A GEOGRAPHIC UNDERSTANDING

OF BURGLARY HOTSPOTS

IN SAN ANTONIO, TEXAS

THESIS

Presented to the Graduate Councıl
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by

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DEDICATION

For Mommie Dearest,

You are my best friend and the

best mother anyone could ever have.

Thanks for helping me stick with it.

ACKNOWLEDGEMENTS

I would like to begin by giving thanks to my mom and dad, Lori and Herb Montanez, because without them, I never would have found, pursued, and conquered my dreams. I would also like to thank all of my family for being so encouraging, especially my grandparents, Robert and Marcella Heising, and my sister, Monica Montanez. I would also like to thank Allison Snyder for all of her assistance.

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ABSTRACT

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Increasing crime rates in expanding urban areas demand immediate attention. Geographic Information Systems (GIS) are used as a device to identify concentrations of crimes, but could prove beneficial as a tool to prevent crime. Routine Activity Theory maintains that to understand why crimes occur there must be an understanding of where criminals target, who is being targeted, and who is committing the crime. This paper presents a method to detect differences between crime hotspots and non-hotspots of burglaries, based on physical and demographic characteristics of census block groups in two police substations, Prue and Central, in San Antonio, Texas. By employing Spatial and Temporal Analysis of Crime (STAC), areas associated with high burglary incidents were identified. These areas were used to conduct a logistic regression based on components created in a factor analysis. This analysis could lead to a better understanding of the characteristics of high crime areas. The logistic regression for classifying characteristics inside and outside hotspot areas was significant. Comparison of the similarities and differences between the equations created for the Prue and Central substation offered insight into the importance of Routine Activity Theory and geography in crime hotspot identification.

CHAPTER I

INTRODUCTION

Criminal activities might make one person a victim, but the entire community feels the ramifications. Criminal activities affect the target of the crime, the police officers that respond to the crime, and the taxpayers who support the police department (Murray *et al.* 2001). Crime prevention is important to the individual who suffers and to the community that is threatened. Some cities are successful at curtailing crime while others are not. In 2003, the FBI reported that the national rate for violent crimes was 475.0 crimes per 100,000 persons and for property crimes was 3588.4 crimes per 100,000 persons. For the same year in San Antonio, Texas, the FBI reports that there were 485.0 violent crimes per 100,000 persons and 5715.9 property crimes per 100,000 persons (Federal Bureau of Investigation 2004). San Antonio has not been successful at lowering property crime rates over the last decade (Table 1).

The San Antonio Police Department uses geographic information systems to try to prevent crime. Using ArcGIS technology, the police department is able to identify areas of high crime, or hotspots, and reassign officers to these areas. While these tools are great sources for identifying where a problem is, they do not necessarily indicate why a problem is occurring in those areas (Mamalian and LaVigne 1999).

Table 1. San Antonio Burglary and Larceny Incidents by Year (SAPD 2004)

Year	Burglary	Larceny
1995	13,961	52,370
1996	13,685	60,488
1997	13,230	57,555
1998	11,984	53,301
1999	10,944	53,898
2000	11,604	60,952
2001	14,018	66,694
2002	13,368	65,251
2003	14,619	62,179
2004	14,720	60,868

Studies on why crimes occur are conducted by criminologists, sociologists and psychologists through analysis of deviant behavior, studying crime, and studying the effects of crime on society. Interest in the demographics of crime-prone areas began to heighten in the late 1970's and early 1980's with the introduction of sociological theories on crime (Miethe, Hughes, and McDowall 1991). These theories involved attributes of persons and their connection to crime. Currently, there are national surveys conducted yearly to create an understanding of most frequently targeted demographics. The National Bureau of Justice, using information from twelve cities in the United States, conducts these studies which report individual characteristics and involve little geography.

While the surveys conducted by the National Bureau of Justice are invaluable, they are aggregate surveys conducted in only twelve cities and lack relevance to cities that are different from those included in the survey. For example, all of the cities included in the last survey were less than 50% Hispanic; however, San Antonio, Texas is nearly 60% Hispanic (United States Census Bureau 2000). Therefore, a study that indicates Hispanics are more likely to be in high crime areas than whites seems inconclusive in a city that is predominantly Hispanic. It is the inability of the survey to identify with every city's history, demographics, and economics that mandates further studies at the city level (Rountree and Land 2000).

With increased studies on the demographics of high crime areas in the 1970's and 1980's came the development of theories that contributed to the understanding of what attracts criminals to an area. The development of Routine Activity Theory (Cohen and Felson, 1979) and the Lifestyle Exposure Theory (Hindelang, Gottfredson, and Garofalo, 1978) led to more research on the demographics of high crime areas, but still these studies lacked a spatial component.

Therefore, it appears reasonable that studies regarding demographics in high crime areas should not only focus on the parameters by which the crime was able to be committed, but should include location. A logistic regression analysis of the variables related to Routine Activity Theory in areas of high and low crime will show the demographics and physical characteristics related to those locations. Through the study of Routine Activity Theory and crime the following questions will be answered:

- Can geography help explain what the characteristics of high crime areas are?
- What are the demographics of high crime areas in San Antonio?
- Can Routine Activity Theory explain the differences between crime rates in hotspots and non-hotspots?
- Are there demographic differences between hotspots and non-hotspots?

This study is important because it will help address the lack of geography in the study of demographics and crime. Previous studies were conducted to generate an understanding of what areas are victimized, in the hopes of creating programs that will help prevent crime. However, the desire to prevent crime in an area mandates that geography be included in the equation.

For the purposes of this study it is important to understand how certain terms are being used. A high crime area, or hotspot, is an area that has higher than average crime or has a large share of the crimes for a whole region (University of Bradford 2003). The crime analyzed will be burglary, which is "the act of illegal entry with the intent to steal" (Gifis 1996, 61). Vehicular burglary is not included in this study, since automobiles are mobile and can be stolen from outside their ownership area. Inability to link an automobile to its area of ownership makes it difficult to determine if routine activities of a neighborhood or owner were related to the crime.

The study area will be limited to the area patrolled by the San Antonio Police Department (SAPD), since they will be the source of crime data. It will not include annexed cities within San Antonio. Two sections of the SAPD Patrol Beat will be examined, the Prue and Central Beats (Figure 1). The Central Beat includes the downtown, tourist district of San Antonio, an area with a greater population density and occurrences of crime. The Prue Beat includes the largest four-year university in San Antonio, the most recent high-scale, suburban developments, and the medical district of San Antonio. Analysis of these two distinct areas of San Antonio will permit comparison of the differences and similarities linked to high crime areas in the two beats.

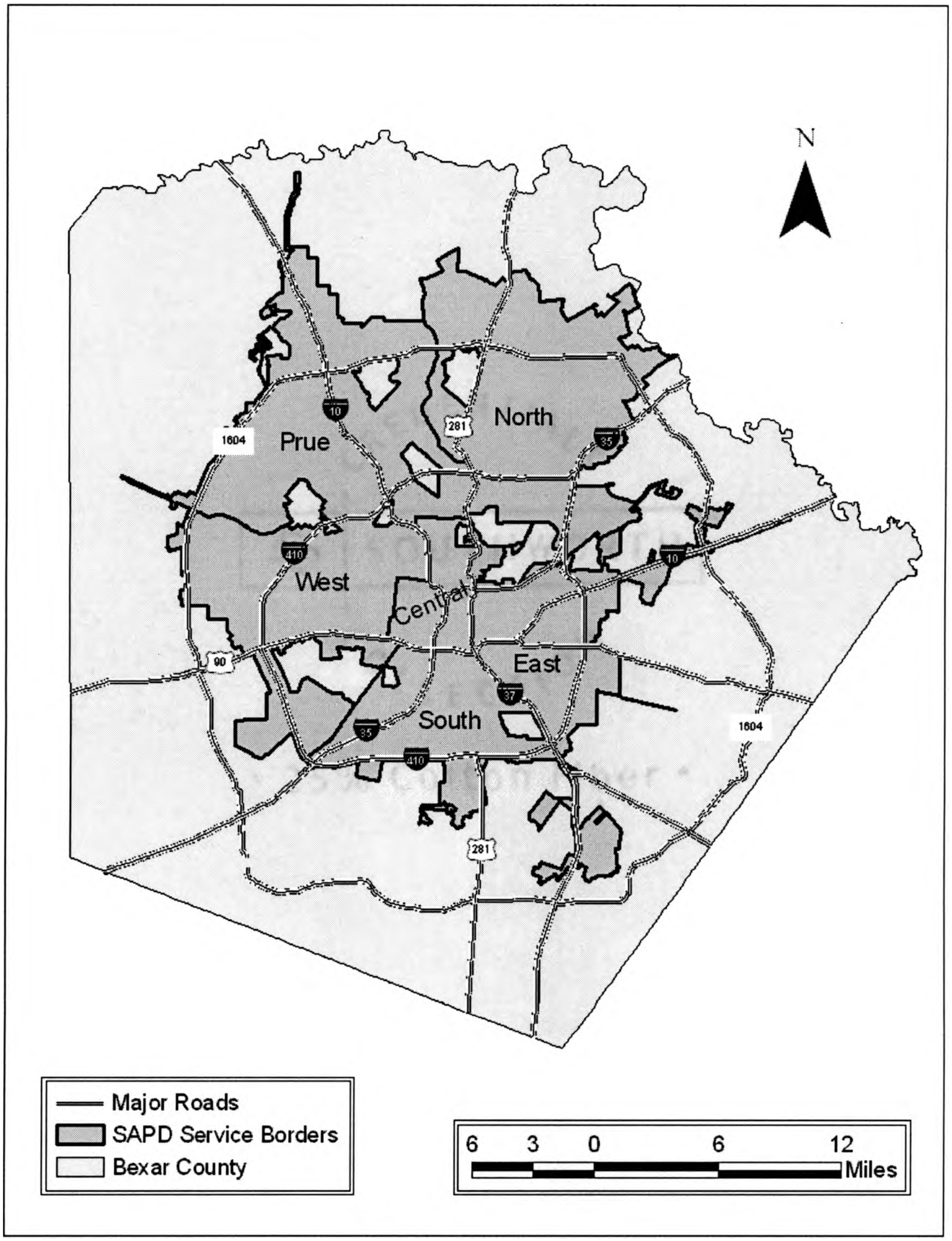

Figure 1. San Antonio Police Department Substation Districts

CHAPTER II

LITERATURE REVIEW

Explanations of the occurrences of crime are modeled in studies that focus on national victimization demographics, crime opportunity theories, and computer technology. By understanding the research in all three fields, the link between them can be created.

