables. For example, from the
Atlanta results, restaurants were frequently ranked within the top three variables of importance. For Fayetteville, gas stations were commonly ranked within the top three variables of importance. Lastly, for Rochester, both grocery stores and liquor stores were commonly ranked within the top three variables. From these findings, the classification for places of business takes up four of the possible nine top three variable positions across the three study locations. In terms of the theoretical relevance of this classification, prior literature demonstrates that many places of business, such as restaurants and food stores, are predictors for the occurrence of commercial burglaries (Brantingham & Brantingham, 1995; Clarke & Webb, 1999; Hakim & Shachmurove, 1996; Yu & Maxfield, 2014). For these places of business, it is entirely possible that the identified relationship is due to the fact that these facilities could be the target of commercial burglaries.

The overall top three variables for commercial burglary that were identified across all three study locations align quite well with the identified clusters for each area. Specifically, as noted, the overall top three variables for commercial burglary include variables from the classifications Places of Business, Population Metrics, and Transit and Recreation. From the results of the cluster analysis in Atlanta, Cluster One contained high values of both commercial burglaries and street robberies. Additionally, this cluster identified similar variables to what was identified within the overall top three discussed above. Of note, Cluster One contained LandScan day, bus stops, restaurants, gas stations, and liquor stores. Cluster Five from the Fayetteville dataset is similar in this regard. This cluster contained high levels of commercial burglaries and street robberies, while also having elevated values for LandScan day and bus stops.
Lastly, Cluster One from the Rochester data, also contains high levels of criminal activity, as well as the aforementioned Place of Business, Population Metrics, and Transit and Recreation variables already noted. The results of this cluster analysis give us more insight into the relationship between these independent variables and the outcomes of interest. Specifically, the results of the random forest provide us with an understanding of which variables are most influential in explaining the crime types selected for the current study. The subsequent cluster analysis gives us an idea of how these variables might cluster together spatially. Within the context of the current study, because the Multivariate Clustering tool does not separate dependent and independent variables, it is possible to identify clusters that exist that do not contain concentrations of the dependent variables. This allows for the assessment of clusters that are absent criminal activity. This notion will be examined below after the discussion of the least important variables.

In terms of the least influential variables for all commercial burglary models, one commonality would be the presence of one At-Risk variables. More specifically, the vacant properties variable was frequently within the bottom three of all models for commercial burglary, across all temporal units of analysis. Theoretically speaking, vacant properties can provide an area for potential offenders to loiter, evade detection, or possibly even store tools that are necessary for the commission of specific criminal acts (Brantingham & Brantingham, 2017). Moreover, a property that is vacant is not likely to have individuals present that are willing to report suspicious activity to law enforcement. While there is a theoretical basis for the inclusion of vacant properties within the current study, the results do not support the notion that vacant properties are
important for the prediction of commercial burglary incidents. It is important to note that
the operationalization of this variable may have had an impact on these results.
Specifically, for all random forest models, this variable was operationalized as a count
variable, which is a measurement of the density of this variable per grid cell. Within the
Random Forest Classification and Regression tool, there are two possible
operationalizations for this type of variable—density and distance. The extremely low
rated levels of importance of this variable through the Random Forest Classification and
Regression tool could be indicative that there is not enough variability of this measure
across the study location. To elaborate, because of the low overall number of vacant
properties, relative to the number of grid cells for each study location, most of the grid
cells will be populated with zeros. Because of the scarcity of these variables across a
study location, it may be difficult to get an accurate measure of the impact of these
variables. Thus, operationalizing this variable as a distance measure would more than
likely improve the importance of this variable within the presented models.

Apart from At-Risk Properties, another classification that was commonly found
within the bottom three for commercial burglary would be that of Transit and Recreation.
The specific variables that are noted from the bottom three within this classification
would be parks, trails, and bus stops. These three variables account for four of nine
bottom three positions for the commercial burglary models. While bus stops are ranked
in the overall bottom three for two study locations (Atlanta and Rochester), it is
interesting to note that this variable was ranked in the top three most influential
variables for Fayetteville. Thus, the findings of the current study somewhat align with
previous research. Specifically, the results from Fayetteville align with previous research
that found bus stops and other transit locations to be a statistically significant predictor of commercial burglaries (Gallison, 2017; Yu & Maxfield, 2014). The theoretical explanation for this relationship would be that public transit nodes extend offender mobility (Gallison, 2017; Gallison & Andresen, 2017; Yu & Maxfield, 2014). Alternatively, the presence of bus stops within the overall bottom three of two study locations contradicts these results. As noted within the discussion for the temporal distribution of commercial burglaries and street robberies, there is an element of contextual dependency between study locations (Haberman et al., 2018; Kim & Wo, 2021). To elaborate on this notion, the spatial and temporal predictors of criminal activity will inherently vary by study location. Just like different study locations are impacted differentially by weather brought about by seasons (Haberman et al., 2018; Kim & Wo, 2021), the influence of a variable, such as bus stops, may vary greatly by study location. One possible reason for this could be different levels of usage for public transit by study area. Additionally, how these services are operated could vary greatly from city to city, which could influence if and how these services are utilized by offenders.

