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A Spatial Analysis of Crime for the City of Omaha

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THESIS ACCEPTANCE

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ABSTRACT

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The spatial patterns of four types of crimes (assault, robbery, auto-theft, and burglary) and their relationships with the selected socio-economic characteristics for the City of Omaha, Nebraska, were examined in this research. The crime data were based on the 2000 police reported crime and the socio-economic data were extracted from the 1997 American Community Survey and land use data from the 2000 Omaha parcel file. The location quotients of crimes (LQCs) were used to measure the relative specialization and structure of crimes for each census tract, and as the dependent variables for the statistical analysis. GIS techniques such as geocoding, spatial aggregation, and spatial analysis were used for crime mapping and crime analysis. Factor analysis and multiple regression models were employed to reveal the crime-causation relationships. Major findings of this research include: (1) LQCs highlight the specialization of crime and can be effectively used for GIS-based visualization and statistical analysis of crime; (2) the North Omaha and the downtown areas (high-crime districts) have relatively higher occurrences of violent crime and diversified structure of crimes while west Omaha (low crime districts) has a relatively specialized crime structure that is dominated by property crimes; (3) a modest proportion of the variance of crimes can be significantly explained by the statistical models.

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Chapter One

INTRODUCTION

Crime is one of America's top domestic concerns. The research on the geographical distribution and the search for explanations of the spatial variations in crime has long been a prominent area of analysis for both researchers and practitioners.

Criminologists and sociologists believe that crime is a reflection of antisocial aggression and influenced by regional socio-economic characteristics (Reith, 1996). From the perspective of spatial analysis, geographic studies suggest that crime has a geographic dimension and is disproportionately distributed across various spatial units --- from neighborhoods and cities to regions, nations, and the global scale. In city and metropolitan areas, crime is highly concentrated in relatively few, small areas. U.S criminal statistics show that the percentage of population living in cities and metropolitan areas is 75 percent, but more than 95 percent of all crimes occurred in urban areas (Ousey, 2000). A quantitative study made by Sherman et al. (1989) finds that 3.3 percent of street addresses and intersections in Minneapolis were responsible for 50.4 percent of all dispatched police calls for service. Similar patterns of crime are also found in other cities (Pierce et al., 1988; Sherman, 1992; and Weisburd and Green, 1994). Researchers also find that urban crime occurs most frequently in stressful and disadvantaged areas, and socio-economic factors, such as poverty, income inequality, unemployment, over-crowding, racial heterogeneity, youth concentration, and environmental risks, etc. are the most important contributors of crime distribution (Garrett, 1995).

Statistical analysis methods such as factor analysis and multiple regression models have long been utilized in the analysis of crime. Factor analysis is an effective approach in crime causation analysis to abstract the major underlying independent components (Tachovsky, 1983; Acherman, 1998; Krivo and Peterson, 1996). Taking the occurrence of crime, such as crime rate or count, as the dependant variable, the selected socio-economic attributes as the independent variables, regression analysis plays a critical role in the explanation of the causation of criminal activities (Anselin, et al., 2000).

Choosing different measures of crime may result in a different profile of crime for a region and directly affect the results of statistical analysis. The most important concern for crime analysis is to select appropriate indicators to measure the crime occurrence. Conventional measurements such as crime rate or count of crime are commonly used by researchers to indicate the level of crime activity across areas. Though popular, there are limitations for these two indicators. For example, they are often affected by the population size and density and may result in biased conclusions (Brantingham and Brantingham 1995; Carcach and Muscat 2002). Beyond these limitations, the location quotient was incorporated into crime analysis to evaluate the relative concentration or specialization (compared to the larger reference area) of specific crime for certain areas in recent years.

Historically, crime mapping is a significant aspect of crime control and crime analysis. The recent advance of computer mapping and GIS techniques accompanied by the development of spatial analysis methods has greatly enhanced our understanding of the dynamics of crime (Carcach and Muscat, 2000). Compared with the conventional statistical methods, geographical information systems (GIS) provides the added potential for linking criminal incidents with geographic locations and graphically displaying the spatial relationship between crime and the socio-economic factors. There are dozens of analysis methods for displaying the crime distribution and the correlated socio-economic characteristics. These techniques range from simple point map to three-dimensional density displays. More advanced use of GIS technology involves overlaying crime incident maps with other socio-economic features to explore the correlation with high crime concentrations and variation over space (Gisela and Johnson, 2001). GIS is not only instrumental in helping society to visualize the linkages between crime and socio-economic stress factors within an area, but also is beneficial for the public to cooperate with the law enforcement agencies to trim down the stress level and prevent the occurrence of crime in their neighborhoods and the whole city (Murray, et. al. 2001).

1.1 Nature of the Problem

In people's general perception, crime in Omaha occurs more frequently in the eastern part, generally east of 72nd street, while west Omaha is almost free from crime. The Omaha World-Herald released a special report of Omaha crime based on seven and half years of crime data. Their conclusion:

> "*... The east-west (divided by the 72nd Street) perception oversimplifies crime's impact on Omaha. While crime is more prevalent in the east, the most common crime – theft - invades every part of the city. ... Crime is concentrated most in the northeast area, particularly from Cuming Street to Ames Avenue, between the Missouri River and 48th Street. The northeast suffers from high unemployment, a lower median income and more decaying infrastructure than the rest of the city. The area is home to many of the city's poor and African-Americans....*" (Napolitano, 1998)

This report also indicates that socio-economic characteristics are important but not the only factors related to the occurrence of crimes across neighborhoods. Other issues such as access to large shopping centers, apartment complexes, interstate highways, and major roads also have important links to crime. While the World-Herald report provides very detailed descriptive picture of crime and useful information for the public in Omaha, it lacks statistical analysis to support its claims.

Except for the Omaha World-Herald's descriptive survey, there is little research on the systematic analysis of spatial differentiation and the causation of crime for the City of Omaha. To further examine the distribution pattern and explore the underlying major correlates of crime variance across neighborhoods of Omaha, an in-depth empirical analysis integrating advanced GIS techniques and statistical models was undertaken for this research.

1.2 Objectives

Reported crime data for the year of 2000, including assault, robbery, auto-theft, and burglary were collected for analysis. The purpose of this research was to display the distribution patterns of the four types of crimes and explore the relationship between the selected socio-economic characteristics and land use with crimes in the City of Omaha. Specifically the objectives include:

- Examining the spatial variation of crime using the GIS techniques of address matching, spatial aggregation, and spatial analysis;
- Using the location quotients to measure the specialization and structure of crimes and as dependent variables to conduct the statistical analysis.

- Comparing the statistical predictability of location quotient models with the model using conventional measure (count of crime) for identifying the effects of the selected socio-economic characteristics on the spatial variations of crimes across census tracts.

1.3 Hypotheses and Rationale

Three hypotheses tested by this research:

First, crime is disproportionately distributed in the City of Omaha. GIS techniques can be employed to display the spatial distribution pattern of crime across the city.

Second, LQC as an alternative measure of crime rate can be effectively used for mapping the specialization and structure of crimes and used as dependent variables for the regression analysis in explaining the effects of the selected socio-economic variables.

Third, the spatial differentiation of the assault, robbery, auto-theft, and burglary can be statistically explained to a significant degree by the selected socio-economic characteristics. Specifically, social stress variables such as percentage of African American, percentage of Hispanics, female-headed households, poverty, vacant house, and unemployment rate are thought to be positively correlated with the occurrence of crimes, while other variables such as house ownership and median house income (or house value) should have negative relationships with crime. In addition, the land use patterns, such as multifamily and commercial parcels are also hypothesized to exert positive contribution to the occurrence of crime.

The rationale that underlies this research is based on the following three points. First, this research is based on the two predominant crime theories: social disorganization theory and the routine activity theory, and previous researchers have provided sufficient support of empirical research on these two theories. Both social disorganization and routine activity theories were used to select explanatory indicators for this research. Second, most of the independent variables in this research have been widely used and found to have statistically significant associations with the spatial variation of urban crime. Third, LQC is one of the most extensively used indices to assess the relative specialization of local economic activities, and has been applied for crime analysis by previous researchers. Carcach and Muscat (2002) have examined the statistical properties of location quotient and conclude that it can be used as the dependent variable for statistical analysis of crime.

1.4 Study Area

The study area of this research is the City of Omaha. The Omaha metropolitan area enjoys a reputation as one of the safest midsize cities in the United States. The City of Omaha is the major part of the metropolitan area and has 54.4 percent of the total population. In 2000, the crime rate of all categories of crimes in Omaha was 5,319.2 per 100,000 population. According to the 2000 FBI Uniform Crime Report, Omaha ranked in the lowest quartile in violent crime rate of the 276 cities surveyed in the United States.

However, crime is still one of the major concerns for the people of Omaha. According to the results of Omaha Conditions Survey (1990) on the fear of crime:

> … 91.5 percent of the respondents in Omaha were worried about crime. 47 percent were very worried about crime. Especially, nonwhite and female respondents *were most worried about crime* (Marshall, 1990).

A recent poll on crime conducted by Omaha World-Herald in 1998 reinforced the conclusion above and found that approximately half of the residents surveyed worried about being victims of crime (Napolitano, 1998). From the results of these two surveys, it is apparent that the study of the spatial variation of crime in Omaha is important to analyze. The research can also help citizens of Omaha to better understand the spatial pattern of crime, so that they do not have unreasonable fears.

The 2000 crime data collected from the Omaha Police Department provide the basic information of crime incidents in the city. The original data file includes seven kinds of crimes including homicide, assault, robbery, larceny, auto-theft, burglary, and misdemeanor (Table 1.1). Though not identical with the Uniform Crime Report, it is an accurate representation of crimes committed in Omaha. In this research, assault, robbery, auto-theft, and burglary, which represent the general profile of crime in Omaha and are of concern to the police and public, were selected for the crime mapping and statistical analysis.

Table 1.1 Crime incidents in Omaha, 2000

Crime Type	Homicide	Assault	Robbery	Larceny	Auto-theft	Burglary	Mis-Demeanor
Counts	23	591	855	16490	3923	3267	1103

Source: Omaha City Police Department, 2000.

1.5 Significance of Research

Combining the current GIS techniques and statistical analysis methods, this research provides very important reference for both geographers and criminologists. Specifically, from the perspective of spatial analysis of crime, the significance of this research lies in four aspects:

- Firstly, it provides a better understanding of the geographical differentiation of crime in the City of Omaha;
- Secondly, the results of this research have implications for testing the social disorganization and routine activity theories of crime variation;
- Thirdly, it sheds light on the crime mapping and statistical analysis of crime by using location quotients as an alternative measure to reveal the specialization and structure of crimes across census tracts;
- Finally, it is beneficial for law enforcement and the public to visualize the distribution patterns of crime and its linkage to socio-economic characteristics. Therefore, it is helpful for the prevention of potential crimes.

Because location quotients can highlight the relative concentration of different types of crimes across census areas, this research will greatly help police department take effective measures to tackle present crimes and prevent potential offenses in different neighborhoods. Also, using location quotients is potentially helpful in studying fear of concern about crime. This research is informative for addressing people's unreasonable worries of crime and answering public questions such as: "Where is the highest risk area for a certain type of crime?" "What's the dominant crime type in a certain area?" and

"Which characteristics account for the occurrence of a specific type of crime being high in this area?"

1.6 Summary of Chapter

Both criminologists and geographers have long emphasized research on the spatial distribution and the underlying causes for the variation of crime. Utilizing GIS techniques and statistical analysis methods, this research aims to reveal the spatial pattern of crime and explore the relationship between socio-economic characteristics and crime across census tracts in the City of Omaha. The major hypothesis is that the selected socio-economic and land use indicators can significantly explain the variation of crime.

The remainder of the thesis is divided into four major sections. Chapter Two reviews the literature in both theoretical and empirical research in the spatial variation of crime, the measures of crime, crime mapping, and statistical analysis of crime. Chapter Three provides the framework designed to comprehensively depict the picture of crime and statistically analyze the crime-causation relationships. Chapter Four presents the results of the crime mapping and statistical analysis. The last chapter is the conclusion of this research discussing the major findings and potential for future work.

Chapter Two

LITERATURE REVIEW

2.1 Introduction

The analysis of the geographical patterns of crime can be traced back to the work of two French social ecologists and statisticians Guerry and Quetelet during the middle of 19th century, who first declared that crime incidents were distributed unevenly across geographic space (Anselin et al., 2000). In the United States, it was H. V. Redfield (1880) who did a pioneer work on studying the spatial distribution of crime and found that the southern states experienced higher crime rates than the rest of the country. The Chicago School in the early 20th century opened the American history of sociological research in crime by conducting an investigation of juvenile crime across community areas for Chicago. Since the 1960's, the geographical focus of crime analysis had shifted from regional areas to city neighborhoods (Ousey, 2000).

2.2 Theories on the Spatial Variation of Crime

Sociologists and criminologists focusing on spatial variation of crime at the community level have offered several explanations for the fact that crime rates are highly concentrated in stressful and disadvantaged neighborhoods. The dominant explanation derives from Shaw and McKay's (1942) social disorganization theory, which was reinterpreted and developed by subsequent researchers. The main points of this theory are that the socio-economic stress factors will ultimately reduce the level of social control and result in the disruption of community social organization, which in sequence accounts for high crime and delinquency rates (Agnew 1999, Ackerman, 1998). Other similar theories that proposed to explain community crime differences include the social stratification (or structure) theory, subculture theory, absolute and relative deprivation theory, and general strain theory. The commonality of these theories is that either socio-economic stress, or culture or social strain is the major source of criminal motivation.

The social disorganization theory was suggested by several empirical studies (e.g., Bellair 1997; Sampson and Groves 1989; Sampson et al. 1997). Despite being broadly exploited in the analysis of urban crime, however, the weakness of social disorganization theory is that it implicitly assumes that plentiful opportunities to commit crime are always available, and those who are disadvantaged are supposed to be more prone to commit a crime (Rice and Smith, 2002). Critics of this theory argue that social disorganization theory reinforces the "class bias" or racial discrimination and cannot explain the occurrence of crimes in "stable" and "organized" wealthy districts in the urban areas. They also argue that there is a failure for social disorganization theory to explain the deviation between the spatial distribution of offenders and the distribution of crime incidents (criminals do not necessarily commit crime in the area where they live) (Herbert, 1980). Though flaws exist, social disorganization still draws attention and is further developed by recent researchers by incorporating "social network" and "community attachment" into the disorganization model to mediate the role of the socio-economic stress factors in shaping the profile of community crime (Bursik 1988; Kasarda and Janowitz, 1974; Ousey, 2000; Sampson 1987; Warner and Rountree 1997)

Another major theory for explaining the distribution of crime is routine activity theory. First introduced by Cohen and Felson (1979), the routine activity approach claims that criminal incidence and victimization are related to the environment and behavior patterns of people. Three key elements are indispensable for the occurrence of crime: desirable targets, motivated offenders, and absence of capable guardianship (Sherman and Burger, 1989). In a review paper, Anselin et al. (2000) states:

> *"... The distribution of crime is determined by the intersection in time and space of suitable targets and motivated offenders. ...Routine activities that bring together potential offenders and criminal opportunities are especially effective in explaining the role of place in encouraging or inhibiting crime. The resulting crime locales often take the form of facilities --- places that people frequent for a specific purpose --- that are attractive to offenders or conductive to offending. " (Criminal Justice 2000, Vol. 4, pp 213-235)*

From the viewpoint of routine activity theory, crimes most frequently occur at places where abundant opportunities are available for the most profitable crime and the least chances of surveillance or capture. Empirical research based on the routine activity theory finds that land use and environmental conditions are important indicators for diagnosing the hot spots of crime concentration. Locations with "target-rich environments" such as 24-hour stores, large parking lots, and bars are frequently plagued by varieties of crimes (Anselin et al., 2000; Roncek and Maier, 1991).

Social disorganization theory and the routine activity approach share some common points: such as (1) both theories stress the role of social control in reducing the occurrences of crime in communities; and (2) they also have similar assumptions on the motivation of the offense, however they focus on a different scale of in the spatial aspect of crimes (Rice and Smith, 2002). While social disorganization theory explains the spatial variance of crime from the macro scale (i.e., 'the nested neighborhood') (Slovak 1986), routine activity theory attempts to account for the association between crime and the specific places from the micro level (i.e., 'the immediate visible environment surrounding a potential crime event') (Rice and Smith, 2002). Therefore, when analyzing the spatial distribution pattern (both areal and hot spot analysis) of urban crime, it is necessary to integrate these two theories. Actually, some theorists and researchers have proposed that social disorganization and routine activity theories are "complementary" and a "combined model" may be more effective in accounting for the crime variance across space (Bursik and Webb, 1982; Miethe and Meier 1994; Rice and Smith, 2002).

In general, although many different views have been proposed to explore the causation of spatial divergence of crime, in fact, different theories shed light on different aspects of the crime activity and are only suited for the explanation of certain types of crimes. From this point, all theories are partially valid and have respective limitations. Agnew (1999) notes that a satisfactory explanation of community differences in crime rates needs to integrate a range of theories covering both the stimulation and control perspectives of community crime. In this research, both social disorganization and routine activity theories are used to guide the map interpretation and statistical analysis of crimes.

2.3 Empirical Research

Empirical studies involving socio-economic correlates of crime on the aggregate levels have always tried to find a link between the social-economic factors and crime to test the above theories. A large body of research by geographers and other social scientists has generated considerable supporting evidence on the distribution and spatial dynamics of metropolitan and neighborhoods crime (Ackerman, 1998; Beasley and

Antunes, 1974; Harries, 1994; Kohfeld and Sprague, 1988; Krivo and Peterson, 1996; Roncek and Meier, 1991; Weatherburn and Lind, 1997 and 2001). Factor analysis, correlation, and regression models are frequently used to explore the relationship between stress factors and crimes. Factor analysis can transform a collection of large, highly correlated explanatory variables into fewer principal factors and keep as much predictive power as the original indicators regarding the dependent variable. It has been widely employed in socio-economic research for data reduction and handling severe multicollinearity in multiple regression models. Using the occurrence of crime as the dependent variable and demographic variables as the independent variables, regression analysis plays a crucial role in the attempts to explain the causes of criminal activities (Anselin et al., 2001).

Beasley and Antunes (1974) analyze the determinants of crime for Houston, Texas, and use predictor variables, including median income, median value of owner occupied homes, population density, and percentage of African Americans, for the regression analysis with data aggregated to twenty police districts in the city. After a series of regression analyses (i.e., bivariate, multiple linear, polynomial, and special regression models), they conclude that the selected variables can statistically explain almost all of the variance in the rates of major crimes (85 percent for the personal crime, and about two-thirds for the property crime) that they examined. They also suggest that social stress and the potential economic profit account for the variation of personal or violent crime and property crime respectively.

Tachovsky (1983) uses factor analysis and correlation analysis to investigate the relationship between selected socio-economic characteristics and the observed patterns of crime rates in New Castle County, Delaware. Eighteen-month time series data on nineteen crime components were selected for 107 census tracts, which serves as the basic unit for statistical analysis. Factor analysis is used to extract both the major crime dimensions and the principle components of socio-economic variables respectively. The major finding of Tachovsky (1983) is that more than 50 percent of all criminal offenses can be statistically explained, and the canonical model was more successful in delineating and predicting the property crime than the violent crime.

