A Risk Terrain Model of Residential Burglaries in Valdosta, Georgia

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ABSTRACT

Crime has four aspects: an offender, a victim, a law that is broken, and a place where the crime occurs (Brantingham & Brantingham, 1991). This research will look at this fourth aspect to determine what environmental features, if any, affect residential burglaries. It's not about why people commit burglaries, but why offenders choose the targets they do. Rather than focusing on the biological or social reasoning behind an individual's criminal behavior, environmental criminology instead focuses on the locations in which crime occurs. The goal is to find significant patterns in crime locations and look for environmental features that may help explain the increased criminogenic activity. In this particular research, which utilizes a process called Risk Terrain Modeling to assess burglaries in Valdosta, Georgia, these identified environmental risk features are weighted and a map of places at risk for burglary is created that can then aid police officers and city planners in allocating resources in a cost-efficient manner and possibly developing preventative measures.

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Chapter I

INTRODUCTION

In 2015, burglaries cost Americans $3.6 billion in property loss according to the Federal Bureau of Investigation's Uniformed Crime Reports. But worse than the monetary loss is the feeling of violation felt by many victims that can lead to psychological distress and hyper-vigilance about one's security (Caballero, Ramos, & Saltijeral, 2000), and in some cases even post-traumatic stress disorder (Chung, Stedmon, Hall, Marks, Thornhill, & Mehrshahi, 2014). Most people do not go through their days worrying about their homes being burglarized, especially if they feel that they live in a "safe" neighborhood, or that they have taken appropriate security measures. However, burglaries do not only happen in high-crime areas. On the contrary, burglaries often happen in neighborhoods that exhibit more wealth, where residents appear to have items with a higher resale value to steal, but yet feel safe enough to relax their security measures.

While burglary is a crime that can strike anywhere, there are definite areas where burglaries cluster within cities (Eck, Chainey, Cameron, Leitner, & Wilson, 2005). Law enforcement and city officials have been using crime mapping techniques for decades to determine where clusters of criminal activity occur in an effort to reduce crime by targeting these areas. One of the first and most well-known measures is the COMPSTAT program that took off in New York City in 1995, which uses computer statistics to generate reports about crime patterns (NYPD, 2016). Since the 1990s, cities and law enforcement have started developing more efficient ways of recording and utilizing spatial crime data. Hot spot mapping, which uses statistics to determine the most significant clusters, can help law enforcement allocate their resources in the most efficient ways. Hot spot maps also show that clusters tend to occur in the same areas over many years (Shaw & Mackay in Kennedy, Caplan, & Piza, 2012). Law enforcement can continue to focus their efforts on these areas, or they can determine what it is about those areas that make them hot spots and possibly change the environment, thereby reducing criminal activity.

Brantingham and Brantingham (1991), the pioneers of environmental crime theory, suggested that these hot spots of crime could be explained by studying the "environmental backcloth" of these areas. Combinations of certain features in an environment can contribute to the amount of criminal activity in that area (Kennedy, Caplan, & Piza, 2011). Features that are found to be common to areas with a high number of a specific crime type (e.g., burglaries) are considered "risk factors" for that crime. Criminal activity doesn't always occur at places where risk factors converge, but these areas are thought to be more at risk than other areas without these combinations. As the environmental backcloth for every study area differs, so do the features that affect different types of crime. By examining existing literature on burglaries, we can determine which features are most common to this crime.

Surveys of Burglars

Perhaps one of the best ways to understand how burglaries happen is to observe what burglars themselves have to say. According to a 1994 survey among active burglars, offenders locate their targets in three main ways: knowing the occupants, receiving a tip, or observing a potential target (Wright & Decker, 1994). The most common way is by observing a target (62%). This is done by watching a home to learn the occupant's schedule and habits or by working a job that gives access to the home (a painter, a gardener, an alarm installer, a furniture delivery person, etc.). Wright and Decker found that most burglars target homes they have some familiarity with. Occasionally burglars will choose a target on the spur of the moment (like in the case of seeing a family leaving for vacation), but often times these crimes are planned in advance (Wright & Decker, p. 100). Very few burglars will target a home where it is unknown whether occupants are at home. In addition, burglars stated they tended to keep away from neighborhoods with a high elderly population since older individuals tend to be home during the day and watch out for their neighbors (Wright & Decker, p. 92).

The Wright and Decker (1994) surveys tell us that offenders tend to choose targets from those they see during their daily routine activities (going from home to work, to school, to friend's homes, to recreational areas, to shopping, etc.). The Routine Activities Approach, developed by Felson and Cohen in the late 1970s, tells us that crimes take place when there is a likely offender, a suitable target, and an absence of a capable guardian (Felson & Eckert, 2016). A simple explanation of the theory, which can be gleaned from applying it to what the Wright and Decker surveys told us, is that as someone goes about their daily routines, they see suitable targets. When they feel motivated to commit a burglary, they look for the absence of a guardian (resident, neighbors, police) to determine where and when to strike.

One of the most interesting points that came up in the survey of burglars, and one that affirms the routine activities approach, was the fact that many offenders already have a target in mind before they decide to commit a crime (89%). Wright and Decker state that burglars are continually “half-looking” for targets as they go about their daily routines (p. 80). Many burglars stated that they look for large homes with manicured lawns and nice cars as this shows that the goods on the inside will be worth their troubles. Though for some, burglary is fueled by perceived necessity and a fast and easy target is better than one that will maximize returns. Drugs are a major factor in choosing targets. A study of 422 incarcerated burglars in North Carolina, Kentucky, and Ohio found that 51% of burglaries were motivated by a need to acquire drugs and 37% were motivated by a need for money, which was often needed to purchase drugs (Blevins, Kuhns, Lee, Sawyers, & Miller, 2012, pp. 26-27). The motivation behind the burglary, which this study does not directly address, affects the kinds of residences that are targeted.