The other two variables within the Transit and Recreation classification that are noted within the overall bottom three variables of importance for commercial burglary are parks and trails. The theoretical relationship of these variables to the commission of commercial burglaries would be that offenders could use these activity nodes and pathways to loiter and scout out potential targets for their crimes. Additionally, an offender could use parks and trails alike, to make an escape or to blend into individuals using these recreational areas for legitimate purposes (Brantingham & Brantingham, 2017). From the cluster analyses, it can be seen that several of the overall bottom three
variables tend to cluster together in the absence of criminal activity. Specifically, Cluster Four from the Atlanta data, which is low on values of both crime types, has tree canopy coverage and vacant properties clustered together. Cluster Two from the Rochester data is similar in that it has low levels of criminal activity, while also being low in values for tree canopy coverage and trails. As noted above, each of these variables were found to be the least influential in the models for commercial burglary. While they were found not to be influential in the prediction of criminal events, the clustering of these factors could prove useful in the prediction of an absence of offending.

For street robbery incidents, the most common classifications that are within the top three variables of importance across all models would be At-Risk Properties, Protective Factors, and Places of Business. In terms of At-Risk Properties, both public housing and vacant properties were identified as two highly influential variables. The theoretical explanation for the inclusion of these variables for street robbery would be the same as noted above for commercial burglary. Specifically, that vacant properties provide an area for offenders to hide out, escape detection, and loiter while looking for potential targets (Brantingham & Brantingham, 2017; Connealy, 2021). Indeed, prior quantitatively based research has identified vacant properties and lots as being a statistically significant predictor of street robbery incidents (Connealy, 2021).

Apart from vacant properties and lots, there has been some discussion on the impact of public housing on street robberies (Kim & Wo, 2021; Nelson et al., 2001). Specifically, while research finds that the presence of public housing generally has a positive relationship with street robberies (Kim & Wo, 2021; Nelson et al., 2001), some scholars have made note that this impact is not constant across study locations (Kim &
To elaborate, Kim and Wo (2021) assessed the stationarity of the impact of public housing across a single study location. Findings would indicate that not all public housing developments had a positive impact on criminal activity. In fact, some public housing developments had a negative relationship with crime (Kim & Wo, 2021). These findings would point towards the notion that the influence of predictors may not necessarily be constant throughout a given geographic area (Kim & Wo, 2021). This notion would extend the discussion of the contextual dependency of these relationships. Of note, prior discussions of contextual dependency began with this notion that the seasonality of crime will vary depending on the local context (Haberman et al., 2018). Thus, it is possible this contextual dependency could occur at even smaller units of analysis than cities, possibly even between neighborhoods or block groups.

In terms of the Protective Factors classification, police stations were identified within the overall top three for two study locations, Rochester and Fayetteville. This finding is particularly interesting because of the anticipated relationships of this variable to the behavior under study, which would be that of street robbery. Specifically, prior qualitative literature that examines individual who commit street robberies has found that individuals prefer to stay away from police stations when committing their acts (Wright & Decker, 1997). Common sense would also dictate that individuals may prefer to commit a violent criminal act, such as street robbery, away from individuals who have the potential to not only stop the criminal act from occurring, but also to arrest the individual responsible for the act itself. Thus, it was not originally anticipated that this variable would end up in the higher end of the output rankings from the Random Forest Classification and Regression tool. Nonetheless, there is a valid explanation for this
finding. The identified relationship of police stations being useful for the prediction of street robbery incidents may not be indicative of offenders selecting these locations because they are near police stations, but that the stations themselves were placed in areas that already had existing crime problems. Prior research within this domain has found that criminal activity is lowest immediately surrounding police departments (Blesse & Diegmann, 2022; Jones & Pridemore, 2019); however, the frequency of criminal activity increases after a certain point (Fondevila et al., 2021). Additionally, research has found that the removal of a police station can increase criminal activity within an area, which suggests a deterrence effect was present when that station was operational (Blesse & Diegmann, 2022). Lastly, research has also made note that what police do around a police station is important for reductions or increases in local criminal activity (Cabrera-Barona et al., 2019). Thus, merely the presence of a police station or precinct is not enough to explain the occurrence or absence of criminal activity, but what enforcement activities that police are engaged in locally is equally important to consider (Cabrera-Barona et al., 2019).

For the overall top three variables relating to Places of Business for street robbery, there are grocery stores and gas stations. Gas stations were identified within the overall top three for Fayetteville, and grocery stores were identified within the overall top three for Atlanta. These general findings align with prior quantitative research which has found both of these variables to be statistically significant predictors of street robbery incidents (Caplan et al., 2020; Caplan & Kennedy, 2016; Kim, 2018). Within crime pattern theory, these variables are considered activity nodes (Brantingham & Brantingham, 1981; 2017). As noted in previous chapters, an activity node is a place
that is frequented by many individuals throughout their routine schedules (Brantingham & Brantingham, 1981; 2017). This concept would include various types of places, such as grocery stores, gas stations, restaurants, bars, etc. (Brantingham & Brantingham, 1981; 2017). Because activity nodes are frequented by many individuals, this increases the amount of criminal opportunity within these areas by increasing both the number of possible motivated offenders and suitable targets.

Relating these results to the cluster analyses, there are several similarities to describe. From the Atlanta data, Cluster Five contains high values of both commercial burglaries and street robberies. And, just like the overall top three for street robbery, contains variables from the classifications Places of Business (gas stations and grocery stores), Protective Factors (police stations), and At-Risk Properties (public housing). From the Fayetteville cluster analysis, Cluster Three best aligns with the overall top three identified from the street robbery random forests. This cluster, in particular, has mid-range values of commercial burglaries and high values for street robbery. Much like Cluster Five from Atlanta, this cluster also contains Places of Business (gas stations and grocery stores) and At-Risk Properties (public housing). Likewise, from the Rochester data, Cluster One contains high levels of both crime types and a mixture of the aforementioned classifications, including Places of Business (gas stations and grocery stores) and At-Risk Properties (public housing).

