A SIMPLE RISK TERRAIN MODEL FOR BURGLARY IN COLORADO SPRINGS

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ABSTRACT

Apartment complexes, drug markets, foreclosures, bus stops, and public housing in Colorado Springs (COS), Colorado consistently created high-risk areas for residential burglaries over four years (2013-2016). The crime mapping technique called Risk Terrain Modeling (RTM) determined these five place features from an examination of 25 different features. RTM determines which place features correlate to and attract burglaries and allows for the creation of a risk terrain map showing high-risk areas at a 276ft x 267ft resolution—276ft is the average half-block length in COS. A simplified RTM for 2015 was created using the above five features and had the same predictive ability for burglaries as a composite RTM made out of the seven place features that correlated to burglaries for the same year. In 2015, COS had 0.84% of its area that was designated high risk for burglaries, and that area accounted for 10.9% of 2016 residential burglaries. The high-risk areas that predicted 2016 burglaries had a 13 times higher rate for burglaries as determined by the Prediction Accuracy Index. Also, residential burglaries cluster in COS.
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CHAPTER I

INTRODUCTION

Crime mapping, traditionally, analyzes crime by using retrospective data to predict future crime locations. These crime locations and concentrations have correlated to unique place features such as pawn shops and transit stops based on proximity to or density of features. These place features create an environmental backcloth that generates and attracts crime. Each city has their unique environmental backcloth based on the distribution and presence of particular place features along with other variables. Current environmental crime research efforts are trying to determine which place features generate and attract crime, such as burglaries, across several cities and over short temporal periods. Focusing on uncovering the distinctive place features of a city over time may lead to reliable and actionable crime analysis.

Burglary, as defined by the Federal Bureau of Investigation (FBI), is “the unlawful entry of a structure to commit a felony or theft” (FBI, 2010). The use of force to gain entry need not have occurred to classify as an offense. The FBI’s Uniform Crime Reporting (UCR) program has three sub-classifications for burglary: forcible entry, unlawful entry where no force is used, and attempted forcible entry. National arrest data from 2016 showed that 87% of burglars are male and 39.2% of burglars are among the ages of 25-39 with Whites committing 68.4% of burglaries while African Americans accounted for 29.1% (FBI, 2017). In 2016, burglaries exacted $3.6 billion in property losses and the average dollar loss per burglary offense was $2,361 (FBI, 2017).

The purpose of this research is to determine which Colorado Springs’ (COS), Colorado, place features generate and attract residential burglaries over four years (2013-
2016) to develop an accurate and simple burglary model. This research has four primary objectives. The first objective is to determine which place features consistently create a risk for burglaries. The second is to produce a straightforward Risk Terrain Model (RTM) out of place features that create the most risk for burglaries. The third is to simplify the model creation process. The last objective is to provide a baseline to assist future crime mapping research in COS and cities with similar attributes. This thesis’ results may also assist the city of COS and the Colorado Springs Police Department (CSPD) to develop strategies and approaches to mitigate and prevent future burglary crimes along with increasing the efficiency of policing operations.

**Problem Statement**

To enhance law-enforcement measures and to understand the environment’s role on residential burglaries in COS, one needs to determine which place features generate and attract residential burglaries over the years (2013-2016) to develop a simple and predictive burglary model.

**Hypothesis**

Analysis of which COS’ place-based risk factors that consistently correlate to residential burglaries over a four-year period will allow for the development of a risk map from a simplified RTM that will have a predictive ability within 10% of a risk map from a composite RTM.
CHAPTER II

LITERATURE REVIEW

Crime analysis is only a few decades old but is fundamental in criminal apprehension, crime and disorder reduction, and crime prevention and evaluation. Rachel Santos defines crime analysis as “the systematic study of crime and disorder problems …including sociodemographic, spatial, and temporal factors” (Santos, 2013). Crime mapping is integral in crime analysis and has become common over the past 20 years (Santos, 2013). Police departments are using crime mapping to aid intelligence, support criminal investigations, reduce and prevent crime, and increase performance and efficiency (Elmes et al., 2014). Crime mapping, as defined by Rachel Boba, is “the process of using a geographic information system (GIS) to conduct spatial analysis of crime problems and other police-related issues” (Boba, 2005, p. 37). The United States (U.S.) Department of Justice’s (DOJ) research and development institute, the National Institute for Justice (NIJ), defines GIS as “computer programs that capture, analyze, store, and present spatial data” (NIJ, 2009). Maps, produced by GIS, visually present spatial crime data that assists in understanding the criminal environment. GIS spatial representation also aids police decision-makers in developing new approaches and aids in the allocation of resources to combat crime, especially in the current fiscally constrained epoch. Crime mapping’s prediction ability has assisted the Los Angeles Police Department (LAPD) to preemptively allocate patrol units which have decreased violent crimes by 5.4% and homicides by 22.6% in one LAPD district (Uchida et al., 2012). Also, public released crime maps give the opportunity for collaboration and outreach.
between the community and police departments to develop crime prevention measures (Dağlar and Argun, 2016).

**History of Crime Mapping**

Crime mapping can trace its origins back to 1829 when Adriano Balbi, an Italian geographer, and Michel Guerry, a lawyer, created the first crime maps using crime statistics from 1825 to 1827 and demographic data from France (Santos, 2013). In the 1820s, the London Metropolitan Police Department was the first police department to use the push pin method to track crimes on maps (Levine, 2006). Also during this period, Belgian statistician Lambert Adolphe Quetelet used maps to link crime events to social and environmental variables such as climate, poverty, transportation routes, educational levels, and ethnic and cultural variations (Wang, 2012).

Crime mapping in the U.S. lagged behind Europe. The first substantial spatial analysis of crime in the U.S. did not occur until the 1920s and 1930s. Two urban sociologists, Clifford Shaw and Henry McKay, mapped juvenile delinquency in Chicago, Illinois (IL) in the early to mid-20th century (Shaw and McKay, 1969). They observed the distribution of juvenile crime followed the concentric zone urban-ecological model developed by Ernest Burgess in 1925 (Barnum et al., 2017). Chicago’s juvenile delinquency analysis began “with a study of its geographical location” (Shaw, 1929, p. 5) illustrating the value of mapping in crime ecology (Wang, 2012).

Most of the initial crime mapping conducted in both Europe and the U.S. examined aggregated levels of crime by area (Santos, 2013). The geographic methods remained relatively uncomplicated, and sociologists primarily focused on the sociological factors of crime (i.e., parental influence, education performance, peer influence, etc.).
This sociological focus is partially attributable to the substantial amount of time and effort required for collecting crime data and the arduous process of manually drawing maps (Weisburd and McEwen, 1997). The 1960s saw the advancement of computing processing of large computers to aid spatial analysis, but not until the early 1980s did client-server technology develop to the point that made GIS more available to law enforcement (Santos, 2013).

In 1989, the NIJ-funded Drug Market Analysis Program (DMAP) brought police departments and researchers together to determine if mapping methods could be used to assist police efforts to reduce street-level drug sales (Rich, 1995). Under DMAP, five cities developed sophisticated computerized drug information and mapping systems. This program demonstrated how law enforcement could use GIS as a “central part of crime control initiatives” (Santos, 2013, p. 11).