2.1 Victimization Studies

To understand the demographics related to crime rates, victimization studies are conducted by the United States Department of Justice every year. There are a variety of reports to help generate understanding of criminal victimization. Crime and demographic specific reports are published on victims of violent crimes, child rape victims, elderly victims, crime and neighborhoods, and crime and urban areas. The most comprehensive report created yearly is the Criminal Victimization survey. The last survey reported that property crimes were more likely to occur in urban areas, rented residences, in houses with a household income less than $35,000, to females, blacks, Hispanics, and persons ages 12-25 (Catalano 2004). This survey creates estimates from data collected using the National Crime Victimization Survey (NCVS), which interviews about 75,000 persons in 42,000 households twice annually. Participating cities were: Chicago, IL, Kansas City, MO, Knoxville, TN, Los Angeles, CA, Madison, WI, New York, NY, San Diego, CA, Savannah, GA, Spokane, WA, Springfield, MA, Tucson, AZ, and Washington, DC (U.S. Department of Justice 2004). These surveys are used as the basis for many studies, but unfortunately lack geographic information. These studies are also not the best predictors for routine activities and crime because they are aggregated data collected from a small percent of the population (Lauritsen 2001; Miethe and Meier 1990). These studies also focus more on the characteristics of the individual, but victimization is more likely to be a result of the characteristics of the social and economic make-up of the neighborhoods where a person resides as well (Baldwin and Bottoms 1976).

2.2 Criminal Opportunity Theories

Criminal opportunity theories were created to explain why crimes occur where they do and why there is variation between places. In the late 1970's, two theories were developed that changed the way people studied crime and its victims. Lifestyle Exposure Theory (Hindelang, Gottfredson, and Garofalo 1978) and Routine Activity Theory (Cohen and Felson 1979) fall under the domain of criminal opportunity theories because they help explain circumstances for the occurrence of crime (Miethe and McDowall 1993). These two theories share similarities with Rational Choice Theory (Becker 1968, Cornish and Clarke 1987) and Situational Crime Theory (Bennett 1986). While these theories are not the focus of the study, they are important because of what they add to theories on criminal opportunity.

Rational Choice Theory is based upon the economic theory of cost-benefit analysis, which maintains that decisions are based upon comparisons of risk and profit (Becker 1968). Action is taken by criminals based on the information they have on the conditions under which they will be acting. Situational Crime Prevention Theory concludes that the final decision to commit a crime is determined by immediate situations and circumstances, and therefore a situation will not motivate an unmotivated offender, but will encourage a person who is committed to the offense. This person has already considered the costs and benefits, made a rational choice to offend, and is motivated to commit by the situation (Bennett 1986). Therefore, certain places and situations are attractors of criminal activity and by understanding and managing these situations, crime is minimized. Both theories imply that crime occurs when a criminal is knowledgeable of the situation and perceives that they can make the most profit with the least risk. It is not an increase in motivated offenders that leads to an increase in crime, but an increase in situations that make crime more possible with fewer risks. If a constant level of offender motivation is assumed, variability in crime is explained by variations in structural conditions that are conducive to crime opportunities (Miethe, Hughes, and McDowall 1991).

Lifestyle Exposure Theory suggests that the characteristics or demographics of a person affect his choice in personal lifestyle. Certain lifestyles might make a person a better target for criminals. "These lifestyles, in turn, may be related to being in places and situations with high opportunities for criminal victimization. The patterns of personal characteristics that combine to yield low probability of victimization may be associated with behavior patterns that do not as frequently place the person in high opportunity situations (Hindelang, Gottfredson, and Garofalo 1978, 121)." Risky behavior is linked to different age groups, sexes, household types, etc. It can also be said that changes in an individual's activities increase crime rates due to increased contact with offenders, greater target attractiveness, or decreased guardianship (Miethe, Hughes, and McDowall 1991).

Routine Activity Theory maintains that a convergence of three variables leads to the execution of a crime and integrates the aforementioned theories to understand crime. Cohen and Felson (1979) assert that there must be a motivated offender, a suitable target, and the absence of a capable guardian. While all three variables must be present for a crime to occur, increased opportunities do arise when there are targets that are more suitable and absent guardians. Therefore, understanding what motivates offenders might be the key to decreasing crime. Using each of these theories in combination with each other aids in the understanding of what makes a person or neighborhood more vulnerable to crime (Figure 2).

While there are many different types of crime, crime opportunity theories, more specifically Routine Activity Theory, work best at explaining certain types of crime. Since Routine Activity Theory is contingent upon the absence of a guardian and the suitability of a target, it is best at explaining property crimes and not personal or violent crimes (Bennett 1991; Cantor and Landing 1985; Cohen and Felson 1979; Miethe, Stafford, and Long 1987). More specifically, crime opportunity theories work best for explaining property crime when studies make a distinction between burglary and larceny (Robinson 1999; Thompson and Fisher 1996). Many studies have been conducted on Routine Activity Theory and property crime. While many of these studies lack a spatial component, most report similar indicators of high crime areas based on Routine Activity Theory.

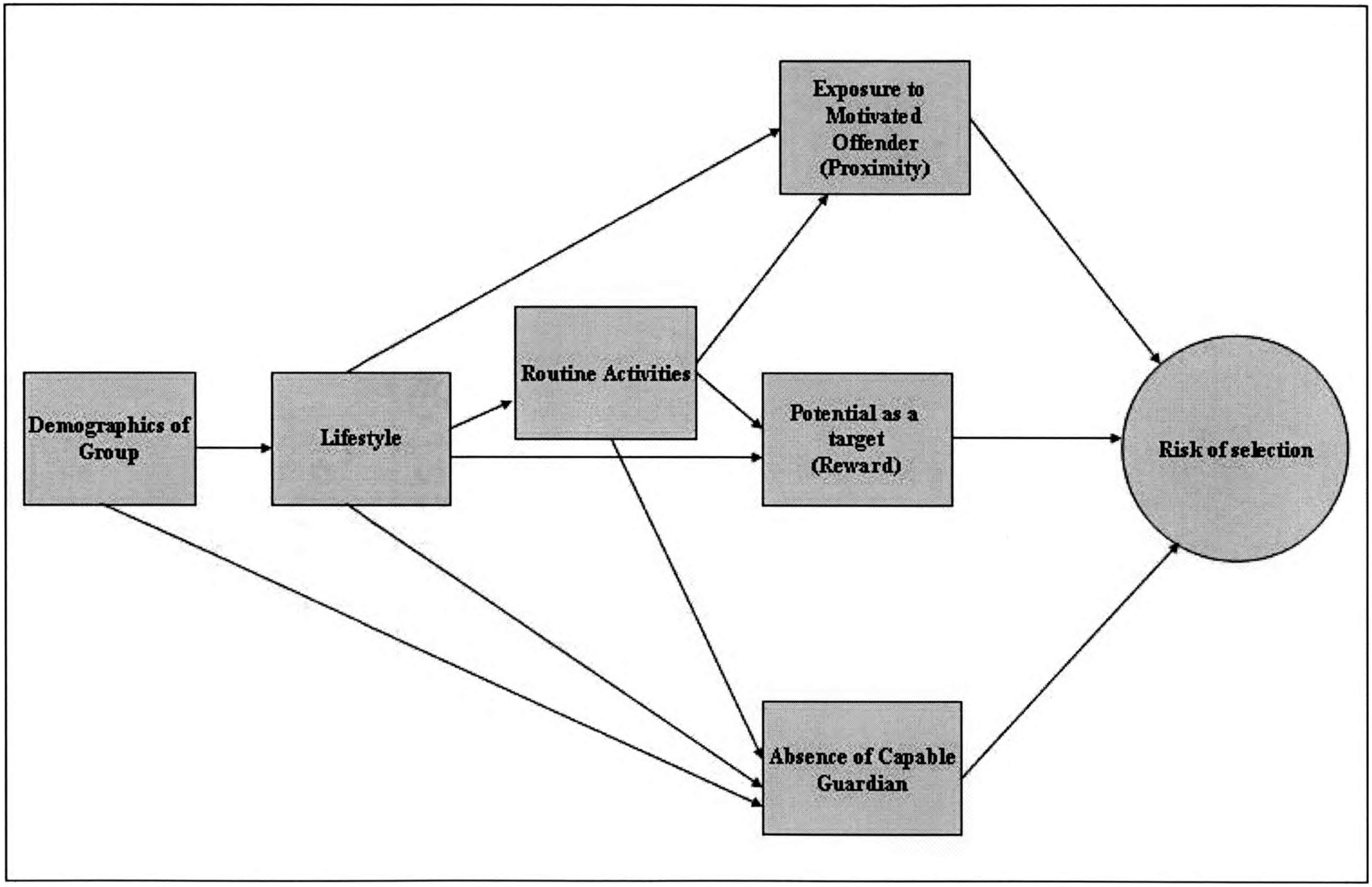

Figure 2. Breakdown of Routine Activities Theory (Hough 1987)

A motivated offender is a person that sees an opportunity to commit a crime, has a motive, and has the means to execute the crime (Maxfield 1987). This implies that the greater the number of motivated offenders in a neighborhood, the greater the chance of a neighborhood being victimized. Areas with high population density increase the likelihood that an offender will be amongst the population (Bennett 1991; Cohen, Klugel, and Land 1981). However, motivation is necessary to fuel the offender. In the case of burglary and larceny, money is the motivation. It is through an offender's execution of routine activities in an area where they are familiar through non-criminal activities that they are able to observe possible targets (Eck and Weisburd 1995, 6). It is theorized that offenders prefer to stay in their own neighborhood or side of town because they are familiar with the surroundings. Therefore, if a person wishes to steal something for profit, chances are they will steal from within the area they live (Warner and Rountree 1997). Low-income, high density neighborhoods become at risk for crime due to the motivation of the offender to commit a crime in a familiar area. There are certain socioeconomic characteristics that are related to low income areas that create high motivation for offenders. These characteristics make a person more susceptible for reasons that relate to the three components of routine activity. These socioeconomic characteristics include disabled persons, female head of household with children, greater percentage of males, persons with no high school diploma, young adults age 19 to 24, one-person households, and renters (Cahill and Mulligan 2003).