For the overall bottom three variables for street robbery across all study locations, several classifications stand out—At-Risk Properties, Places of Business, and Transit and Recreation. For the At-Risk Properties classification, the variable identified within the bottom three for two study locations, Atlanta and Fayetteville, was vacant
properties. As noted above, one possible reason for this low ranking is the selected operationalization. It is possible if they were operationalized as a distance variable, particularly for the larger study locations, Atlanta and Fayetteville, their overall impact would have been a bit higher. The finding of vacant properties within the overall bottom three for the current study contradict prior research, which found vacant properties and lots to cluster within hot spots of street robbery (Connealy, 2021).

The Place of Business variable that was identified twice within the overall bottom three for street robbery is gas stations. This variable was identified within the bottom three consistently within the models for Atlanta and Rochester. As noted above, gas stations are considered an activity within a crime pattern theory framework. As an activity node, these are places where both motivated offenders and suitable targets may intersect. As also discussed above, prior research has found gas stations to be a statistically significant predictor of street robbery incidents (Caplan et al., 2020; Caplan & Kennedy, 2016; Kim, 2018). Thus, the finding of gas stations being ranked in the bottom three for two study locations contradicts prior research.

The last classification within the overall bottom three for street robbery and for all study locations is Transit and Recreation. Specifically, the two variables trails (Atlanta) and bus stops (Rochester) were identified as low in terms of overall variable importance. The theoretical justification and impact of bus stops on criminal activity was discussed above. The ranking of bus stops within the overall bottom three contradicts these prior studies that have found a positive relationship between bus stops and street robbery (Gallison, 2017; Gallison & Andresen, 2017; Yu & Maxfield, 2014). In terms of trails, the theoretical justification for examining this variable is that trails are pathways
that individual use to travel throughout a given environment. Not only can these pathways be used to travel from one location to another, but they can also be utilized for the purposes of identifying potential targets (Brantingham & Brantingham, 1981; 2017). Additionally, prior research has found that pathways with a high number of users is likely to experience lower levels of criminal activity due to higher levels of guardianship. It is possible that this is the explanation for why street robberies are not explained by the presence of trails within the current study.

As noted, the overall bottom three variables of importance for street robbery would include vacant properties, gas stations, and trails. It should also be noted that tree canopy coverage was identified within the overall bottom three in one out of nine possible positions. Thus, in terms of the cluster analyses, there is some overlap with these results. To elaborate, Cluster Four from both Atlanta and Fayetteville and Cluster Two from Rochester are all low on values of commercial burglaries and street robberies. Additionally, both Cluster Four from Atlanta and Cluster Two from Rochester have identified tree canopy coverage as a variable that clusters with the absence of criminal activity. Cluster Four from Fayetteville and Cluster Two from Rochester share the identification of trails as a variable of interest in the absence of criminal activity. From Atlanta, Cluster Four also contains vacant properties. Overall, this demonstrates a decent amount of overlap between the least influential variables for street robbery and the identified clusters for each study area.

The noted amount of variability between study locations for the overall top and bottom three variables helps answer the first research question, which states, “how do spatiotemporal characteristics impact offender site selection for commercial burglary
and street robbery?” More specifically, the spatiotemporal characteristics, as anticipated, did vary considerably between study locations. Additionally, the synthesis of the cluster analyses to the discussion of the overall top and bottom variables of importance helped answer the second research questions, which asks, “how do environmental characteristics cluster within crime sites for commercial burglary and street robbery?” A more in-depth theoretical discussion of the impact of these variables and the associated temporal variability within the noted classifications will be presented below. This upcoming discussion will help answer the second component of the first research question which assesses the temporal variability of predictors across the identified unit of analysis.

**Temporal Variation of Predictors**

The results of the Random Forest Classification and Regression tool identified a considerable amount of variation within and between the temporal units of analysis, as well as between the study locations. Below, a discussion of the temporal variability identified within the current study is presented. This discussion is structured by the classification of the variables. Within this, noteworthy temporal relationships from the results will be highlighted.

To start, with reference to commercial burglary and Places of Business within Atlanta, several relationships can be identified. First, in terms of seasonality, restaurants in Atlanta were identified as the number one variable of importance across three of four seasons (spring, summer, and winter). Within fall, however, this variable fell to fourth place overall. Within Atlanta, there might be a difference in the overall population within this city that could impact the number of individuals attending restaurants. For example,
because Atlanta is a southern-based city within the United States, the overall population of the city may increase during the winter months. Theoretically speaking, this could impact the routine activities of individuals within this city (Cohen & Felson, 1979). Also, within Atlanta, the influence of restaurants fall slightly from weekdays (1st overall) to weekends (3rd overall). The reason for this change in importance could be related to a difference in the routine activities of individuals during the weekday vs weekend (Cohen & Felson, 1979; Brantingham & Brantingham, 2017). Specifically, these results indicate that there could be some other activity nodes that are more frequented over the weekend, which reduces the impact of restaurants during this time period. Lastly, while restaurants were ranked quite high for the T2 (1st overall; 2:00am – 5:59am) and T3 (2nd overall; 6:00am – 9:59am) models, they were ranked quite low in T1 (8th; 10:00pm – 1:59am), T5 (12th; 2:00pm – 5:59pm) and T6 (12th; 6:00pm – 9:59pm). Because this variable was ranked high for the time period 2:00am – 9:59am (T2 – T3), it is possible that this is due to these establishments being targeted for commercial burglaries. This can be inferred because most restaurants will be closed during these time periods. Additionally, the lowest rankings for this variable are during what would be considered normal operating hours for a restaurant.