The significant improvements in computer technology and police data systems in the mid-1990s made electronic crime mapping a more practical tool for police and researchers (Santos, 2013). Geographic data such as street and census information became widely available in electronic format at this time too, which allowed the field of crime mapping to advance beyond manual methods and the use of large and costly mainframe mapping systems. According to Weisburd and Lum, innovative criminology research played a central part in this diffusion of computerized crime mapping owing to the openness of law-enforcement practitioners and to their interaction with the scientific community (see Figure 2.1) (Weisburd and Lum, 2005).
During this same time, under the advocation of Vice President Al Gore, the U.S. federal government provided increased support for crime mapping technology and methods (Santos, 2013). In 1996, the NIJ allocated $15 million to establish the CMRC to promote crime mapping as an analytical tool, and the center was renamed Mapping and Analysis for Public Safety (MAPS) in 2002 (Herbert, 2015). The program supports research that helps agencies use GIS to enhance public safety by using maps to analyze crime and spatial data along with promoting maps to help researchers evaluate programs and policies (NIJ MAPS, 2017). The NIJ also funded the Crime Mapping and Analysis Program (CMAP) from 1998 to 2007. The CMAP provided initial and advanced GIS, crime, and intelligence training to a significant number of crime analysts and officers at the local and state levels (Santos, 2013).

MAPS research grants funded the development of the CrimeStat program. CrimeStat is a Windows-based spatial statistics program used for analysis of crime-incident locations, and it can also interface with GIS programs (Levine, 2006). CrimeStat is a free program used by many law-enforcement agencies throughout the country.
Currently, there is no comprehensive historical study of crime mapping’s adoption by law enforcement, but it is evident that crime analysts see the utility of crime mapping in their efforts. When you overlay and imbue environmental criminology theories into crime mapping, you bring the real value of it out. The next portion of this literature review will discuss the prominent place-based crime theories.

**Environmental Crime Theories and Concepts**

Environmental criminology theories seek to explain crime patterns in regards to the environment’s influence on crimes (Wortley and Mazerolle, 2008). This branch of criminology is a departure from the focus on people as the unit of analysis (Weisburd, 2015). In 1989, leading criminologists coined the term “criminology of place” and suggested that certain geographic areas in cities are concentrations of crime (Sherman et al., 1989, p. 27).

Shaw and McKay’s (1969) research in Chicago, IL on juvenile delinquency led them to pioneer the social disorganization theory. This theory stemmed from their findings that a neighborhood’s ecological conditions influence crime rates more than characteristics of individuals, families, and community. Thus, the ecological characteristics of neighborhoods shape crime patterns and concentrations.

The rational choice theory developed by Derek Cornish and Ronald Clarke established the basis for the criminality of place. Rational choice views criminal behavior as purposive, rational, and involves decision-making similar to that of law-abiding citizens. This theory elucidates that criminal offenders use reason and cues present in the environment to guide their decisions about whether, or not, to commit particular crimes and if so, how to commit them (Cornish and Clarke, 2008). This
perspective views criminals as humans who have practical decision-making that directs their actions based on their circumstance that includes physical place.

The routine activity theory developed in 1979 by Marcus Felson and Lawrence Cohen is a micro and macro theory of how crime rates emerge (Felson, 2008). This approach states that most criminal acts require the spatial and temporal convergence of likely offenders, suitable targets, and the absence of capable guardians (Cohen and Felson, 1979). The spatial portion of the convergence is present in all three requirements for criminal acts. Clarke and Eck took routine activity a step further and made the problem analysis triangle (see Figure 2.2) that incorporated managers and handlers (Clarke and Eck, 2005). Managers have either financially or custodial responsibility of a place while handlers are individuals who have influence or control over a potential offender and their actions (Santos, 2013).

![Problem Analysis Triangle](image)

Figure 2.2. DOJ’s Problem Analysis Triangle (Clarke and Eck, 2005)
Routine activity was a noticeable shift from conventional criminology that viewed crime as a pathology that emerged from social ills. Routine activities considered crime in a situational context that emphasized place/time or spatiotemporal setting (Wilcox, 2015). This spatiotemporal setting brings us to another group of criminologist’s research that espoused the criminality of place features.

Patricia and Paul Brantingham (1995) have studied and published on the criminality of place for decades. Significant concepts of their research are crime generators, crime attractors, nodes, paths, and edges. Crime generators are particular areas which attract people for reasons unrelated to any specific criminal motivation—some examples are shopping and entertainment districts or sports stadiums. Crime generators engender crime by providing a nexus of place, time, people, and other targets conducive to criminal acts. Crime attractors are places which create criminal opportunities for motivated criminal offenders—some examples are bars, drug markets, and public transit exchanges (Brantingham and Brantingham, 1995). Nodes are routine and specific places in people's lives where people commit crimes such as their homes, work, school, and shopping centers. Paths are important in shaping routine activities because paths determine where people go and what the know about their city (Brantingham and Brantingham, 1995). This feature is important because street networks, traffic, and transit patterns influence the distribution of crimes (Brantingham and Brantingham, 1995). Edges are places where there is a distinct change from one physical feature to another. Parks, residential areas, and land use zoning all have edges. Brantingham and Brantingham note that crime rates are higher in areas around edges because edges create areas where strangers—possible crime offenders—are present and
may contain crime generators or attractors. All of these features and their arrangements form an area’s “environmental backcloth,” and its elements contribute to the choice of targets and target areas by offenders (Brantingham and Brantingham, 1995, p. 7). The next theory applies all these concepts along with the other mentioned crime approaches.

Crime pattern theory is the seminal work of Brantingham and Brantingham that integrates the notions of routine activities theory, rational choice theory, and the environmental backcloth concept (Barnum et al., 2017). The theory argues that crime is not random in space and time but clusters. Clustering is influenced by where people live, how and why they travel, and how networks of people who know each other spend their time (Brantingham and Brantingham, 2008). This theory’s aspects require a spatiotemporal framework to create crime templates, determine crime locations and concentrations, and crime attractors and generators (see Figure 2.3).

Figure 2.3. Crime Pattern Theory (Rossmo, 2000).

The clusters mentioned in crime pattern theory are known as hotspots. Criminology defines hotspots as those predictable areas where there is a high frequency
of crime or a type of crime (Sherman, 1995). The concentration of crime in a few places became evident in a prominent study in Minneapolis, Minnesota from 1986. The study analyzed 323,000 calls to the police and found that 3% of places produced 50% of calls for police dispatch. They also found that 2.2% (robberies), 1.2% (rapes), and 2.7% (auto theft) of the 115,000 city addresses accounted for 100% of the city’s predatory crimes (Sherman et al., 1989). Recurrence of crime at a location increases after a crime such as a case with robberies. A robbed house in Minneapolis had a 28% increased chance of having a second robbery and 40% chance of a third robbery after the second (Sherman, 1995). Concentrations of crime in hotspots is evident from this significant and widely cited study.

The Pareto principle, called the 80/20 rule, is an important concept of crime concentration and repeat victimization. In general, this concept comes from the observation that 80% of some outcomes are the result of only 20% of related causes (Santos, 2013). This rule in a crime context illustrates that a large number of offenders repeatedly target a small portion of people and places, small numbers of locations account for large number crime events, and a small percentage of offenders accounts for a large proportion of offenses (Clarke and Eck, 2005). This rule’s 80/20 split is often used to represent the large/small attributes of crime patterns; the actual numbers depend on the environmental backcloth and other variables of a study area (Santos, 2013).

Crime prevention guided by these crime theories and crime mapping results in a change in the crime phenomenon. Two concepts that stem from crime prevention measures are displacement and diffusion of benefits. Displacement is when crime phenomenon moves to another time, place, or takes another form. Diffusion of benefits
may occur when there is the elimination of one crime activity that drives crime reduction in other types of crime (Santos, 2013).