Recent statistical analysis include: Krivo and Peterson's (1996) case study that uses census tract data in the city of Columbus, Ohio, and shows that disadvantaged communities have qualitatively higher levels of crime than less disadvantaged areas, and that this pattern is evident for both black and white communities. This research suggests that census tracts are the "best local areas" considering the data availability for crime analysis and have been successfully used by former researchers. Also, they use three years (1989-1991) average data of crime to reduce the annual fluctuations and permit including crime incidents in tracts where crime does not occur every year.

Ackerman (1998) employs factor analysis and step-wise regression models to analyze the crime differentials between 111 smaller communities in Ohio. Seven index crimes of murder, rape, robbery, aggravated assault, burglary, larceny, and auto-theft were gathered from the FBI's Uniform Crime Report for the years 1976 through 1994. Fourteen socio-economic variables were selected to evaluate the social stress gradients of different cities. After the factor analysis, four principal components (race/weak family structure, economic marginalization, human capital deficiency, and youth) were abstracted and used as the independent variables for the later regression analysis. Finally, the statistical results indicate that crime is primarily related to the concentration of minorities, female headed households, poverty, unemployment, population, vacated house, education deficiency, and high ratio of young people. Also, this research exhibits that while race and weak family structure contribute more in explaining the violent crime variation than economic marginalization, population size, human capital deficiency and youth, property crime is most closely related with poverty and disadvantaged neighborhoods than race and weak family structure. These findings are consistent with theoretical expectations and with former empirical results from studies of metropolitan areas. Yet, the problem is that only half of the variation of crime rates can be explained by the selected socioeconomic and demographic factors.

Weatherburn and Lind (2001) use the census data based on postcode level and the linear regression models to determine, which combination of the measures of social and economic stress (poverty, unemployment, stability, single parent families and crowded dwellings) will be most effective in explaining juvenile participation in crime in New South Wales, Australia. This research concludes that poverty, single parent families, and crowded dwellings are the most important stress predictors of juvenile delinquency. On the contrary, neither unemployment nor stability is necessary in predicting juvenile participation in crime.

Based on the integration of social disorganization and routine activity theory, Rice and Smith (2002) study the variation of auto-theft crime across face blocks (both sides of a street at the block level) for a southeastern U.S city with a population about 250,000. They select both social disorganization variables (including low building value, African Americans, racial heterogeneity, single parent families, and distance from city center) and routine activity variables (including apartment value, number of vacant houses, number of parking lots, number of commercial places, etc), and including an automobile potential to control for spatial autocorrelation. The results demonstrate that the integration of both the social disorganization and routine activity theory can better explain the variance of auto-theft crime.

Researchers have developed a large inventory of social and demographic factors to account for the areal differentiation of crime, such as poverty, inequality, overcrowded neighborhoods, unemployment, transient, racial heterogeneity, youth, land uses, and the number of commercial facilities (Ackerman, 1998; Beasley and Antunes, 1974; Carcach and Muscat, 2002; Glaeser et al., 1996; Rice and Smith, 2002; Roncek and Maier, 1991; Tackovosky, 1983; Weatherburn and Lind, 2000; Zhao and Thurman, 2001).

In general, while a majority of crime studies found a positive link between social stress and urban crime, others failed to produce a significant finding. In addition, some studies have found evidence of an inverse association between crime correlates (such as unemployment and income inequality) and crime (Chiricos, 1987; Belknap, 1989). Review papers by Weatherburn and Lind (2001) and Box (1987) suggest that the pattern of empirical test results appears to depend on the time period, the data type of crime (offenders, victims, or incidences), the data source (Uniform Crime report data or self-reported data), the sample size and the methodology (time series or cross-sectional analysis) employed for the explanation of the social stress-crime relationship.

2.4 Measures of Crime Occurrences

To represent the crime pattern accurately, special caution is needed for the selection of crime measures, such as counts of incidents, crime rates, etc. Utilizing different measurements can produce different conclusions about the level of crime in areas and lead to different results when comparing the crime variation across geographic areas and conducting statistical analysis (Carcach and Muscat, 2000). While most of the previous studies use crime rates or counts of crime to assess the crime occurrence and perform statistical analysis, there exist some problems with the employment of crude incident counts and crime rates for regional comparisons. This is because both the absolute crime count and the population based crime rate can produce a misleading profile of the spatial pattern of crime due to variations of population size and density in the regions (Carcach and Muscat, 2000). For example, using counts of incidents cannot reflect the difference between two areas with the same number of crimes but with different areal size. Crime rates for peripheral areas of the city may be exaggerated because the small size of population. On the contrary, crime rate in the densely populated areas may be underestimated.

For these reasons, it is important to employ alternative indicators to eliminate the bias of the conventional measures. The location quotient, a relative indicator that has been commonly used in geographical, regional science and regional planning research, is extended to the field of crime mapping and statistical analysis (Brantingham and Brantingham, 1995; Carcach and Muscat, 2000 and 2002). Brantingham and Brantingham (1995) did pioneering work by using the location quotients of crimes (LQCs) to study the hot spots of crime in Canadian cities and confirmed that LQCs could be employed to understand how one area is different from another in crime structure and concentration. LQCs compare the relative share of a certain kinds of crime in a small area to the total of this kind of crime in the bigger area and help identify whether a specific crime pattern is disproportionately high or low in a particular place regardless of the area's total amount of crimes or population (Carcach and Muscat, 2002).

Lu (2000) investigates the pros and cons of different point pattern analysis methods of crime and concludes that the location quotient has the unique advantage for revealing the specialization pattern across areas over other techniques (such as pin map, cluster analysis, and kennel density). Carcach and Muscat (2002) extends the previous research on the general fields of location quotients and examines on the exploitation of the "statistical properties" of LQCs. They claim that LQCs follow a multivariate log-normal distribution and can be used for standard statistical procedures to examine the influence of socio-economic disadvantage over LQCs. Their case study for the Wollongong and the Blue Mountains (Sydney, Australia) uses location quotients of different crimes (i.e., robbery, assault, residential burglary, non residential burglary, vehicle theft, drug offenses, etc,) for each postal area as the dependent variables and uses the census characteristics of corresponding arca units as the predictor variables in a multiple regression model. The general conclusion from this analysis is that socio-economic characteristics are the main factor in shaping the crime profiles of postal areas of Wollongong and the Blue Mountains in Sydney, Australia.

2.5 GIS and Crime Analysis

Using maps to display the spatial pattern of crime and the risk determinants has long been an indispensable part of the crime mapping and crime analysis (Harries, 1999). After the mid-1960s, computer-mapping techniques were broadly used for mapping crime occurrence. In the last twenty years, with the integrated functions of database management, spatial analysis and visualization, GIS has emerged as an outstanding instrument in crime mapping and spatial analysis for both researchers and practitioners. Graphically displaying the spatial distribution and associated socio-economic characteristics and allowing the examination of the spatial relationship between crime and the associated demographic factors are the distinctive advantage of GIS.

Harries (1994) examines the spatial relationships between juvenile gun crime and social stress in Baltimore 1980-1990 using GIS techniques. He first geocoded the 2,639 juvenile gun crimes on the map and developed a social stress index comprising the percent black, percent under age of 18, persons per occupied housing units, percent female and median home value at the census tract level. Then, GIS spatial analysis is used to overlay the census tract, the social stress indices, and the crime data layers to assess the relationships between social stress, selected demographic attributes and the distribution of gun crimes. Finally, Harries concludes: (1) African-American youths were heavily over-represented in the commission of gun crimes; (2) there exists a general spatial association between high social stress and high frequencies of crime incidents over the 11-year period. In the guidebook "*Mapping Crime: Principle and Practice*", Harries presents a systematic exposition of the principles and techniques of GIS and includes more than 110 maps to illustrate how GIS works in the application of crime mapping and analysis. Murray et al. (2001) discuss the application of GIS and quantitative techniques for better understanding the relationships of crime occurrence in Brisbane, Australia. This research lists the detailed approaches of GIS capabilities, such as proximity analysis, spatial containment, scatter-plot map and cluster analysis for the analysis of crime in urban regions. Lu (2000) portrays the picture of hot spots of the unauthorized use of vehicles using location quotients as measure of crime occurrence for the City of Buffalo, NY in 1996.

Brimicombe et al. (2001) integrate statistical analysis and GIS techniques to identify the contribution of neighborhood effects to the rate of allegations of racist crimes and harassment in the Borough of Newham, London. GIS plays an important role in finding further possible predictor variables by creating a range of map visualizations of racial incidents against demographic variables.

Generally, the major applications of GIS in crime can be integrated into five aspects:

- Relative ease of displaying crime incidents and socio-economic factors on maps;
- Permitting flexible measurements at various levels of spatial aggregation (Anselin et al., 2000);
- Capability to integrate crime statistics with census and other spatial dimensions (Murray et al. 2001; Anselin et al, 2000);

- Operating spatial analysis, such as density analysis, proximity analysis, and neighborhood analysis, etc;
- Performing spatial statistical analysis and the mapping of the geographical distribution of the statistical results.

2.6 Summary of Chapter

The leading theories on the causes of crime variation across communities, empirical analysis, the measurement of crime, and GIS visualization of crime were reviewed in this chapter separately. The following points need to be highlighted for constructing the methodology of this research:

- Social disorganization and routine activity are the two most predominant theories in explaining the spatial variation of urban crime. These two theories are complementary and can be integrated to account for the distribution pattern of crime across urban areas.
- Factor analysis and regression models have been commonly used in abstracting the principal components of socio-economic characteristics and evaluating the crime-causation relationship.
- Independent variables reflecting social disorganization and routine characteristics, including poverty level, female or single headed households, unemployment rate, racial heterogeneity, education deficiency; multi-family housing, vacant houses, instability or transient, commercial places, and entertainment places, are frequently selected and have been proven as satisfactory predictors of crime occurrence.

- Choosing appropriate crime indicators is important for crime mapping and statistical analysis. Compared with the crime rate and the count of incidents, the LQC possesses distinctive advantages for analyzing the local concentration of crime and in comparing crime specialization over time and space.
- GIS is not only an important tool for mapping the distribution of crime, but GIS may also be able to enhance, supplement and extend the traditional quantitative techniques in spatial analysis of crime, such as the techniques of density analysis and the visualization of results of regression models (Murray et al., 2001).

In general, although there is enormous previous literature on spatial and statistical analysis methods to delineate the distribution pattern of crime and explaining the causation for spatial variation of crime, little emphasis has been put on integrating GIS techniques and statistical analysis to portray the spatial pattern and explore the internal mechanism of crime-causation relationship, particularly employing location quotients as the measurement of crime specialization to conduct the crime mapping and statistical analysis across census tracts within a city. Based on this point, this thesis aims to combine the GIS visualization functions and statistical analysis methods to depict the profile of the geographical distribution and causation of crime for the City of Omaha.

Chapter Three

METHODOLOGY

3.1 Introduction

This chapter presents the methodology to analyze the data and test the hypotheses. The major procedures for performing the GIS visualization and statistical analysis of crimes for the City of Omaha are displayed in Figure 3.1. The justification and explanation of the methodological design including data description, measurement choice, GIS visualization, and statistical analysis models are described in this chapter.

3.2 Data Description

Data for this research were gathered from three principal sources: (1) Crime data from the Omaha City Police Department, and (2) Demographic data from the 1997 American Community Survey; (3) the land use parcel file from the Omaha City Planning Department. The reason for using community survey data instead of the 2000 census data is that the 2000 Census attributes were not available when this study began. In addition, it is important that the demographic data precede the crime data for analyzing the causation of crime. Other digital data required for the mapping of crime includes the Omaha street shape file and the 1990 census tract shape file. To investigate the spatial patterns of crime and examine the statistical relationship between crime and socio-economic variables, a geo-referenced dataset was compiled at the census tract level for the study area.

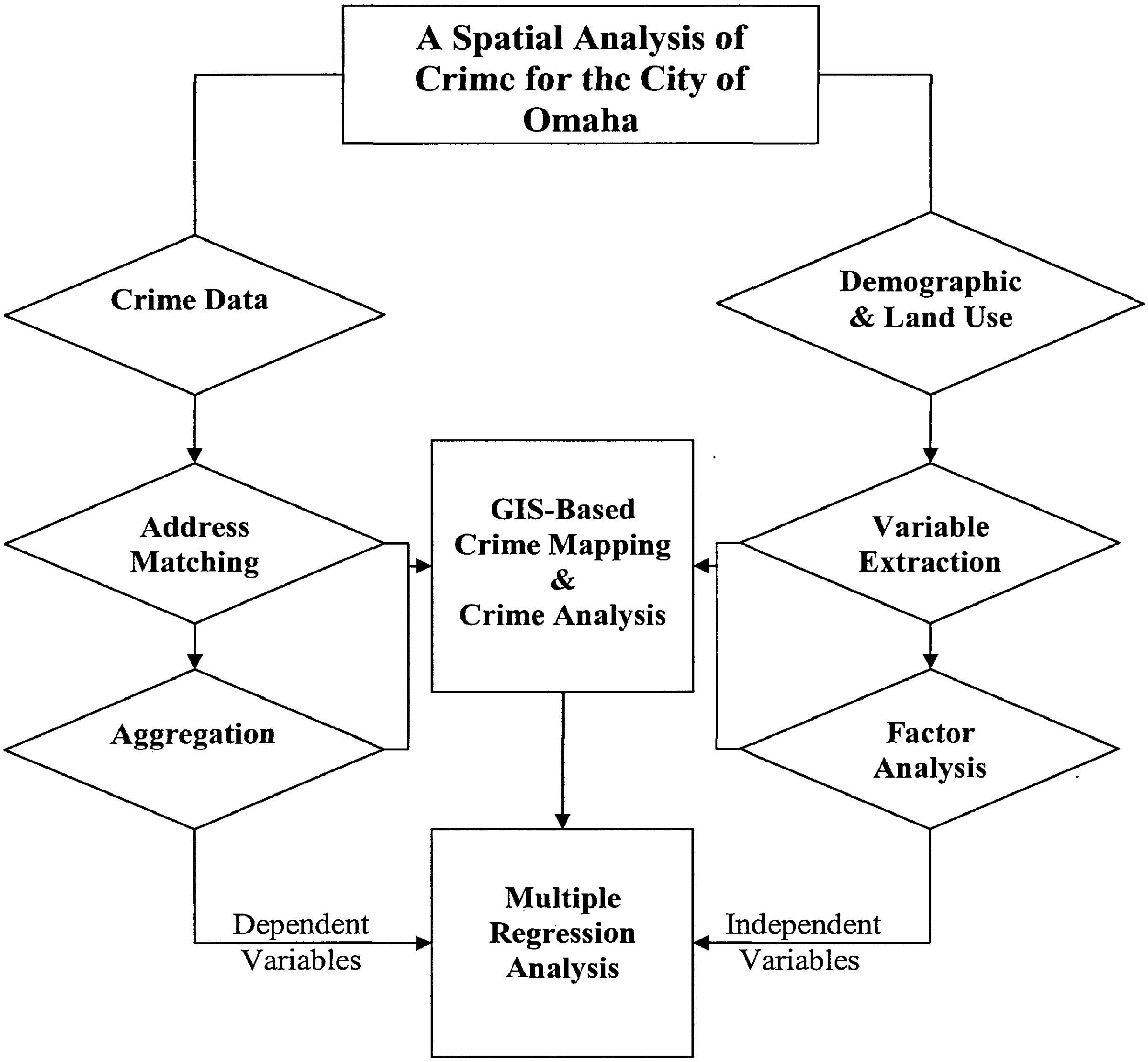

Figure 3.1 Methodological design of crime analysis in Omaha

The census tract is the most appropriate areal unit for which the required socio-economic data are available, and has been used by previous research in crime analysis (Krivo and Peterson, 1996; Harries, 1994; Kohfeld and Spraque, 1988; McClain, 1989). Since the demographic data for this research were extracted from the 1997 American Community Survey, it is most appropriate to use the 1990 census tracts. One problem with using census tracts as the unit of analysis is that the borders of census tracts do not match with the city's jurisdictional boundary. Following the general practice, the city boundary was used to "cookie cut" the Douglas County census tract shape file. All tracts that are completely within or partly intersect with the boundary of the city limits were included in the study area. There are three exceptions: tract 7303, 7307 and 7503. Although these tracts intersect with the city boundary, they were excluded for two reasons: (1) only very small portions of these tracts are within the city boundary; (2) these tracts have very small populations. Another exception is census tract 7399, which is very small (with an area 0.00002 sq miles) there is no demographic information from the 1997 American Community Survey for this tract. It was also deleted from the data set. In the end, 102 census tracts were utilized for this analysis (Figure 3.2).

3.2.1 Crime data

For the crime data, four major types of reported crime data were obtained from the Omaha Police Department: assaults, robbery, auto-theft, and burglary. The assault and robbery crimes belong to the category of violent crime, whereas auto-theft and burglary are referred to as property crimes. The original crime data are recorded in the format of a Microsoft Excel Worksheet (see Appendix I-1). The attributes of each crime incident include crime type, report number, street address, and date, such as "*Assault, S34996, 4116 N 60 AV, 01/01/00.*" For geocoding, these data were transformed into a Database Format 4 (dbf4) file. Through address matching, the crime data can be placed on maps, and further GIS visualization and statistical analysis could be carried out based on these geocoded databases. Table 3.1 shows the crime indicators and selected socio-economic characteristics (used as dependent and independent variables respectively for the multiple regression analysis). For the crime variables, LQCs were used first to display the specialization of crime and to conduct the statistical analysis. Then, the counts of crimes were examined and compared to the LQCs for showing the spatial variation of crimes across space and performing multiple regression models.

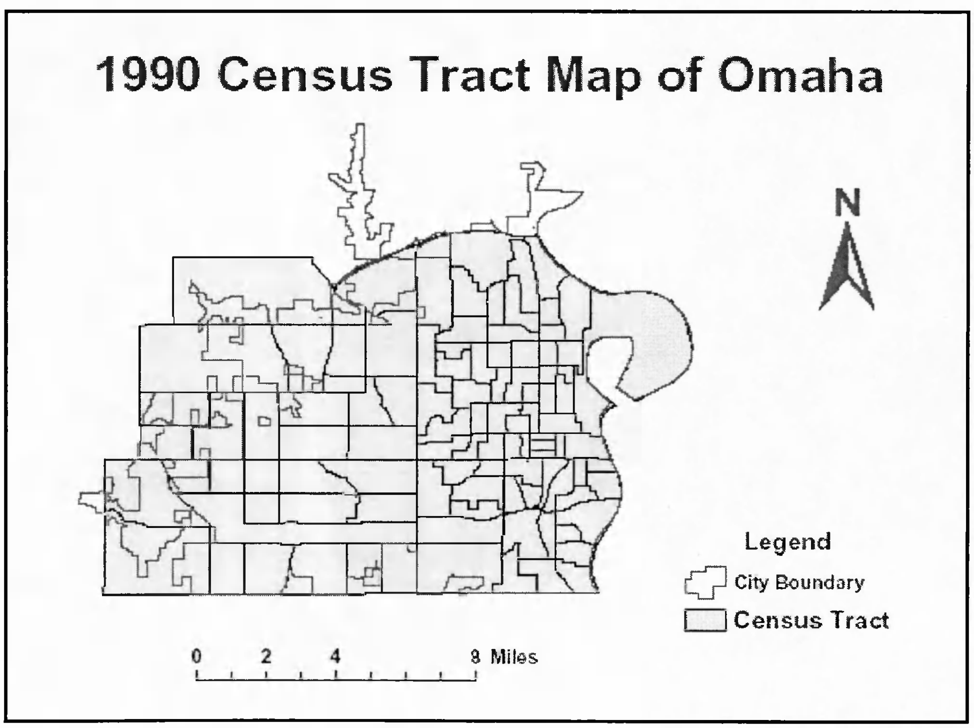

Figure 3.2 Map of census tracts in Omaha, 1990

3.2.2 Socio-economic variables

Socio-economic characteristics such as socioeconomic status, racial/ethnic heterogeneity, a young population, and weak family structure are frequently used to evaluate the effects of crime correlates (Ackerman, 1998; Beasley and George, 1974; Harries, 1994; Rice and Smith, 2002; Roncek and Maier, 1991; Tachovsky, 1983; Weatherburn and Lind, 2001). Keeping consistent with previous research in the etiology of crime variation across space, a list of 19 socio-economic variables were included for this research (Table 2.1)

In the independent variables column in Table 3.1, the first three variables: area of the census tract (AREA), total population of each census tract (TPOP), and population density (PDEN) represent the general population characteristics of each census tract (Roncek and Maier, 1991; Mencken and Barnett, 1999). Percentage of African Americans (PBLK) and percentage of hispanics (PHISP) are two variables reflecting the racial and ethnic heterogeneity of the neighborhood. It has been established that minorities are relatively more involved in crimes and more likely to be victimized than whites (Ellis and Walsh, 2000). Percentage of young males between ages 15-24 (PYM) and percentage of persons 16-19 years old neither working or in school (PNSJ) are two variables representing the conditions of young people in each census tract (Ackerman, 1998; Krivo and Peterson, 1996). The justification for including these two indicators is that research in the correlation between youth and crime has found that criminal behavior is concentrated in teens and 20s. Those who drop out of school and without employment are also more involved in crimes (Ellis and Walsh, 2000).