A suitable target could involve characteristics of both the house and the neighborhood. The characteristics of the house would involve its tenure, age, and size because to motivate offenders there must be something of value that is easy to obtain

(Hakim 1995; Hakim, Rengert, and Shackmurove 2001; Miethe and Meier 1990). The neighborhood affects suitability because of the attributes that make the area accessible (Felson 1983). First is the issue of road access. Studies have shown that areas that are on streets with the most possible routes make attractive choices for offenders (Bevis and Nutter 1977; Buck *et al.* 1993; Hakim, Rengert, and Shachmurove 2001; Rengert and Wasilchick 1985). The farther a person is able to travel on a road network, the probability that they can escape with stolen goods increases (Lu 2003). Bus stops are also related to the attractiveness and accessibility of a site, where areas closer to these stops have higher rates of victimization (Groff and LaVigne 2001; Miethe and McDowall 1993; Murray *et al.* 2001).

The last variable of Routine Activity Theory relates to the presence of a guardian. At the social level, this could imply many different characteristics. Criminals want to avoid being visible and visibility is increased based on the type of people and housing in a neighborhood (Bennett 1991; Cromwell, Olson and Avary 1991; Wright and Decker, 1994). First, as the number of people per square mile increases, so does the chance that there will be someone to see a crime committed (Bennett 1991; Cantor and Land 1985; Cohen, Klugel, and Land 1981). Urban areas and areas where the land use is residential and commercial are more densely populated (Bowers and Hirchfield 1999; Groff and LaVigne 2001; Sampson and Groves 1989; Shaw and McKay 1942; Veysey and Messner 1999). Areas where there are neighborhood associations or areas close to police stations are also avoided by criminals (Bennett 1991; Murray *et al.* 2001). If a target is by vacant housing, parks, or wooded areas, they have lower levels of guardianship (Buck, Hakim, and Rengert 1993; Groff and LaVigne 2001; Hakim 1995; Hamik, Rengert, and

Shachmurove 2001; Miethe and McDowall 1993; Shover 1996). Housing becomes more attractive to those hoping to avoid residents based on the occupants and tenure of the housing (Bowers and Hirchfield 1999; Groff and LaVigne 2001; Spelman 1993).

On the individual level, guardianship is implied by a person's demographics. Communities where older persons, the unemployed, and large-sized households exist are victimized less. This occurs because there is a greater chance that someone will witness a crime or be in the house when a crime is committed (Reppetto 1974; Smith and Jarjoura 1989). The racial mixture of the neighborhood also plays a factor in the area's suitability. More homogenous neighborhoods are more closely tied together, whereas neighbors that do not have strong ties are more likely to be victimized (Rountree and Land 2000; Sampson and Groves 1989; Shaw and McKay 1942; Smith and Jarjoura 1989; Veysey and Messner 1999). Neighbors are also more likely to be close when residents have lived in the area longer and there is little disruption and turnover of residents in the area (Miethe and McDowall 1993; Rountree and Land 2000; Sampson and Groves 1989; Shaw and McKay 1942; Smith and Jarjoura 1989; Veysey and Messner 1999). Also related to the guardianship of a house are the work and travel habits of the houses occupants. Since burglaries are more likely to occur at night, a house is more likely to be a target if the occupants work during the night time. Also, if the occupants work long hours, this leaves more time when the house is unoccupied and unguarded (Robinson and Robinson 1997).

2.3 Geographic Information Systems and Statistics

While most studies of geographic information systems and crime involve finding the best means to identify hotspots of criminal activity, some studies have analyzed victimization. Studies on hotspots and victimization are seldom conducted together. Usually, results from hotspot analysis are used to conduct where criminal justice resources should be allocated instead of using the analysis to see what might cause crime in the area (Rich 1999). Most studies closely related to this study are either based on statistics or geographic information sciences.

Bowers and Hirschfield (1999) conducted a study on the distribution of crime and the demographics of income and prosperity. Through the use of GIS, the authors conducted crime pattern analysis to uncover hotspots in their study area in England. The authors retrieved demographics for three of the hotspot areas. Demographics were also used to create raster data classifying the lifestyle types of neighborhoods. This raster was overlaid with the hotspot ellipses for comparison. The study determined that high density areas with single parent families, young adults, and high unemployment suffer the most crime.

A study of three cities was conducted to determine the generalizability of burglary prediction models based on crime opportunity theories. The goal of the study was to determine if similar indicators could predict crime in three cities with distinct economic histories and racial compositions. Logistic regression was used to create to burglary victimization models based on individual and neighborhood variables. The authors concluded that the inclusion of community-level characteristics decreased a model's variation in burglary victimization across neighborhoods and the effects of individual level characteristics are constant across neighborhoods (Rountree and Land 2000).

A study examined the likelihood of a house being burglarized based on physical characteristics. Using logistic regression, they were able to determine which houses were most vulnerable based on the characteristics of the home, preventative measures used by the owners, and its situation in space. This study was only conducted on the individual characteristics of a home however, and did not include neighborhood variables. The study concluded that single family, detached homes were more prone to burglary (Hakim, Rengert, and Shachmurove 2001).

Raster calculations were used to create a predictive model of crime based on crime opportunity theories in another study. By finding attributes that relate to crime opportunity theories, the authors created Boolean rasters of each variable. By calculating the product of these rasters, the authors were able to predict areas that should have a high crime rate. Through comparison to hotspots of crimes that occurred in previous years, the authors deduced that they had a somewhat accurate predictive model. They determined that areas close to major thoroughfares, bus stops, and vacant and wooded areas were at high risk for victimization (Groff and La Vigne 2001).

To understand the patterns in violent crime and demographics through Social Disorganization Theory, a study was conducted that integrated regression and geographic information systems in Tucson, Arizona. Based on the variables linked to Social Disorganization Theory, a GIS was used to create a predication map. From a set of 27 variables linked to Social Disorganization Theory, a factorial analysis was conducted. Based on the five resulting factor loadings, the authors narrowed the 27 variables to 10 variables related to Social Disorganization Theory and the five components. An Ordinary Least Squares Regression was conducted for three different measures of crime. Of the three types of crime measurements, comprehensive violence rate proved the most productive for a model. The comprehensive violence rate measured the rates of aggravated assault, homicide, robbery, and sexual assault per thousand persons living in a block group. The authors concluded that Social Disorganization was a valid theory for the explanation of crime patterns in Tucson, Arizona (Cahill and Mulligan 2003).

CHAPTER III

DATA AND METHODOLOGY

Two types of data had to be addressed with separate methodologies. First, measures had to be employed to differentiate between hotspots and non-hotspots of point crime data. Secondly, methods had to be employed to determine if demographics of census block groups differ between areas of high and low crime. Both methodologies made use of geographic information systems or computer statistical packages.

3.1 Data

The San Antonio Police Department maintains a website with information about crime activities over the last two years (http://www.ci.sat.tx.us/sapd). There are crime data sheets in Excel format for all six police subdivisions. These tables include the date of occurrence, the type of crime, the address, and x-y coordinates of the occurrence.

Data was gathered for November 2004 for both the Prue and Central Police Substations. These two districts were chosen because of their distinct differences in population, income, and development. The Central area is the downtown portion of San Antonio, which is completely urban, and tends to have more crime and a high population density. The Prue area is on the northwest side of town, is mostly suburban, and is known as an area of town where more affluent people live. In November 2004 there were 179 burglaries in the Central beat and 194 burglaries in the Prue beat (Figure 3 and Figure 4).