There is also some element of seasonality identified for restaurants and street robbery. More specifically, restaurants were found to be ranked lowest in winter for both Atlanta and Fayetteville. Thus, the seasonal influence of restaurants varies by crime type. As noted above, restaurants were ranked lowest within the fall months within Atlanta. Because commercial burglary and street robbery are different crime types, the influence of restaurants may vary between them. Street robbery, for example, is a
violent, person-to-person based offense. Commercial burglary, on the other hand, is a property offense where the target is a place. It is possible that the influence of restaurants for street robberies is lower during winter because of potential lower levels of patronage during this season. These lower levels of patronage will reduce the opportunity for a street robbery to occur around these establishments because of the reduced number of potential offenders and targets (Cohen & Felson, 1979).

Another interesting temporal trend identified from the results of the Atlanta dataset is related to gas stations. Specifically, this variable is most influential during what would be considered the most active hours out of a day 6:00am – 9:59pm (T3 – T6). During this time period, individuals are leaving for and coming home from work. Additionally, after the hours of 5:00 or 6:00pm, individuals may have other responsibilities to take care of before retiring for the night. Thus, this finding supports the notion that crime patterns are the product of aggregate routine activities (Brantingham & Brantingham, 2017; Cohen & Felson, 1979).

Within the Fayetteville dataset, one Place of Business variable has a noteworthy temporal trend. In particular, this variable would be liquor stores. The identified trend would be that liquor stores are more important on the weekends (6th) than the weekdays (9th). While the overall difference in terms of the rank may appear quite small, the unique context of Fayetteville makes this difference seem a bit larger. To elaborate, North Carolina has very strict liquor laws, at least in comparison to the other study locations. Within North Carolina, all liquor stores are owned and operated by state government. One implication of this is that there are fewer liquor stores in Fayetteville than in Atlanta and Rochester. Additionally, these government operated liquor stores
are closed on Sundays. Within the current study, weekends consist of both Saturday and Sunday. Weekdays, on the other hand, consist of Monday – Friday. This means that the identified relationship is largely being driven by the business being conducted on Saturday.

Apart from Places of Business, several relationships can be identified within the Population Metrics classification for commercial burglary. Specifically, in Fayetteville, the variable LandScan day, which represents the daytime ambient population in an area, was found to be ranked within the top three for all four-hour time blocks, except T2 (2:00 – 5:59am). For Rochester, LandScan day was ranked within the top three for all four-hour time blocks under study. In Atlanta, LandScan day was ranked within the top three for all four-hour time blocks. The fact that a measure for daytime ambient population is influential all throughout the day, even at night, is somewhat puzzling. That being said, it is possible that would-be offenders use the daytime to scout out potential targets. This could explain why the daytime ambient population has an impact on offending throughout the day. Prior research makes note of the utility of including ambient population as a measure to explain criminal activity (Andresen, 2006, 2010, 2011; Andresen et al., 2012; Ristea et al., 2018; Schaefer, 2021). This prior research, however, primarily used the LandScan global data, which is not only at a lower resolution, but also does not differentiate between day and nighttime populations. The current study was one of the first to use the LandScan USA dataset to examine criminal activity. Thus, the current study provides insight into how both day and nighttime population might differentially impact criminal offending.
The Schools classification also presents some unique results that are worthy of discussion. In terms of the seasonal impact on commercial burglaries, in Atlanta, the influence of both schools (K-12) and colleges drops off during the summer. As noted, the routine activities of individuals are incredibly important for understanding identified crime patterns (Brantingham & Brantingham, 2017; Cohen & Felson, 1979). From these results, the routine activities of kids and college students could be influencing this identified trend. Both schools (K-12) and colleges see a drop in attendance during the summer months so this drop in student population could be responsible for the drop in overall influence of this variable during this season. It is important to note that this implies students are the individuals that are responsible for some level of commercial burglaries around schools. This notion is supported by the results from the random forests for the four-hour block increments in Atlanta. Specifically, schools were identified as the 1st overall variable of importance between T4 – T6 (10:00am – 9:59pm). This time period is when students are attending school, and it also could include times when students are staying after for sporting or other events at school.

With reference to street robberies, colleges also have some noted seasonal variation. Of note, for both Fayetteville and Rochester, colleges were ranked higher during the fall months compared to other seasons. The academic year for colleges starts every fall, thus this influx of new and returning students could help increase the opportunity for offending around these locations. Prior research makes note that street robbers target college students because of a perception that they are easier targets that often have items of value on their person (Wright & Decker, 1997). It is also possible that colleges act as a crime generator, which are places that have elevated levels of
criminal opportunity due to high volumes of individuals being present at these locations for reasons unrelated to criminal conduct (Brantingham & Brantingham, 1995). Apart from seasonality, within Atlanta, colleges were found to be more influential during the weekends than weekdays. The reason for this elevated level of importance over the weekend could be related to activities that occur on and around college campuses. For example, students may be more likely to party over the weekend for various reasons. College campuses and the surrounding areas can act as crime generators if there is an event that is drawing a large crowd of individuals, such as a sporting event or graduation (Brantingham & Brantingham, 1995, 2008).