Table 3.1 List of dependent and independent variables

Independent Variables		Dependent Variables
General population		LQC of Assault LQC of Robbery LQC of Auto-theft LQC of Burglary Count of Assault Count of Robbery Count of Auto-theft Count of Burglary
AREA.	Area of the census tract	
TPOP.	Total population for each census tract	
PDEN.	Population density (persons per sq. miles)	
Racial & ethnic		
PBLK.	% of African Americans in total population	
PHISP.	% of Hispanics origin in total population	
Youth		
PYM.	% Male at age of 15-24 in total population	
PNSJ	% of persons 16-19 years old neither working or in school	
Social status		
PNHD.	% Adults (25 years and over) without high school diploma	
PFEM.	% of female headed households	
Economic status		
MHIN	Median household income	
MHV.	Median house value	
PUEM.	% Unemployment.	
PPOV	% of residents with income below poverty level	
PM1.01	% of population who live in housing with 1.01 or more persons per room	
House ownership		
POWH	% of owner-occupied houses	
PVH.	% of vacant houses.	
P5YRS	% of persons who live in the present house for more than five years.	
Land use pattern		
PMFP	% of multifamily parcels	
PCMP	% of commercial parcels	

Percentage of adults (25 years and over) without high school diploma (PNHD) and percentage of female-headed households (PFEM) reflect the education attainment and family status of each census tract because people with low education background and female (or single) headed household are two important indicators for crime analysis (Roncek and Maier, 1991; Zhao and Thurman, 2001). Median house value (MHV), median household income (MHIN), percentage of residents with income below poverty level (PPOV), percentage of unemployed people in labor force (PUEM), and percentage of population who live in housing with 1.01 or more persons per room (PM1.01) are a group of variables representing the economic status (Beasley and Antunes, 1974; Kohfeld and Sprague, 1988). Both theoretical and empirical literature has concluded that low economic status is highly associated with crimes. Since census tracts have relatively homogeneous socio-economic characteristics, median household income was used to represent the general income level of each tract (although income inequality is often used by the literature as an indicator of the relative social deprivation) (Ackerman, 1998; Belknap, 1989; Box, 1987; Braithwaite, 1978; Weatherburn, 2001).

Percentage of owner-occupied houses (POWH), percentage of vacant houses (PVH), and percentage of people who live in the present houses for more than five years (P5YRS) were dimensions used to capture the housing characteristics and the community mobility. This has been found by prior research to be highly correlated with crime (Ackerman, 1998; Ellis and Walsh, 2000; Rice and Smith, 2002; Tockovsky, 1983; Zhao and Thurman, 2001). The last two variables - percentage of multifamily parcels (PMFP) and percentage of commercial parcels (PCMP) were selected to test the effects of commercial and multifamily land uses on the occurrence of crimes (Olligschlaeger, 1997). It is commonly believed by citizens that these two kinds of land uses are more prone to attract crimes than single residential houses.

In general, based on the relevant theories and previous research, these 19 variables can be briefly divided into two categories: stress and control variables. PBLK, PHISP, PYM, PNHD, PFEM, PM1.01, PVH, PUEM, PDEN, PPOV, PNSJ, PMFP, PCMP are referred as stress variables, while AREA, TPOP, MHV, MHIN, POWN, P5YRS are referred as control variables regarding the statistical analysis.

3.3 LQC as the Measure of Crime

The location quotient can be used to evaluate the degree to which a region specializes in a certain crime at various levels of geographical scales. This research uses Brantingham and Brantingham's (1995) equation for calculating the location quotients of assault, robbery, auto-theft, and burglary crimes for each census tract.

$$LQC_{i_n} = \frac{C_{i_n} / C_{t_n}}{\sum_{n=1}^{N} C_{i_n} / \sum_{n=1}^{N} C_{t_n}} \qquad \text{(Equation 1)}$$

Where:

LQC_{i_n} is the location quotient of crime i for small area n.

n = small area unit (census tract) under study

N = total number of area units (total number of census tracts across the city of Omaha)

Ci = count of crime i

Ct = total count of all crimes.

The LQC for crime *i* within an areal unit (n) is an index that compares the area's share of crime *i* with crime *i*'s share of the total crime across the larger area. If LQC is bigger than 1, it means that the small area has a higher relative occurrence of crime *i* compared to the reference area. The advantage of LQC is that it highlights an area's relative specialty in crimes regardless of the area's total number of crimes or population size (Carcach and Muscat, 2002). However, there are two problems with using of LQC as the measure of crime: (1) values below the reference average are compressed between 0 and 1; but above the norm it can rise to any value (Shaw and Wheeler, 1994); (2) if an area has a very a small number of crimes, such as 1 or 2 with the same crime type for the entire year, the LQC for this kind of crime in this area must be bigger than 1. In this case, LQC can also give people a misleading impression of the profile of crime occurrence. Another problem is that the sampling distribution of location quotients as a spatial index is not clearly known (Shaw and Wheeler, 1984), although Carcach and Muscat (2002) use LQCs as dependent variables to statistically analyze the crime distribution in Australia. So the significance of using location quotients as the dependent variable needs to be tested in this research.

3.4 GIS-based Crime Analysis

3.4.1 Data Geocoding

To locate the crime incidents, the geocoding process is the first step. Geocoding is the method of matching the crime records with street addresses in the database with the corresponding points in the digital (target) map file. It is the fundamental step for displaying the spatial pattern of crimes and for getting data to perform further statistical analysis. Crime records almost always have street addresses or other location attributes, and this information enables the link between the database and the map. The street shape file of Omaha was used as reference map to match the crime incident data in the ArcView program.

Understanding how ArcView matches addresses and how modifying the default setting in Geocoding Editor can help users improve the accuracy of geocoding. The Geocoding Editor in ArcView uses a specific set of steps to find a match for an address. First it standardizes the addresses by dissecting the address into four components, including street number, street name, street direction and street type. Second, it searches the geocoding reference data to find potential candidates. Next, each potential candidate is assigned a score based on how closely it matches the address. Finally, the address is matched to the candidate on maps with the best score above the minimum match limit (Minami, 2000). Users can set a different standard for geocoding preferences, such as spelling sensitivity, minimum match score, and minimum score to be considered a candidate according to different requirements of address matching. Besides interactive matching, locating addresses manually can be used to increase the "hit rate". For getting a higher hit rate and increasing the accuracy of matching, the three indices of geocoding preferences were first set to 100 percent to do the Batch Match, and then they were changed to relatively low values, so Interactive Match Tool could be used to locate the unmatched addresses after the first round match.

There are a variety of reasons why not all addresses for crime could be geocoded. Common field errors include: Sometimes the exact location of a crime is unknown.

Human errors can happen at several steps in the process. For example, the wrong street type may have been recorded, the order of two digits in an address was reversed, the street type is input incorrectly into the category of the street name or an extra zero was inadvertently added during data entry. The reference street files also may contain errors describing street segments. The computer software cannot recognize certain addresses that actually exist in the real world, but are not present in the street database. Even when a crime is geocoded, however, it could still be placed in the wrong position on the map. For example, during the geocoding process, the incident of "Assault, 1114 N 26 Street" can be easily drawn to the N 264th street (with highest matching score of 87) by the software. Although this kind of error is rare, such errors are occasionally encountered in large data files. In this case, interactive re-matching is very important.

3.4.2 Data aggregation

Once the addresses of offenses are successfully geocoded on the map, the point data need to be aggregated to the census tract level. One of the most powerful analytical functions in GIS software is the flexible spatial aggregation capability to facilitate the measurement of place-based crime. In this research, the spatial join tool in ArcView was used to aggregate the point pattern of crime to the census tract level. To do this, first the attribute tables of both the census tract and the geocoded crime shape files need to be opened and then the "join" from the table menu needs to be clicked. The last step is to use the "summarize" function to get the total number of points within the boundary of each tract.

3.4.3 Crime mapping and crime analysis

For visualizing the spatial distribution pattern of assault, robbery, auto-theft, and burglary crimes in Omaha, three kinds of mapping methods were used to display the crime distribution. The three map methods are pin (point) map, grid cell analysis (density map), and choropleth map. The reason that different mapping methods were used is because each method has its advantages and limitations and can only provide certain perspective of the thematic information to the map-readers. For getting the big picture of crime variation in Omaha, it is necessary to combine several map methods. Software packages such as ArcView, ArcGIS, and Adobe Illustrator were used to make all these maps.

1. Point maps.

Point maps are probably the most frequently used maps for crime analysis, as they can precisely show incident locations. After geocoding, the crime incidents of assault, robbery, auto-theft, and burglary were mapped. The advantage of the point map is that it can give map viewers the best information where crime events happen and the frequencies of the occurrence. The disadvantage is that with the large amount of "stacked" points close to each other and even overlapping (such as the auto-theft and the burglary crimes in this research), it is almost impossible to identify the individual spots, although people can figure out the general pattern of crime distribution (Harries, 1999; Lu, 2000).

2. Grid cell analysis and density maps.

Grid cell analysis is an effective method for displaying the dense concentration of crime incidents and revealing the location of hot spots of crimes. A grid cell is superimposed over the point map of crime incidents, and points within cells, or within the designated radius from the centers of the cells, are assigned to the cells. The points are transformed into a smooth surface with data generalized to cells, and different shadings can be used to show the density change of crimes (Harries, 1999). Density is calculated for each cell by summing the points found in the *Search Radius* and dividing by the area of the circle in area units. The output density values will be the occurrences of the measured number of points per specified area. The grid cell method combines the advantages of both point maps and choropleph maps and can be efficiently used to identify the hot spots of urban crime (Harries, 1999; Lu, 2000; Ratcliffe and McCullagh, 1998).

The spatial Analyst Extension in ArcView 3.3 was used to get the density maps of the four types of crimes. The Search Extent was set to the Omaha tract file, and the grid cell size and the search radius were set at 100 meters and 1500 feet (about 0.2841 mile). Thus a grid of 178X268 (rows and columns) was wrapped onto a map of the study area. The ArcView "Kernel" density method was used to interpolate the study area and draw the density map.

3. Choropleth maps.

After aggregating crime point data into areas, choropleth maps were used to display the spatial variations of crime across census tracts in Omaha. Compared to pin maps, choropleth map lose the positional accuracy and some of the characteristics of geographical features may be dampened and suppressed during the process of data transformation (Lu, 2000). In addition, because of the need of data simplification and generalization, using a different classification method for map presentation may convey different information of spatial variation of crime to map-reader (Harries, 1999 and Lu, 2000). As the "rule of thumb," the natural breaks classification method was used to classify the crime data.

For comparing the difference of using LQC and the count of crime for crime mapping, both kinds of measurements were used to create choropleth maps to examine the spatial variation of crimes across census tracts in Omaha.

Choropleth mapping method was also used to display the distribution pattern of the selected socio-economic variables for visually checking their association with the four types of crimes.

3.5 Statistical Analysis

The database organization and data evaluation were completed before any of the statistical procedures were implemented. Crime data were extracted from the GIS-based *dbf* file corresponding to the geocoded crime shape file. Demographic data downloaded from the 1997 American Community Survey needed to be processed to get the specific variables for this research. The two land use variables --- percentage of multi-family parcels (PMFP) and the percentage of commercial parcels (PCMP) were summarized from the database of the Omaha parcel file. For conducting the final statistical analysis, these three kinds of data were combined using SPSS statistical package.

3.5.1 Descriptive statistics

Before the regression analysis, it is necessary to check the descriptive statistics of the dependent variables, i.e., the location quotients and count of the four types of crimes.

Descriptive statistics include the mean, variance, range, standard deviation, skewness, and kurtosis. Dispersion statistics such as the standard deviation, variance, and range are designed to measure the spread or variation of the data set. Kurtosis and skewness are statistics that characterize the shape and symmetry of the data distribution. Meanwhile, the multicollinearity underlying the independent variables also needs to be checked, and *Pearson correlations* were used to create the correlation matrix of the predictor variables.

3.5.2 Factor analysis

Factor analysis is designed to simplify the correlation matrix and reveal the small number of factors that can explain the correlations. It is an important method of data independence analysis and has been employed effectively by previous literature to delineate underlying structures in data sets (Tachovsky, 1983; Ackerman 1976, 1997; Krivo and Peterson, 1996). There are three main stages for performing factor analysis: (1) the construction of a correlation matrix; (2) transformation of the correlation matrix into the component matrix; and (3) obtaining the matrix of component scores (Cadwallader, 1996).

All of the variables were entered in the factor analysis and rotated with the orthogonal Varimax rotation method. The aim of rotation is to un-correlate all of estimated factor score coefficients to ameliorate the potential effect of multicollinearity. Finally, the score values of the factors are added into data set as independent variables for regression analysis.

3.5.3 Multiple regression analysis

Multiple regression analysis is designed to predict and explain the variation of dependent variables (variable Y), from a number of independent or explanatory variables (variable X) (Shaw and Wheeler, 1985). The formula for performing multiple regression analysis:

$$Y = a + b_1 X_1 + b_2 X_2 + \dots B_i X_i + e \qquad \textit{(Equation2)}$$

Where, a= the intercept value

b_1 to b_i = partial regression coefficients

e = error term

The aim of multiple regression models is to explain the corresponding variation of the dependent variable following the variations of the independent variables (Hair et al. 1987). In this research, multiple regression models were utilized to explore whether the spatial variation of crime could be statistically explained by the socio-economic factors. Specifically, the b*ackward* regression method in SPSS was selected to conduct the regression analysis. One advantage of the *backward* regression method is that it enters all the variables first and then removes them once at a time (Folster, 2001). This allows users to select different models depending on the different removal criterion. Since the modest number of observations (102) in this research, the *Stepping Method Criteria* was set at *Entry*: 0.01 and *Removal* at 0.05 to make sure the important variables can be included in the models. Statistics such as Variance Inflation Factor (VIF) were included in the regression analysis to test the multicollinearity underlying the independent variables.

For comparing the difference of the predictability of demographic variables to the location quotient change of crime in each tract, the count of the four types of crimes was also employed as dependent variables in the regression analysis. In total, four regression models were carried out for exploring the relationship between crimes and the associated socio-economic attributes. Model 1, Model2, and Model 3 use the location quotients of assault, robbery, auto-theft, and burglary as the dependent variables respectively, and Model 4 uses the count of each of the four crimes as the dependent variables. Model 1 input all the original variables into the regression process, while Model 2 just leaves indicators that are significantly correlated with the dependent variables with VIF values within the reasonable range. Model 3 uses the principal components of the original demographic indicators as the predictor variables, and was designed as a control model to mediate the biased results of the LQCs.

3.6 Summary of Chapter

The methodological design for crime mapping and the statistical analysis of crimes was presented in this chapter. The data used for this research consists of the counts and location quotients of assault, robbery, auto-theft and burglary, and the 19 socio-economic variables for the statistical analysis of crimes. Three types of mapping methods were described to display the distribution pattern of crimes. Pin maps show the detailed location of the crime incidents, density maps display the concentration of crime "hot spots", and choropleth maps portray the spatial variation of crime across census tracts. Factor analysis was designed to extract the principle components of demographic variables and the factor scores were used as the independent variables for the regression analysis. The backward regression method was used to examine the co-variance between the dependent and the independent variables. Two types of dependent variables (count and LQCs) and two kinds of explanatory variables (original variables and principal components) were used to produce four models and the statistical results of different models were supposed to be compared.

Chapter Four

RESULTS AND ANALYSIS

4.1 Introduction

This chapter provides the major results of this research, which include two major parts: the crime mapping and the statistical analysis. In the GIS part, the analysis of the distribution of crime incidents, the location of hot spots, and the areal differentiation of the four types of crimes were presented. For the statistical analysis, the explanation and justification of each of the statistics were specified and used to test the hypotheses of this research. Finally, the major findings from this research were compared with the previous research.

4.2 Visualization of Crime with GIS

GIS provides a fundamental technique for this research in two aspects: (1) it permits the geocoding and aggregation of the crime data; and (2) it permits the crime mapping through different kinds of mapping methods. Following is the major outcome of crime mapping and crime analysis with GIS.

4.2.1 Point maps

In terms of address matching, getting a high "hit rate" is fundamental for receiving an accurate map and for the statistical analysis based on the geocoded database. Table 4.1 shows the geocoding results of the four types of crimes. *Good Match* means a match score between 75 and 100 and *Partial Match* means a score less than 75 but above the minimum match score. Actually, most of the crime incidents received a *Perfect*

Match (with a score of 100) (86 percent for assault, 87 percent for robbery, 86 percent for auto-theft, and 89 percent for burglary). After manual encoding, about 93 percent of the assault, 95 percent of the robbery, 95 percent of the auto-theft, and 96 percent of the burglary crimes were successfully address-matched.

Table 4.1: Geocoding results of assault, robbery, auto-theft and burglary crimes

Match Rate / Crimes	Batch Match*		Interactive Match			Final Match Rate	
	Good Match	No match	Good match	Partial Match	Manually Located	Total Match	No Match
Assault	86% (507)	14% (84)	91% (540)	1% (6)	1% (6)	93% (552)	7% (39)
Robbery	87% (748)	13% (107)	92.5% (792)	1% (5)	1.5% (13)	95% (810)	5% (43)
Auto-theft	86% (3375)	14% (548)	94% (3701)	0% (6)	1% (26)	95% (3733)	5% (189)
Burglary	89% (2905)	11% (362)	96% (3142)	0% (2)	0% (1)	96% (3145)	4% (121)

**: Geocoding preferences for the spelling sensitivity, minimum match score, and minimum score to be considered a candidate were all set to 100% for getting accurate batch match results.*

Figure 4.1, 4.2, 4.3, and 4.4 are point maps from address matching that depict the distribution of those four types of crimes for the year of 2000 in Omaha. These maps show the general pattern of the selected four types of crimes. Both violent crimes (assault and robbery) and property crimes (auto-theft and burglary) are highly concentrated in the eastern part of Omaha, especially in the North Omaha and the downtown area, although there are also some small clusters of hot spots spreading across the western part of the city. Sincc too many points arc overlapped with each other in the eastern part of Omaha and other clusters, especially for the auto-theft and burglary maps, you cannot clearly identify the location of all crimes.