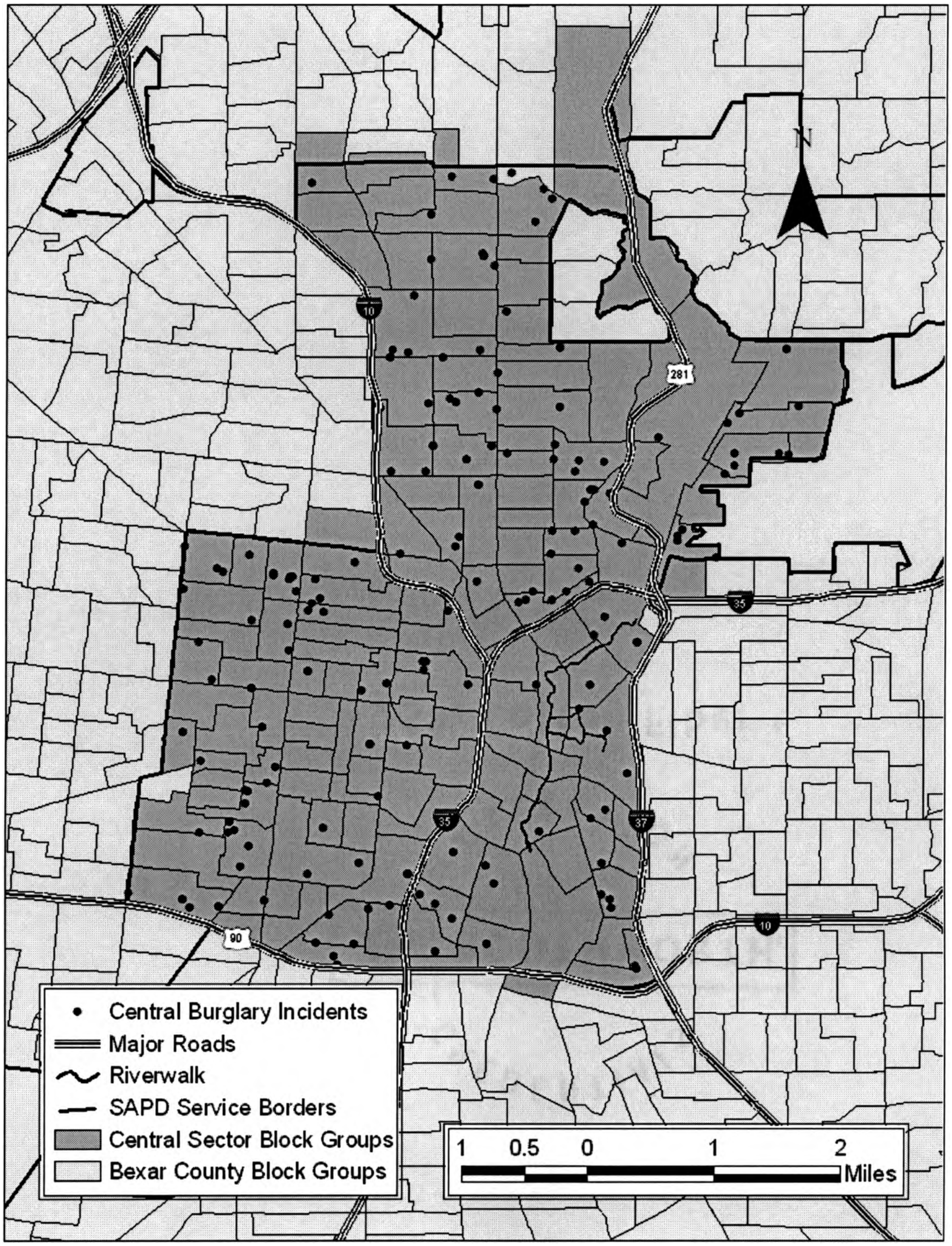

Figure 3. Burglaries and Block Groups in Study Area, Central District

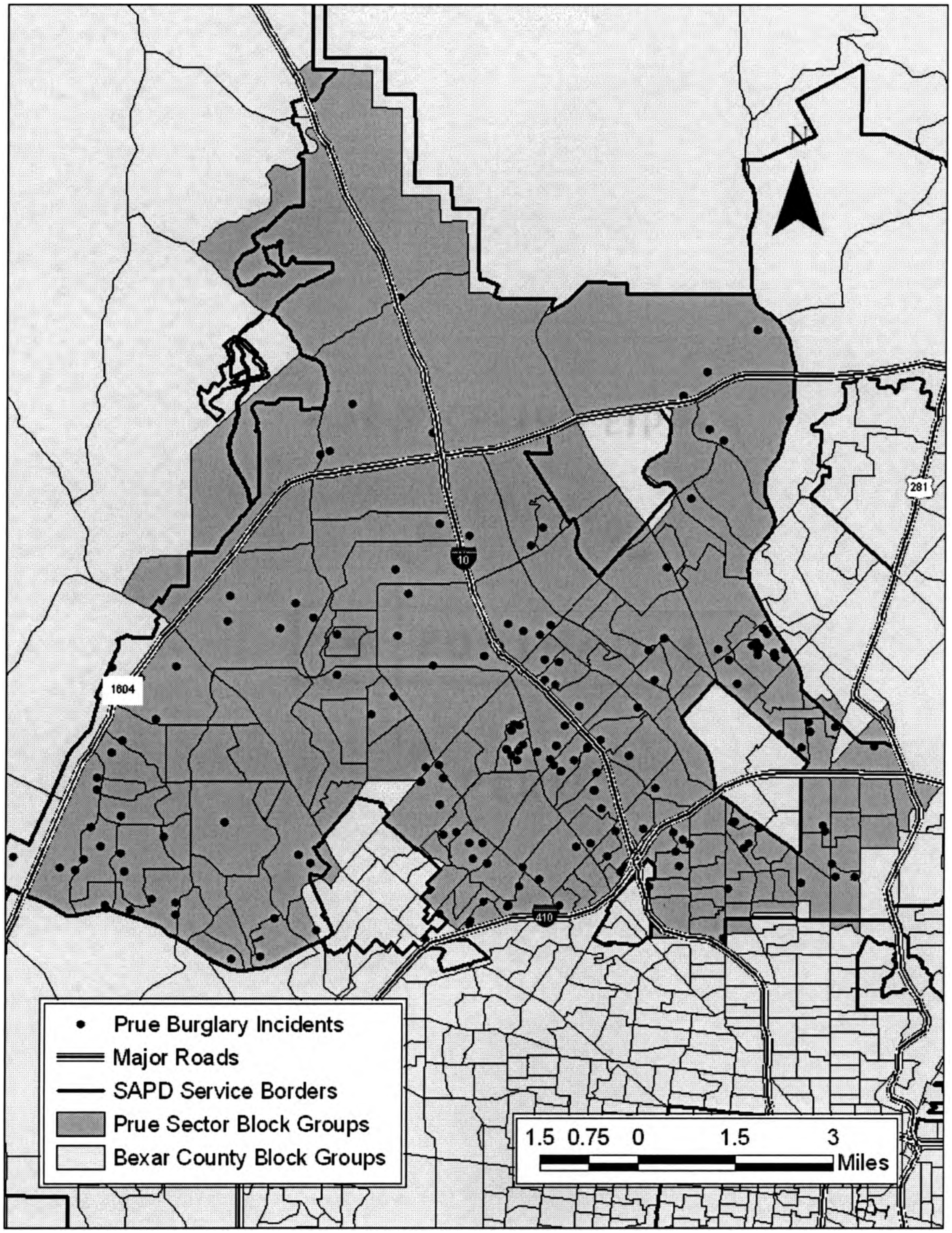

Figure 4. Burglaries and Block Groups in Study Area, Prue District

From the SAPD table, crimes were extracted that related to burglary, excluding vehicular burglary. These crimes were added to a GIS using the x- and y- coordinates. They were used to conduct an analysis of hotspots and non-hotspots of criminal activity.

Individual demographic data for Bexar County in 2000 was accessed from the Census Bureau Summary File 3 (SF3). These summary files present detailed population and housing data collected from a 1-in-6 sample and weighted to represent the total population. The demographic data at the block-group level includes information about tenure, housing, race/ethnicity, age, sex, family and marital status, employment, and income. All variables were divided by the total population or amount of housing in each block group to obtain ratio-level data for each (See Table 2).

Land use and land cover information was available from Texas Natural Resources Information System. It is downloadable in the form of shapefiles for use with ArcGIS. It includes aggregate information on the dominant land type for Bexar County and was clipped to calculate the number of different land use/land covers per block group in each of the two police beats.

Data regarding parks, bus stops, neighborhood associations, and police patrol areas was obtained from the City of San Antonio website (http://maps.sanantonio.gov). This data was downloadable in the form of shapefiles formatted for ArcGIS. They were ready for use upon downloading and were used to calculate the number of each object per block group.

Data for Bexar County for census block groups and roads were available from ESRI in the form of shapefiles. The block group and roads shapefile contain names and

Table 2. List of Census and Physical Variables and Their Descriptions

	Variables	Description
Demographics	AVE_HH_SZ	Average household size
	BUILT_90	Percent of houses built before 1990
	DISABLE	Percent with any disability
	FHH_CHILD	Percent of female head of household with child
	N/WHITE	Heterogeneity index[1]
	MALES	Percent male
	MD_ROOM	Median number of rooms per house
	MOVE_95	Percent of persons who moved in after 1995
	NODIPLO	Percent of persons with no high school diploma
	OVER_65	Percent over 65 years old
	P_19_24	Percent of 19 to 24 years old
	PERSON_1	Percent of one-person households
	POVERTY	Percent receiving poverty assistance
	RENTERS	Percent of renters
	UNEMPLOY	Percent unemployed
	VACANT	Percent of vacant housing
	WRK_35	Percent of persons working more than 35 hours a week
	WRK_4	Percent of persons leaving for work between 4:00 p.m. and 11:59 p.m.
Physical	BUS_STOP	Number of bus stops per square mile
	NEIGHBOR	Number of neighborhood associations per block group
	NUM_LULC	Number of different land use/cover in block group
	PARK_ACR	Acreage of parks per block group
	POL_ST_D	Distance of police departments from block group
	PP_SQML	Population per square mile
	ROAD_LN	Miles of road per block group
	NUM_RDS	Number of roads per block group

[1] Heterogeneity Index was calculated with the following equation: $1-\sum \rho_i^2$, where ρ_i is the proportion the population that is Hispanic and Black. The index ranges from zero (most diverse) to one (homogenous) (Cahill and Mulligan 2003, 593). For this study it is important to remember that more homogeneous areas are likely to comprise of more Hispanics, since San Antonio is over 60% Hispanic.

variables that were useful for computation of routine activity variables. Since some census block groups do not fall completely within the San Antonio boundary only census block groups that are at least 50% inside the Prue and Central police beat boundary were included in the analysis (Figure 3 and Figure 4).

3.2 Hot Spot Analysis

The determination of hotspots and non-hotspots was conducted on the crime point data from the San Antonio Police Department using a tool designed specifically for crime hotspot analysis. The Spatial and Temporal Analysis of Crime (STAC) is available through CrimeStat 2.0, a free downloadable software package created for the analysis of crime data. The STAC tool uses point data to identify the densest clusters and create density hotspots with best fitting standard deviation ellipses. STAC uses a scan-type clustering algorithm, and combines elements of partioning and hierarchical clustering (Block and Block 2002).

The scan-type clustering algorithm lays circles repeatedly over a grid and the number of points within each circle are summed; however, the STAC algorithm also combines overlapping clusters until there are no longer any overlapping circles. The search circles are part of partioning clustering and the agglomerated circles are part of hierarchical clustering. STAC has a seven-step procedure for calculating hotspot areas, described here with modification for this analysis in San Antonio. First, a 20-by-20 rectangular or triangular grid is laid out on the area, defined by the boundaries of both police service areas. Next, a circle with radius 1.414 (units based on search radius) is placed on every node in the grid. The number of incidences in each circle is counted, allowing for the ranking of each circle in descending order. The software stores any nodes with two incidents inside the search radius, along with the incident count for that node. From these stored node values, the program selects the top 25 search areas. These 25 search areas are combined if there are similar points in them. Combination continues until there are no overlapping circles. This creates hot clusters, which are only created if there are at least 5 incidents in the cluster. The software then calculates one standard deviation ellipses that best fit each hot cluster. One standard deviation is used to prevent overlapping ellipses (Block and Block 2002).

Using the point data for burglary, STAC was run on both the Prue and Central data. In ArcGIS, x and y boundaries were determined for each beat. These boundaries were inserted into STAC so that it could calculate the clusters based on the area monitored by the police substation. Based on preliminary testing of data, certain parameters were determined for the Prue and Central block groups. For the Prue substation, a triangular STAC was run because the street network in the area is irregular. The STAC was also run on a half mile search radius. Conducting STAC with a larger search radius causes exaggerated ellipses, and a smaller search radius creates insignificant ellipses. For the Central substation, a rectangular STAC was conducted since the streets are grided throughout the area. Since the Central substation is about half the size of the Prue substation area, a quarter mile search radius was employed. For both STAC searches, a minimum of five crimes must occur within the search radius for it to save the ellipses. This number was selected because it made the size of the ellipses most manageable.