Within the Transit and Recreation variable classification, there are a few patterns to discuss for both commercial burglary and street robbery. Of note, for commercial burglary, bus stops contained a high degree of variability within the four-hour block temporal unit of analysis. To start, in Atlanta, bus stops were found to be ranked higher in the model for T2 (8th; 2:00am – 5:59am) than other time blocks (12-15th). Additionally, in Fayetteville, bus stops were ranked very high within T1 (3rd), T2 (4th), and T6 (1st), and lower for T4 (12th) and T5 (8th). From a crime pattern perspective, variation in this manner is to be expected. Surprisingly, however, in Fayetteville, the influence of bus stops is highest outside of normal operating hours for public transit in this city (Monday through Friday: 5:30 AM - 7:00 PM; Saturday: 7:00 AM - 7:00 PM; Sunday: 8:50 AM - 7:00 PM). A similar pattern is seen for Atlanta, which, as highlighted, has bus stops ranked highest for T2 (2:00am – 5:59am). The public transit in Atlanta has a schedule that is similar to Fayetteville (Weekday: 5am to 130am; Weekend: 5am – 1230am). As noted, public transit helps facilitate offender movement throughout a given area.
Moreover, the transit node itself is not always the concern, but the area immediately surrounding it (Block & Block, 1995). This is one explanation for why public transit nodes are influential outside of normal operating hours, because the immediate surrounding area can influence behavior just as much as the node itself (Block & Block, 1995).

There is also some noted temporal variation relating to the Natural Environment variable classification. This variation, in particular, is identified across seasons for both commercial burglary and street robbery. As discussed in previous chapters, the natural environment in its relation to criminal activity is understudied. Thus, it is important to highlight the influence of this classification for the current study. Within this classification, there is one variable of interest—tree canopy coverage. This variable can influence behavior in several manners. First, tree canopy coverage can block surveillance of specific areas, whether that be mechanical or natural (Lab, 2020). This can make it easier for offenders to take targets by surprise, in the case of street robbery, or help offenders generally evade detection by making it harder for CCTV cameras to identify the subject. Common sense would also dictate that the influence of tree canopy coverage may vary by season due to the fluctuation of a canopy throughout a year. During winter, for example, tree canopy coverage may be lighter than other season, which would reduce the influence this variable might have during this season. In terms of commercial burglary, in Fayetteville, tree canopy coverage was ranked highest during the summer months, and, in Rochester, this variable was ranked highest in spring. For street robbery, the same pattern is identified, with tree canopy coverage
being ranked highest in summer for the Atlanta and Fayetteville datasets. These results align with the noted expectation of tree canopy coverage being most influential outside of seasons where canopy coverage may be least influential (fall and winter).

For both crime types, there is a considerable amount of variation relating to the Protective Factors classification. This variation was found predominantly within the four-hour time block unit of analysis. In Atlanta and for commercial burglaries, police stations were ranked 3rd overall for the T5 (2:00 – 5:59pm) time block and lower in others. Fayetteville had police ranked within the top three for T2 (2:00 – 5:59am), T4 (10:00am – 1:59pm), and T5 (2:00 – 5:59pm). In Rochester, police stations are ranked quite high overall, with a 1st overall ranking in T5 (2:00 – 5:59pm) and 4th – 6th in others. These temporal patterns are also seen for street robbery. Within Fayetteville, police stations were ranked within the top three for T1 (10:00pm – 1:59am), T2 (2:00 – 5:59am), and T6 (6:00 – 9:59pm). In Rochester, once again, police stations were ranked quite high overall throughout all four-hour time blocks. As discussed above, there are spatial patterns relating to police stations (Blesse & Diegmann, 2022; Cabrera-Barona et al., 2019; Fondevila et al., 2021; Jones & Pridemore, 2019). These spatial patterns, however, have not been assessed for temporal variability. The current study demonstrates that the influence of police stations varies throughout the day.

The last temporal pattern to be discussed comes from the At-Risk Properties classification. Specifically, for street robberies in Rochester, the variable vacant properties was ranked within the top three under every model, except for T2 (7th; 2:00 – 5:59am) and T3 (11th; 6:00 – 9:59am). This represents a significant drop off in terms of overall importance for explaining street robbery incidents. Also of note, the models T5
and T6 have this variable ranked 1st overall, while T1 and T4 have it ranked 2nd overall. Within crime pattern theory, vacant properties can provide a hideout or stash house for would-be offenders (Brantingham & Brantingham, 1995; Connealy, 2021). The time periods in which vacant properties are influential within the Rochester dataset would be between the hours of 10:00am – 1:59am. One possible explanation for this pattern is that offenders might be better able to blend into a vacant property or lot during the daytime. At night, if inside a vacant property, offenders may need light to guide themselves through the property, which can attract unwanted attention. Additionally, in Rochester, street robbery incidents are least frequent within the T3 time period (6:00 – 9:59am). This reduction in criminal activity could be responsible for the lower overall impact of this variable.