Compared with auto-theft and burglary (property crimes), both assault and robbery (violent crimes) are more concentrated in the eastern part of the city. Although property crimes (auto-theft and burglary) are also disproportionately distributed in the north and downtown area, they are spread throughout the whole city.

These findings are consistent with the crime survey results conducted by the Omaha World-Herald in 1998. In terms of the spatial patterns, from the robbery and auto-theft maps, one can find a linear pattern of crimes along the 90^{th}, the 72^{nd}, Dodge, L Street, and the downtown areas where a lot of business stores, apartment complexes, and unguarded parking lots are located. These areas are frequently the location of robbery and auto-theft crimes. By overlaying the crime incidents with the commercial and multifamily parcel maps, a clear pattern can be found that almost all of the robbery crimes occurred within or near multifamily and commercial land parcels (Figure 4.5). a similar positive correlation can also be observed when overlaying the commercial and multifamily parcels with the assaults and auto-theft crimes (Figure 4.6 and Figure 4.7).

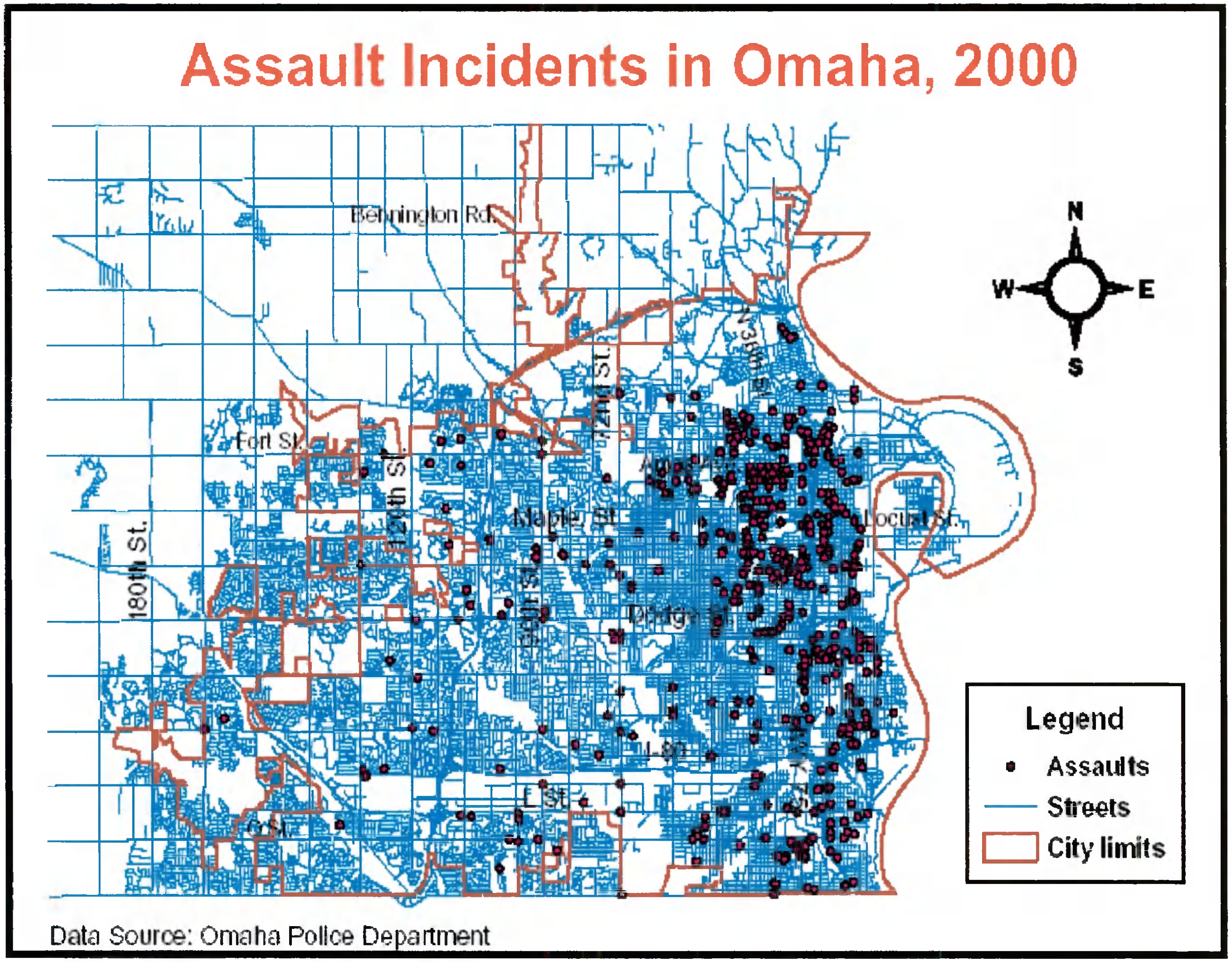

Figure 4.1 Assault crime incidents in Omaha, 2000

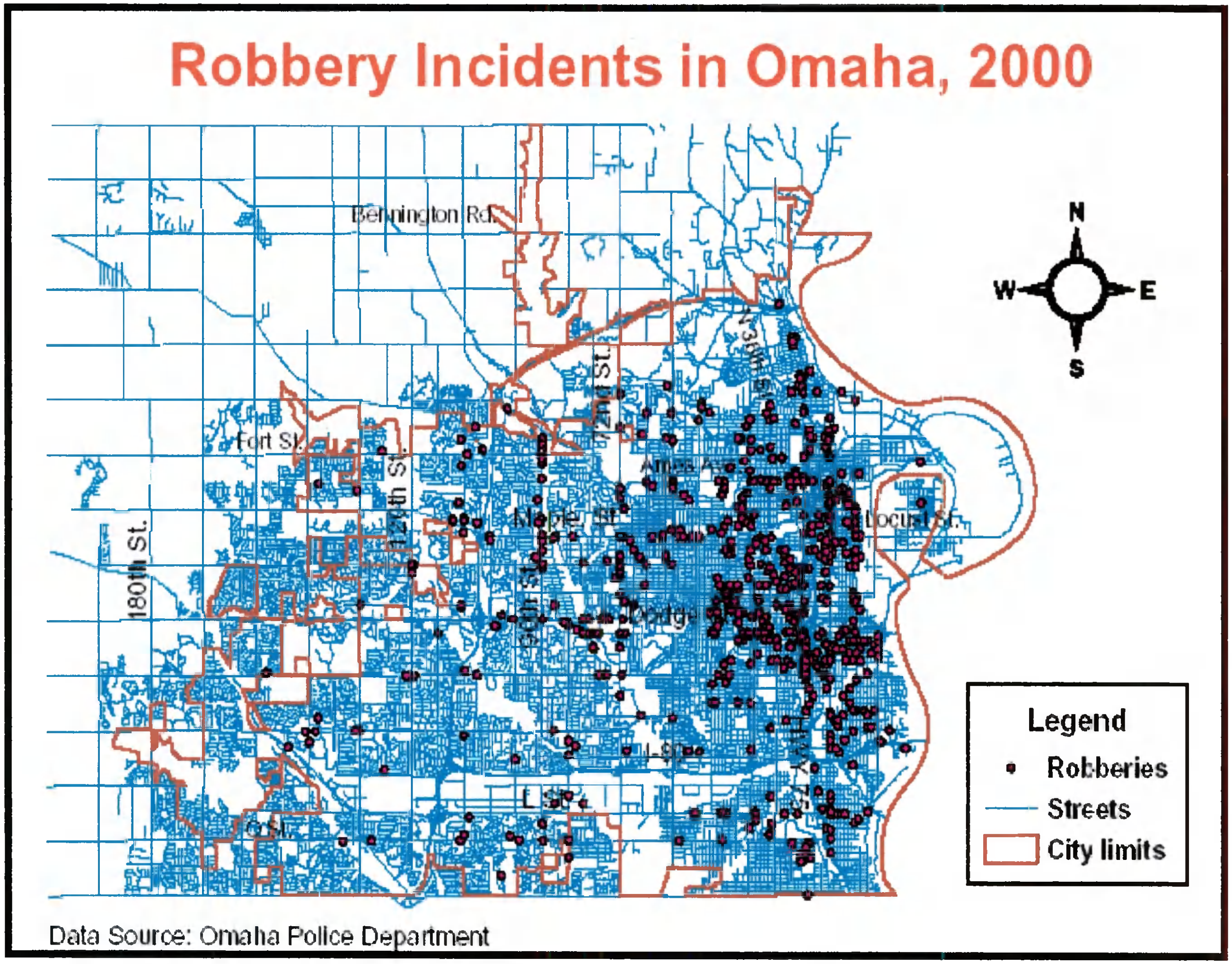

Figure 4.2 Robbery crime incidents in Omaha, 2000

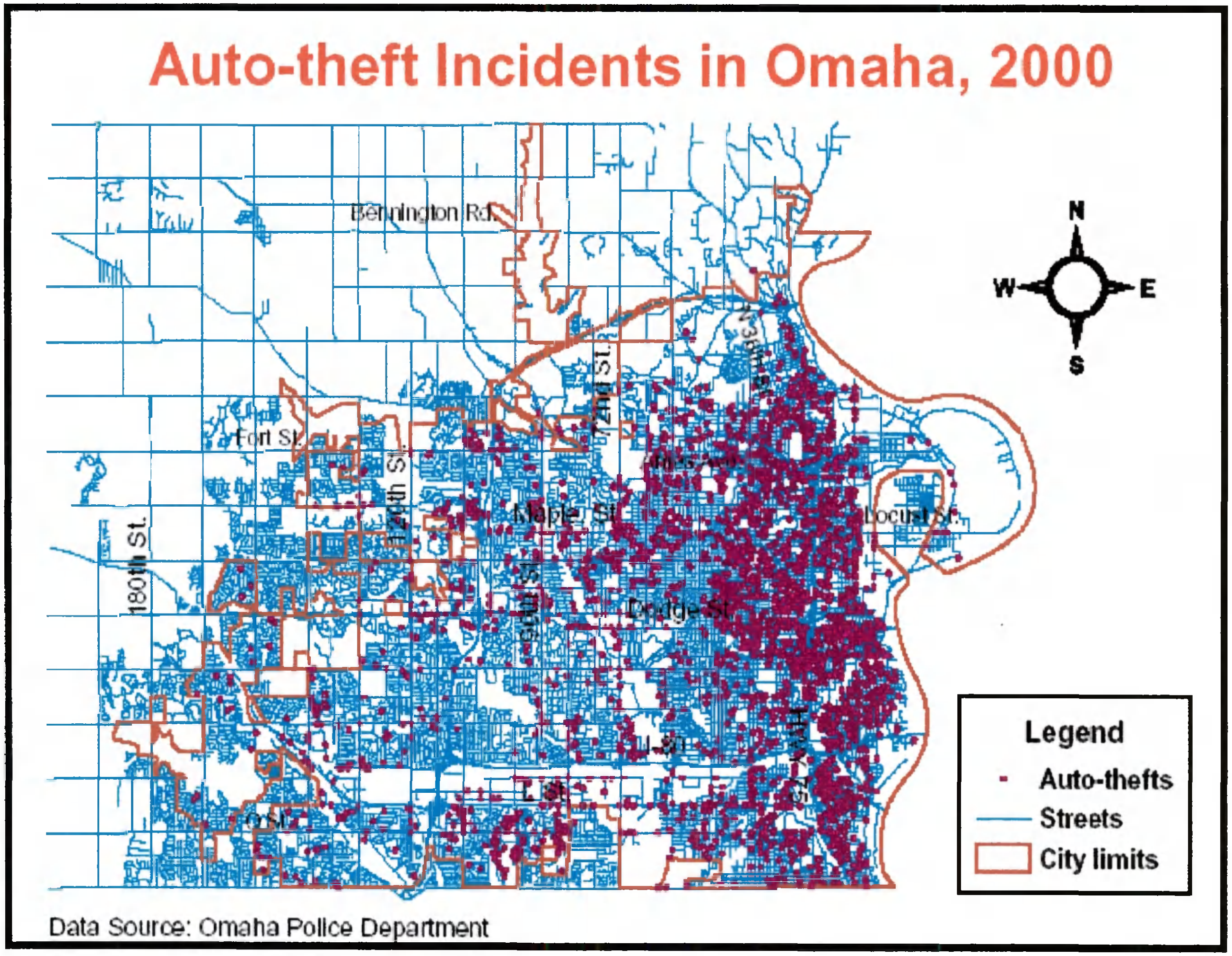

Figure 4.3 Auto-theft crime incidents in Omaha, 2000

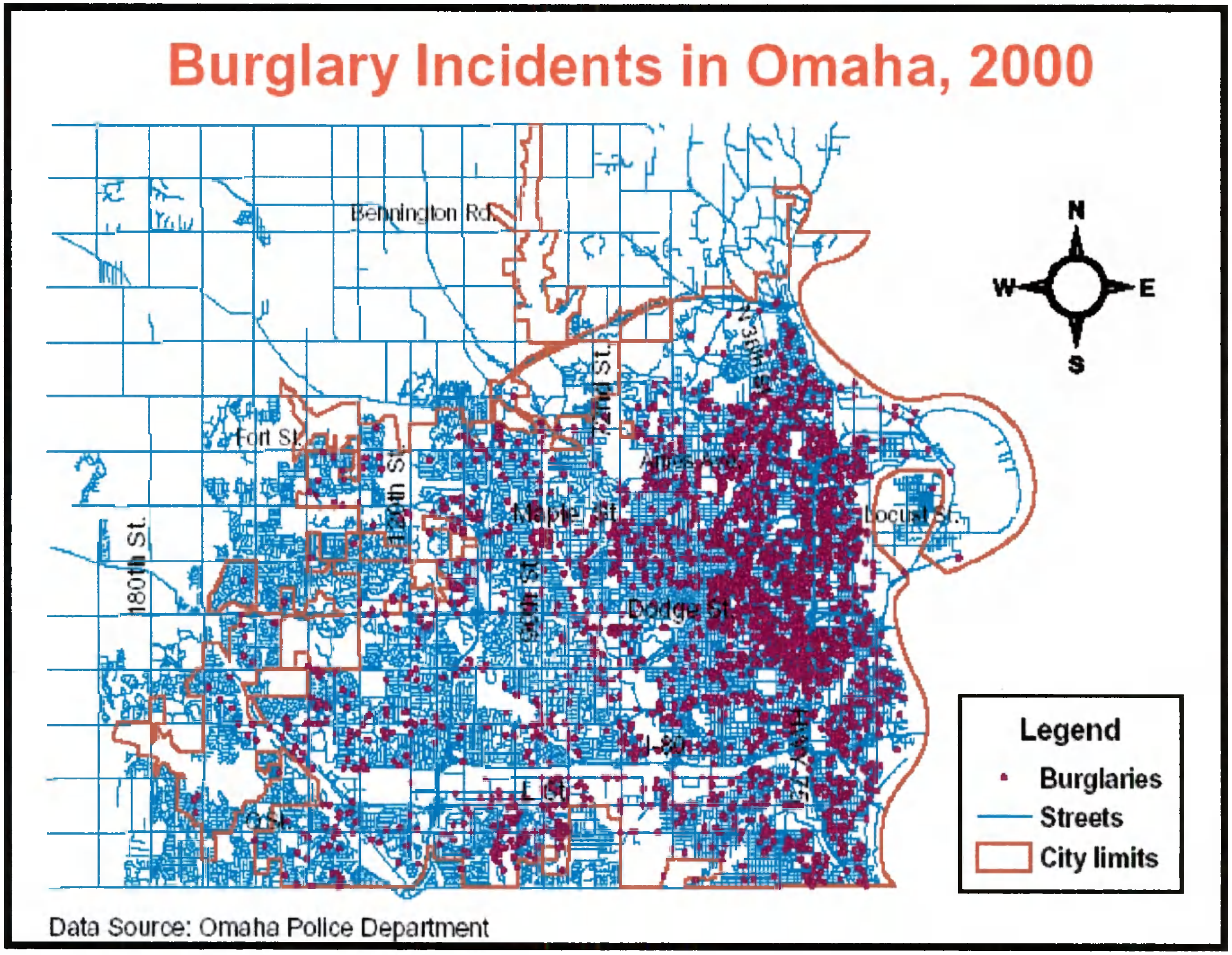

Figure 4.4 Burglary crime incidents in Omaha, 2000

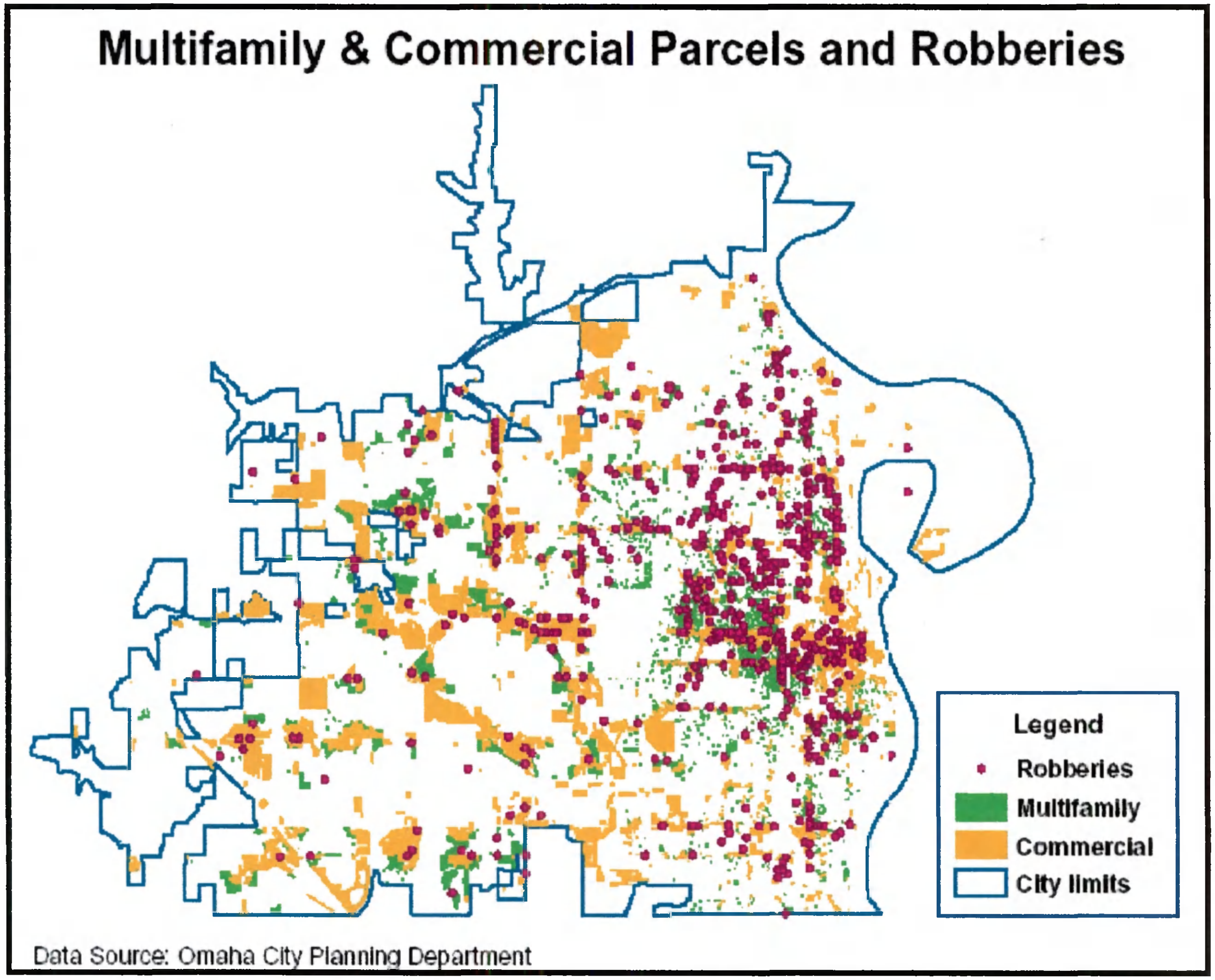

Figure 4.5 Multifamily & commercial parcels and robberies

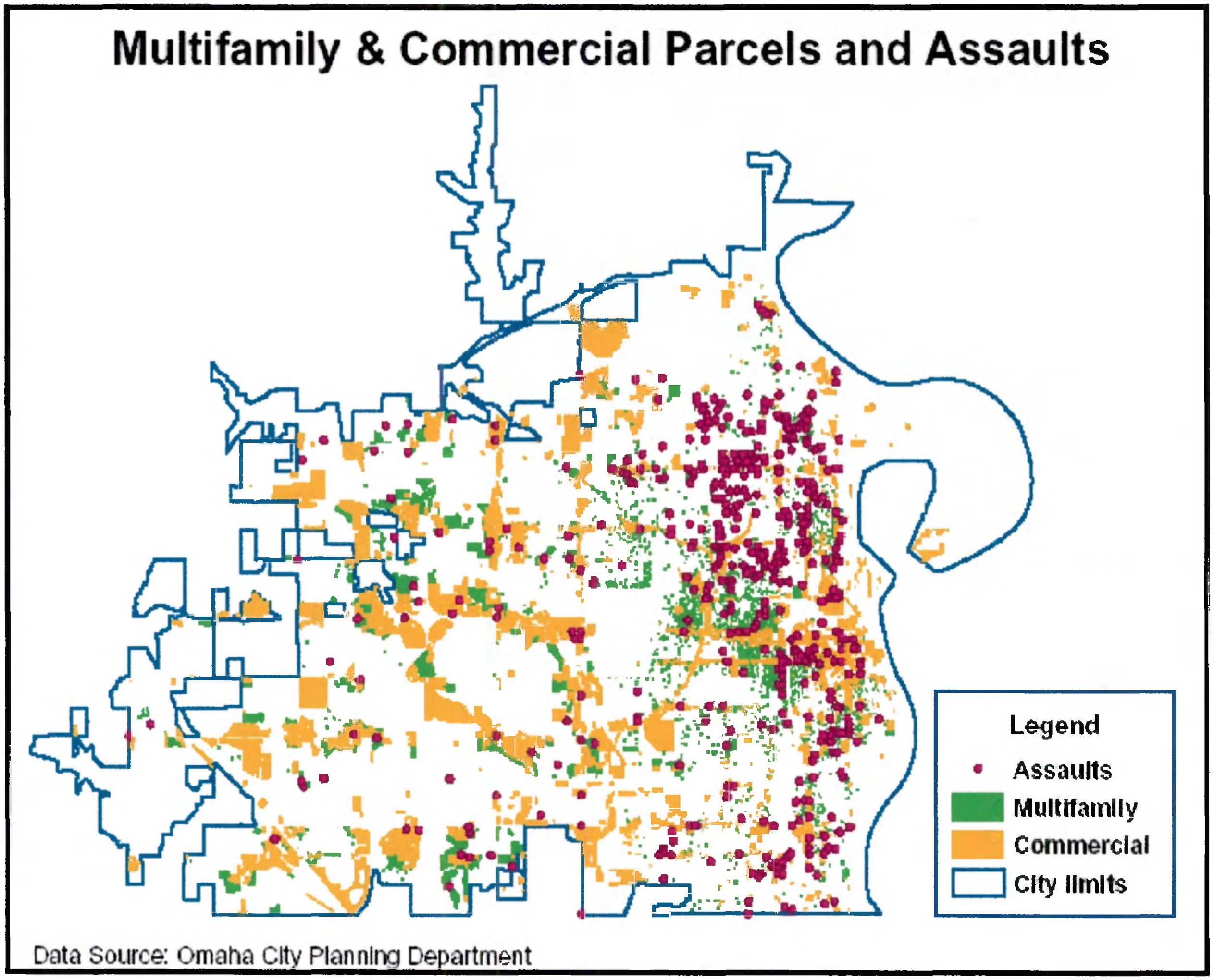

Figure 4.6 Commercial & multifamily parcels and assaults

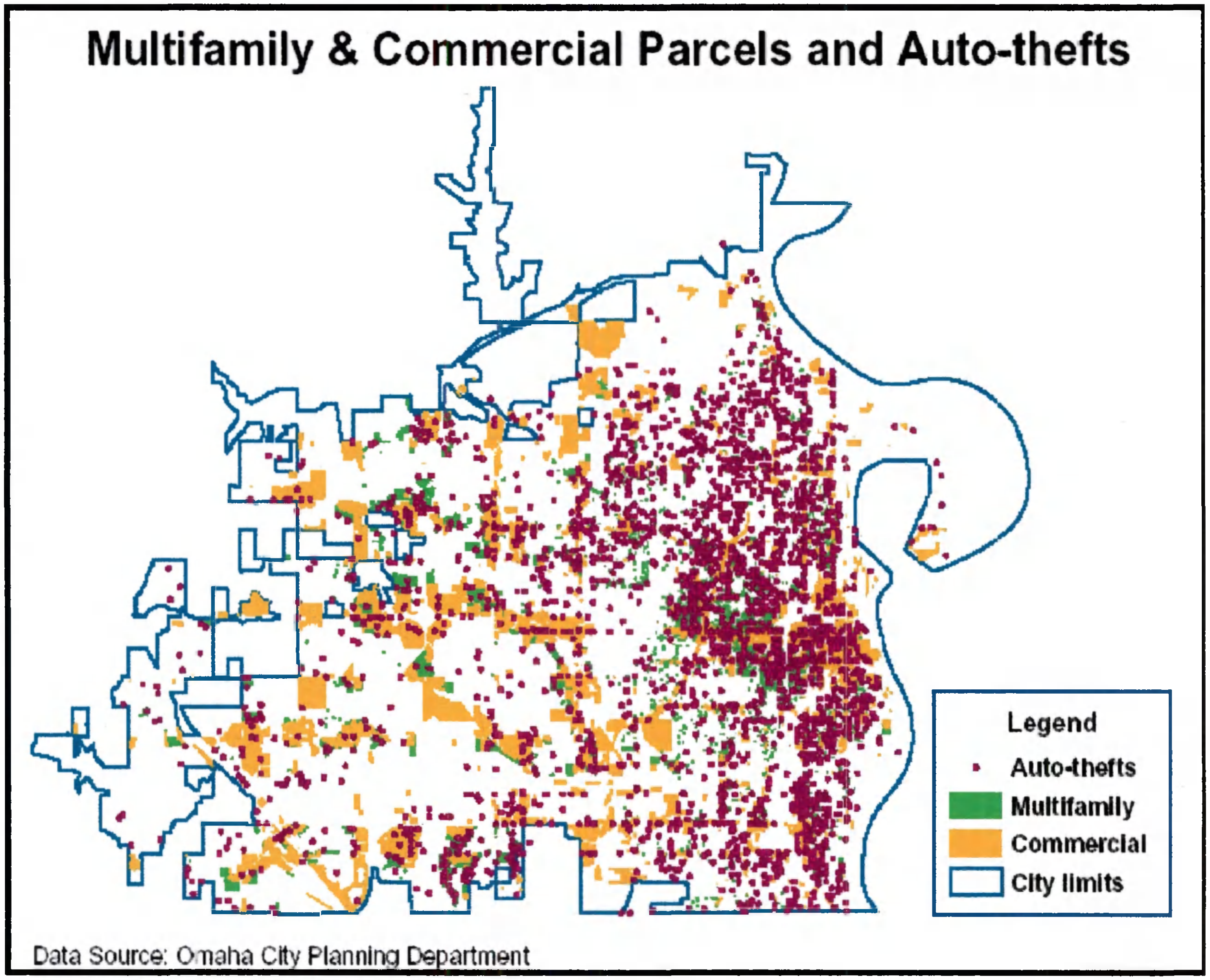

Figure 4.7 Multifamily & commercial parcels and auto-thefts

4.2.2 Grid cell analysis and density maps

Utilizing the *Spatial Analyst Extension* in ArcView, density maps of crime incidents were produced. Figure 4.8, 4.9, 4.10, and 4.11 display the density distribution of the four crime incidents respectively. The "hot spots" of assault, robbery, auto-theft, and burglary are clearly drawn out on these maps. The common characteristic of the hot spots of these four types of crimes is that they are mainly concentrated in the eastern part of the city, especially in North Omaha. Assaults are highly concentrated in the several clusters in North Omaha and the downtown area. The downtown area also suffers high occurrence of robbery, auto-theft, and burglary crimes.

To explain the distribution pattern of these hot spots, both the social disorganization and routine activity theory are needed. The social disorganization theory can be used to explain the high concentration of crimes in North Omaha. North Omaha has serious social stress characteristics, such as African Americans, female-headed households, unemployment, poverty and vacant houses, identified as indicators of crime occurrence (referred to Appendix III-5, 9, 13, 14 and 16).