The ellipses were then used to determine which block groups intersect hotspots. Those block groups that intersect the hotspot ellipses were marked with the value of one.

All other block groups were marked with the value of zero. These values were used for the logistic regression.

ArcGIS was also used to prepare data for the statistical analysis. Individual and housing variables were included in the census block group data, but physical characteristics were not. ArcGIS was used to compute the number of bus stops, the number of streets, the miles of streets, the acreage of parks, the number of neighborhood associations, and the number of different land uses per census block group. ArcGIS was also used to calculate the average distance of a census block group from the nearest police station. Once all of the data was merged together, it was exported for use in SPSS.

3.3 Testing Routine Activity Theory

Computations were conducted on each of the demographic variables to make sure that they reflect the percentage of the population per block group related to that variable. These computations were conducted in Microsoft Excel. Ratio data was acquired by finding the number of variables compared to the population of each census block group.

After all of the attributes had been determined for the block groups, a factor analysis was conducted to reduce the number of variables included in the regression. The analysis was run using varimax rotation and a maximum of 25 iterations. Only factor loadings with eigenvalues greater than one were used in the logistic regression. The top three variables in each factor loading were considered to explain the variable represented by the factor scores, since most components consisted of only two or three variables. For larger components, all high loading variables were used to determine the factor name. Factor loadings were calculated for both the Prue and Central Patrol Beats. The factor loading scores were stored as regression variables for use in a logistic regression. A binary logistic regression was used to compare the factor loadings for hotspot block groups to non-hotspot block groups (based on the values of one and zero explain earlier) in both the Prue and Central Patrol Beats. This helped determine the percent of variance in the dependent variable explained by the independent variables, rank the importance of the independent variables, and assess the interaction effects of the independent variables. A backward stepwise method was used to determine which factors significantly predict the dependent variable. The resulting scores created a model that predicts which group of demographic and physical characteristics, both individual and community level, are distinct between areas that are hotspots and those that are non-hotspots. The -2 Log Likelihood statistics were used to gauge the fit of the model. Odds ratios were used to determine if an increase of the predictor variables will increase the odds of classification. The Model chi-square was used to measure the improvement of the fit of the model compared to the null model. The Wald statistic was used to test the significance of individual logistic regression coefficients for each independent variable (Mertler and Vannatta 2002). The models for both the Prue and Central Patrol Beats were compared to determine if the components in the models are similar, or if location indicates different patterns in burglary hotspots.

CHAPTER IV

RESULTS

The results from the hotspot analysis, factor analysis, and logistic regression are all presented on the demographics and physical characteristics of high crime areas. These results were used to interpret the predictive model created by this study.

4.1 Hotspot Analysis

To determine areas of high crime, the burglary events in the Prue and Central Patrol Beats were analyzed using STAC to create hotspot ellipsoids (Table 3). For the Central district, there were nine ellipsoids which were scattered throughout the area, most located near the Interstate Highway 10 corridor (Figure 5). For the Prue district, there were only four ellipsoids which were located near the southern edge of the district (Figure 6). The numbers for each STAC ellipsoid on the following maps correspond to the ellipsoids listed in Table 3. In all there were 26 block groups completely or partially included by STAC ellipsoids in the Central district and 11 block groups completely or partially included by STAC ellipsoids in the Prue district (Figure 7 and Figure 8). Of the crimes committed in each district, the hotspots in the Central area contain 34% of the crimes for November, whereas the Prue hotspots only contain 16% of the crimes committed. The hotspot block groups cover about 19% of the total area in the Central district and cover only 6% of the total area in the Prue district. While the Central area has hotspots that spread over a larger area, one third of the crimes are concentrated

Table 3. Evaluation of Hot Spot Ellipses for both Districts in San Antonio

Police Beat	Cluster ID	Crimes per Cluster	Area of Cluster (in square miles)
Central			
	1	12	0.167
	2	9	0.091
	3	8	0.081
	4	6	0.114
	5	6	0.150
	6	5	0.229
	7	5	0.067
	8	5	0.075
	9	5	0.042
Prue			
	1	11	0.137
	2	9	0.018
	3	5	0.300
	4	5	0.589