**Crime Mapping Techniques**

A primary form of crime mapping relies on retrospective data to identify crime hotspots and where policing resources and measures should occur (Chainey et al., 2008). Conventional hotspot mapping techniques are spatial ellipses mapping, thematic mapping of geographic areas (e.g., census areas), grid thematic mapping, dasymetric mapping, kernel density estimation (KDE) (see Figure 2.4), and the new RTM.

Spatial ellipses mapping finds the densest concentration of points on the map, hot clusters, and then fits a standard deviational ellipse to each one. The ellipses themselves indicate through their size and alignment the nature of the underlying crime clusters. The Spatial and Temporal Analysis of Crime is the spatial software that finds and examines hotspot areas within the study area and creates the ellipses. A benefit of spatial ellipses is that it derives hotspots without relying on defined boundaries such as census units or police-administrative boundaries and requires few parameters (Chainey et al., 2008).

One criticism of the ellipses method is that crime hotspots do not naturally form into convenient ellipses, so the generated hotspots do not represent the actual spatial distribution of crime and can often mislead analysts.
Figure 2.4. Common Hotspot Mapping Techniques: (a) point mapping (b) standard deviational spatial ellipses, (c) thematic mapping of administrative units, (d) grid thematic mapping, and (e) KDE (Chainey et al., 2008).

Thematic mapping of geographic areas uses the number of crimes that fall within a geographic unit area as determined by the governance administration or police usage and aggregates them to create shades. The non-crime determined geographic boundaries can beguile the concentrations of crime, so this technique can fail to reveal patterns in the study geographical-boundary areas (Chainey et al., 2008). Grid-based thematic mapping is an alternative to arbitrary boundaries. The grid-based approach has its limitations too.
The grids can skew or mask the spatial resolution of crime hotspots because the crime events have to conform to particular grid dimension (Chainey et al., 2008).

Dasymetric mapping reveals concealed information in the aggregated data of a boundary area. Dasymetric mapping shows the actual distribution of data found in rigid boundaries or grid-based areas by using a second spatial variable to increase the resolution of the map. Dasymetric crime mapping does this by incorporating land use or census data to show the most likely concentrations of some phenomenon within a given boundary. This helps to reveal clusters of crime typically masked in conventional-thematic maps (Poulsen and Kennedy, 2004).

The KDE mapping is regarded as an accurate spatial analysis technique when compared to other techniques because of its aesthetic visualization of crime map data and its perceived accuracy of hotspot identification (Chainey et al., 2008). KDE overlays a two-dimensional grid on the study area, measures the distance between the center point of each grid cell to each crime incident (Hart and Zandbergen, 2014). Then weighs that distance based on a particular method of interpolation (e.g., kernel function) to create a density surface or hotspot. The resulting output is a map of a continuous risk surface illustrating the inputted crime points flattened over the study area (Hart and Zandbergen, 2014). The crime analysts may choose the grid cell size, the search radius or bandwidth, and the interpolation method for kernel density functions (e.g., normal, quartic, or triangular). The grid cell values determine the density—the number of crime occurrences per unit area. The ability to select the parameters of the KDE largely affects the identification of hotspots and allows for variation in KDE output maps that may or may not accurately determine crime hotspots (Chainey et al., 2008). Analysis of the hotspot
mapping techniques (minus dasymetric mapping), mentioned above, from 2008 showed that KDE method performed the best at predicting where crimes may occur in the future and spatial ellipses appeared to be the worst (Chainey et al., 2008).

**Risk Terrain Model**

RTM is an innovative mapping method that uses aspects of KDE and is growing in police department usage across the country and has been utilized by CSPD (Caplan et al., 2015). RTM is an approach combining separate map layers created in GIS representing the spatial influence of features of the environment to produce a composite risk terrain map which provides an assessment of risk. The composite map points to locations where the potential for crime is high (Caplan et al., 2015).

RTM defines risk as the likelihood of an event occurring in an area, and ordinal values quantify the risk. The terrain of an RTM is the continuous raster surface of places that represent where risk exists (Kennedy et al., 2011). Modeling broadly refers to the abstract representation of real-world places.

The Rutgers Center on Public Security (RCPS) developed desktop software to build RTMs called Risk Terrain Modeling Diagnostic (RTMDx) Utility funded by NIJ. According to the developers, RTMDx Utility offers “a statistically valid way to articulate risky areas at the microlevel according to the spatial influence of landscape” (Caplan et al., 2015, p. 12). Researchers using RTM have studied burglaries in Chicago, IL, Kansas City, Missouri, Newark, New Jersey (NJ) and violent crimes in Newark, NJ (Barnum et al., 2017; Caplan et al., 2015; Caplan et al., 2011).

RTM operationalizes the spatial influence of criminogenic features. Crime pattern theory describes how place features can act as crime generators and attractors
(Barnum et al., 2017). There are three primary ways to operationalize crime generator or attractor place features: (1) presence or absence of features, (2) density of features, or (3) distance from features (Caplan, 2011). Kernel density or buffer techniques are used by RTM to analyze the operationalization of place features. A buffer is a selected area around a feature on a map used for spatial analysis in GIS (Santos, 2013). This operationalization technique allows for an increased understanding of the landscape of areas.

**Crime Mapping Considerations and Limitations**

When developing crime maps, the crime analysts should be aware of a few limitations and challenges. If the crime analyst does not consider these factors, they will find the accuracy of their results questionable. The following section will discuss data accuracy, geocoding, the range of spatial scales, and seasonal trends.

A limiting factor for all research conclusions and accuracy is the input data used for analysis. This limitation is no different for crime mapping. Crime mapping input data can be inaccurate for three main reasons. One reason is due to the reported and unreported crime activity. Some crimes such as assaults are reported more frequently or have great responsiveness from police than other types of crime (Santos, 2013). Thus, unreported crimes never get accounted for in crime analysis. The second reason is that individual police agencies classify crimes differently based on their jurisdictions (Santos, 2013). The federal government has had a national crime classification system called UCR since 1930, but participation in the system is voluntary. The third reason for possible inaccuracy in crime data is due to the entry of crime records into database
systems. Those who enter crime information carelessly into databases may result in unreliable data or repeat crime entries that skew data.

Error in crime mapping input data ultimately affects the ability to map the location of criminal offenses. This process is called geocoding in GIS and is the task of converting locations, such as the addresses of burglary victims, into map grid coordinates. Inaccurately recorded street addresses in police records makes it difficult to map the incidences precisely. If a portion of crime data is unmappable, the accuracy of crime map will be dubious. Jerry Ratcliffe found that to generate a statistically reliable map for crime analysis, 85% of crime input data must be geocoded (Ratcliffe, 2004). Although, with the proliferation of global positioning systems utilization by police departments and GIS’ upgraded geocoding abilities, geocoding issues should be more negligible (McCarthy and Ratcliffe, 2005).

The third consideration for mapping crime is the area unit of analysis. Many crime mapping methods use predetermined geographical areas—such as in the thematic mapping method or the grid cells dimensions in KDE and RTM—for analysis. The area size used for analysis will affect the clustering of crime, effect analysis conclusions, and the allocation of police resources. This aggregation-spatial issue is called the modifiable areal unit problem. Many researchers are exploring the different accuracies of analysis units. A new unit of analysis that is emerging is the street segment, and this is due to the realization that most crimes occur and police resources are deployed at the street level (Rosser et al., 2016). RTM uses street blocks or half-street blocks for its unit of analysis, so it is nested with emerging techniques.
The final consideration is the temporal aspect of crime specifically, for this review, the seasonality of crime where certain types of crimes are more pronounced at different times of the year. One study found that crimes—rape, burglary, larceny, and motor vehicle theft—peak in July or August and all fall to their low points in February. The authors of the study found that the crime variations in seasonality are not explainable by monthly temperature differences between areas (McDowall et al., 2012).