The routine activity theory can provide better an explanation of the distribution of hot spots in downtown Omaha and hot spots scattered in west other parts of the city. These areas concentrate many business stores, unguarded parking lots, mobile population, and apartment complexes, which provide offenders more attractive targets and opportunities to commit crimes (referred to figure 4.5, 4.6, and 4.7). Routine activity theory is also used for explaining the hot spots of auto-theft, burglary crimes in the west Omaha. Affluent districts tend to attract property crimes more intensely than the disadvantaged areas from the perspective of profitable targets for committing property crime (referred to Figure 4.7, Appendix III-11, and III-12) (Cascach and Muscat, 2000).

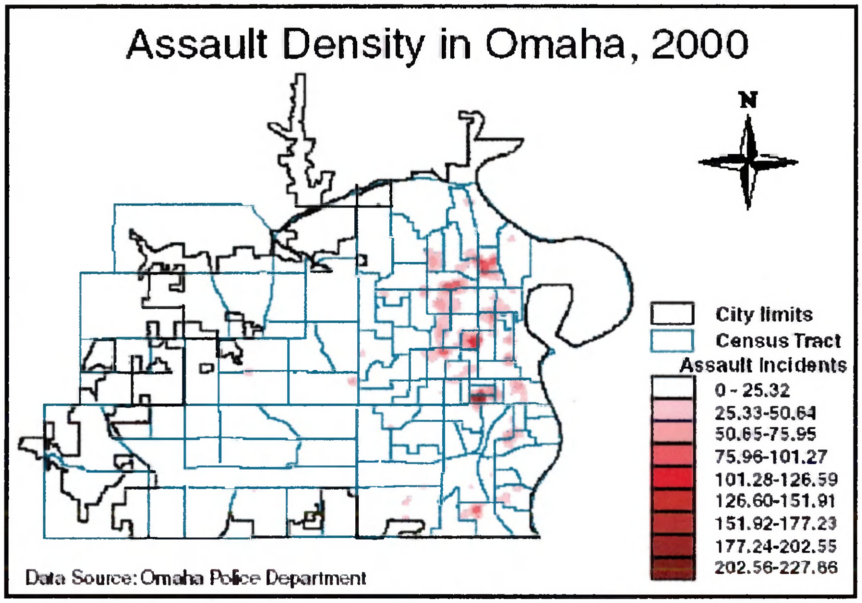

Figure 4.8 Density map of assault crime in Omaha, 2000

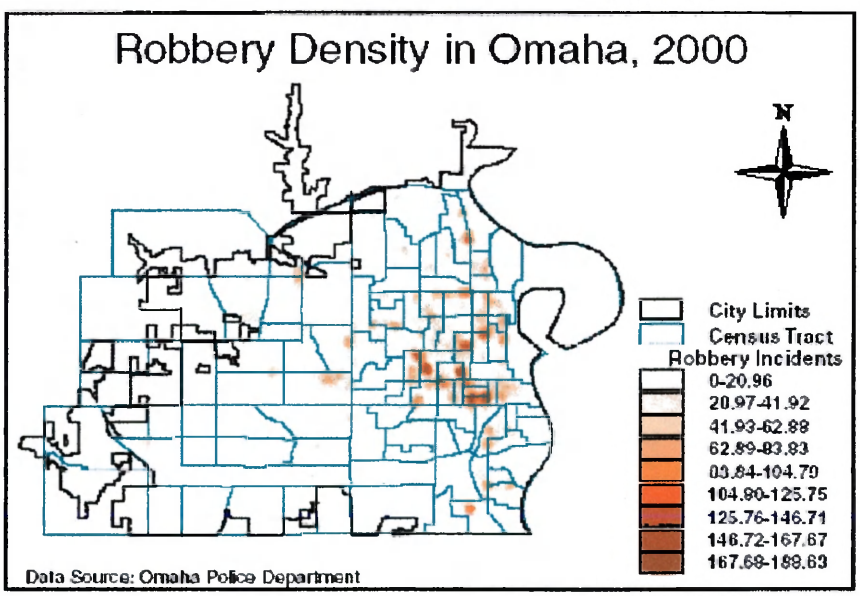

Figure 4.9 Density map of robbery crime in Omaha, 2000

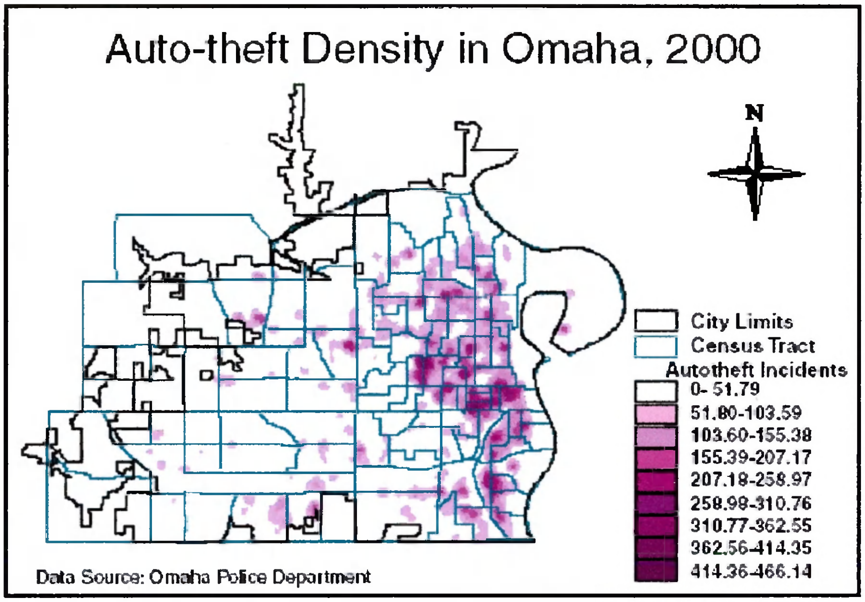

Figure 4.10 Density map of auto-theft crime in Omaha, 2000

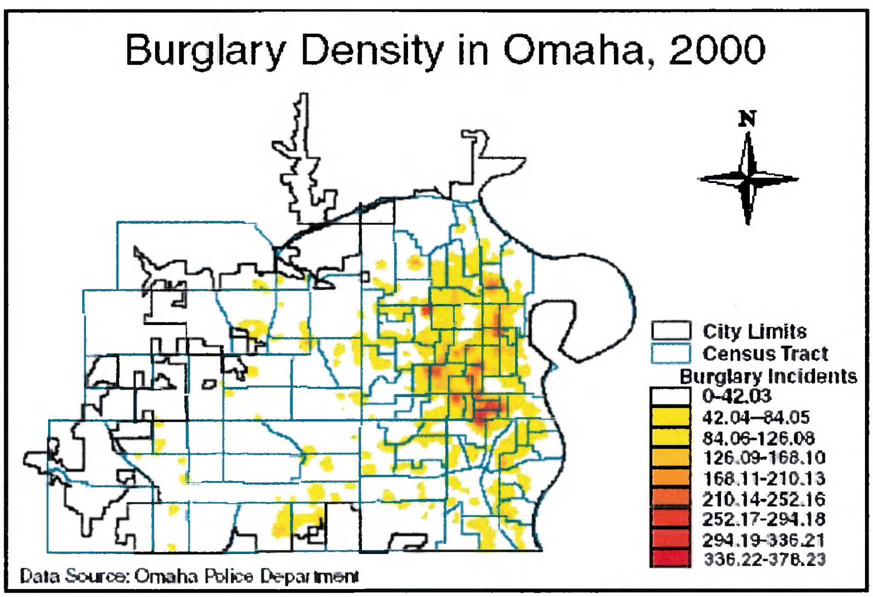

Figure 4.11 Density map of burglary crime in Omaha, 2000

4.2.3 Choropleth maps

1. LQC maps

The LQCs were used as alternative measure to map the spatial variation of crimes. Figure 4.12, 4.13, 4.14, and 4.15 are choropleth maps showing the variances of LQC for each of the four crimes across census tracts in Omaha. Figure 4.12 shows the LQC map of assault crime. North Omaha and the downtown area have high values of LQC. In addition, several tracts in south Omaha and west Omaha display relative high LQC values as well. This means these areas have a relatively higher frequency of assault crimes in the comparison to the city average. A similar pattern appears in Figure 4.13 that maps the LQC of robbery. In general, the LQC maps of assault and robbery also show that the North Omaha and downtown area have higher concentration of violent crimes.

The situations for auto-theft and burglary are distinctively different from that of violent crime. North Omaha and the downtown area show relatively low LQC values, while west Omaha and other areas have relatively high LQC values.. This means west Omaha has a relatively high ratio of property crime in comparison to all crimes over the city as a whole.

For a complete picture of the specialization and structure of crimes for each census tract, all census tracts were labeled into nine different LQC categories: auto-theft (A); burglary (B); auto-theft and burglary (A/B); robbery and auto-theft (R/A); robbery and burglary (R/B); robbery, auto-theft, and burglary (R/A/B); assault (S); assault and auto-theft (S/A); assault, auto-theft and burglary (S/A/B); assault and burglary (S/B); assault and robbery (S/R); assault, robbery and auto-theft (S/R/A); and assault, robbery and burglary (S/R/B) according to their dominant crime structure (with the criterion of LQC > 1.00) (Figure 4.16). From this structure map of dominant crimes, there are other interesting characteristics of the distribution of crime. Census tracts in North Omaha and downtown areas (high-crime districts) exhibit diversified structure of dominant crimes (such as S/R/A, S/R/B or S/A/B), but tracts in west Omaha (low-crime areas) generally have very specialized crime structure (such as A or B or A/B). This information would not only support police in identifying where resources should be deployed in response to a particular type of crime but also help citizens determine what the dominant crimes are in their neighborhood (Canter, 1995).