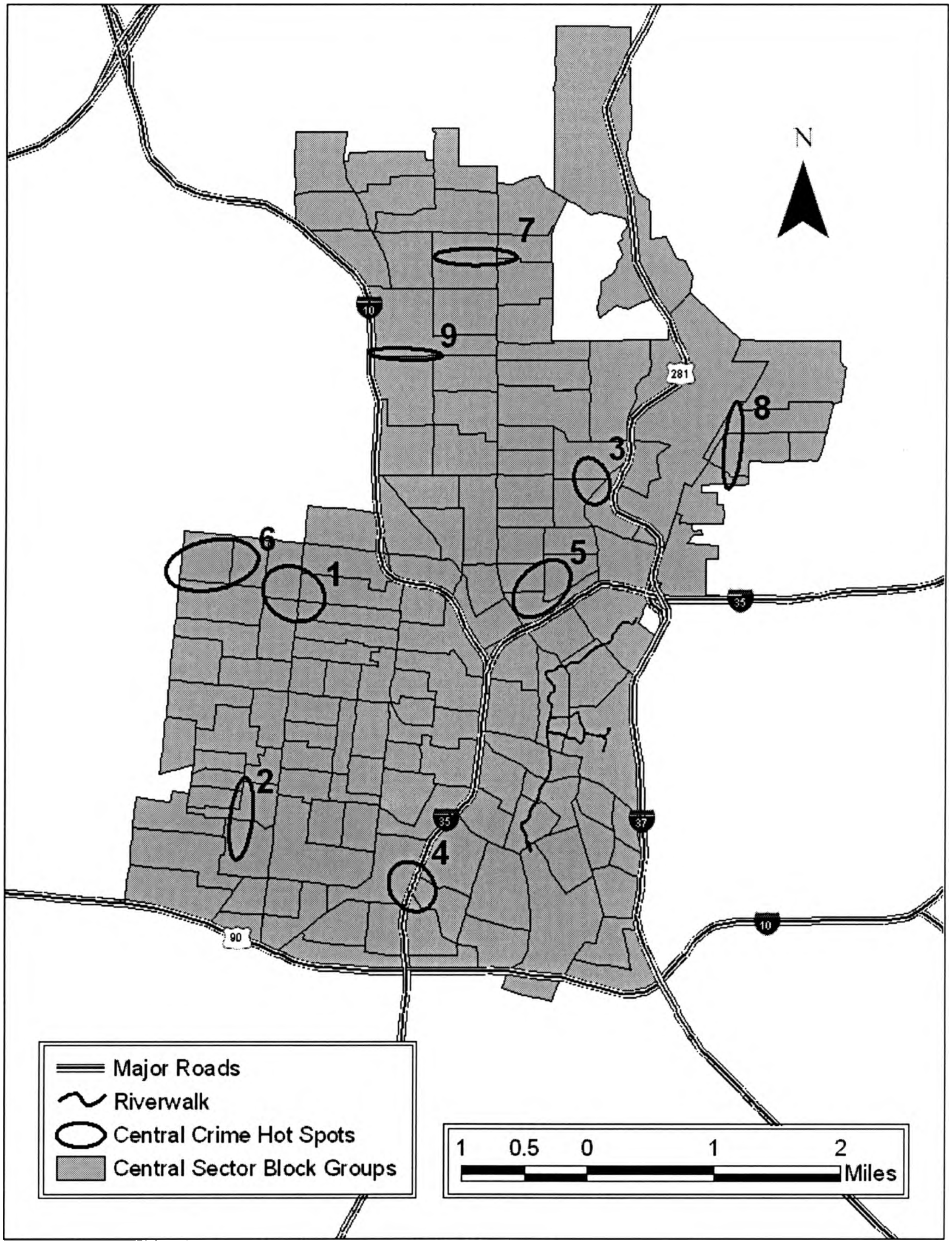

Figure 5. Analysis of Central District with STAC Ellipsoids

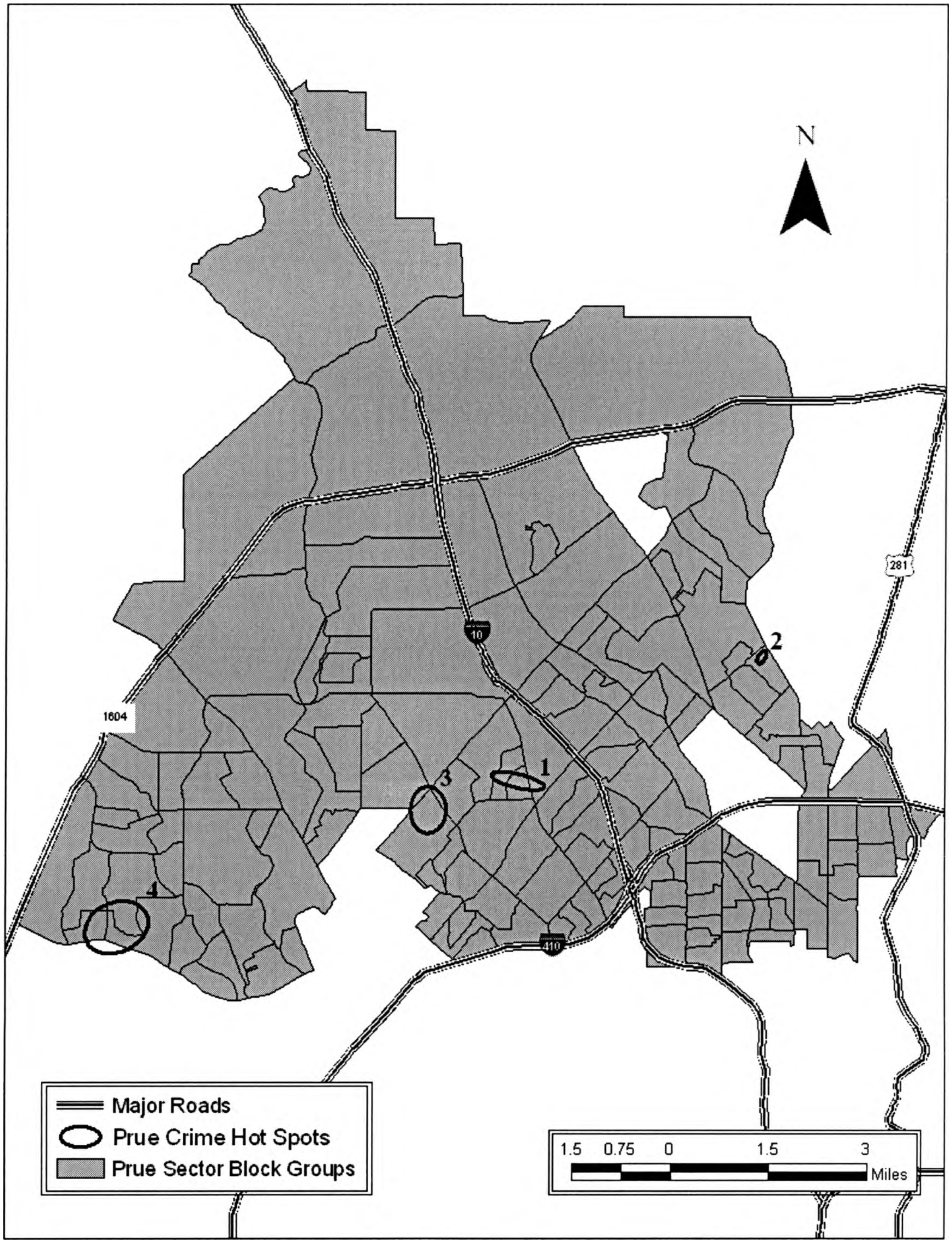

Figure 6. Analysis of Prue District with STAC Ellipsoids

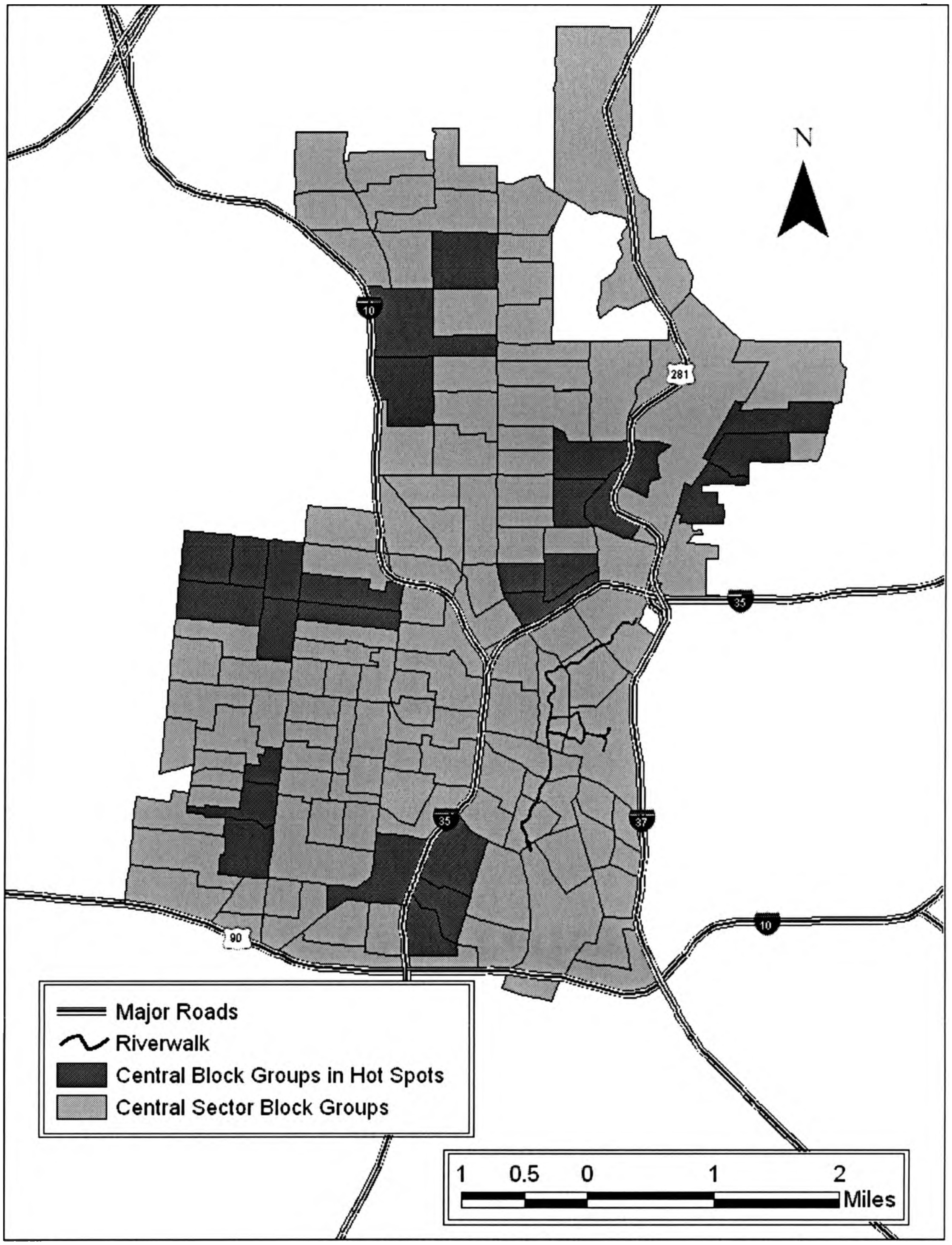

Figure 7. Hotspot Block Groups, Central District

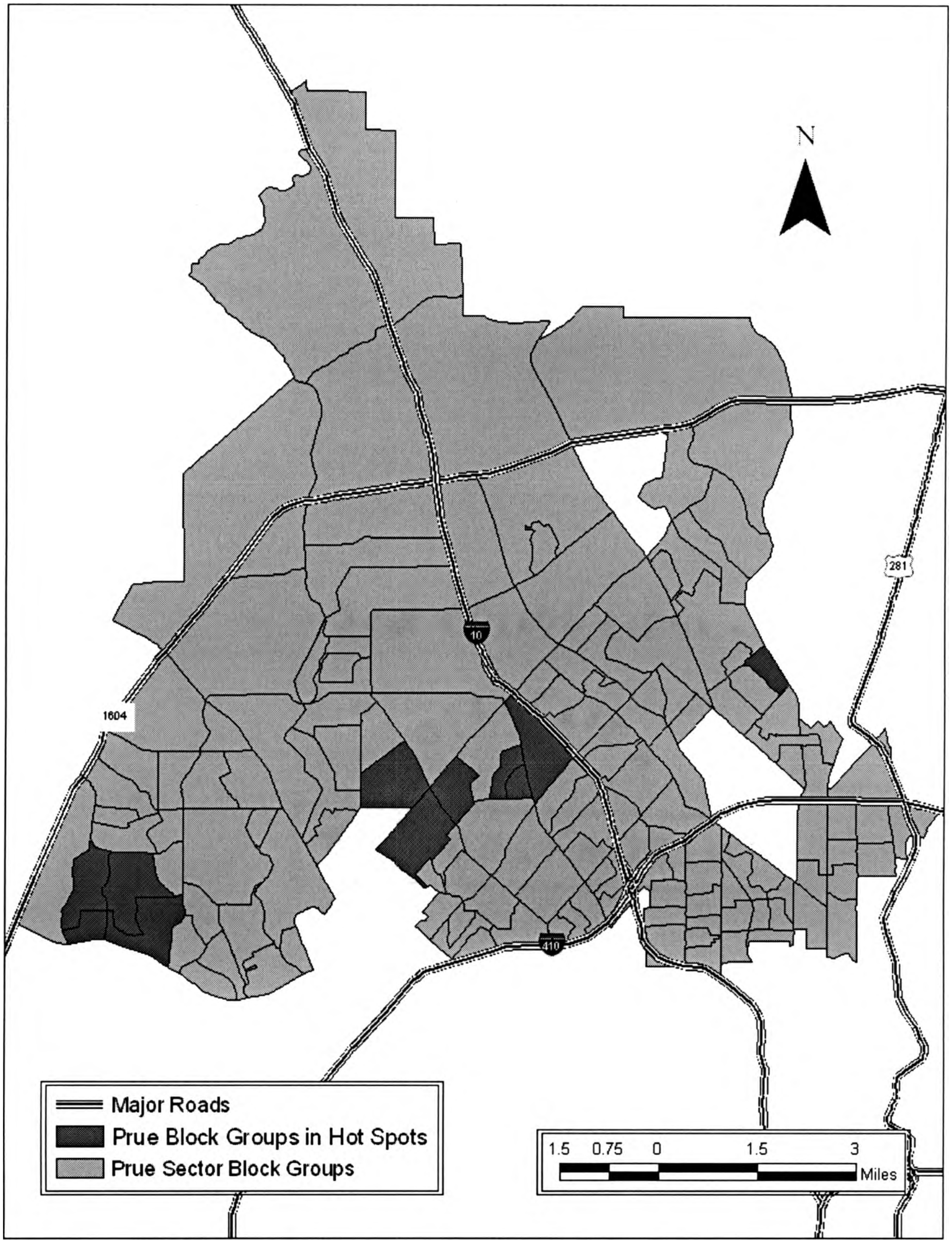

Figure 8. Hotspot Block Groups, Prue District

in one fifth of the Central area. The Prue area hotspots are concentrated into a smaller area, but fewer crimes are accounted for in these hotspots. It is important to remember that Prue is more than twice the size of the Central area, making crime much more concentrated in the Prue district.

4.2 Factor Analysis

For both the Central and Prue districts a factor analysis was conducted on all 26 variables. The highest three or two major loadings were used to determine the meaning and name of each component. For factors with more than three loadings, all high value loadings were used in consideration of the component name.

Central Police District

The variables in the Central district were reduced to eight components (Table 4). In all, the eight components accounted for nearly 74% of the variance in the Central District block groups (Table 5). The first component, Socioeconomic Status (SES), was comprised of the heterogeneity index, percent of persons with no high school diploma, and average household size. However, also weighing heavily in the component was percent of families that were female head of households with children, population per square mile, and percent of persons receiving poverty assistance. These variables are all indicative of an areas socioeconomic status.