**Literature Review Summary**

A significant aspect of crime is location. Geographic features generate or attract crime and the physical features of nodes, paths, and edges shape crime patterns. Crime analysts and researchers are utilizing crime mapping to determine crime hotspots, analyze the influence of spatial features, and examine spatiotemporal aspects of crimes. The criminal understanding that stems from crime maps and analyses allows police departments to allocate their limited resources to crime prevention measures and interdiction actions efficiently. The typical crime mapping methods rely on retrospective data to predict crime, but the new RTM technique is capitalizing on environmental criminology theories to use spatial features as the predictive mapping foundation. Predictive accuracy is the key to crime mapping along with finding which environmental-place features generate and attract crime.
CHAPTER III

RESEARCH

There is little to no research that has attempted to study whether place features consistently generate or attract burglaries over several years in a specific city. Such analysis can allow for the development of a crime model that will be more accurate and constant.

Burglary Characteristics and its Execution

One’s home is where many feel the safest and where the Fourth Amendment protects U.S. citizens against unwarranted government searches. A burglary is one of the most intrusive violations of one’s privacy and can leave a resident fearful and emotionally distressed. This intrusiveness is one reason why residential burglary is this research’s focus. The second reason is due to the low clearance rate (calculated by dividing the number of burglaries with an arrest or charge by the total number of burglaries) CSPD has for burglaries. COS had 2,343 commercial and residential burglaries in 2015 with only 18.1% clearance rate which is the lowest clearance rate out of all crimes in COS (CSPD Strategic Information Center, 2015). The third reason for burglary’s selection was because burglaries possess premeditated planning while only a few are due to opportunity, for instance, when a willing offender causally comes upon a soft target (Mawby, 2007). Many other crime types, such as aggravated assaults, occur at the moment or based on ephemeral emotions. Also, standard reduction measures such as increased police patrols in burglary hotspot areas and a neighborhood watch seldom reduce burglary occurrences (Mawby, 2007).
Before the RTM analysis, the level of clustering, or concentrations, of burglaries was examined. A completely random pattern would mean an RTM would have little predictive ability. Highly clustered patterns allow for modeling since some cause is driving those areas of concentrations. So, the final reason for this study came from the fact that residential burglaries in COS are not random, but cluster and have a pattern throughout the city and may have a cause generated by the environment. See Figures 3.1 and 3.2 for a map of 2015 residential burglary locations and a burglary-clustering map (clustering analysis is outlined in Chapter IV). Thus, modeling may determine which urban features generate and attract burglaries allowing for novel policies and measures to be introduced that reduce the attractiveness and increase the risk of committing a burglary.

There are four primary risk considerations for residential burglars as outlined by R.I. Mawby. One is a home’s visibility exposure and accessibility. The second concern involves a home’s level of guardianship and protection—such as the presence of a resident or a security system. A home’s attractiveness factors into the risk calculation, if there is a significant loot prospect than the risk may be worth the reward. Finally, the proximity of potential targets from a likely offender is a factor (Mawby, 2007).
Figure 3.1. 2015 Residential Burglaries in COS.
Figure 3.2. 2015 Residential Burglary Clustering in COS.
Ultimately, burglars want to perpetrate a break-in, find the desired valuables, escape, and convert the stolen property into cash in an expedient manner. For burglars to commit a successful crime, they must assess the surveillability of the target home. If detected by occupants, neighbors, passers-by, or a family dog, there is a reduced chance of a successful break-in. If an occupant is present, the crime can escalate into a robbery, assault, or even homicide. Burglars must also determine the accessibility of the residence by ascertaining the presence or absence of window locks, alarms, or open windows (Mawby, 2007).

Burglars, through surveys, have expressed the main reason to commit a burglary is an immediate need for cash (Wright and Decker, 1994). The pull of drugs is often why offenders burglarize to obtain the money for their habit (Cromwell and Olson, 2004). Committing a burglary can be described in a three-phase process: preparation, execution, and closing/benefit. In the preparation phase, an offender begins selecting potential targets and starts assessing the risk of each target, if premediated. Residential targets, many times, are chosen because the offenders had tips or personal knowledge of a target from their daily activities (Wright and Decker, 1994). Personal knowledge may require some form of reconnaissance of a neighborhood either by vehicle or foot; this is where transit stops can serve as embarkment. Place features such schools, gas stations, or recreation centers bring many visitors or patrons to an area and desensitize locals to possible offenders who are reconnoitering. The execution phase is the actual breaking and entering a residence and the stealing of property. The last phase is the closing out of the crime and trying to maximize the benefit of the burglary. Most offenders don’t consider their burglary completed until they convert the stolen goods into cash. A
burglar may sell stolen goods and property to a professional fence (someone who knowingly purchases stolen goods for resale), pawn shops, drug dealers, friends/acquaintances, or less frequent, to strangers at areas such as gas stations (Wright and Decker, 1994). So, during the last phase of a burglary, place features facilitate the converting of stolen goods into cash.

**Study Area**

The study area is composed of the city of COS which equals 208.9 miles² and had a population of 442,040 in 2015 (U.S. Census Bureau, 2017). COS’ race composition was 79.9% White, 17.2% Hispanic, and 6.1% African American in 2015 (U.S. Census Bureau, 201). COS is in central Colorado at the base of Pikes Peak and the Front Range of the Rocky Mountains. This study uses 276ft as the unit of analysis which is half the average block length in COS and is the RTM’s raster cell size. See Figure 3.3 for a satellite image of COS.

Sub-study areas were used to find if there are differences in risk factors on a smaller scale. The four CSPD divisions: Sand Creek, Gold Hill, Stetson Hills, and Falcon delineate the sub-areas. The selection of this aggregation level is due to its ability to be processed in RTMDx Utility, and that it helps operationalization results to CSPD. See Figure 3.4 for a map of the sub-study areas.
Figure 3.3. COS Study Area.
Figure 3.4. CPSD Division Areas.
Data

Residential burglary is the dependent variable for this research. Burglary and drug arrest data were received from CSPD on 7 July 2017. See Table 3.1 for COS’ residential burglaries numbers for 2013-2016 (National Crime Information Center codes: 2202 (forced entry-residence) & 2204 (No forced entry-residence)).

Table 3.1. Residential Burglaries by Year.

<table>
<thead>
<tr>
<th>Year</th>
<th>Residential Burglary #</th>
<th>Percent change</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013</td>
<td>2511</td>
<td></td>
</tr>
<tr>
<td>2014</td>
<td>1833</td>
<td>-27%</td>
</tr>
<tr>
<td>2015</td>
<td>1625</td>
<td>-11%</td>
</tr>
<tr>
<td>2016</td>
<td>1636</td>
<td>1%</td>
</tr>
<tr>
<td>Total</td>
<td>7605</td>
<td></td>
</tr>
</tbody>
</table>

25 different place features were analyzed as an independent variable to determine risk factors. Incorporation of nine of those place features are due to findings in other research, and the remaining 16 features were added at the request of CSPD crime analysts to explore as many place features as possible. Residential burglary data had at least 98.8% of inputs geocoded for all study years. See Table 3.2 for a full list of place features. It is assumed that all place-feature counts and locations were consistent throughout the four years minus drug arrest (clusters determine drug markets) and foreclosures, which are fleeting. Therefore, numbers and locations of these two place features change each year. Public-housing properties were confirmed constant throughout the four years. Bus-stop count and locations were largely constant and incorporated the last major bus-stop change that occurred in 2013 and early 2014.
Table 3.2. List of All Place Feature Used as Independent Variables.