While LQCs can be successfully used to display the specialization and structure of crimes for each area, caution needs to be paid when interpreting areas with extraordinary low or high crimes. Table 4.2 lists three census tracts to illustrate the misleading nature of LQCs. Located in the western part of the city, tract 7405 experienced only 8 crimes in the year of 2000, with only one assault and one robbery (very rare frequencies of crime occurrence). However, the LQCs of these two types of crimes are 1.87 and 1.27, which are higher than the city average. Tract 0060 is in North Omaha and belongs to the high-crime area with 208 total crimes in 2000. Although auto-theft and burglary have higher occurrences than the other violent crimes within the tract, the LQCs for auto-theft and burglary are less than 1.00 and LQCs for assault and robbery are higher than 1.00. Tract 6801 has a more ordinary level of crime occurrences in which the higher counts of crime (auto-theft and burglary) lead to higher corresponding LQC values.

Bear in mind that LQC is calculated by dividing the percentage of a particular crime in the census tract with the percentage of this crime in the city as a whole. LQC is sensitive to both the occurrence of other crimes in the same tract and the total frequencies of the particular crime in the whole city. Therefore, special caution needs to be exercised when interpreting the geographical meanings of LQCs.

Table 4.2 Count and LQCs of three example tracts

Tract Fips*	Count of Crime**					LQCs**				Comment
	S	R	A	B	Sum	S	R	A	B	
7405	1	1	3	3	8	1.87	1.27	.83	.98	West Omaha, low-crime area
0060	30	26	90	62	208	2.15	1.27	.96	.78	East Omaha, high-crime area
6801	3	5	41	32	81	.55	.63	1.12	1.03	Medium-crime area

* Tract Fips are referred to Appendix II
** S-Assault; R: Robbery; A: auto-theft; and B: burglary

LQC emphasizes the relative specialization of the specific type of crime in the particular census tract. It should not be confused with conventional measurements that mainly reflect the absolute number of crimes. For the tracts above, although the count of assault and robbery is very small in tract 7405, the total count of crimes in it is also small, and this makes these two types of violent crimes have higher concentrations relative to the whole city (high LQCs). Tract 0060 is the opposite of tract 7405, although auto-theft and burglary have a higher percentage than assault and robbery within the tract, the city has an even higher percentage of these two property crimes.

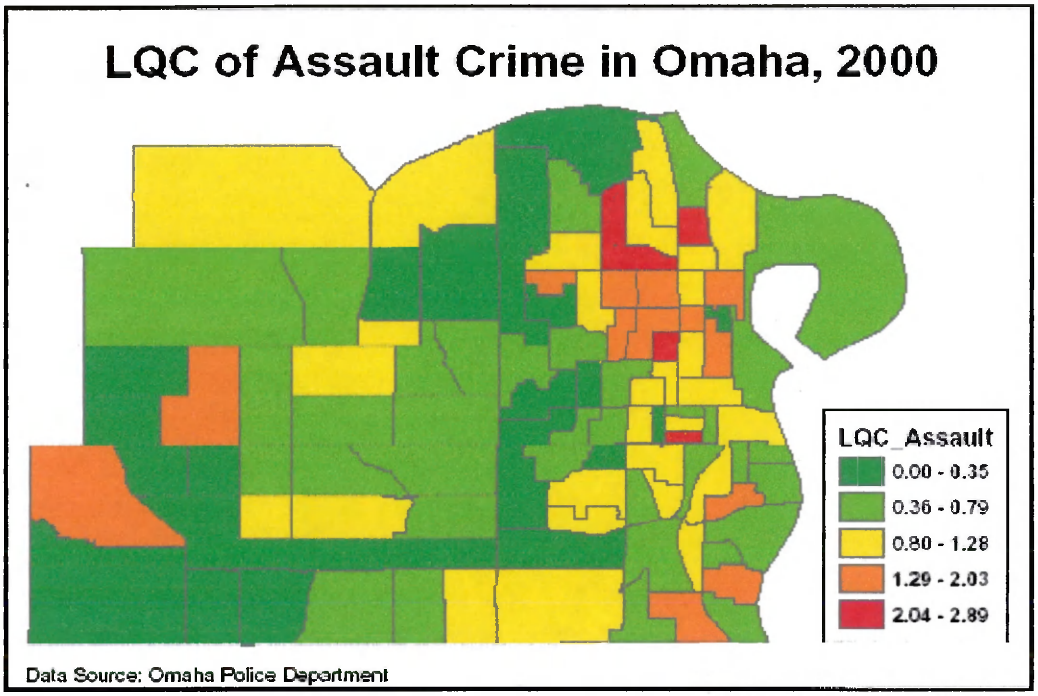

Figure 4.12 Location quotient of assault crime in Omaha, 2000

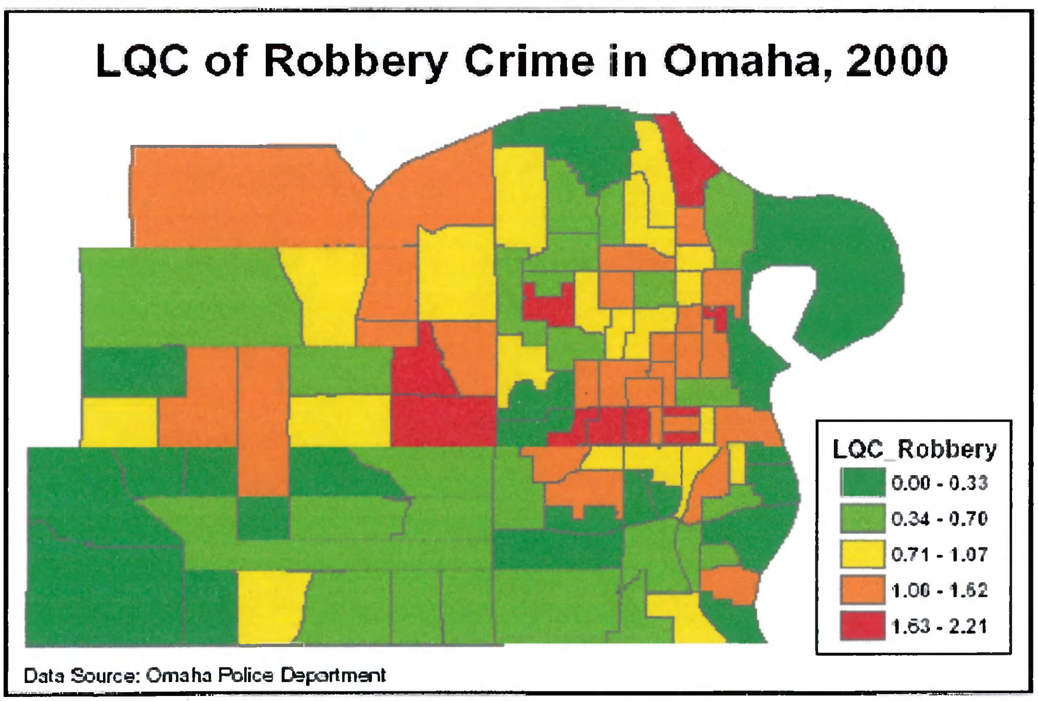

Figure 4.13 Location quotient of robbery crime in Omaha, 2000

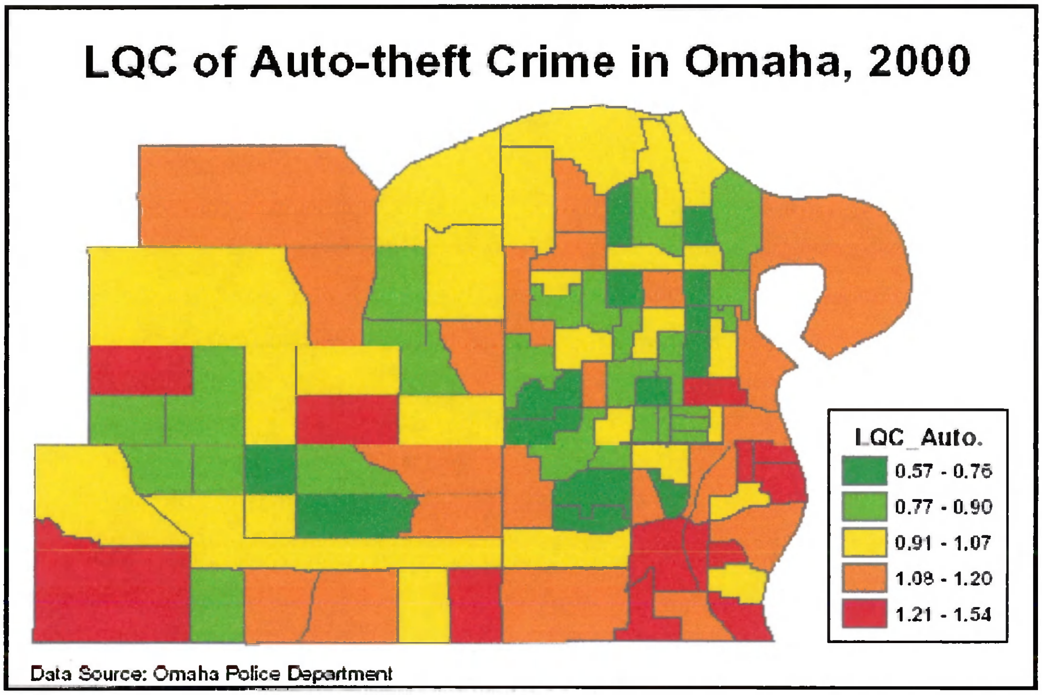

Figure 4.14 Location quotient of auto-theft crime in Omaha, 2000

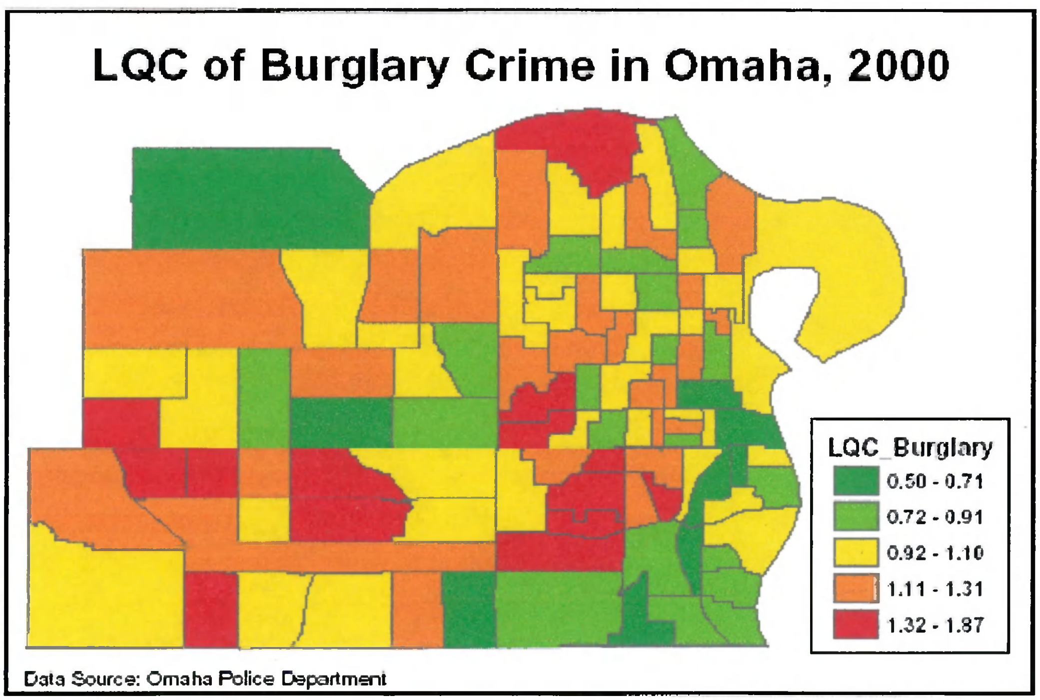

Figure 4.15 Location quotient of burglary crime in Omaha, 2000

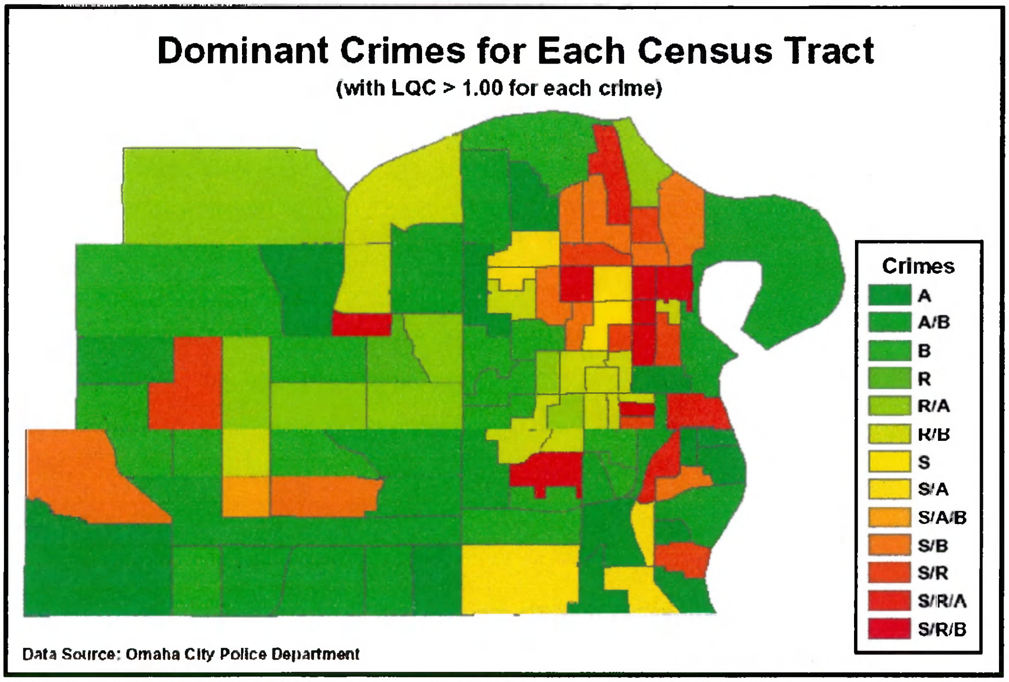

Figure 4.16 Map of the crime structure for each tract, 2000

2. Count maps

Because of the reasons explained above, the spatial patterns of crimes shown in LQC maps may be different from the maps using conventional measurement of crime (such as frequencies of crime). It was decided, therefore, that ordinary crime count maps also needed to be produced for this research (Figure 4.17, 4.18, 4.19, and 4.20). These count maps show a similar spatial pattern of the crimes as compared to the point and density maps. Assault and robbery crime are disproportionately concentrated in east Omaha, while auto-theft and burglary crimes are broadly spread across the city. North Omaha and the downtown area show the highest rates of both violent and property crimes. It is also noteworthy that some individual census tracts in other parts of the city show high crime levels for robbery, auto-theft, and burglary crimes than the surrounding areas, such as the census tracts located at the large business area near the intersection of 72nd and Dodge, the large apartment complex along north 72nd street, and the industrial corridor along the L street.

Compared with the LQC maps, the count maps show similar features in terms of assault and robbery crimes. But, for the auto-theft and burglary crimes, the count amps and LQC maps are distinctively different. In LQC maps, west Omaha has high values while east Omaha has low values for the property crimes. One exception is in southeast Omaha, where both LQC and count maps show a high occurrence of auto-theft crime.

By comparing the two groups of maps (LQC maps and count maps), one can get a comprehensive profile of crime in the City of Omaha, including both the specialization and the seriousness of crime occurrence.