The second component, Housing Status, consisted of percent of renters, percent of persons who moved into their home after 1995, and median number of rooms. The percent of vacant houses was also a small part of the component. These variables relate to housing status because they are characteristics of the age, tenure, and size of the house.

Table 4. Variables Contributing Most to Components for San Antonio's Central Substation[1]

Factor	Component Name	Main Loadings 1 Variable	1 Loading	2 Variable	2 Loading	3 Variable	3 Loading
1	**Socioeconomic Status**	**N/WHITE**	**.848**	**NO_DIPLO**	**-.844**	**AVE_HH_S**	**-.830**
2	Housing Status	RENTERS	.904	MOVE_95	.830	MD_ROOM	-.605
3	**Accessibility of Neighborhood**	**RD_LNGHT**	**.921**	**RD_SUM**	**.856**	**PARK_ACR**	**.642**
4	Employment and Guardianship	UNEMPLOY	.871	DISABLE	.749		
5	Housing Ownership	MALES	.806	BUILT_90	.648		
6	**Household Guardianship**	**WRK_35**	**.791**	**OVER_65**	**-.535**		
7	**Neighborhood Surveillance**	**NUM_LULC**	**.754**	**POL_ST_D**	**-.559**		
8	Pool of Offenders and Nighttime Offenses	P_19_24	.849	WRK_4	.512		

[1] Bolded factors are part of the logistic regression predictive models.

Table 5. Total Variance Explained by Variables in the Central and Prue Factor Analysis

District	Factor ID	Factor Name	Percent of Variance	Cumulative Percent
Central	1	Socioeconomic Status	17.329	17.329
	2	Housing Status	11.760	29.089
	3	Accessibility of Neighborhood	9.8730	38.952
	4	Employment and Guardianship	9.730	48.682
	5	Housing Ownership	6.584	55.267
	6	Household Guardianship	6.247	61.514
	7	Neighborhood Surveillance	6.100	67.613
	8	Pool of Offenders and Nighttime Offenses	5.893	73.506
Prue	1	Non-family Area	22.468	22.468
	2	Socioeconomic Status	17.471	39.940
	3	Suburban Family	12.909	52.849
	4	Access/Guardianship	9.266	62.115
	5	Pool of Offenders and Nighttime Offenses	6.287	68.402

Also related to housing is the fifth component, which includes the percent of males and the percent of houses that were built before 1990. This area has older houses, with more likelihood that these are male head of household families. This factor, therefore, is related to Household Ownership.

The third component was Accessibility of Neighborhood. It consisted of the miles of roads in each block group, the total number of roads per block group, the total acres of parks per block group, and a small contribution from the number of bus stops per block group. More roads and bus stops make for easy access and the number of parks creates more activity in the neighborhood.

The last several components are closely related in that they relate to the guardianship level of the block groups from different perspectives. The fourth component is composed of variables related to Employment and Guardianship. The percent of unemployed persons and the percent of disabled persons indicate that the area consists of people who might not work, and therefore have more time at home, thus the relation to guardianship. The sixth component is Household Guardianship, which includes the percent of persons who work more than 35 hours a week and the percent of persons who are over 65 years old. If an area has more persons who are at work and away from home, there are less people to guard their homes. If the area also has fewer elderly, there are fewer people who are at home. The seventh component relates to Neighborhood Surveillance, which consists of the number of different land uses per block group and the distance of the block group from the closest police station. These variables also relate to the guardianship level of the block group. The closer a police station to an area, the greater the level of guardianship and response time. Similarly, the greater the number of land use/land cover, the more likely an area is a mixed urban area, meaning houses might not be as easily visible. The eighth and last component, Offender Pool and Evening Offenses, is comprised of the percent of persons age 19-24 and the percent of persons who go to work between 4 p.m. and 11:59 p.m. Younger persons are more likely to go out in the evening, leaving a house abandoned at night. Also, persons between ages 19-24 are more likely to commit crimes. Persons who work at night leave the house unguarded as well.

Prue Police District

In all, the variance explained by the five components in the Prue district was about 69% (Table 5). The variables in the Prue district were reduced to five components (Table 6). The major variables contributing to the first component are the percent of one-person households, the percent of renters, and the average household size. Also contributing is the percent of persons age 19-24. These variables are indicative of a Non-Family Area since there are more renters, younger persons, and smaller household sizes.

The second component is composed of the percent of persons with no high school diploma, the heterogeneity index, and percent of female head of household with child. Also contributing are the percent receiving poverty assistance, and the percent of disabled persons. These variables are related to the Socioeconomic Status index, much like in the Central district.

The third component consists of persons age 65 and over, percent of persons who work more than 35 hours a week, and percent of houses that were built before 1990. These variables relate to the new suburban areas in the Prue district. Most of the houses

Table 6. Variables Contributing Most to Components for San Antonio's Prue Substation

Factor	Component Name	Main Loadings 1 Variable	1 Loading	2 Variable	2 Loading	3 Variable	3 Loading
1	**Non-family area**	**PERSON_1**	**.894**	**RENTERS**	**.890**	**AVE_HH_S**	**-.877**
2	Socioeconomic Status	NO_DIPLO	.891	N/WHITE	-.818	FHH_CHILD	.821
3	**Suburban family**	**OVER_65**	**-.879**	**WRK_35**	**.823**	**BUILT_90**	**-.618**
4	Access/Guardiansh ip	NUM_LULC	.732	RD_LNGHT	.707	RD_SUM	.613
5	Pool of Offenders and Nighttime Offenses	MALES	.619	UNEMPLOY	.541	WRK_4	.519

in the area are brand new, housed with middle aged persons with high paying jobs that require them to work more (doctors, lawyers, etc).

The fourth component is comprised of the number of different land use/land cover per block group, the total miles of roads per block group , the total number of roads per block group, and also contributing is the number of bus stops per block group . These variables are related to the Accessibility and Guardianship of the block groups because more roads and bus stops creates greater access, but more diverse land cover creates greater ability to burglarize and not be seen. These conditions create optimum conditions for completion of a crime without witnesses.

The fifth component, Pool of Offenders and Nighttime Offenses, which consists of the percent of males, the percent of unemployed, and the percent of persons who go to work between 4 p.m. and 11:59 p.m. is related to the pool of available offenders and low guardianship. Men are more likely to offend. Unemployed persons are more likely to be motivated offenders. Persons who are at work in the evening leave their houses unguarded at a time more likely to lead to burglary.

4.3 Logistic Regression

A logistic regression was conducted on the factor scores stored as regression variables for each component created for the Central and Prue districts. Each logistic regression used a backwards stepwise method to determine the predictors of hotspots of crime.

Central Police District

The logistic regression for the Central district required five steps and there were four predictors that contributed to the difference between hotspot and non-hotspot block groups (Table 7). Results indicate a model with four significant components (ρ<.015), Socioeconomic Status, Accessibility of Neighborhood, Household Guardianship, and Neighborhood Guardianship, distinguish between hotspots and non-hotspots. The model correctly classified 82.6% of the cases (Table 8). The predictive model created is:

Log odds (Hotspot Status) = -.432*Socioeconomic Status + .410*Accessibility of Neighborhood + .455*Household Guardianship - .434*Neighborhood Surveillance – 1.769*Constant.

This equation indicates the relationship of each component indicating crime hotspot status. For Socioeconomic Status, there is a negative relationship to the equation. This implies that the loadings inside the component have an opposite effect on hotspot status. The same applies to Neighborhood Surveillance. However, for Accessibility of Neighborhood and Household Guardianship, there is a positive relationship; therefore the variables in the components are distinguished hotspots in the expected direction. These components confirm that Routine Activity Theory and geography are useful for interpreting the differences between hotspots and non-hotspots of crime.

Prue Police District

The Prue district required four steps and there were two factors that contributed to the differences between hotspots and non-hotspot block groups (Table 7). Results indicate a model with two significant components (ρ<.005), Non-Family and Suburban Family Households, distinguish between hotspots and non-hotspots. The model classified 92.4% of the block groups correctly (Table 8). The predictive model created is:

Log odds (Hotspot Status) = .717*Non-Family Household + 0.921*Suburban Family Households – 3.026*Constant.

Table 7. Variables in the Predictive Model for Both Districts in San Antonio[1]

District	Component	B	S.E.	Wald	Sig.	Exp(B)
Central	Socioeconomic Status	-.432	.240	3.249	.071	.649
	Accessibility of Neighborhood	.410	.225	3.331	.068	1.507
	Household Guardianship	.455	.275	2.738	.098	1.575
	Neighborhood Surveillance	-.434	.272	2.555	.110	.648
Prue	Non-Family Area	.717	.296	5.875	.015	2.048
	Suburban Family	.921	.431	4.568	.033	2.512

[1] The degrees of freedom (df) for each variable in the equation was 1

Table 8. Logistic Regression Scores for Both Districts in San Antonio

	Central	Significance	Prue	Significance
Number of Steps	5		4	
Model Chi Square	12.410	.015	10.677	.005
df for Model Chi Square	4		2	
-2 Log Likelihood	115.112		67.201	
Cox & Snell R Square	.086		.071	
Nagelkerke R Square	.143		.171	
Goodness-of-Fit	20.090	.010	13.886	.085
Percent Predicted Correct	82.6		92.4	

This equation indicates that there is a positive relation of the components related to non-family households and suburban households. Therefore, the variables in the components are distinguishing hotspots in the expected direction. This also confirms that Routine Activity Theory and geography are essential to uncovering the differences between demographics in hotspots and non-hotspots.

CHAPTER V

DISCUSSION AND CONCLUSIONS

This section addresses the analysis of components created by the factor analysis and the predictive models created by the logistic regression to aid in the understanding of similarities and differences of crime hotspots in the Central and Prue Police Districts. Also included in the section are the conclusions reached by hotspot analysis, factor analysis, and the logistic regression.

5.1 Factor Analysis

While hotspot analysis was used to compare similar demographic and physical factors, there are certain traits that stand out amongst the two police beats that are not included in this study. The pattern of burglary hotspots in the Central district indicates activity near major roads, more specifically next to the Interstate I-10 corridor and away from the Riverwalk (Fig. 5). The pattern of burglary hotspots in the Prue area seem to be located in the areas closer to the southern border of the district. Exclusion of these unique variables limits the strength of the predictive model.