<table>
<thead>
<tr>
<th>Name (Total: 25 Risk Features Plus Dependent Variable)</th>
<th>Feature Count</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adult Entertainment Clubs</td>
<td>3</td>
<td>RCPS</td>
</tr>
<tr>
<td>Apartment Complexes</td>
<td>250</td>
<td>Yellow Pages (via Internet)</td>
</tr>
<tr>
<td>ATM at Banks</td>
<td>55</td>
<td>RCPS</td>
</tr>
<tr>
<td>Bars</td>
<td>111</td>
<td>RCPS</td>
</tr>
<tr>
<td>Bowling Centers</td>
<td>7</td>
<td>RCPS</td>
</tr>
<tr>
<td>Bus Stops</td>
<td>945</td>
<td>City of COS</td>
</tr>
<tr>
<td>Coffee Shops</td>
<td>22</td>
<td>RCPS</td>
</tr>
<tr>
<td>Convenience Stores</td>
<td>77</td>
<td>RCPS</td>
</tr>
<tr>
<td></td>
<td>849</td>
<td></td>
</tr>
<tr>
<td></td>
<td>991</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1100</td>
<td></td>
</tr>
<tr>
<td></td>
<td>480</td>
<td></td>
</tr>
<tr>
<td></td>
<td>424</td>
<td></td>
</tr>
<tr>
<td>Gas Stations</td>
<td>59</td>
<td>RCPS</td>
</tr>
<tr>
<td>Healthcare Centers &amp; Gymnasiums</td>
<td>43</td>
<td>RCPS</td>
</tr>
<tr>
<td>Liquor Stores</td>
<td>89</td>
<td>RCPS</td>
</tr>
<tr>
<td>Motels and Hotels</td>
<td>107</td>
<td>RCPS</td>
</tr>
<tr>
<td>Night Clubs</td>
<td>15</td>
<td>RCPS</td>
</tr>
<tr>
<td>Parking Stations &amp; Garages</td>
<td>6</td>
<td>RCPS</td>
</tr>
<tr>
<td>Pawn Shops</td>
<td>24</td>
<td>Yellow Pages (via Internet)</td>
</tr>
<tr>
<td>Public Housing (Section 8)</td>
<td>701</td>
<td>COS Housing Authority</td>
</tr>
<tr>
<td>Recreation Centers</td>
<td>7</td>
<td>RCPS</td>
</tr>
<tr>
<td>Restaurants Sit-down</td>
<td>537</td>
<td>RCPS</td>
</tr>
<tr>
<td>Restaurants Take-out</td>
<td>299</td>
<td>RCPS</td>
</tr>
<tr>
<td></td>
<td>1822</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1608</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1617</td>
<td></td>
</tr>
<tr>
<td>Retail Shops</td>
<td>55</td>
<td>RCPS</td>
</tr>
<tr>
<td>Schools (Elementary, Middle, and High School)</td>
<td>106</td>
<td>RCPS</td>
</tr>
<tr>
<td>Variety Stores</td>
<td>20</td>
<td>RCPS</td>
</tr>
<tr>
<td>Walmart</td>
<td>9</td>
<td>Yellow Pages (via Internet)</td>
</tr>
</tbody>
</table>
Potential Risk Features From Other Research

Bus stops, pawn shops, public housing, apartment complexes, gas stations, recreation centers, foreclosures, drug markets, and schools were selected due to significance in previous RTM and criminology studies (Moreto et al., 2014; Kennedy et al., 2015; Caplan et al., 2015). The following is the reasoning for incorporating these place features into the analysis.

Bus stops and pawn shops have correlated to burglaries in other RTM studies in Newark, NJ, Arlington, Texas (TX), and Chicago, IL (Kennedy et al., 2015; Moreto, 2010; Caplan et al., 2015). Transit stops such as bus stops act as connectors for burglars to reach, access, and exit a neighborhood while reducing suspicion that may come from an out-of-place vehicle scoping a neighborhood (Moreto, 2010). Pawn shops provide a venue for burglars to offload incrementing evidence from the burglary while also allowing them to convert stolen goods for cash (Moreto, 2010).

Public housing areas are commonly socially disadvantaged, more so than areas of different socioeconomic status. Thus, research has shown that areas around public housing have higher levels of crime due to lack of security measures, collective efficacy, and high residential mobility (Moreto, 2010). An RTM study conducted in Arlington, TX found the presence of apartments increased the risk of burglaries three times more than any other place feature (Kennedy et al., 2015). Apartments may suffer the criminal ills of social disorganization found in neighborhoods with concentrations of public housing while also offering a place for burglars to disappear. Apartment complexes’ density of residents along with the constant vehicle and visitor flow may act as a screen for burglars. This screen attribute is akin to a pickpocket disappearing into a large crowd.
after the theft. Foreclosure properties represented the most significant risk factor in an RTM study in Chicago where such properties correlated to three times the risk of burglaries than any other place features (Kennendy et al., 2015).

In crime mapping, clusters of drug arrests determine the location of drug markets thus signifying drug activities and usage in the immediate vicinity. The RTMDx Utility will determine drug markets by clusters of arrests. Research has shown that 60 to 70% of burglars are drug abusers so if drug markets are near, the potential for burglary may be higher (Cromwell and Olson, 2004; Moreto et al., 2014).

Schools draw people to areas during school hours especially at the start and end of the school day. The increased presence and frequency of people makes it hard for neighborhood residents to recognize strangers, who may be burglars. One study showed that the street blocks surrounding high schools in San Diego, California had one additional burglary than the areas without high schools nearby (Roncek and Lobosco, 1983). Another study showed proximity to schools directly correlated to burglarized residences (Cromwell et al., 1991). Recreation centers and gas stations are also potential features due to inclusion in other burglary studies because they bring people to areas in a similar manner as high schools.

Methods

Overview

This research uses RTM’s development process to determine which COS place features attract burglaries in one-year increments to find the features that consistently correlate to burglaries. Using year increments accounts for and incorporates seasonal trends normally observed with burglaries. This research used 2015 risk factors to create a
simplified (composed of the top five risk factors) and a composite risk map (composed of seven risk factors) for prediction of 2016 burglaries. Also, 2015 residential burglaries clustering analysis is outlined below. Table 3.3 outlines the methodological process of the thesis.

**RTMDx Utility Functionality**

The RTMDx Utility (education version) facilitates the analysis. The RTMDx Utility allows for the statistical determination of which place features are risk factors for burglaries, their operationalization (either proximity or density based), their spatial influence (measured in feet but equal to street-block lengths; e.g., 276ft and 552ft equal to half and one block), and their burglary-influence weight.

The RTMDx Utility allows for processing of up to 30 risk factors, eight different spatial-influence distances at half block intervals for each risk factor, determines the operationalize of all risk factors, and calculates a relative risk value (RRV) for each factor, all of which are used to create an RTM. The Utility allows for determining spatial influence up to four blocks. A three-block limit was used for this study because crime-prone areas’ spatial influence and concerns diminish after a few blocks (Taylor, 1997).

RRV is a weight of risk factors, and if a pawn shop feature has a 4.31 RRV compared to a bus stop feature RRV of 1.23, the pawn shop has more than three times higher risk of crime than the bus stop (4.31/1.23 = 3.5). A limitation of the Utility is that it only accepts vector-point features for input. Large place features like apartment complexes can occupy a large area and only allow a point to represent such a feature which can reduce its spatial influence and correlation to crime.
Table 3.3. Thesis Methodology Steps (See following pages for more details on steps).