**Practical Implications**

Apart from theoretical and methodological considerations, the results of the current study also have several practical implications. To start, crime analysts could use the Random Forest Classification and Regression tool to predict locations within the relevant jurisdiction that are subject to the occurrence of heightened levels of criminal activity. While the overall goal of the current study was not to maximize the out of bag prediction rate for the models, this would need to be a priority for a crime analyst looking to use this tool. The reason for this is because out of bag prediction rate is a measure of how accurate the model is at predicting (Breiman, 2001). From the current study, only one crime type was used as the dependent variable in each of the respective models. Increasing the number of criminal incidents within the dependent variables is one method that is likely to increase the prediction rate of the models through random forest.
Machine learning techniques, in general, are reliant on being trained on a high volume of data, thus increasing the amount of data used for training increases the overall accuracy of the models produced (Breiman, 2001). This can be accomplished in three ways.

The first is to increase the number of years being included for the analysis. The second is to include other crime types in the analysis. For a crime like street robbery, one could include other types of violent offenses that also occur in a street setting, such as assault and battery. Because these offenses are all violent crimes that occur in a similar setting, it is likely that the environmental predictors of these events will be similar (Brantingham & Brantingham, 1993). Thus, the overall predictive accuracy of the model will be enhanced with the inclusion of similar crime types. Lastly, the Random Forest Classification and Regression tool can be run with a categorical dependent variable, as opposed to continuous. The continuous dependent variable can thus be transformed into a categorical variable, such as low, medium, and high crime grid cells. This will make it easier for the model to predict the dependent variable, which should increase the overall out of bag prediction rate. By maximizing this out of bag prediction rate, an analyst would be able to identify specific grid cells, or groups of grid cells, that are predicted to have elevated levels of criminal activity.

Couple this with the Multivariate Clustering tool and an analyst would be able to identify specific clusters of variables that may be influencing the identified pattern. Additionally, an analyst would be able to identify which predictors are soaking up the variability in the random forest models by comparing the variable importance lists. Lastly, by splitting the data into various temporal units of analysis, an analyst would be
able to identify how the importance of these variables might shift throughout the week, seasons, and day. This multistage process would assist analysts and decision-makers alike in being able to allocate resources to specific places and times.

From the results of the current study, there are several implications relating to resource deployment. Specifically, results from the forest-based analysis indicate public housing helps in the prediction of commercial burglary incidents. Moreover, the cluster analyses demonstrate that commercial burglary incidents tend to cluster with public housing as well. Thus, targeted patrols could be allocated to business districts that surround public housing. Additionally, schools were shown to be highly influential within the forest-based models, therefore targeted patrols could be sent to areas that have businesses clustering around schools. One other consideration for these targeted patrols would be to target these activities at specific time periods. Results from the current study indicate that schools are most predictive of commercial burglaries between the hours of 10am and 10pm. The targeted patrols, then, should be sent within this time period. This would help free up those resources for other activities outside of this time period.

In terms of street robbery, one potentially effective response would be foot patrols within areas of interest. From the results of the current study, these areas of interest could be the identified clusters from each study location that had a high value of street robbery incidents. Some of these clusters included variables such as bus stops, parks, and public housing. In support of this approach, prior research demonstrates that foot patrols within known hot spots are quite effective in reducing violent crime, such as street robbery (Groff et al., 2013; Piza & O’Hara, 2014; Ratcliffe et al., 2011). Therefore,
saturating these areas with an increase in officer presence could be effective in reducing the overall number of street robberies that occur within these areas. It would also be beneficial to target both foot and vehicle patrols around specific bus stops, which were found to not only cluster with, but also have a relatively high variable importance ranking for both crime types. One method of identifying these areas could be to aggregate nearby offenses to each individual bus stop. The bus stops with the highest concentration of offenses would then be selected for heightened levels of patrol. As noted above, there is also a temporal component to be considered. From the current study, within the Atlanta dataset, it was found that bus stops were only influential during the T1, T3, T4, T5, and T6 time blocks. The overall importance ranking of bus stops dropped off during the T2 time block. Thus, targeted patrols should be allocated only within these time periods.

From a crime analysis standpoint, the techniques used in the current study could aid in the identification of potential offenders for specific crimes. More specifically, there were two population metric variables used within the selected models, LandScan Day and LandScan Night. The LandScan Day variable is a measure of ambient population within an area. The LandScan Night variable is a measure of nighttime residential population. Depending on which of these variables is higher in terms of overall importance, this could help narrow down what population might be responsible for specific offenses. For example, if the LandScan Night variable is identified as a high ranking variable of importance with a string of commercial burglaries, this could suggest the local residential population is responsible for these offenses. This could aid local law enforcement in identifying potential suspects.
Apart from implications for the allocations of resources, there are also implications from a situational crime prevention (SCP) standpoint. SCP is a crime prevention technique that is based on the rational choice perspective in that prevention techniques should be oriented towards increasing the effort and risk, reduce the rewards and provocations, and remove excuses (Cornish & Clarke, 2003). From the results of the current study, tree canopy coverage was found to be least important during the winter months for street robberies and commercial burglaries in Fayetteville. Alternatively, in this same study location, the summer months had this variable ranked higher. Because of the expected weather patterns during these months, it can be anticipated that tree canopy coverage would be less prominent during the winter and most during the summer. These higher levels of tree canopy coverage could be blocking CCTV cameras or allowing potential offenders to hide more easily. From an SCP perspective, this would reduce the overall risk that offenders might face when committing an offense. Thus, ensuring that tree canopy coverage does not block existing CCTV cameras is one prevention method that could be implemented.