However, since the model was created based on the use of similar variables for both areas, these similarities and differences should be given more attention. Based on the components created by the factor analysis, there are some similarities between the Central and Prue districts. Both districts have components related to accessibility of the area and guardianship in the area. The third component for the Central district, High Accessibility has variables regarding road networks and parks. Similarly, the fourth component in the Prue district, Accessibility and Guardianship, has variables regarding the road networks and land use. While the road networks load higher for the Central district, the direction of the relationships are similar in each component and the road networks are in the top three loadings. Also, the number of bus stops was in both of these components, though not in the top three loadings. The similarity of these components in both districts suggests that transportation and accessibility are important, regardless of the demographics of an area.

The most interesting similarities are in the components regarding Socioeconomic Status. For both areas, the heterogeneity index and percent of persons who did not complete high school were related to socioeconomic status. While the final predictive model for Prue did not include the SES component, both areas had similar results in the factor analysis. Other similar components included the presence of persons over 65 years old and persons who work more than 35 hours. These variables were included in components that related to the guardianship level of the area. These variables also ended up being in components that were included in both predictive models. There was also a component that was related to the accessibility of the neighborhood for both components. The number of roads and the total length of roads were contained in components by for both districts. The similarities of the components in each district emphasize their relationship to high crime areas, as concluded by previous studies.

The percent of variance indicated by the factor analysis (Table 5) also tells about the influence of each component. The highest loading component for the Central district was socioeconomic status, which explained about 17% of the variance. However, six of the components explained less than 10% of the variance each, and cumulatively explained only about 45% of the variance. In all, the eight factors explained about 74% of the variance, which does explain much of the variance, however, it took several components to explain three quarters of the variance. The highest loading for the Prue district explained 25% of the variance and the second highest explained 18% of the variance. These two variables explained about the same amount of variance as the last six components in the Central district. In all, the five components explained 69% of the variance, which while less than the Central district, it explained the variance with three fewer components.

There was difficulty in naming certain components due to the unpredicted relation of certain variables, the lack of enough distinctive variables, or the inclusion of too many distinctly different variables. Several variables under one component label decreases the importance of each variable related to crime rates. Perhaps if a few individual variables were used instead of creating components through factor analysis, a better prediction could have been made.

5.2 Predictive Model

The use of factor analysis might have an effect on the predictive power of the logistic regression run on each district. For the Central district, the regression was able to predict the placement of 83% of the block groups. However, when this is broken down into what was classified correctly, it seems that the regression is unable to predict hotspot membership (Table 9). The same applies for the Prue district. While the model can predict 100% of non-hotspots, it was unable to predict any hotspots. Due to the large

Table 9. Predictive Model Classification Table for Hotspots and Non-Hotspots in Both Districts in San Antonio

District	Observed	Predicted Non-hotspot	Predicted Hotspot	Percentage Correct
Central	Non-hotspot	113	1	99.1
	Hotspot	23	1	4.2
	Overall Percent			82.6
Prue	Non-hotspot	134	0	100.0
	Hotspot	11	0	0.0
	Overall Percent			92.4

amount of non-hotspot block groups, the model overall was able to classify 93% of the block groups correctly. In other words, the model created predicts where crime will not be, and not necessarily where it will be.

The inability to correctly classify hotspots might have to do with the factors used to create the regression. Since the original independent variables were not used, the overall strength of the most critical variables might have been undermined.

It is also important to note the similarities and differences in the logistic regression created for both districts. The final regression for the Central district is composed of four components: Socioeconomic Status, Accessibility of Neighborhood, Household Guardianship and Neighborhood Surveillance. The regression for the Prue district in composed of only two components: Non-Family Households and Suburban Families. Both regressions include the components that explained the greatest percent of variance. Of the variables included in the components, there are only three that are in common: average household size, percent of persons who work more than 35 hours, and percent of persons over 65 years old. Each of these variables relate to the guardianship level of an area.

Also important are the components and the direction of their effects upon hotspot inclusion. For the Central district, Socioeconomic Status and Household Guardianship had a negative relationship to hotspot status. The variables in these factors change the direction of their influence. For Socioeconomic Status, the heterogeneity index is negatively related, percent of persons without high school diplomas are positively related, and the average household size is positively related. This implies that the socioeconomic status related to crime hotspots in the Central District is low socioeconomic status. For

Household Guardianship, persons who work more than 35 hours is negatively related and persons over 65 are positively related. This relationship is not as expected since the relationships of these variables imply high guardianship. Perhaps the characteristics of these persons in a low income areas makes them more susceptible targets, despite the guardianship level of the household. The other two components included in the model, Accessibility of Neighborhood and Neighborhood Surveillance have a positive relationship to hotspot status. The variables for Accessibility of Neighborhood imply that there is high accessibility due to the number and miles of roads and the availability of access from parks. The variables for Neighborhood Surveillance imply low guardianship due to coverage from various land uses and greater distance from the police department.

For the Prue district, both components in the equation had a positive relationship to hot spot status. Therefore, the variables in the factor maintain their directional influence. For Non-family Areas, there are more one-person households, more renters, and smaller households, leaving the houses unguarded and better targets. For Suburban Families, the lack of persons over 65, the greater number of persons who work more than 35 hours, and the greater number of new houses creates an environment of attractive, unguarded households.

While guardianship is connected to the characteristics of each component, it was individual characteristics, and not physical characteristics that affected guardianship in Prue, whereas the Central area included more physical characteristics.

The -2 Log likelihood scores for each model indicate that the models are not particularly good predictors, but have relatively low scores (Table 7). The Prue district has a much lower score than the Central district, indicating that the Prue model is a better predictor of high crime areas. The model chi-square for both the Prue and Central area are at the 95% confidence level. The confidence interval for the components loadings should also be discussed. For the Prue district, the two components were significant with in the 95% confidence interval. For the Central district, the top three components were within the 90% confidence interval and the last component was within the 89% confidence interval. While the components are not within the 99% confidence interval, they are still significant at a high confidence interval. The odds ratio for the Prue districts components are rather high (2.048 and 2.512), and indicate that for every increase in non-family status or suburban family status, the odds of being classified as a hotspot is multiplied by two. The odds ratios for Central are slightly different. For SES and Surveillance, a unit increase of these variables increases the odds of classification by a multiplier of 0.65. For High Accessibility and the other measure of Guardianship, one unit increase of these variables increases the odds of classification by a multiplier of 1.50.

CHAPTER VI

LIMITATIONS AND FURTHER RESEARCH

Certain problems were encountered by the study. First, the reliance on census block group demographics from census SF3 files limits the accuracy of the equation. The SF3 files are weighted estimates based on 1-in-6 persons in the census block group. The census block groups also increase in size as they reach the outer limit of the city, making estimates on the amount of crime prone to error based on size. Also, the hotspots were determined through the STAC program, which does not create hotspots based on the shape or location of block groups, therefore, the hotspots might barely touch a block group or may be in a small part of the block groups; however, for the study, the entire block group has to be significantly included since the variables associated with the block groups are tied to those boundaries. Also because the block-group level was selected as the level of study, the aggregation of data might not be as strong of a predictive measure as would data about the actual individuals who were victimized.

This led to problems in the selection of block groups in a hotspot. The ellipsoids were simply overlaid on the block groups and intersection with an ellipsoid determined their status. However, there were no distinctions made as to the number of crimes in that hotspot or a comparison of what made a block group a hotspot in each district. The Central district had many more ellipsoids, but based on percentages, it had more small hotspots (Table 3). If ellipsoid were on the border of a block group, that block group was not included in the study, but this does not mean that there might not have been a contribution of that block groups characteristics to the crimes committed in the area. Also, the hotspots were created from only one month of burglary data, which might not be the best gauge of chronic hotspot areas.

Thirdly, since backwards elimination was used for the logistic regression, variables that are related to Routine Activity Theory were eliminated, decreasing the contention that the theory will hold true for San Antonio, Texas. Also the inclusion of multiple independent variables might have caused collinearity problems, undermining variables that might be strongly related to crime in an area. Perhaps the use of a couple unrelated independent variables would have created a better predictive model. The predictive model might have also proved different with another statistical method, like discriminant analysis.

Fourthly, the independent variables used in the study focused more on the characteristics and demographics of individuals. However, the one similar component created for both police beats was related to accessibility and road networks. The inclusion of more or more detailed variables related to accessibility and transportation might have led to different conclusions.

Lastly, while STAC is useful for hotspot analysis because it can create unequally sized clusters due to combination of overlapping search radii, it has its drawbacks because standard deviation ellipses are best fit to the clusters, eliminating some of the hotspot areas (Craglia, Haining, and Wiles 2000). Also, STAC is only useful for uncovering "hotspots". This study and the predictive models might have benefited from comparisons between hotspots and coldspots, areas of extreme low crime or no crime at all, of crime in the San Antonio area. By uncovering areas that have very low or no crime, perhaps stronger predictive models could have been created. Each of the problems encountered by the study opens the door for further research into the demographics of crime in San Antonio.

By uncovering demographic and physical differences between census block groups in hotspots and non-hotspots, new solutions to prevent crime can be proposed. The ability to identify hotspot areas based on an areas characteristics would be extremely useful for law enforcement. The ability to predict crime can help identify areas that need extra protection due to their physical design and social factors (University of Bradford 2003). By removing or reducing the profit of targeting certain areas, the incentive for committing crime is reduced (Waters 1998). However, in this study, the correlation between place and crime lacked the ability to predict hotspots, the implying that hotspots and non-hotspots are heterogeneous and make crime prevention more difficult (Eck and Weisburd 1995).

This type of study takes a step towards focusing on the factors that arbitrate human susceptibility to crime and which demographics are most relevant to crime-prone areas, something that is the focus of few studies integrating crime and geography. This information is vital to the well being of individuals and their neighborhoods and communities (Sharpe 2000). This study contributes to the literature on the characteristics of hotspots of crime because it takes a different approach to analyzing crime. Not only is Routine Activity Theory analyzed, but geography is introduced in this study. Contributions are also made to the literature by conducting demographic analysis on a city that has very unique demographics compared to cities that are studied by the United States Bureau of Justice.

The current study demonstrates the importance of routine activities to the prediction of crime and indicates the Routine Activity Theory is relevant to the prediction of burglary. It also indicates that different parts of a city will have different predictors of crime. Studies that conduct analysis on an entire city, rather than looking at different parts of the city might mute the significance of crime and demographics in certain areas. This study also argues for more geographic approaches in national studies on victimization and crime.

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