Methodology Steps:

1. Determine all possible risk factors by reviewing literature and inputs from CSPD crime analysts.
2. Collect all possible risk factor, drug arrest, and burglary data (2013-2016) from multiple sources.
4. Conduct visual analysis of research data in ArcMap.
5. Determine significant risk factors by year (2013-2016) using RTMDx Utility along with their operationalization and spatial influence.
6. Determine top five risk factors from individual study years by using ordinal and coefficient-weight averages.
7. Determine the top five risk factors’ relative risk value, operationalization, spatial influence, and coefficient weight.
8. Determine the top risk factors in each CSPD division across the four study years to see if they are similar to the study areas top risk factors and if there is a spatial phenomenon in risk factors.
   a. Proximity risk factors (buffers with a radius of the spatial influence).
      i. Convert to raster surface and reclassify so that the area within the buffer is coded as 1 and the area outside the buffer is coded 0. 1 indicates risk area and 0 indicates no risk.
   b. Density risk factors (kernel density using search radius equal to spatial influence).
      i. Convert to raster surface and reclassify so that the area within the two standard deviations of the kernel is coded as 1 and the area outside the buffer is coded 0.
   c. Use map algebra to combine all risk-factor raster surfaces to create a weighted risk map with relative risk scores using RTMDx Utility coefficient-weight formula.
10. Test predictive ability of simplified and composite RTMs for 2016 residential burglaries using Prediction Accuracy Index.
   a. Process for spatial and clustering analysis.
   b. Create cluster maps if p-value < 0.05.
With such a large number of variable evaluations, the Utility uses cross-validation to build a penalized Poisson regression model (Heffner, 2013). Cross-validation is a statistical technique to evaluate predictive models by partitioning the original data to have a training set to test the model; Utility does this by generating five randomized areas (one area used to test the four other), each of which is balanced with burglary counts. The Poisson regression uses a Poisson distribution that expresses the number of random events occurring in a fixed period. The penalized portion of the regression uses two penalized methods: L1, the sum of the absolute value of coefficients (called least absolute shrinkage and selection operator) and L2, the sum of square coefficients (called rigid component). This penalization step shrinks the estimates of the regression coefficients towards zero, relative to the maximum likelihood estimates (Goeman, 2016). The Utility uses two fixed L2 values and optimizes an L1 value for each L2 penalization. Through this process, Utility selects the optimal amount of coefficient penalization using cross-validation by selecting one L2 model with the best likelihood (i.e., best fit). Thus, this process reduces a large set of variables down to a small set with all non-zero coefficients that are considered potentially useful for the modeling step.

This next step uses a bidirectional stepwise regression to determine the best RTM. A stepwise regression considers each explanatory variable (those previously selected by the Utility) to add or subtract from the model. The Utility starts with no variables (null model) and measures the Bayesian information criterion (BIC) score which balances the model complexity against fit (Heffner, 2013). The BIC, developed by Gideon E. Schwarz (1978), fits models by determining the likelihood of adding parameters and
accounts for overfitting. Overfitting occurs when a model describes the random error in the data rather than the relationships between variables.

Next, the Utility adds a new variable such as pawn shops (proximity) with a spatial influence of 276ft and measures the BIC score for comparison to the null model. The modeling selects the lowest score variable for the new potential model. It continues to add variables like pawn shop (proximity) with a spatial influence of 552ft until no addition improves the BIC score. During this stepwise regression process, the Utility generates two models, one using a Poisson distribution and the second one using a negative binomial distribution. The Poisson process may not produce the best model because crime events are largely related to one another and influence each other which breaks some Poisson assumptions (Heffner, 2013). So, the Utility also examines a negative binomial distribution that is derived from the number of failures before the xth success in a sequence of binomial trials; this distribution with a parameter to represent overdispersion of counts allows for the model to incorporate reliance between crime events (Forbes et al., 2013; Heffner, 2013).

The Utility selects the model with best BIC score along with determining the operationalization impact to BIC scores by exploring proximity utilizing a uniform/step kernel and density using an Epanechnikov kernel (a parabolic kernel similar to the kernel-density function found in ArcMap). Finally, the Utility checks if the risk factors are statistically significant based on p < 0.05.

**Determining Top Risk Factors**

An ordinal average (e.g., bus stops ranked #1 risk factor for 2013 based on RRV and ranked #3 for 2014, then averaged over the four years) approach plus the risk factors’
The coefficient-weight (produced during the stepwise regression) average was used to select the five factors. Two selection methods were used to determine if the top risk factors were consistent when reviewing different factors’ attributes. The five risk factors were then used to create the simplified 2015 RTM.

The four CSPD division areas were analyzed to determine if different risk factors were significant on a smaller scale. All determined risk factors from all years were studied at each division to see if different top risk factors would be found in a smaller area.

**Building an RTM**

The results of the Utility process yields a list of the most appropriate risk factors, their coefficient weight, operationalization, and spatial influence. This information is used to create a composite raster map in ArcMap. Risk factors and their operationalization along with spatial influences are used to develop individual-raster surfaces. If the operationalization is proximity, all the area within the risk factor’s spatial influence is indicated as 1 for risk and all the area outside the influence distance is 0 for no risk. For the density operationalization, all the area within two standard deviations (SD) of a kernel density radius based on spatial influence are coded as 1, and the area outside as 0. These raster surfaces along with risk factors’ coefficient weight are combined using map algebra, and the result is the final composite-weighted RTM. The completed risk map has relative risk scores (RRS) for each raster cell. A risk map, for example, may have RRSs from 1 (lowest risk place) to 250 (highest risk place; there is no fixed maximum). A cell or cells with an RRS of 245 have an expected rate of a burglary that is 245 times higher than a cell with a value of 1 (Caplan and Kennedy, 2016).
Predictive Ability of RTM

The Prediction Accuracy Index (PAI) developed by Spencer Chainey, Lisa Tompson, and Sebastian Uhlig tested the predictive accuracy of the two 2015 burglary RTMs against 2016 burglary data (Chainey et al., 2008). The PAI determines the hit rate against the areas where crimes are predicted based on the RTM against the size of the COS study area (Chainey et al., 2008). See Equation 3.1.

Equation 3.1. PAI.

\[
\frac{\frac{n}{N} \times 100}{\frac{a}{A} \times 100} = \frac{\text{HitRate}}{\text{AreaPercentage}} = \text{Prediction Accuracy Index}
\]

Where \(n\) is the number of burglaries in areas where burglaries are predicted to occur, \(N\) is the number of crime burglaries in COS, \(a\) is the area of the areas where burglaries are predicted to happen from the RTM, and \(A\) is the area of COS. A higher value of PAI indicates a better prediction ability of the model.

The simplified 2015 RTM is composed of the top five risk factors while the composite 2015 RTM is composed of all relevant factors determined by the Utility and in this case, there are seven. The PAI primarily uses those areas with RRS equal to or higher than two SDs from the mean RRS for prediction accuracy since these areas represent the most significant crime areas (Drawve, 2016).

Clustering Analysis of Burglaries

After the RTM analysis, burglary areas were analyzed to see if and how this crime type clusters in COS. Two spatial pattern analysis techniques were utilized individually to determine spatial autocorrelation and clustering—Getis-Ord and Moran I. Both techniques analyzed global autocorrelation and clustering. Using two different techniques give significance to the presence of clustering if they both determine it.
The Getis-Ord Gi* technique found in the spatial analyst toolbox of ArcMap allowed for the analysis. Three different conceptualizations of spatial relationships were analyzed: fixed distance and inverse distance, both using 1656ft which is equivalent to three COS blocks, and contiguity edges corners (also known as the Queen method, which takes areas sharing any boundary to a polygon as neighbors for inclusion into a spatial weight matrix). Clustering analysis has been used by researchers from RCPS to analyze if crime clusters in study areas (Kennedy et al., 2015; Caplan and Kennedy, 2010).