Additionally, from a crime prevention through environmental design standpoint, enhancing the natural surveillance capabilities of an area helps reduce the likelihood criminal activity will occur (Lab, 2019). Natural surveillance refers to the ability of individuals in or around a place to be able to surveil an area for possible suspicious behavior (Lab, 2019). Ensuring the tree canopy coverage does not block sight lines and does not allow pedestrians to hide would help enhance the natural surveillance of an area.
Relating specifically to commercial burglary, businesses have several potential actions within an SCP framework that can be taken to reduce this type of activity. The results of the current study note that grocery stores and liquor stores are often ranked high within the variable importance lists from the random forest models. This could be because these places themselves are targets of commercial burglaries. Within the VIVA and CRAVED frameworks discussed above, offenders typically target places or individuals that have items that they desire (Clarke & Webb, 1999; Cohen & Felson, 1979). Both of these places have desirable products, whether that be money, food, or liquor. Thus, for these establishments, shatter proof glass or burglar bars could be installed on main access points to increase the effort required to break into the establishment (Cornish & Clarke, 2003). Additionally, adequate lighting could be installed on the perimeter of the establishment to increase the risk of the offender being identified through CCTV cameras or by individuals that are nearby (Cornish & Clarke, 2003). Adequate lighting around establishments could also be used to help prevent street robberies for the same reasons. Moreover, potential targets of street robberies would be more likely to see a potential offender if there is adequate lighting in an area, which could be impacted by place managers or by the relevant public entity.

In terms of place management, there is a lot that can be done to reduce the likelihood of criminal activity in and around certain establishments. To start, a place manager is simply an individual that has a stake in a place of business or entity (Clarke & Richler-Robertson, 1998). This could be an individual that owns the establishment or that has control over the facility in some capacity, like a shift manager. From the results of the current study, several places were identified as being influential in explaining the
occurrence of both commercial burglaries and street robberies. These places would be gas stations, grocery stores, and liquor stores. Each of these places of business have similar place management techniques that could influence crime problems in and around these establishments. For example, these managers could place no loiter signage around their places of business (Eck, 2015). Moreover, after placing this signage, they should enforce these policies. They should also actively report suspicious activities, such as drug dealing and prostitution (Eck, 2015).

Apart from gas stations, grocery stores, and liquor stores, restaurants were also found to have a high variable importance score for commercial burglaries. In particular, it was found that the overall variable importance school was higher during the weekday versus the weekend. Place managers, therefore, should increase prevention measures overall to reduce the likelihood of being targeted. This could include the installation of CCTV cameras to the outside premise or add additional locking mechanisms to potential entrances. One variable from the current study that was frequently identified within the top three variables of importance for street robbery would be public housing. Prior literature has made note of how place management can influence crime in and around areas with reduced income housing (Clarke & Richler-Robertson, 1998). In particular, much like place managers of places of business, property managers can report suspicious activity to police for further investigation. They can also install CCTV cameras to increase the likelihood of offenders being identified should they commit a crime. Moreover, property managers can hire security for the premise to help stop the commission of crime within the area. Lastly, the property manager can implement strict rules for drug use and other criminal activities, which, if violated, would result in the
tenant being removed from the property. Overall, these practices would reduce the likelihood of crime problems festering into much larger issues (Clarke & Richler-Robertson, 1998).

Other places that would benefit from place management practices would be schools. While these are not traditionally discussed within the place management literature base, school administrators could have a similar role in controlling crime problems around their premises. The results of the current study indicate that schools are influential in the prediction of commercial burglary incidents within the hours of 10am and 10pm, which suggests that the school population may be responsible for these incidents. Administrators of schools should pay close attention to students who skip school and attempt to leave school grounds during the school day. Additionally, there should be extra security for school events that occur after school hours. This could help reduce the likelihood of commercial burglary incidents occurring around the school.

One final practical implication to be noted would be relating to public policy. In recent years, policy makers have been attempting to limit the building of specific types of stores that are potentially criminogenic in nature. Additionally, it is thought that some of these establishments contribute to the overall society decay that may be present within lower socio-economic areas. The main type of establishment being referenced within this public policy is that of dollar stores (Smith, 2023). This legislation aims to limit the concentration of these establishments within certain areas. Thus, if the overall goal is to reduce criminal activity, the techniques used within the current study can help identify clusters of establishments that contribute to overall crime problems within our
cities. With the clusters identified, then public policy can target and limit further concentration of these establishments.

**Future Research**

While the current study provides a timely contribution to the spatiotemporal literature, there are plenty of avenues for the extension of the discussion provided above. For example, future research could examine commercial burglary and street robbery using geographically weighted regression (GWR). This technique allows for the assessment of spatial stationarity, which is the notion that the influence of a variable is constant across a study location (Fotheringham et al., 2000; 2002). Prior research demonstrates that some predictors of criminal activity, such as public housing, may not be constant across a study area (Haberman et al., 2013). Thus, using a statistical technique that specifically examines the spatial stationarity of variables could be quite informative.

While the current study had to remove a variable that captured the slope of the study locations, the inclusion of this variable in future research could be influential in expanding the discussion of the impact of the natural environment on criminal activity. Certainly, tree canopy coverage is not the only element of the natural environment that can be studied. Adding in other variables within this domain, then, would give us a better understanding of how the natural environment compares with the noted influence of the built, physical environment (Andresen, 2014; Connealy, 2021; Eck et al., 2007; Walsh, 2019).