The commentaries of the burglars offer a good bit of information about how offenders choose their targets, which can help researchers, law enforcement, and city officials determine what factors may be influencing the hot spots of crime. Potential offenders are always aware of their surroundings as they go about their daily routines (Wright & Decker, 1994). A home's proximity to these places and routes could potentially increase the likelihood of them being targeted. In addition, as the burglars stated, and as the routine activities approach tells us, offenders are less likely to burglarize a home if someone is home or if there are neighbors watching the neighborhood (guardians). Therefore, it is likely that in areas with greater occupancy turnover, neighbors would be less able to discern who does and does not belong. These assumptions can be tested with computer software to determine if they really are a significant contributing factor to burglary locations. That is what this research seeks to do: to use Geographic Information Systems (GIS) computer modeling software to determine whether environmental factors influence where burglaries occur and what environmental factors, if any, are statistically significant.

Risk Terrain Modeling

Risk Terrain Modeling (RTM) is a systematic mapping process that uses GIS software to analyze crime locations and their spatial relationship to risk features in the environment (Caplan & Kennedy, 2016). This is used to build a model that shows areas at risk for future criminal activity throughout the entire study extent, whether crime has previously occurred at those areas or not. Possible environmental risk factors are identified from criminological theory as well as from the expertise of local law enforcement professionals and previous studies in the field. Crime locations and risk features are mapped using GIS software. Researchers are able to determine which environmental features may put an area at risk for a certain type of crime through statistical analysis. Current software like the RTMDx Utility (Risk Terrain Modeling Diagnostics Utility) created by Rutgers University (www.rutgerscps.org/software) not only helps to identify statistically significant features, but also performs complex statistical analysis that assigns a coefficient, or "weight," to each feature. This results in risk values for each feature that show the extent of the impact each risk factor poses. Individual density maps of the statistically significant risk features are created and these raster layers are then compiled to build a risk terrain model for the crime being studied. Risk terrain models are not prediction models, but are instead a method of analyzing risk. It is simply saying: this is the environment in which crimes have occurred in the past, therefore, similar environments may also be at risk for this crime. A high-risk area is one that “promotes, stimulates, sustains and/or enables” criminal activity due to the features of the environment (Moreto, October 2010, p. 1).

Risk Terrain Modeling is a 10-step process that begins with determining what specific crime is being studied and what the study area will be. The setting of the study will affect the outcome, so it is important to be intentional in making this selection. The area can encompass an entire city, a police beat, a neighborhood, or even specific streets within a neighborhood (Caplan, Kennedy & Piza, 2013, p.15). Crime varies at locations within cities, so concentrating on smaller, micro-level places might give a better explanation of why crime is happening in those locations city (Kennedy, Caplan, & Piza, 2012, p. 16). Most RTM studies are conducted on the city level (Caplan & Kennedy, 2011, p. 46). Once risky areas are identified or if a law enforcement agency already knows of problem areas, they may choose to perform an analysis on those specific areas. At a neighborhood level, researchers can look at additional risk features that have been known to affect burglary rates, including lighting, shrubbery, fencing, characteristics of houses, security measures taken by residents, and the layout of streets (cul-de-sacs, dead ends, and access to thoroughfares all affect accessibility to houses) (see Johnson & Bowers, 2010; Ward, Nobles, Youstin, & Cook, 2014; Davies & Johnson, 2015; and Montoya, Junger, & Ongena, 2016).

Spatial crime analysis of burglaries in a city must also take into account how burglary patterns may change depending on the time of year. School breaks increase the number of juveniles without supervision during the summer, and the holiday season (November and December) increases the amount of new items that can entice would-be burglars. The time-frame of the study must be taken into account especially when comparisons are being made. Areas with more juveniles may have higher burglary rates during the summer while areas exhibiting more wealth may have higher burglary rates during the holidays. A 1-year study would take all of this into account, however, agencies may choose to use shorter time-frames to determine where to most efficiently allocate their resources during various times of the year. The time period chosen for the study should be meaningful to the particular research question being addressed.

The technical details of Risk Terrain Modeling will be explained in more detail in later chapters. A literature review of RTM studies of burglaries will assess how other researchers applied the process in their communities and what risk features they found to be significant. This will help determine which risk features will be tested for this study and how they will be analyzed. The methodology for this study will be explained in Chapter 3. A step-by-step explanation of how the burglary data for Valdosta is examined and how the risk terrain model is produced, in addition to a comparison of the model and burglary data from the 6 months following the study period will be given in Chapter 4. This study will conclude with a discussion of the findings and what they mean for law enforcement and city officials, along with the limitations of the study, and suggestions for future research.

Chapter II

LITERATURE REVIEW

The most important aspect of the risk terrain modeling process is identifying all possible risk factors. Specific crimes will have their own sets of risk factors; for instance, proximity to ATMs may be a significant factor for robberies, but will present little risk for burglaries. These two crimes are very different and likely occur in very different environments. They are both influenced by features in the environment, but not the same features. When attempting to identify the possible risk features for the crime being studied, it is important to keep the nature of the crime in mind. Criminological theory, prior research, and the knowledge and expertise of law enforcement and city officials should be considered.