The second technique is the local Moran’s I test for autocorrelation to determine if residential burglaries cluster by other burglar occurrences (Caplan and Kennedy, 2010). The same three conceptualization of spatial relationship used for the Getis Ord Gi* were analyzed for Moran I too.
CHAPTER IV

FINDINGS

Risk Factors, Operationalization, and Spatial Influence

The RTMDx Utility analysis of four years of residential burglary data determined only nine of the inputted 25 place features, or 36% of the features, were risk factors for burglary during 2013-2016 (Table 4.1). Ordinal average ranking across the four years of all nine risk factors determined the top five risk factors. Averaging the coefficient weight across years selected the same top five factors as the ordinal ranking. The top factors were limited to five because of the drop-in ordinal average and coefficient weight after five factors. Also, see Table 4.2 for risk factors by year and Table 4.3 for a chart of key RTM attributes across all study years.

Table 4.1. RTMDx Utility Determined Risk Factors (2013-2016) by Coefficient-Weight Average.

<table>
<thead>
<tr>
<th>Rank #</th>
<th>Risk Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Apartment Complexes</td>
</tr>
<tr>
<td>2</td>
<td>Foreclosures</td>
</tr>
<tr>
<td>3</td>
<td>Drug Markets</td>
</tr>
<tr>
<td>4</td>
<td>Bus Stops</td>
</tr>
<tr>
<td>5</td>
<td>Public Housing</td>
</tr>
<tr>
<td>6</td>
<td>Schools</td>
</tr>
<tr>
<td>7</td>
<td>Sit-Down Restaurants</td>
</tr>
<tr>
<td>8</td>
<td>Convenience Stores</td>
</tr>
<tr>
<td>9</td>
<td>Liquor Stores</td>
</tr>
</tbody>
</table>
Table 4.2. Risk Factors’ Coefficient Weight by Year.

<table>
<thead>
<tr>
<th>Risk Factors</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2013</td>
</tr>
<tr>
<td>Apartment Complexes</td>
<td>0.99</td>
</tr>
<tr>
<td>Bus Stops</td>
<td>0.30</td>
</tr>
<tr>
<td>Drug Markets</td>
<td>1.42</td>
</tr>
<tr>
<td>Foreclosures</td>
<td>1.76</td>
</tr>
<tr>
<td>Public Housing</td>
<td>0.51</td>
</tr>
<tr>
<td>Convenience Stores</td>
<td></td>
</tr>
<tr>
<td>Liquor Stores</td>
<td></td>
</tr>
<tr>
<td>Schools</td>
<td>0.26</td>
</tr>
<tr>
<td>Sit-down Restaurants</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.3. Key RTM Attributes Across All Study Years in the Study Area (Spatial Influence Columns Equal ½, 1 ½, 2 ½ and 3 blocks).

<table>
<thead>
<tr>
<th>Year/ # of Identified Risk Factors (RF)</th>
<th>Operationalization #/ # of RFs by Year</th>
<th>RFs' Spatial Influence (# in Distance Category/ # of RFs by Year)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Density</td>
<td>Proximity</td>
</tr>
<tr>
<td>2013/7</td>
<td>1/7</td>
<td>6/7</td>
</tr>
<tr>
<td>2014/7</td>
<td>2/7</td>
<td>5/7</td>
</tr>
<tr>
<td>2015/7</td>
<td>2/7</td>
<td>5/7</td>
</tr>
<tr>
<td>Simplified 2015/5</td>
<td>2/5</td>
<td>3/5</td>
</tr>
<tr>
<td>2016/7</td>
<td>2/7</td>
<td>5/7</td>
</tr>
<tr>
<td>Total:</td>
<td>9/33</td>
<td>24/33</td>
</tr>
<tr>
<td>Percentage</td>
<td>27.3%</td>
<td>72.7%</td>
</tr>
</tbody>
</table>

Proximity was a prominent risk-factor operationalization throughout the research along with the risk-factor spatial influence of ½ and three blocks. This information is useful to understand the risk factors’ impact on the COS’ environment along with the risk factors’ near (½ block) and far (three blocks) spatial influence on residential burglaries.

The top five risk factors—apartment complexes, drug markets, foreclosures, public housing, and bus stops—were used to create the simplified 2015 RTM. The simplified RTM’s predictive accuracy for 2016 residential burglaries was compared against the composite 2015 RTM accuracy (Table 4.4).
Table 4.4. Comparison of Simplified and Composite 2015 RTMs’ Attributes.

<table>
<thead>
<tr>
<th>Risk Factor</th>
<th>Simplified 2015 RTM</th>
<th>Composite 2015 RTM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Operationalization/</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Spatial Influence (ft.)</td>
<td>RRV</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Apartment Complexes</td>
<td>Density/276</td>
<td>8.81</td>
</tr>
<tr>
<td>Drug Markets</td>
<td>Density/276</td>
<td>3.63</td>
</tr>
<tr>
<td>Foreclosures</td>
<td>Proximity/1656</td>
<td>3.14</td>
</tr>
<tr>
<td>Bus Stops</td>
<td>Proximity/1656</td>
<td>2.48</td>
</tr>
<tr>
<td>Public Housing</td>
<td>Proximity/1656</td>
<td>1.87</td>
</tr>
<tr>
<td>Sit-down Restaurants</td>
<td>Proximity/1656</td>
<td></td>
</tr>
<tr>
<td>Schools</td>
<td>Proximity/1656</td>
<td></td>
</tr>
</tbody>
</table>

**Top Risk Factors at CSPD Division Level**

The division level analysis found four of the same top risk factors—apartment complexes, foreclosures, drug markets, and public housing—as at the city level. Bus stops and schools tied for the fifth factor based on the average-coefficient weight and ordinal rank. Overall, there was no major difference between the study area and the division level, so, therefore, there is no need to alter the city-level top risk factors.

**Simplified versus Composite RTM Risk Maps**

**2015 Residential Burglaries**

There were 1608 (geocoded) residential burglaries in COS during 2015. Figure 3.1 in Chapter III shows where these burglaries occurred.

**2015 Simplified and Composite RTM Risk Maps**

The RTMDx Utility selected the negative binomial model for both the simplified and composite RTMs. The simplified RTM has RRSs from 1 (lowest risk) to 467 (highest risk), and the composite has RRSs from 1 to 597. Both risk maps have high-risk
areas located in the downtown, Old Colorado City, and Sand Creek areas (Figures 4.1 and 4.2).

**Prediction Accuracy**

Both RTMs were composed of 77,871 raster cells of which 1,342 contained residential burglaries or 1.7% of the entire city area in 2015. Since both risk maps had the same predictive ability at two SDs for 2016 residential burglaries, the analysis also explored areas that were equal to or greater than one SDs from the mean too.