The results of the current study highlight the utility of using machine learning techniques to bolster our understanding of criminal activity. Within the current study, two
machine learning techniques, random forests and multivariate clustering, were explored. Prior research highlights the utility of using these techniques to explain and predict various criminal justice related outcomes (Alghamdi, 2017; Biswas & Basak, 2019; Ek et al., 2022; Green, 2021; Irandegani et al., 2019; Solomon et al., 2022; Wheeler & Steenbeek, 2021). Using an approach highlighted by Ek and colleagues (2022), the current study used the Random Forest Classification and Regression tool to identify the variables of importance for two crime types, street robbery and commercial burglary. Overall, results highlight a significant amount of variation between the study locations with relevance to the ranked ordering of the independent variables within the current study. Following this analysis, the Multivariate Clustering tool was used to assess how these independent variables clustered together spatially. Indeed, this two-step approach to evaluating the spatial and temporal variation of the associated predictors provided a lot of insight into these crime types. Future research should continue the exploration of machine learning techniques to maximize our understanding and predictive capabilities of criminal activity.

Additionally, the current study utilized a 1000x1000ft grid cell for the spatial unit of analysis. This spatial unit of analysis was selected using the overall justification provided by the Theoretical Model of Crime Site Selection (Brantingham & Brantingham, 1978). Specifically, this unit of analysis corresponds to what the Brantingham’s referred to as a crime site, which would be a small geographic area that is suitable for offending. This crime site is located within a larger area that offenders operate within and generally has attributes that make it more desirable for offending than other areas within that larger noted context (Brantingham & Brantingham, 1978). Originally, the current study
operationalized this unit of analysis as a 200x200ft grid cell. Due to limitations of the
data, primarily that of scarcity in terms of geographic dispersion, this unit of analysis
was not applicable. Thus, a larger grid cell had to be selected. The 1000x1000ft grid
cell, subsequently, was the smallest grid cell size that could be utilized for the data
gathered for the current study. Future research would benefit from continuing the
examination of crime sites at the smallest spatial units of analysis possible, such as the
200x200ft grid cell.

Apart from using various statistical and machine learning techniques and
extending the analysis of the natural environment, another possible avenue for future
research would be to assess days of the week specifically, instead of just comparing
weekday to weekend. As findings from the current study demonstrate, there is a high
degree of variability within the various included temporal units of analysis. Breaking
down the weekday and weekend datasets into specific days of the week will help
identify further variation that could be occurring at this smaller unit of analysis. It is
possible that specific days of the week may contain more incidents than others, and it is
also possible that spatial predictors could vary depending on the day of the week under
study. Moreover, prior literature discusses the concept of confluence flashpoints
(Nelson et al., 2001). This concept refers to a tendency of criminal activity to cluster
together both spatially and temporally. Specifically, a confluence flashpoint refers to a
specific time and place that is experiencing a heightened level of criminal activity
(Nelson et al., 2001). An example of a confluence flashpoint would be an entertainment
district around the time when alcohol is no longer served, which is commonly 2:00am.
Thus, an entertainment district with many bars and nightclubs will likely experience a
A large population of individuals attempting to leave these areas at the same time. This leads to a higher level of criminal opportunity present in these areas at that particular time (Nelson et al., 2001). Gaining a better understanding of confluence flashpoints will better help practitioners in their attempts to reduce criminal activity.

Another potential avenue for future research would be to examine possible interaction effects among environmental predictors. For example, the variable slope might have an interaction effect with various types of sidewalk pavement throughout a study location. Some forms of pavement could mitigate the impact of a higher degree of slope by providing more stability or more grip. An uneven cobblestone sidewalk, for example, might be harder to walk on with higher degrees of slope than a smooth concrete sidewalk. Thus, the influence of slope is not directly related to the degree of incline, but also a factor of what type of surface is used for pavement. From a crime pattern theory standpoint, offenders prefer to commit crimes in areas where they are most comfortable and most able to commit the offense without issue (Brantingham & Brantingham, 1981; 2017). An uneven cobblestone sidewalk on a street with an incline would present difficulties in not only the commission of an offense, but also when attempting to flee the scene. With this consideration, it would be expected that offenders would identify areas with an incline or decline and certain types of surfaces to be unsuitable for offending.

**Summary**

Guided by the Theoretical Model of Crime Site Selection (Brantingham & Brantingham, 1978) and Crime Pattern Theory (Brantingham & Brantingham, 2017), the current study examined the spatiotemporal characteristics of commercial burglary and
street robbery in three unique study locations—Atlanta, Georgia, Fayetteville, North Carolina, and Rochester, New York. To examine these spatiotemporal characteristics, several techniques were employed. First, to identify the spatial and temporal distributions of the crime types under study, KDE and DD were utilized. These tools highlight the spatial distributions of criminal activity in the study areas. Unique spatial patterns were present for each study location. Temporal distributions were identified by comparing the frequency of offenses across various temporal units of analysis. The two main techniques used for the current study were random forest and multivariate clustering, both of which are machine learning techniques. Findings of these analyses demonstrate considerable variation in terms of the spatial predictors for both commercial burglary and street robbery. Moreover, various temporal patterns were identified within the selected temporal units of analysis, which included seasons, weekday and weekend, and time of day. The current study contributes to a growing body of literature that uses machine learning techniques to extend our understanding of various phenomena. Lastly, the current study extends the crime and place literature by highlighting various spatiotemporal patterns within three study locations.
LIST OF REFERENCES


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