Features that are often studied are places that receive a lot of traffic during the day while people are going about their daily routines. Schools, restaurants, grocery stores, retail shops, and gas stations are just a few that are often considered. The routine activities approach also tells us that crime happens when there is a lack of guardians in an area (Felson & Eckert, 2016). So additional features that may be studied include signs of social disorganization like a high number of apartments, rental houses, foreclosures, and vacancies. The knowledge of law enforcement officers who are out in these communities is often one of the best sources of information. Officers can provide intelligence on drug activity, gang territories, vacant buildings, and other problem areas. Some cities also have a 3-1-1 non-emergency line where residents can report suspicious persons and vehicles, as well as when street and alley lights are out. These calls for service can also be used to pinpoint problem areas.

Identifying Risk Factors from Previous RTM Studies

In an October 2010 brief on the risk factors of urban residential burglaries, Moreto suggested using proximity to public housing, pawn shops, and bus stops as aggravating factors. In a pilot study of burglaries in Newark, New Jersey (Moreto, November 2010), Moreto found statistical spatial significance among bus stops, pawn shops, and at-risk housing. This last variable was operationalized from data provided by the Newark Police Department and the Newark Housing Authority. This included public housing as well as privately owned complexes that were known to be associated with illegal drug activity.

A 2012 RTM study of burglaries in Arlington, Texas found spatial significance among apartment complexes, schools, foreclosures, pawn shops, variety stores, convenience stores, and gas stations with convenience stores (Kennedy, Caplan, & Piza, 2015). A 2013 study in Lawrence Township, Mercer County, New Jersey, found significance among bus stops, calls for service for suspicious persons, and calls for service for suspicious vehicles (Gale, 2013).

The pioneers of risk terrain modeling, Caplan and Kennedy, along with Barnum and Piza (2015) created a guide specifically for burglaries based on a study conducted in Chicago. The risk factors they tested included 3-1-1 service requests for street lights out, alley lights out, and abandoned vehicles, as well as apartment complexes, foreclosures, problem buildings, gas stations, grocery stores, laundromats, retail shops, schools, variety stores, bars, nightclubs, bus stops, banks, gyms, homeless shelters, malls, parking stations and garages, post offices, recreation centers, rental halls, and liquor stores. However, the last nine were not included in their final model. The feature operationalized as “problem buildings” was based on intelligence collected by the Chicago Police Department for their internal uses regarding locations that are reported as possible problem areas due to vacancy, drugs, gangs, etc. “Insider info” like this is extremely helpful to the study. This list of features from the Chicago study is suggested as the best starting point for a burglary model.

Weighting Risk Models

Not every feature that is found to be statistically significant is going to impact a risk model in the same way. An unweighted model would assume that every risk factor carries the same amount of risk. In Gale's 2013 study, he began with an unweighted model. He tested three risk factors he assumed to have a significant spatial relationship with burglaries: bus stops, calls for suspicious persons, and calls for suspicious vehicles. This model contained three risk map layers. Cells where a risk factor was present were coded as 1 and cells where a risk factor was not present were coded as 0. Therefore, when these risk layers were combined, the risk values ranged from 0 (no risk factors present) to 3 (all risk factors present). The problem with the process up to this point is that we do not know the extent of risk each factor poses. Is an area affected by bus stops equally as risky as an area that contains suspicious persons or vehicles?

Gale answers this by using a binary logistic regression model to first make sure that each variable tested had a statistically significant impact on burglary locations, which they did. The regression model output Odds Ratios that were significantly higher for both bus stops and calls for suspicious vehicles. This indicates that these two features have more of an impact on creating risk than the calls for suspicious persons. Gale then converted the parameter estimates from the regression for each feature into probabilities for crime prediction (see Gale, p. 7, probability formula from Hosmer & Lemeshow, 1989). These probabilities allowed for an easier explanation of how the three features impact risk. He determined that areas with a high concentration of suspicious vehicles are approximately 28% more likely to experience burglaries than those without (Gale, 2013, p. 7). Gale was able to use these probabilities to weight his model, which produced more accurate levels of risk.

Utilizing a regression model in this way was common in early RTM studies. However, a potential problem occurs when using a logistic regression that requires a binary variable. Cells must be coded as 0 (no crime event) or 1 (presence of a crime event), which means multiple incidents within a cell are not accounted for (Caplan & Kennedy, 2016). "Such undercounting of incidents may depreciate the validity of the model, particularly by underestimating the predictive capacity of risk terrain models" (Chapter 2, Footnote 4). This is why Rutgers University developed the RTMDx Utility, which automates the process of testing multiple models and provides the coefficients for weighting the best model. Caplan, Kennedy, and Piza (2013) assert that "the statistical methods for risk factor selection and validity testing that are included in this utility are far superior to prior manual methods" (p. 31).

To date, there have not been many RTM burglary studies published, especially not of rural areas. This is what makes Gale's study of Lawrence Township unique. Larger cities have different infrastructure and while it may seem like the risk features found to be significant in previous research should be universal, many of these may not even exist in smaller towns. Each city and town attempting to utilize risk terrain modeling should keep their city or town's unique characteristics in mind. The study will also be limited by the amount of information that is available for researchers. Smaller towns may not have the same data storing capabilities as larger cities.

Chapter III

METHODOLOGY

This study utilizes the RTM process to determine if features in the environment have a significant effect on where burglaries occur in Valdosta, Georgia, and if so, which features pose the most risk. The GIS Software, ArcGIS 10.2, along with the Spatial Analyst toolbox, the RTM toolbox, the RTMDx Polygon-to-Points tool, and the Intervention Planning Intel Report (IPIR) Toolset from the National Institute of Justice will be used for this study. The latter three tools are available free of charge from Rutgers University (rutgerscps.org/software). In addition, the RTMDx utility will be used to identify the most statistically significant model; the utility also outputs coefficients in order to weight the risk map layers, which can then be combined in ArcMap to produce the final risk terrain model.