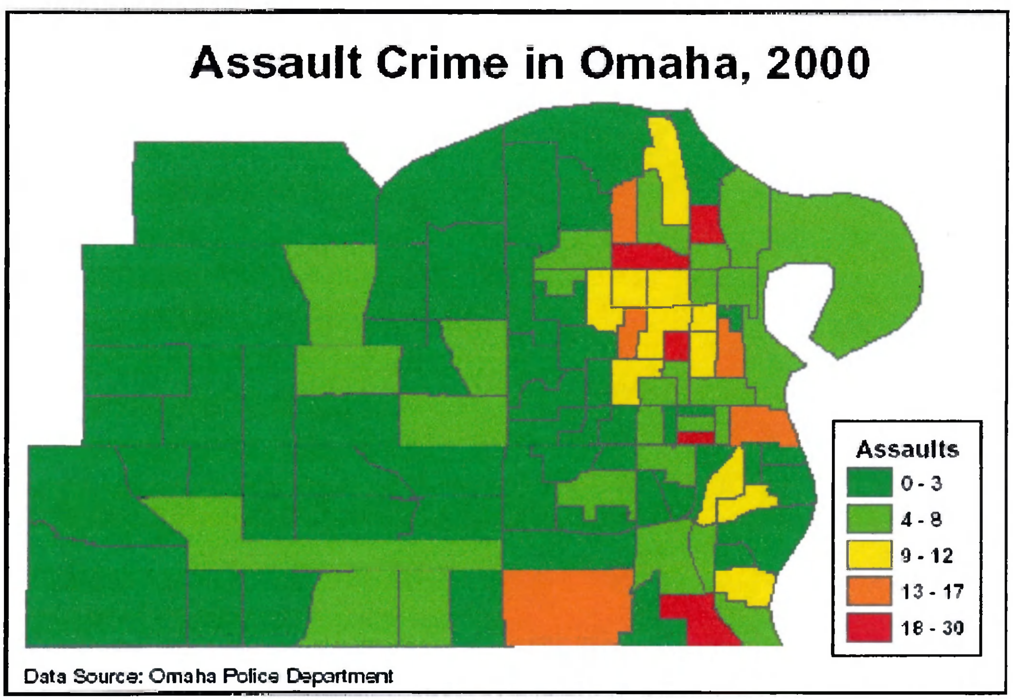

Figure 4.17 Count of assault crime in Omaha, 2000

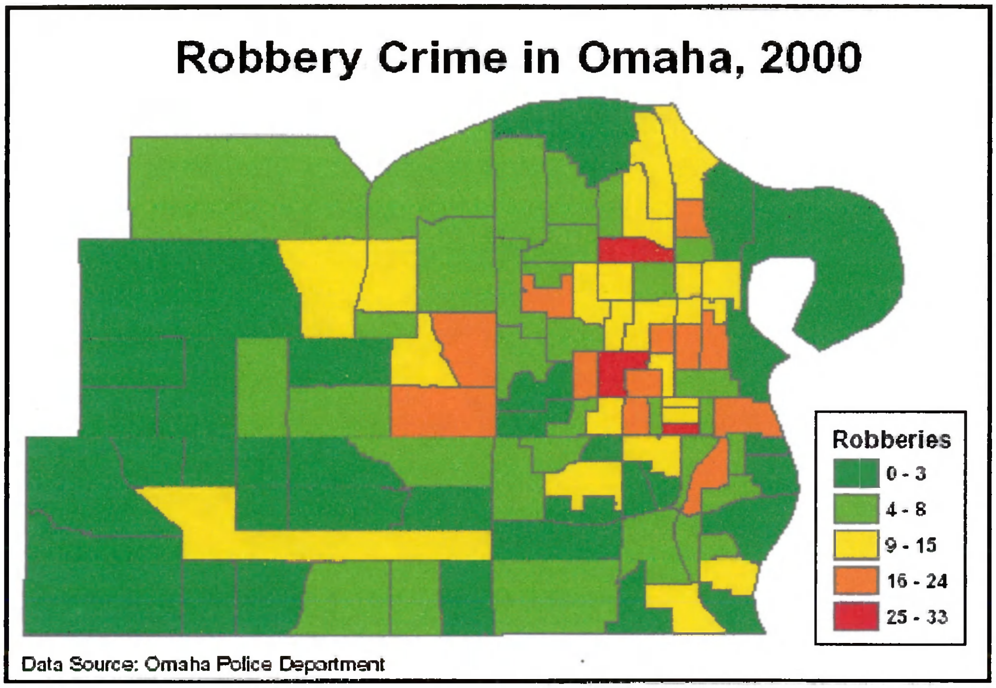

Figure 4.18 Count of robbery crime in Omaha, 2000

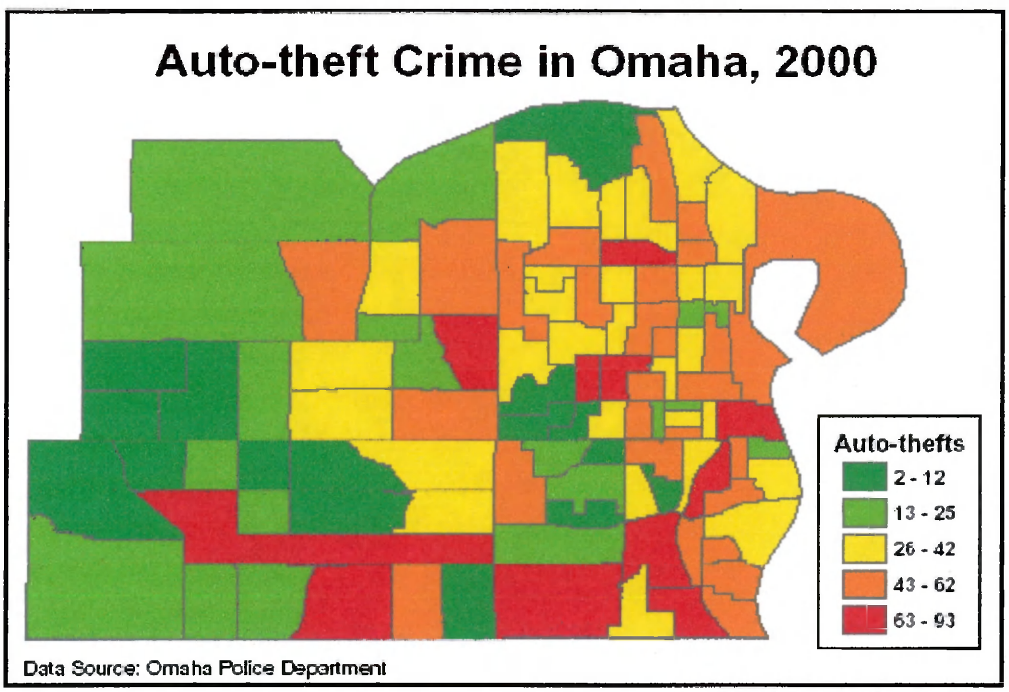

Figure 4.19 Count of auto-theft crime in Omaha, 2000

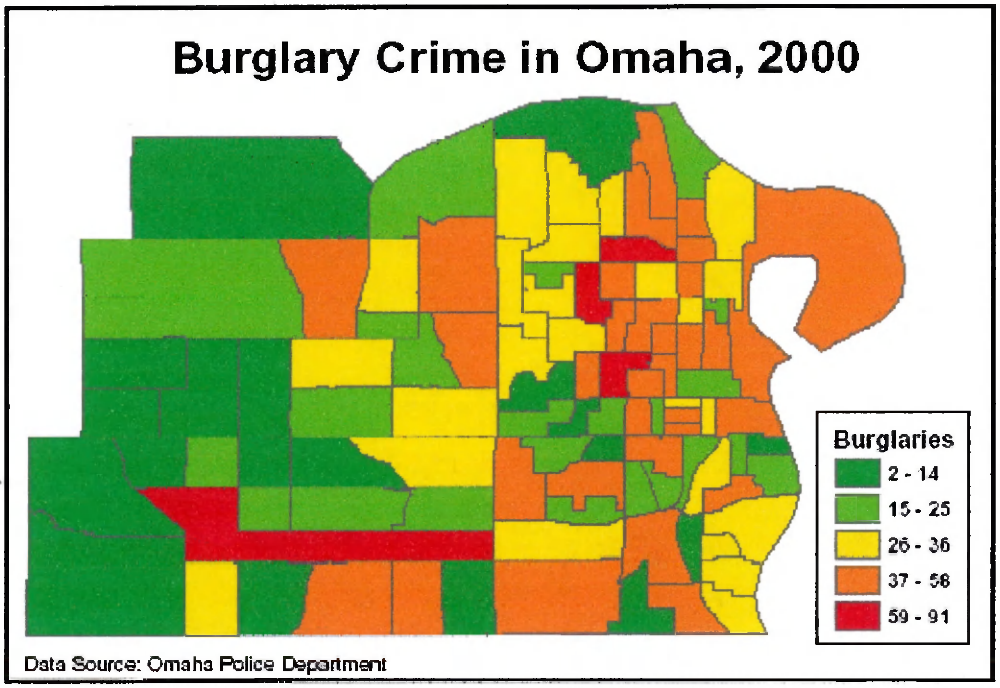

Figure 4.20 Count of burglary crime in Omaha, 2000

4.3 Statistical Results

4.3.1 Descriptive statistics

Table 4.3 shows the descriptive statistics such as Range, Minimum, Maximum, Mean, and Std. Deviation, Skewness, and Kurtosis of both the LQCs and the raw count of assault, robbery, auto-theft, and burglary (written in abbreviation as Count_S, Count_R, Count_A, and Count_B respectively). Comparing the range of LQCs of the four crimes, one can find that LQC_S and LQC_R have higher values (2.89 and 2.21) than the other two types of property crimes (0.96 for LQC_A and 1.37 for LQC_B). This reflects the difference of the distribution pattern between violent and property crimes from another perspective. Violent crimes are more highly concentrated in a small proportion of the urban area while property crimes are more scattered throughout the city.

Skewness measures the asymmetry of the data distribution. A rough guide is that if the skewness value is more than twice of its Standard Error, it indicates a departure from a symmetrical distribution. Table 4.3 shows that all the distributions of LQCs and the count value of the four crimes display positive skewness. The skewness statistics of LQC_S, LQC_B, and the count of all the four types of crimes is more than twice of their Standard Error; this means there is a departure from symmetry for their distributions, especially for LQC_S, Count_S and Count_R.

Kurtosis is a measure of the extent of the observations' cluster around a central point. Positive value means the observations cluster more and have thin tails, and vice versa. LQC_S, LQC_B, Count_S, Counter_R, and Count_B have positive Kurtosis value, while LQC_R, LQC_A, and Count_A have negative Kurtosis value.

Although some of the crime indicators exhibit some positive skewness and evidence of more or less cluster than the normal distribution, ordinary least squares (OLS) regression does not assume univariate normality, so, multiple regression models still can be used to conduct the statistical analysis.

Table 4.3 Descriptive statistics of the dependent variables

Statistics	Range	Mini.	Maxi.	Mean	Std. Deviation	Skewness		Kurtosis	
						Statistic	Std. Error	Statistic	Std. Error
LQC_S	2.89	.00	2.89	.8467	.6279	1.057	.239	1.285	.474
LQC_R	2.21	.00	2.21	.8885	.5782	.245	.239	-.843	.474
LQC_A	.96	.57	1.54	.9923	.2162	.405	.239	-.369	.474
LQC_B	1.37	.50	1.87	1.0648	.2662	.543	.239	.748	.474
Count_S	30.00	.00	30.00	5.3922	5.9071	1.923	.239	4.158	.474
Count_R	33.00	.00	33.00	7.9216	7.2558	1.193	.239	.969	.474
Count_A	91.00	2.00	93.00	36.4804	22.5484	.601	.239	-.155	.474
Count_B	89.00	2.00	91.00	30.7647	16.7280	.599	.239	.697	.474

- S-Assault, R: Robbery; A: auto-theft; and B: burglary

Table 4.4 shows the correlation matrix underlying the independent variables. It is noteworthy that there are high correlations among these predictor variables (indicated in bold), such as correlations between MHIN vs. MHV (.926), PPOV vs. PUEM (.779), and PFEM vs. PPOV (.774); and high negative correlation exists between MHIN vs. PFEM (-.779) and MHV vs. PNHD (-704). Because high correlations among independent variables will violate the regression assumptions and produce misleading results, specific measures need to be taken to reduce the multicollinearity.

Table 4. 4 Correlation matrix of independent variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
AREA (1)	1																		
TPOP (2)	.587	1																	
PBLK (3)	-.241	-.302	1																
PHISP (4)	-.252	-.248	-.233	1															
PYM (5)	-.202	-.110	.226	.050	1														
PNHD (6)	-.329	-.506	.499	.556	.163	1													
PFEM (7)	-.428	-.484	**.722**	.022	.220	.588	1												
MHV (8)	.346	.356	-.472	-.298	-.303	**-.704**	-.690	1											
PM1.01 (9)	-.224	-.338	.287	.496	.188	.651	.379	-.494	1										
MHIN (10)	.401	.393	-.442	-.293	-.340	-.665	**-.779**	**.926**	-.463	1									
POW (11)	.429	.348	-.265	-.258	-.426	-.370	-.591	.499	-.378	.664	1								
PVA (12)	-.256	-.473	.428	.304	.242	.629	.516	-.517	.517	-.556	-.660	1							
P5YRS (13)	.132	.127	-.195	-.307	-.307	-.311	-.341	.256	-.364	.319	**.756**	-.517	1						
PUEM (14)	-.201	-.366	**.729**	.010	.165	.619	.633	-.471	.291	-.482	-.342	.607	-.281	1					
PNSJ (15)	-.181	-.178	.353	-.004	-.033	.285	.232	-.238	.241	-.232	-.161	.327	-.091	.303	1				
PDEN (16)	-.502	-.046	.064	.171	.262	.053	.187	-.270	.232	-.313	-.380	.202	-.223	.086	.136	1			
PPOV (17)	-.364	-.501	**.730**	.179	.254	**.737**	**.774**	-.629	.549	-.663	-.605	**.742**	-.520	**.779**	.288	.183	1		
PMFP (18)	-.331	-.235	-.040	.237	.439	.114	.164	-.238	.258	-.342	-.613	.375	-.470	.117	.104	.648	.309	1	
PCMP (19)	-.141	-.270	-.050	.176	.188	.132	.199	-.221	.245	-.261	-.593	.428	-.528	.007	-.048	-.077	.294	.316	1

4.3.2 Regression analysis

1. Regression Model-1

Table 4.5 shows the first round results (Model-1) of the *Backward* regression analysis. The Adjusted R^2 represents the proportion of the variability in LQCs of each crime. Generally, for the four types of crimes, about one third of the variation of the assault (LQ_S) and burglary (LQC_B), and less than one third of the robbery (LQC_R) and auto-theft (LQC_A) can be explained by the variation of the selected demographic variables. However, two serious problems exist in Model-1: (1) although all the 19 original variables were entered as independent variables, only a few of them show significant t values (PBLK for the LQC_S, PFEM for the LQC_R, PHISP for the LQC_A, and AREA, PHISP and PFEM account for LQC_B), which means most of other variables do not help explain the variances in crime; and (2) some of the variables have very high VIF values which confirms the existence of multicollinearity underlying the independent variables which may seriously violate the assumption of regression analysis. Basically, a VIF value greater than 4.0 indicates the existence of high multicollinearity. However, in Table 4.5, the highest VIF value for MHIN is 23.837, and for MHV is 13.159. Therefore, Model-1 was dropped for the above reasons. For getting valid regression results, the multicollinearity needs to be removed from the regression process.

Table 4.5 Regression summaries of Model-1

	LQC_S		LQC_R		LQC_A		LQC_B		VIF
	B	Beta	B	Beta	B	Beta	B	Beta	
(Constant)	.558		-1.684		.966		1.810		
AREA	4.928E-02	.125	6.747E-02	.186	2.931E-02	.216	-5.993E-02	-.359	3.762
TPOP	-1.330E-05	-.064	-7.842E-06	-.041	1.449E-05	.204	-1.311E-05	-.149	2.977
PBLK	1.094E-02	.486	3.961E-04	.019	-2.646E-05	-.003	-1.946E-03	-.204	6.514
PHISP	9.925E-03	.162	1.106E-02	.196	8.202E-03	.389	-1.433E-02	-.550	3.915
PYM	-3.147E-02	-.124	1.846E-02	.079	-1.828E-03	-.021	3.190E-03	.030	1.676
PNHD	4.653E-03	.090	-9.793E-03	-.205	3.926E-03	.220	-2.839E-03	-.129	8.627
PFEM	4.467E-03	.088	4.171E-02	.897	1.710E-03	.099	-1.369E-02	-.639	7.505
MHV	3.722E-07	.025	2.124E-06	.154	2.743E-07	.053	-9.051E-07	-.142	13.261
PM1.01	1.771E-02	.076	-5.547E-03	-.026	-1.730E-02	-.217	1.840E-02	.187	2.470
MHIN	5.571E-06	.173	7.218E-06	.244	-2.401E-06	-.217	-6.825E-08	-.005	23.837
POWN	-5.794E-03	-.205	1.191E-03	.046	-4.463E-05	-.005	7.414E-04	.062	13.159
PVA	5.256E-03	.052	-2.968E-03	-.032	-1.038E-03	-.030	1.039E-03	.024	4.471
P5YRS	-2.171E-03	-.041	2.968E-03	.061	-7.448E-04	-.041	5.323E-04	.024	5.077
PUEM	4.067E-03	.042	2.116E-03	.024	-9.566E-03	-.289	1.014E-02	.248	3.946
PNSJ	7.434E-04	.009	1.289E-03	.017	2.744E-03	.096	-3.698E-03	-.104	1.430
PDEN	5.440E-05	.211	4.970E-05	.209	-4.912E-06	-.055	-1.623E-05	-.148	4.352
PPOV	-1.933E-03	-.045	-2.154E-03	-.055	-8.030E-04	-.055	1.817E-03	.100	9.375
PMFP	-1.156E-02	-.144	1.827E-02	.247	-5.223E-03	-.189	3.434E-03	.101	4.037
PCMP	-4.271E-03	-.065	1.014E-02	.169	4.412E-03	.197	-7.033E-03	-.254	2.890
R^2	.442		.420		.384		.444		
Adjusted R^2	.313		.286		.242		.315		
F-Test	3.418**		3.132**		2.665**		3.448**		

*: Significant at 0.05 level; **: significant at 0.01 level.

2. Regression Model-2

Model summary

For improving the regression predictability of Model-1, the last round of *Backward* regression results for the four types of crimes were checked and defined as Model-2 (Table 4.6). Model-2 not only increases the *Adjusted* R^2 for all the four types of crimes (.313 to .368 for LQC_S; .286 to .347 for LQC_R; .242 to .302 for LQC_A; and

.315 to .353 for LQC_B), more importantly, most of the variables left have significant *t* values and all their VIF values are reasonable (less than 4.0). The F-Test for all the four

Table 4.6 Regression summaries for Model-2

	LQC_S			LQC_R			LQC_A			LQC_B		
	B	Beta	VIF	B	Beta	VIF	B	Beta	VIF	B	Beta	VIF
(Constant)	.473**											
PBLK	1.401 E-02	.622**	1.057									
PHISP	1.641 E-02	.267**	1.057									
(Constant)				-.835*								
PFEM				3.263 E-02	.702**	2.622						
MHIN				1.119 E-05	.378**	2.890						
PMFP				2.922 E-02	.394**	1.168						
(Constant)							1.077**					
AREA							4.127 E-02	.305**	1.280			
PHISP							9.247 E-03	.438**	1.441			
PM1.01							-1.434 E-02	-.180	1.637			
MHIN							-3.084 E-06	-.279*	1.823			
PUEM							-7.754 E-03	-.234*	1.410			
PMFP							-7.213 E-03	-.261**	1.287			
PCMP							3.825 E-03	.171	1.186			
(Constant)										1.716**		
AREA										-3.768 E-02	-.225*	1.640
TPOP										-2.117 E-05	-.241*	1.802
PHISP										-1.137 E-02	-.436**	1.131
PFEM										-1.111 E-02	-.518**	1.409
PCMP										-5.148 E-03	-.186*	1.108
R^2	.381			.367			.351			.385		
Adjusted R^2	.368			.347			.302			.353		
F-Test	30.428**			18.911**			7.257**			11.997**		

*: Significant at 0.05 level; **: significant at 0.01 level.

types of crimes are significant, which means there is a statistically significant linear relationship between the LQCs and their associated socio-economic variables. The next step is to check the coefficient of each of the explanatory variables.

Coefficient analysis

In table 4.6, *B* is the regression coefficient for each variable. *Beta* is the standard scores of *B* values, and it represents the relative importance of the predictor variables (Folster, 2001). For the assault crime, PBLK and PHISP are the only two variables that contribute to the predictability of LQC_S in Model-2. As expected in the second hypothesis, both variables show positive coefficients (.622 and .267). This is consistent with the theory and previous literature.

For the robbery crime of Model-2, PFEM (.702), MHIN (.378), and PMFP (.394) show significant positive contribution to LQC_R change. It is reasonable to find positive correlation for PFEM and PMFP with LQC_R, because the economic deprivation of female-headed households and the high transition and low-income characteristics of multifamily residential areas are important indicators of robbery. However, the positive sign of MHIN to LQC_R is contrary to the hypotheses and cannot be explained by geographical and criminological theories. Actually, when the two maps of LQC_R and MHIN are overlaid, one can find some negative relationship between them. From this point, unquestioning dependence on the statistical result when interpreting the causation of crimes is ill advised (Shaw and Wheeler, 1994).

For the auto-theft crime of Model-2, although the Adjusted R^2 is just above 30 percent (.302), more variables had significant contributions to the change of LQC_A, and they are AREA (.305), PHISP (.438), PM1.01 (-.180), MHIN (-.279), PUEM (-.234), PMFP (-.261), and PCMP (.171). PHISP contributed most to the change of LQC_A, and then AREA and PCMP had a smaller positive effect on it. PM1.01, MHIN, PUEM and PMFP had negative coefficients on LQC_A. It is understandable that positive correlation exists between AREA and PCMP with LQC_A. The larger the area and the higher the percentage of commercial parcels, leads to a availability of cars for stealing. It is also reasonable that MHIN has a negative sign because rich people usually take more security measures to prevent auto-theft crime. By comparing the maps of PM1.01 (Appendix III-10), PUEM (Appendix III-13), and PMFP (Appendix III-18) with LQC_A, it is easy to see their negative relationship. North Omaha and downtown area have high PM1.01, PUEM, and PMFP values, but low LQC_A values, on the contrary, west Omaha has low values for the three socio-economic variables but high LQC_A values. PCMP shows an insignificant coefficient may indicate that it was a weak measure of available cars in each census tract because of the data generalization.