<table>
<thead>
<tr>
<th>Table 4.5. PAI Results for 2016 Residential Burglaries.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk Map</td>
</tr>
<tr>
<td>Simplified 2015 RTM</td>
</tr>
<tr>
<td>Composite 2015 RTM</td>
</tr>
<tr>
<td>Difference between RTMs by %</td>
</tr>
</tbody>
</table>

The additional two risk factors used in the composite RTM did not provide any additional predictive ability over the simple RTM for areas equal to or greater than two SDs. Although the composite has a higher PAI value than the simple when using areas that are equal to or greater than one SD, the simple model out predicted the composite by 4.3%. Both models found that 0.84% of COS is composed of high-risk areas (≥2SD) and predicted 10.9% of all 2016 residential burglaries. Also, these high-risk areas have 20 to 463 times (simplified RTM; mean RRS 3.24) and 21 to 594 times (composite RTM; mean RRS 3.3) higher expected rate for burglaries than the mean RRSs areas.
Figure 4.1. 2015 Simplified Residential Burglary RTM Risk Map.
Figure 4.2. 2015 Composite Residential Burglary RTM Risk Map.
Spatial Autocorrelation and Clustering Analysis

The two types of clustering techniques—Moran I and Getis-Ord General G—found positive spatial autocorrelation (indicated by above 0 Index and General G values in Table 4.6; higher the value, the more autocorrelation) of 2015 residential burglaries. Also, both global clustering techniques are statistically significant due to large z-scores and p-values below 0.05; both indicate that the data distribution is not random, random being the expected. Local Moran I and Getis-Ord Gi* at different spatial relationships found local clustering for burglaries at p-values < 0.05. A significant clustering mapping was created using Getis-Ord Gi* fixed distance at 1656ft (see Figure 3.2). Global and local clustering analysis of burglaries determined that this phenomenon is not random or uniform in COS.

Table 4.6. Spatial Autocorrelation Results by Technique.

<table>
<thead>
<tr>
<th>Residential Burglaries (2015)</th>
<th>Index Value or General G</th>
<th>Z-score</th>
<th>P-value</th>
<th>Clustering Y/N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Moran I (Inverse Distance: 1656ft)</td>
<td>0.0457</td>
<td>80.33</td>
<td>0.000</td>
<td>Y</td>
</tr>
<tr>
<td>Moran I (Fixed Distance: 1656ft)</td>
<td>0.0381</td>
<td>78.27</td>
<td>0.000</td>
<td>Y</td>
</tr>
<tr>
<td>Moran I (Contiguity Edge Corners)</td>
<td>0.0736</td>
<td>40.90</td>
<td>0.000</td>
<td>Y</td>
</tr>
<tr>
<td>Getis-Ord General G (Inverse Distance: 1656ft)</td>
<td>0.000007</td>
<td>80.59</td>
<td>0.000</td>
<td>Y</td>
</tr>
<tr>
<td>Getis-Ord General G (Fixed Distance: 1656ft)</td>
<td>0.0054</td>
<td>78.37</td>
<td>0.000</td>
<td>Y</td>
</tr>
<tr>
<td>Getis-Ord General G (Contiguity Edge Corners)</td>
<td>0.000662</td>
<td>41.01</td>
<td>0.000</td>
<td>Y</td>
</tr>
</tbody>
</table>

Simplified RTM vs. 2015 & 2016 Residential Burglaries and Top Risk Factors

This last section shows how the areas that are one SD to two SDs and two SDs to the max RRS from the simplified 2015 risk map correspond to the 2015 and 2016 residential burglaries. Also, the following figures show how these same areas align with the top risk factors (apartments, 2015 foreclosures, public housing, bus stops and 2015 drug arrests—used for drug markets).
Figure 4.3. 2015 Simplified RTM High-Risk Areas vs. 2015 Residential Burglaries.
Figure 4.4. 2015 Simplified RTM High-Risk Areas vs. 2016 Residential Burglaries.
Figure 4.5. 2015 Simplified RTM High-Risk Areas vs. Apartments and 2015 Foreclosures.
Figure 4.6. 2015 Simplified RTM High-Risk Areas vs. 2015 Drug Arrests.
Figure 4.7. 2015 Simplified RTM High-Risk Areas vs. Public Housing and Bus Stops.
CHAPTER V

CONCLUSION

The risk factors—apartments, drug markets, foreclosures, bus stops, and public housing—consistently correlated to residential burglaries over four years. This finding gives significance and weight to their spatial influence on crime. Any future study of risk factors in COS or utilization of RTM needs to start with these five factors or can solely use them for their RTM analysis due to their predictive ability. If CSPD chooses to incorporate my findings or utilize them in the future, they can streamline the burglary RTM process. They need not explore 25 or nine place features but just use the top risk factors. Using only these five factors can reduce RTMDx Utility processing time by approximately 70% and allow for the quick creation of risk maps in ArcMap. A crime analyst at CSPD needs only to update the risk factors due to changes in the environment after several years have passed (e.g., new apartment complexes) and obtain a new list of foreclosures from the county, bus stop changes from Mountain Metro Transit, and consolidate new drug-arrest data. Foreclosures and drug arrest are fleeting and change over time so they must always be updated. Updating all of these data is far easier than updating other place feature data that is largely out of the control of local government agencies. This research’s findings can allow for more operationalization of crime mapping into daily and weekly police operations and routines.

This RTM study found that proximity to risk factors and spatial influence of 276ft and 1656ft are the most common RTM operationalization attributes. Also, of importance is that residential burglaries are not random throughout COS but cluster in certain areas. This information is important to understanding COS’ environmental backcloth while
allowing for future crime strategies as was done in COS in 2014 by CSPD after the development of an auto theft RTM by RCPS (Kennedy et al., 2015). Policing measures that diminish the spatial influence of risk factors may allow for a reduction in burglaries or its fragmentation. This reduction in the occurrence of residential burglaries can enable CPSD to show that they are approaching burglaries in a very proactive way versus reactive to overcome the low clearance rate of burglaries.

Apartment complexes are the number one risk factor, and this comports with the outlined burglary characteristics in Chapter III. The density of people and the volume of traffic in and around apartments likely desensitize the surrounding area to potential burglary offenders. Drug markets and foreclosures embodied aspects of the social disorganization theory by having acts such as drug arrests that indicate lack of social cohesion while foreclosures indicate lack of income security and visually shows distress. The closeness of drug markets to burglaries underscores the rational choice theory. Those who have become dependent on drugs may consider burglary a rational action as a way to meet their need for drugs by converting the stolen property to cash to be spent on more drugs. Public housing may also note social disorganization due to Section 8 stigma and the behaviors of public housing tenants. The bus stops may be utilized as part of the burglary process in pre and post-execution to get to target houses and egress the burglary location. The clustering analysis of 2015 residential burglaries indicated that burglaries cluster which agrees with the crime pattern theory that states that crime is not random. So, the top risk factors and findings have a grounding in published research and theories.

Future RTM analysis and research in regards to burglaries should examine which risk factors are prevalent in different seasons (e.g., summer and Christmas season) since
burglaries occurrences increase and decrease at different times of the year. Also, the
significance of the RTM process findings may be influenced by the inability of the
RTMDx Utility to process polygon features. This failure takes a large place feature and
represents it as a single point thus reducing its influence.

In closing, there are risk factors that consistently create high-risk areas that
predict residential burglaries in COS. COS had 0.84% of its area that was designated
high risk for burglaries in 2015. These high-risk areas had 20 to 463 times higher
expected rate for burglaries than the mean RRS city areas—determined from the
simplified 2015 RTM, and that area accounted for 10.9% of 2016 residential burglaries.
Both the simplified and composite 2015 RTMs had a PAI value of 13.0 using areas that
had RRSs equal to or greater than two SDs. This PAI value indicates that the high-risk
areas that predicted 2016 burglaries had a 13 times higher rate of residential burglaries
than other areas in the city. Also, burglaries from 2015 clustered in the city. This
information can allow for prudent and measured actions by law enforcement to combat
residential burglaries.
REFERENCES