Base maps of Valdosta were obtained upon request from the Southern Georgia Regional Commission (SGRC) GIS Department. The SGRC also compiles and supplies all crime data for the Valdosta Police Department. The dependent variables for this study are burglary incidents that occurred in Valdosta during 2015. Burglary locations were supplied as ArcGIS point data (shapefile). This data included addresses of burglary locations within the table in ArcMap. However, the maps used in this study contain no street names or specific identifiers. The only time these locations are pinpointed are on the map of the entire Valdosta city limits shown in Figure 1 and it would be nearly impossible to discern a specific address for a burglary incident in this map. In subsequent maps, burglary information is compiled into areas representing city blocks. Due to the fact that address data of burglary incidents was included in the initial data received, but was not identifiable in the study itself, an Institutional Review Board exemption was filed.

The independent variables chosen for this study were: apartments, schools, grocery stores, convenience stores, liquor stores, bars, night clubs, retail shops, laundromats, foreclosed properties, drug offenses, and areas of high gang activity. Apartment and school point data was supplied by the SGRC in addition to 2015 drug offenses. Only locations of drug selling and manufacturing were used for this study; arrests for possession were excluded as these tended to be spread out over the city since they are most often made during traffic stops. Foreclosure address data was downloaded from the Lowndes County Property website and was geocoded for ArcGIS. Addresses for all other variables were provided upon request by Infogroup Academic (infogroup.com) and were geocoded for ArcGIS. Areas of gang activity were provided on a map by the Valdosta Police Department. The image was imported into ArcMap, polygons were drawn over the highlighted areas, and these polygons were projected to match the projection of the base maps. Since the RTMDx utility only works with point data, the polygons were converted via the Polygon-to-Points tool.

Valdosta was modeled using a grid of 300 ft x 300 ft cells (N = 46,842). Since Valdosta is not designed on a grid system, like many cities, there is no uniform length of a city block. City block length is used in most RTM studies since it is the easiest way to define a micro-level place within the city that is also useful to law enforcement (Moreto, 2011). After several measurements were taken on a map of the city, 300 ft was chosen to represent that length. Previous research tells us that crime-prone places generally encompass an areas of only a few street blocks (Caplan, Kennedy, Barnum, & Piza, 2015). Therefore, the spatial influence of each feature was measured at a distance of one block (300 ft), two blocks (600 ft), and three blocks (900 ft). Features were tested for spatial influence based on proximity or density of features, with the sole exception of gang activity. The gang activity data obtained contained large polygons and the risk terrain modeling process only works on point data. The polygon-to-points tool was used to fill the polygon with points that could then be used in the model. However, this resulted in several dense groups of points that represented gang activity. Since it was unknown whether testing the gang data for density relationship would skew the data and possibly result in a spurious relationship, that feature was only tested for proximity.

The twelve factors, tested at three distances, with two operationalizations (proximity and density) for all but gang activity provides 71 possible variables for the model. The RTMDx Utility then tests the variables to determine the most statistically significant risk terrain model. An explanation of this process is given by Heffner (2013) in the RTMDx User Manual. Steps for manually completing this process can be found in the Risk Terrain Modeling Manual (Caplan & Kennedy, 2010). The Utility provides a regression model with coefficients for each statistically significant risk feature that show the impact that each feature has upon the burglary locations. The student version of the RTMDx Utility was used for this study to obtain the equation that was input into the ArcMap raster calculator in order to combine density maps of the significant risk features, which produced the final weighted risk terrain model. The NIJ Toolbox comes packaged with a tutorial that walks researchers through the process of building the risk terrain model and showcasing the results in a report.

Chapter IV

RESULTS

Modeling Burglary Risk

In 2015, there were 454 residential burglaries reported to the Valdosta Police Department within the Valdosta city limits. A pin map (Figure 1) shows locations of those burglaries. While it is possible to see some clustering, an Average Nearest Neighbor Analysis was run to confirm that the points were indeed clustered (z-score = -21.14, p-value = 0). Clustering shows that there is a pattern to burglary locations and that they are not dispersed evenly throughout the city, nor are the locations the result of random chance. This allows for an analysis into why certain locations are more likely to experience burglaries.

The next step of the process is to determine if the clusters are statistically significant. A grid must be created to cover the study area in order to divide it into equal and useable cells for studying small areas of the city. This is the 300 ft x 300 ft grid, referred to in the Methodology section, as representing an average city block. By joining this grid layer with the burglary layer, we get a map of the city, divided into small sections, with burglary incidents placed in the cells in which they occurred. We can then create a GETIs-ORD Gi* Hot Spot map by using the Hot Spot Analysis Tool in the Spatial Statistics Toolbox in ArcMap. This tool examines whether a high number of burglaries are clustering in an area, which are known as hot spots. The Gi* statistic produced is a z-score. A larger z-score means there is a greater amount of clustering. The tool also outputs a Gi p-value to show which clusters are actually statistically significant. The map output shown in Figure 2 shows only the statistically significant clusters where $p < .05$.

Figure 1. Map of 2015 Burglaries in Valdosta

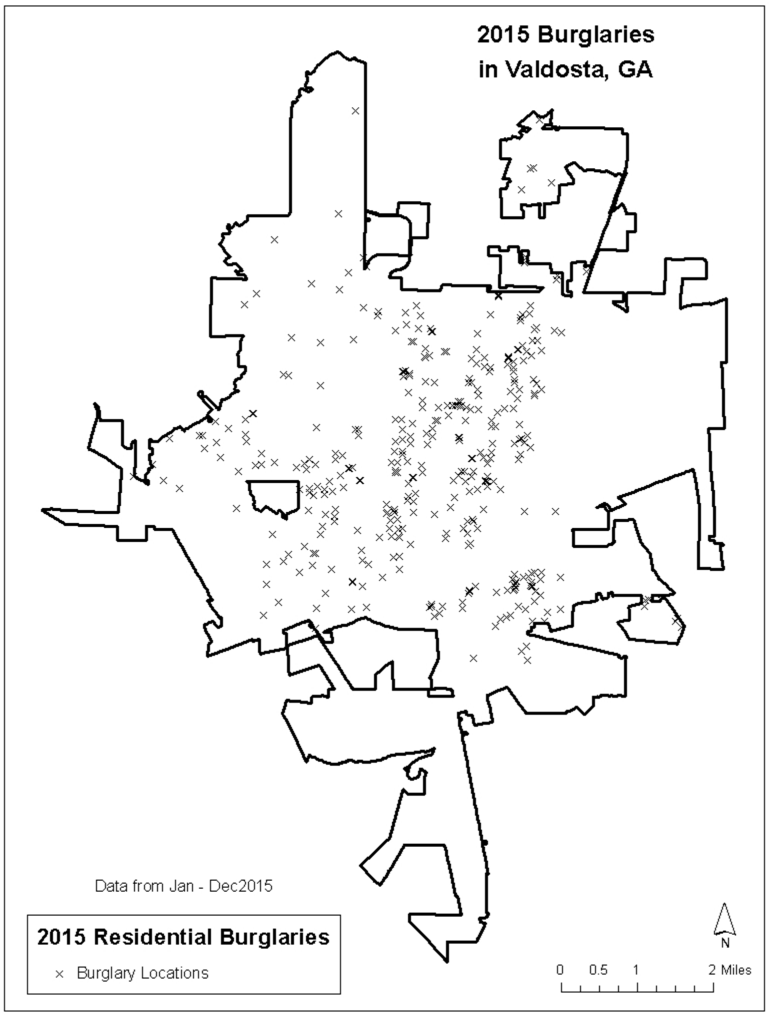
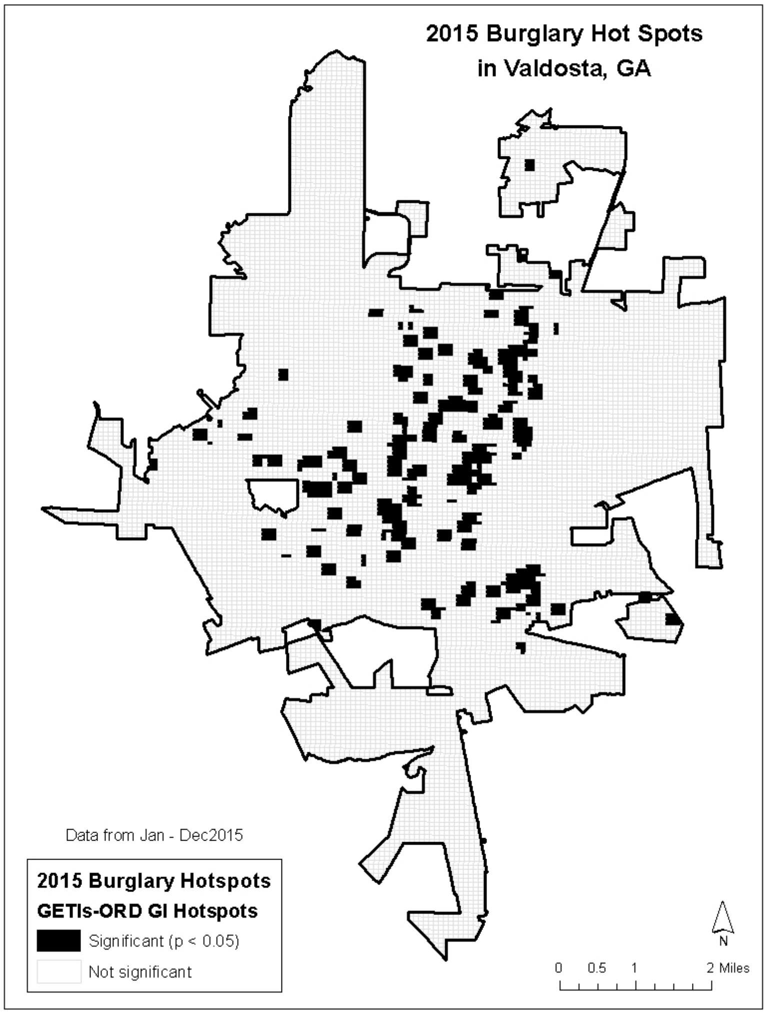


Figure 2. GETIs-ORD Gi* (Hot Spot Map) of Burglaries (p-value < .05)



Since the hot spots are not random, but are clustered, we can find factors that may be common to those areas by using the RTMDx utility. All twelve possible factors that resulted in the 71 variables previously mentioned were loaded into the RTMDx utility. The utility tested these variables against the presence of burglaries in each cell using a Poisson Regression model. The utility assigns a Bayesian Information Criterion (BIC) Score to each model and outputs the model with the highest BIC score. The best model found in this study was a negative binomial type II model with four risk features. (Again, see the RTMDx User Manual for an explanation of this process). Figure 3 contains a table of the features, listed with the best operationalization (whether proximity or density was chosen) and spatial influence, along with their coefficients and relative risk values (RRVs) as determined by the RTMDx Utility. The RRVs can be compared as such: a place influenced by apartments has an expected burglary rate that is over one and a half times as high as a place influenced by foreclosures (3.1922 / 1.9650 = 1.6245).

Type	Feature	Operationalization	Spatial Influence	Coefficient	Relative Risk Value
Rate	Apartments	Proximity	900	1.1607	3.1922
Rate	Drugs	Proximity	600	0.8393	2.3147
Rate	Foreclosures	Proximity	900	0.6755	1.9650
Rate	Gangs	Proximity	300	0.6558	1.9266
Rate	Intercept	--	--	-5.8712	--
Overdispersion	Intercept	--	--	-0.6073	--

Figure 3. Risk Factors for Burglaries in Valdosta (RTMDx Utility Output)

The RTMDx utility output the formula below showing the relationship of each factor that can be used in ArcMap to weight the risk feature layers; this was used to combine reclassified density maps of the four risk factors with the raster calculator in ArcMap. Figure 4 shows the result of that function.

```
Exp(-5.8712 + 1.1607 * "apartments" + 0.8393 * "Drug" + 0.6755 * "Foreclosures" + 0.6558 * "Gang") / Exp(-5.8712)
```

The model was assigned relative risk scores to cells ranging from 1 for the lowest risk cell to 28 for the highest risk cell. These scores allow cells to be easily compared. For instance, a cell with a score of 28 has an expected rate of crime that is 28 times higher than a cell with a score of 1. The red areas of the map in Figure 4 show areas that are 2.8 to 28 times more at risk than other areas. These areas are two standard deviations or more above the mean risk value; therefore they represent the top 5% of risk areas. To better show this, a hot spot map showing the most statistically significant risk areas was created using the GETIs-ORD Gi* tool in ArcMap. That map is presented in Figure 5.

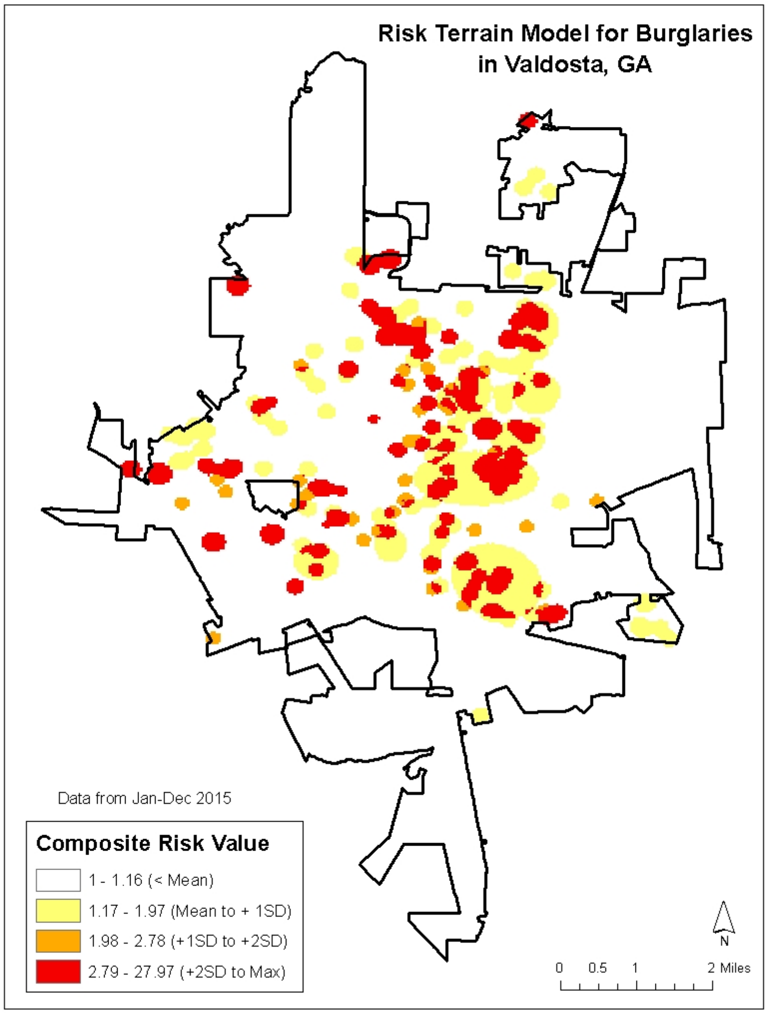


Figure 4. Risk Terrain Model for Burglaries in Valdosta

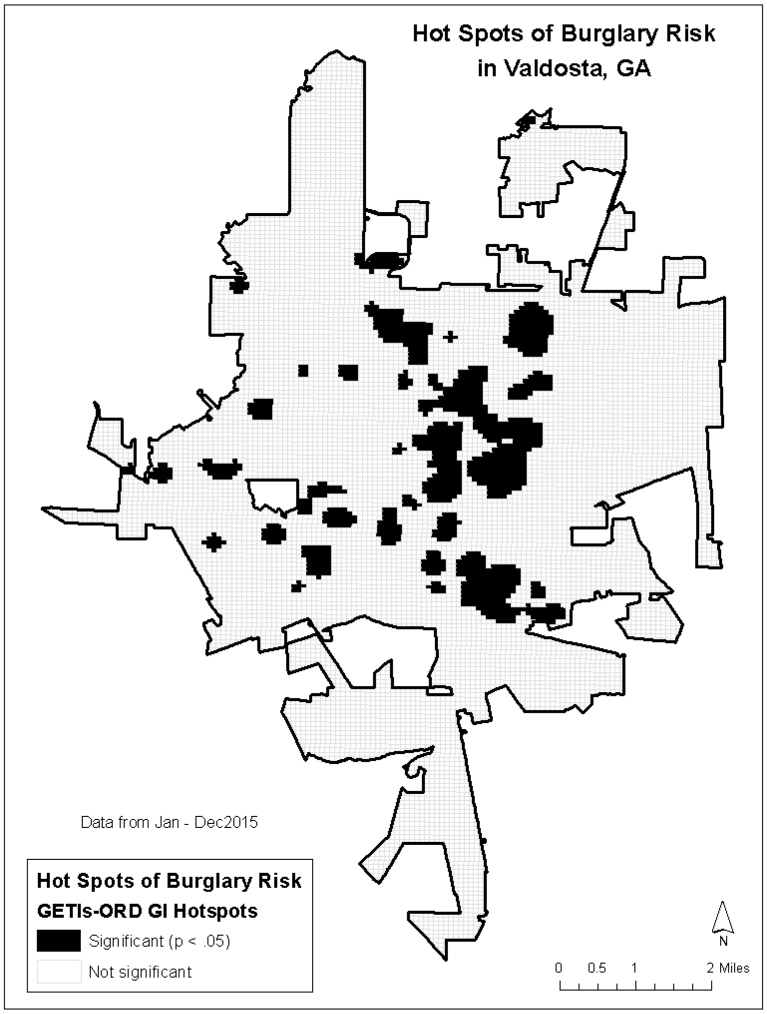


Figure 5. GETIs-ORD Gi* (Hot Spot Map) of Risky Areas (p-value < .05)

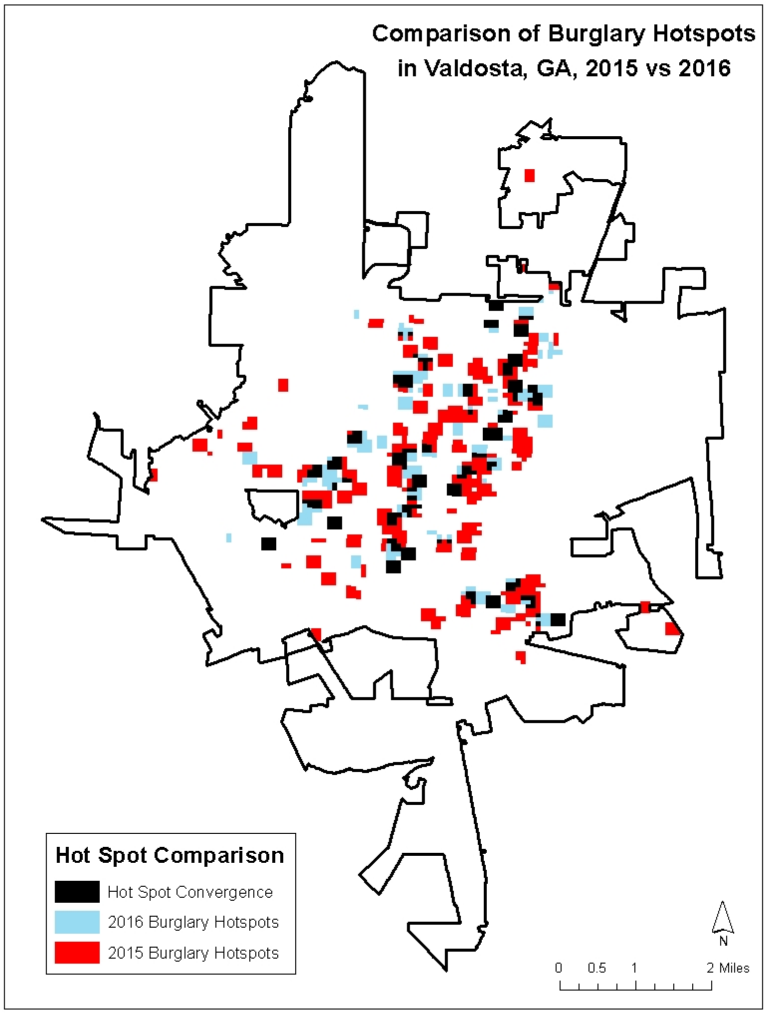
Testing the Model

The risk terrain model for burglaries in Valdosta gives us some insight into what environmental features could influence crime locations and highlights areas of town that are most "at risk" of being burglarized. These risky areas comprise 11% of the total land area in Valdosta. By joining the 2015 burglary locations with a layer containing the significant risk hot spots (shown above in Figure 5), it was determined that 47% percent of 2015 burglaries occurred in these areas. Therefore eleven percent of land area in Valdosta contained forty-seven percent of all burglaries in 2015.

Testing the model with crime data from a subsequent time period can also help determine how useful it will be to law enforcement and city officials in the future. The point of identifying risky areas is to guide policy makers as to how to make the most efficient use of their resources. While risk terrain models are not solely meant to be predictions of future crimes, it can be assumed that the “risky” areas identified will experience a higher rate of crime. Burglary data, supplied by the SGRC for the first half of 2016 (January - June), was mapped in ArcMap. By joining this 2016 data with the significant risk hot spots (shown in Figure 5), it was determined that 39% of burglaries occurred within the top 5% of risky areas.

There is an 8% reduction from 2015 to 2016 in the number of burglaries that occurred in the hot spots of the risk terrain model. While this is not a drastic reduction, it is worth determining whether there was a shift in where crimes were occurring during these two time periods. One of the assumptions of spatial crime mapping is that hot spots of crime do not typically shift significantly over short periods of time unless something is precipitating that move, like a targeted intervention by local law enforcement, or in the case of risk terrain mapping, if risk features change. A comparison of 2015 and 2016 hot spot maps shows that the hot spots for each time frame have shifted slightly to the northeast. Figure 6 shows the hot spots for each time frame and the areas where they converge are shown in black. This shows that the burglary trends have changed within the time-frame of the study. Perhaps a risk terrain model would be more effective at highlighting risky areas if the study was conducted on a more recent set of crime data, but this will be discussed in the next chapter.

Figure 6. Hot Spot Map Comparison for 2015 and 2016



Just as the timeframe of the study limited the applicability of the risk terrain model for future use, there were other limitations of this study as well. The data regarding gang activity received from the Valdosta Police Department was very general in nature and did not contain precise locations (e.g., specific street corners and actual addresses). Having more precise data may have also increased the precision of the risk terrain model.

Using features such as gang and drug activity that could move within the city is different than only using stationary features like apartment complexes or schools or grocery stores. A risk terrain model that utilizes these moveable features would need to be updated more frequently. This would also apply to foreclosures or vacant homes or other buildings in an area. This data is likely to change within just a few months' time. Perhaps using shorter time frames that allow for a re-mapping of risk features as they move may be more beneficial. The knowledge of law enforcement officials who work daily in these areas should guide research as trends change.

Chapter V

DISCUSSION AND CONCLUSION

This study found that areas that included four environmental features: apartments, drug offenses, foreclosures, and gang activity, were found to have higher rates of burglaries and were therefore identified as areas of high risk. The risk hot spots comprised only 11% of land area, but contained 47% of all burglaries in 2015.

The results of testing the risk terrain model with the 2016 burglary data raised some concerns for the application of this risk terrain model, which is why the comparison of 2015 and 2016 hot spots was conducted. It was shown in Figure 6 that the burglary trends were moving slightly northeast. According to a commander with the Valdosta Police Department (VPD), detectives became aware of increased targeting of military homes in 2016. Gang activity increased in the northeast corner of the city and over the border into the county's jurisdiction, closer to Moody Air Force Base. VPD personnel stated that gang members admitted to targeting military homes as they tended to own more firearms and electronics.

Future research should consider the shift of gang activity to these different areas and consider the areas of concentrated military residents. The large population of military members in the community was not initially considered in this study. In addition, more consideration should have been given to the large population of university students. These two groups, military and college students, make up a large portion of the community, a factor that may not have been present in cities and towns that have been previously studied, and was unfortunately overlooked in designing this study. While utilizing the characteristics unique to an individual city may decrease the generalizability of a study's results, it will prove much more useful to the law enforcement and city officials working to combat crime within their own community. Knowing this fact should encourage researchers to thoroughly examine the important characteristics of the community being studied.

This research also suggests that using shorter time-frames for modeling could produce more useful results. Even the best risk terrain models become ineffective once risk factors move. A suggestion for a department wishing to utilize risk terrain modeling is to begin with quarterly models. If it becomes obvious that there is little change between quarters, then the timeframes could be expanded to 6 months or longer. The benefit of conducting these kinds of analysis within a department is that the information can be updated as soon as supervisors become aware of changes in crime trends. Running a risk terrain model is not difficult or time-consuming once the initial data is set up, and as there is little to no cost for the software and training materials, the process of ongoing risk terrain modeling is accessible for any agency.

Law enforcement agencies can use this data to conduct place-based responses to crime before it even happens. By targeting the features in the environment that promote criminal activity, crime can be prevented without being simply displaced. In his 2016 TEDx Talk, Joel Caplan, one of the founders of RTM, gave the example of what can happen when law enforcement, community stakeholders, and city officials come together to understand their crime problem and to utilize the information in a risk terrain model. In Jersey City, New Jersey, gas stations with food marts were identified as the highest risk factor for violent crime, in addition to grocery stores and vacant buildings. The law enforcement officials there agreed that they always felt that gas stations were a problem, though this was really just a gut feeling. A community stakeholder at the meeting explained that many youth tend to hang out at the bodegas, which sell food, drinks, and rolling papers that they can use to smoke at nearby vacant buildings, but these places close at 10 pm. However, gas stations with food marts are allowed to stay open all night. These provide an area for youth to gather at night, which can lead to problems among rival gang members or just typical youth fighting. This explained why gas stations with food marts, grocery stores, and vacant buildings were such important risk factors.

The Department of Public Works suggested prioritizing boarding up vacant buildings and cleaning up vacant lots near the bodegas and gas stations with food marts. Officials from the Parks and Recreation Department and the mayor's office agreed to target the bodegas and gas stations where kids were spending most of their time to advertise their summer activities and job training programs. Caplan (2016) also described how the police agreed to do directed patrols, meet-and-greets with the business owners, referrals for support services for individuals they met in need, and also implemented a new protocol for writing reports that allowed for ongoing risk assessments.

The collaboration of researchers, law enforcement, city officials, and other community stakeholders is crucial to understanding the information that RTM provides and to implementing problem-solving strategies. By focusing on risky places in the way officials did in Jersey City, communities can change the environmental backcloth that allows criminal activity to occur into something positive.

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APPENDIX A:

Institutional Review Board Exemption