For the burglary crime of Model-2, all the five variables in the model have negative signs: AREA (-.225), TPOP (-.241), PHISP (-.436), PFEM (-.518), and PCMP (-.186). this is the same as the combination of PM1.01, PUEM, and PMFP for LQC_A. The negative signs of PFEM and PHISP can also be explained by checking their distribution pattern on maps (referred to Appendix III-6 and III-9). The distribution of LQC_B has a negative association with the distribution pattern of PFEM and PHISP. Another variable that can be reasonably interpreted is PCMP (Appendix III-19). It makes sense for PCMP to have a negative coefficient on burglary because areas with high percentages of commercial parcels (few residential parcels) have relative low occurrences of burglaries. The negative signs of AREA and TPOP are not consistent with their distribution patterns on maps (Appendix III-1 and III-2). This may indicate that these two variables may not capture the socio-economic characteristics associated with the LQC change of burglary crime.

In general, the results of Model-2 are satisfactory for explaining the variance of LQCs of the four types of crimes, particularly for the assault and robbery crimes. Except for LQC_A (with an adjusted R^2 of .302), about 35 percent of the variances of the other three types of crimes can be accounted for by Model-2. Regarding the regression coefficients of predictor variables for the explanation of the violent crimes, socio-economic characteristics, such as PBLK, PHISP, PFEM, PMFP exhibit correct signs (positive) as expected in the hypothesis. But, for the auto-theft and burglary crimes, they have negative signs opposite of what is expected. This result can be attributed to the use of LQCs as a measure of crime and it is consistent with the co-variance pattern of socio-economic factors and the LQCs of crimes on maps. West Omaha shows higher LQCs in terms of auto-theft and burglary on the maps. It can be interpreted that affluent areas tend to experience "theft victimization" more intensively than the disadvantaged areas (Carcach and Muscat, 2000; Harries and Norris, 1986). Unfortunately, Model-2 fails to find positive contribution of control variables to the variance of LQCs of property crimes.

4.3.3. Factor analysis and regression Model-3

1. Factor analysis

The principal components method was used to extract the major socio-economic factors from the original explanatory variables. Table 4.7 shows the total variance of the 19 original variables explained by the 6 factors with eigenvalues over 1.00. These 6 factors can explain over 80 percent of the total variance of the original variables.

Table 4.7 Total variance explained by principal components

	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.756	40.822	40.822	4.998	26.305	26.305
2	2.396	12.609	53.431	2.734	14.387	40.692
3	1.566	8.243	61.674	2.379	12.519	53.211
4	1.484	7.810	69.485	2.313	12.175	65.386
5	1.083	5.701	75.186	1.677	8.828	74.214
6	1.035	5.445	80.630	1.219	6.417	80.630

Table 4.8 shows loadings for each of the original indicators of the 6 principal components after Varimax rotation. Factor_1 has high positive loadings for PBLK, PFEM, PUEM, and PPOV, and high negative loadings on MHV and MHIN. Factor_2 has high loadings for PCMP, PVH (positive) and POWN and P5YRS (negative). Factor_3 has three high loadings for PHISP, PNHD, and PM1.01. Factor_4 combines the characteristics of PYM, PDEN, and PMFP. Factor_5 reflects the influence of AREA and TPOP. The last factor (Factor_6) has high loadings on PNSJ.

Based on patterns of loadings of the original variables on each factor, the 6 factors were in substantive terms defined more comprehensively as low socioeconomic status, commercial land use, Hispanic neighborhoods, apartment & population density, size population, and unemployed dropouts respectively.

Table 4.8 Principal components from the factor analysis

	Principal Components					
	1	**2**	**3**	**4**	**5**	**6**
AREA	-.190	-4.803E-03	-1.000E-01	-.415	**.797**	-4.387E-02
TPOP	-.306	-.205	-.186	7.737E-02	**.805**	-8.621E-02
PBLK	**.880**	-6.115E-03	-.160	-1.303E-02	-5.206E-02	.251
PHISP	-.134	.146	**.894**	9.610E-02	-.146	-3.673E-02
PYM	.311	.248	-3.328E-02	**.528**	.111	-.329
PNHD	.633	9.276E-02	**.669**	-6.701E-02	-.181	.119
PFEM	**.843**	.174	4.854E-02	.112	-.294	-3.531E-02
MHV	**-.720**	-5.053E-02	-.444	-.240	.131	.191
PM1.01	.323	.212	**.691**	.119	-3.032E-02	.183
MHIN	**-.714**	-.151	-.378	-.315	.190	.201
POWN	-.368	**-.711**	-.135	-.432	.186	3.390E-02
PVA	.499	**.543**	.322	9.137E-02	-.139	.301
P5YRS	-.196	**-.790**	-.183	-.251	-.134	-.111
PUEM	**.794**	.123	4.126E-02	-2.239E-02	-4.590E-02	.323
PNSJ	.256	-2.673E-02	7.879E-02	.108	-6.986E-02	**.764**
PDEN	3.156E-02	-5.898E-02	.107	**.896**	-.143	.163
PPOV	**.784**	.373	.215	7.958E-02	-.171	.216
PMFP	-1.966E-02	.438	.112	**.757**	-.129	8.928E-02
PCMP	1.202E-04	**.852**	8.528E-02	-7.119E-02	-.201	-.197
Defined Factors	Low socioeconomic status	Commercial land use	Hispanic neighborhoods	Apartment & population density	Size population	Unemployed Dropouts

2. Regression Model-3

The principal components from the factor analysis were saved as new independent variables for conducting the regression analysis (Model-3). The results of Model-3 are in Table 4.9. After factor analysis, the VIF values of all the predictor variables (principal components) were reduced to 1.00, and this means that the factor analysis completely eliminated the multicollinearity among the original independent variables.

For assaults, Model-3 in Table 4.9 shows that the low socio-economic status (Factor_1) and the unemployed dropouts (Factor_6) are the two factors that have significant coefficients predicting LQC_S. This result complements the explanation of LQC_S in Model-2 by adding unemployed dropouts into the combination of predictor variables.

For robbery, low socio-economic status (Factor_1), commercial land use (Factor_2), and apartment & population density (Factor_4) account for most of the variance of LQC_R. Once again, by integrating Factor_2 (commercial land use) into the combination of predictor variables, Model-3 provides a better explanation for clarifying the citizen's common view that commercial areas and apartment complexes attract more crimes, especially robberies (referred to Figure 4.5).

For the auto-theft, Hispanic neighborhoods (Factor_3) and size population (Factor_5) have positive coefficients for the LQC_A while apartment and population density (Factor_4) and unemployed dropouts (Factor_6) have negative coefficients. The signs of coefficients for Hispanic neighborhoods and apartment and population density match the direction of the two original variables: PHISP and PMFP for LQC_A in Model-2. The same explanation as for LQC_A in Model-2 can be used to account for the negative coefficients of Factor_4 and Factor_6.

For burglary, low socio-economic status (Factor_1), commercial land use (Factor_2), and Hispanic neighborhoods (Factor_3) all have negative signs for LQC_B. For the interpretation of the negative coefficient signs of the associated factors to LQC_B it is useful to examine their distribution maps (Appendix III-5, III-9, III-13, III-14, III-19, and III-6). Same explanations for LQC_A and LQC_B in Model-2 can be used to interpret the regression results.

Although the Adjusted R^2s for all the LQCs of the four types of crimes in Model-3 are lower than the corresponding values in Model-2, Model-3 has advantages in determining a better combination of predictor variables in clarifying the LQC change of crimes, especially for the assault, robbery, and burglary. Furthermore, using comprehensive principal components (defined factors) may be more reasonable to explain the variance of crimes than using the original demographic variables.

Table 4.9 Regression summaries of Model-3

Factors	LQC_S		LQC_R		LQC_A		LQC_B		VIF
	B	Beta	B	Beta	B	Beta	B	Beta	1.000
Constant	.847**		.889**		.992**		1.064**		1.000
Low social status (Factor_1)	.312	.497**	.153	.263**	-3.176 E-02	-.147	-5.588 E-02	-.210*	1.000
Commercial land use (Factor_2)	4.934 E-02	.079	.154	.265**	1.704 E-02	.079	-6.847 E-02	-.257**	1.000
Hispanic neighborhood (Factor_3)	9.846 E-02	.157	-4.976 E-02	-.086	6.945 E-02	.321**	-8.721 E-02	-.327**	1.000
Apartment & density (Factor_4)	1.535 E-02	.024	.173	.298**	-4.454 E-02	-.206*	5.268 E-03	.020	1.000
Total population (Factor_5)	-3.549 E-02	-.056	-8.597 E-02	-.149	4.291 E-02	.199*	-2.214 E-02	-.083	1.000
Unemployed dropouts (Factor_6)	.174	.276**	6.849 E-04	.001	-4.038 E-02	-.187*	1.730 E-02	.065	1.000
R^2	.358		.259		.248		.228		
Adjusted R^2	.317		.212		.201		.180		
F-Test	8.819		5.532		5.224		4.686		

*: Significant at 0.05 level; **: significant at 0.01 level.

4.3.4 Control model

Because most of the previous research in the field of the analysis of crime patterns uses raw count or crime rate as the dependent variable, Model-4 (Table 4.10) was designed as a control model to compare the predictability of LQC as an alternative measure of crimes. In Model-4, the dependent variables are the counts of assaults (Count_S), counts of robbery (Count_R), counts of auto-thefts (Count_A), and counts of burglaries (Count_B) respectively. The backward regression method was also used to conduct the regression analysis. The regression results are shown in Table 4.10. Generally, Model-4 has higher Adjusted R^2 (.430 for Count_S, .412 for Count_R, .310 for Count_A, and .314 for Count_B) than Model-2. The explanation of the specific coefficients of the predictor variables for each type of crimes is as follows:

For the Count_S, stress variables such as PBLK (.450), PM1.01 (.324), and PDEN (.155) have positive coefficients for the occurrence of assaults. This is similar to the regression result in Model-2 in which PBLK and PHISP are significantly associated with LQC_S. The positive effect of PDEN is consistent with social disorganization theory because large population and overcrowding lead to high occurrence of assault crime.

For the Count_R, PFEM (.526), PM1.01 (.244), and PMFP (.321) have positive effects on the occurrences of robbery. PFEM and PMFP also appear as explanatory variables in Model-2 with positive coefficients for the change of LQC_R. However, the negative sign of PNHD for robbery is puzzling.

Table 4.10 Regression summaries of Mode-4

	Count_S			Count_R			Count_A			Count_B		
	B	Beta	VIF	B	Beta	VIF	B	Beta	VIF	B	Beta	VIF
(Constant)	.195											
PBLK	9.525 E-02	.450**	1.09									
PM1.01	.706	.324**	1.147									
PDEN	3.753 E-04	.155*	1.057									
(Constant)				-3.928*								
PNHD				-.159	-.266*	2.308						
PFEM				.307	.526**	1.552						
PM1.01				.654	.244*	1.848						
PMFP				.298	.321**	1.094						
(Constant)							63.104**					
AREA							3.945	.279**	1.336			
PBLK							.230	.284*	2.943			
PHISP							.487	.221*	1.519			
MHV							-1.41 E-04	-.262*	1.885			
POWN							-.401	-.395**	1.528			
PUEM							-.944	-.273*	2.387			
(Constant)										63.713**		
AREA										1.905	.182	1.286
MHV										-1.23 E-04	-.308 **	1.381
POWN										-.407	-.542 **	2.227
PCMP										-.470	-.271*	1.592
R^2	.447			.435			.351			.341		
Adjusted R^2	.430			.412			.310			.314		
F-Test	26.417**			18.694**			8.558**			12.535**		

*: Significant at 0.05 level; **: significant at 0.01 level.

For the Count_A, 6 variables appear to account for the variance of auto-theft. AREA, PBLK, and PHISP had positive effects while MHV, POWN, and PUEM had negative effects. These results basically reflect the distribution pattern of auto-theft in the count map (Figure 4.19). The larger the AREA and the higher the percentage of African Americans and Hispanic population, the higher the frequencies of auto-thefts. The negative signs of MHV and POWN can be explained that security precautions and neighborhood watch efforts reduce the occurrence of auto-thefts. The positive sign of PBLK confirms the second hypothesis that social stress factors have positive association with crime and is compatible with the social disorganization theory. However, it is difficult to explain the negative contribution of PUEM in this model.

For Count_B, PHV (-.308), POWN (-.542), and PCMP (-.271) are the three explanatory variables that have significant coefficients for the frequencies of burglary. The same explanation as for the auto-theft crime can be used to account for the coefficients of PHV and POWN to burglary crime. Intensive security measures and neighborhood watch in affluent areas effectively reduced the occurrence of burglary. The negative coefficient of PCMP can be explained by observing that a high percentage of commercial parcels lead to low share of residential parcels and low burglary crimes.

In general, Model-4 provides a reasonable explanation for the spatial variance patterns displayed in the count maps and is consistent with prior research. Stress variables, such as PBLK, PHISP, PFEM, PM1.01, PDEN, and PMFP, have the expected positive coefficients and the control variables (such as MHV and POWN) have negative signs for the explanation of the occurrence of specific types of crimes.

4.3.5 Evaluation of models

Comparing the results of the Model-2, Model-3 (LQC models), and Model 4 (count model), some commonalities and differences can be identified:

(1) For the two types of violent crimes, the stress variables or principal components show expected positive signs separately or in some combination in these three models, such as PBLK and PHISP for assaults, and PFEM and PMFP for the robberies in Model-2; low social status (Factor_1) and unemployed dropouts (Factor_6) for assault, and Factor_1, commercial land use (Factor_2), and apartment and density Factor_4 for robberies in Model-3; PBLK, PM1.01 and PDEN for assaults, and PFEM, PM1.01, and PMFP for robberies in Model-4.

(2) The difference between the LQC models and count models are evident for the property crimes. The stress variables show different signs for the LQC models (Model-2 and Model-3). PM1.01, PUEM, and PMFP have negative signs for LQC_A and Factor_1 has negative signs for both LQC_A and LQC_B in Model-3, while PBLK, PHISP have positive signs for Count_A. Comparing the LQCs and count maps of the auto-theft and burglary can clarify this difference. On LQC maps, stress variables show a negative relationship with property crimes while on count maps they show positive relationship with property crimes. There are two exceptions, one is PHISP which has the same sign (positive) for both LQC_A and Count_A; the other is PCMP which makes a positive contribution to LQC_A and has the negative coefficient for both LQC_B and Count_B.

(3) The control variables such as MHIN shows expected negative coefficients for LQC_A in Model-2, and MHV and POWN have negative contribution for Count_A and Count_B in Model-4, but MHIN exerts incorrect (positive) contribution to the LQC_R in Model 2.

Only modest proportions of the variations of both the LQCs and count of crimes were explained by the designed models, although these match the general level of predictability of statistical analysis of crime, following four problems may exert negative effects on the predicting of the statistical models in this research.

(1) Crime occurrences are determined by some random elements and numerous factors that are still poorly understood by researchers (Ellis and Walsh, 2000). Demographic factors are not responsible for all the occurrence of crimes in the neighborhoods, and other issues such as access to 24-hour stores, large shopping centers, apartment complex, interstate highways, and major roads are also important stimulators of crime (Napolitano, 1998).

(2) The occurrences of crimes are not necessarily at the place or area where the offenders or victims live. From this point, it is not surprising that using the demographic data at aggregated areal level cannot completely explain the occurrence of crimes in each area;

(3) In this research, one year's data of crime cannot capture fully the general situation of the occurrence of crimes in the City of Omaha, since the fluctuation of the crime rate over years;

(4) Although very high matching rate was achieved during the geocoding process, there was still 7 percent of assault, 5 percent of robbery and auto-theft, and 4 percent of burglary incidents that were not matched. These kinds of technique limitation definitely affect the accuracy and validity of this analysis.

(5) Aggregating point data to the census tract level. Some of the spatial pattern of crime may be dampened or suppressed during the aggregation of point data to the census tract level. The same problem affects the demographic data. Using finer areal units, such as block group or blocks may be useful for getting more satisfactory statistical results.

(6) Particularly, for the LQC models (Model-2 and Model-3), the overestimation or underestimation of the values of LQC for areas with extraordinary low or high crime frequencies may also hamper the predictive power of the models.

4.4 Summary of Chapter

The results of the GIS visualization and statistical analysis of this research were summarized in this chapter. Through geocoding, more than 93 percent of the original crime incidents were successfully geocoded on maps. In total, three types of map methods were used to visually display the distribution of incidents, the location of hot spots, and the areal differentiation of assault, robbery, auto-theft, and burglary crimes in the City of Omaha. The general distribution pattern of these four types of crimes is that they are disproportionately concentrated in the North Omaha and the downtown area. Assault and robbery (violent crimes) dominate North Omaha and the downtown Omaha (high-crime area), while auto-theft and burglary (property crimes) spread to the whole area of the city.

LQC maps and count maps show similar picture in terms of the violent crimes, but show different profile for the two types of property crimes. On the LQC maps, auto-theft and burglary exhibit higher values in west Omaha and low values in the eastern part, while on the count maps they show higher value in the eastern part and low values in the western Omaha. The specialization and structure map of LQCs shows that different areas have different crime specialization and crime structure. High-crime areas such as North Omaha and downtown area generally have a diversified structure of crimes, while low-crime areas such as west Omaha have relatively specialized structure of crime --- mostly property crimes. LQC has advantages in displaying the relative occurrence of crime in each census tract compared to the city average while the count of crime indicates the absolute occurrences (the seriousness of crime) of crime within each tract.

For the statistical analysis, four models were produced. However, Model-1 was discarded for the serious violation of regression assumptions, only Model-2, Model-3, and Model-4 were kept to explain and test the hypotheses. Model-2 uses LQCs as dependent variables and shows that modest proportion (about 35 percent for the assault, robbery and burglary crimes and about 30 percent for auto-theft crime) of the variance of the four types of crimes can be significantly explained by the selected socio-economic variables. The stress variables such as PBLK, PHISP, PFEM, PMFP show expected positive contribution to the violent crime, but show unexpected negative signs for the property crimes. This is because of LQCs were used as dependent variables. But, the control variables such as MHV, POWN, and P5YRS are either not necessary or exert the opposite influence as expected, such as the positive sign of MHIN for LQC_R in Model-2.

Factor analysis not only completely eliminates the multicollinearity underlying the independent variables but also has the advantage of creating reasonable combinations of explanatory variables and results in using principal components as independent variables in Model-3.

Model-4 was included as a control model (using count of crime as the dependent variable) to compare with the LQC models. It had higher Adjusted R^2s than the corresponding LQC models (Model-2 and Model-3). Stress variables such as PBLK, PHISP, PFEM, PM1.01, PDEN, and PMFP separately or in some combination had expected positive coefficients while the control variables such as MHV and POWN had the expected negative signs for both the violent and property crimes. The results of Model-4 match the distribution pattern of crimes on the count maps and is compatible with the social disorganization theory and previous research.

The LQC models and count models share some commonalities and each exhibits distinctive advantages in reflecting different aspects of the occurrence of crime across areas. Model-2 and Model-3 can be integrated for analyzing the relative specialization and structure of crimes across space, while Model-4 is superior in examining the absolute frequencies of crimes.

There are several reasons that may explain the modest predictability of the regression model. Socio-economic characteristics may not account for all the occurrence of crimes, and there are crime factors that are still obscure for researchers. Problems concerning the GIS-based geocoding and generalization problems with data aggregation also reduce the predictability of the regression models. In addition, problems with using LQCs may also hamper the explanation power of the LQC models.

Chapter Five

CONCLUSION

5.1 Overview of Thesis

The major purpose of this thesis is to display the spatial distribution pattern of assault, robbery, auto-theft, and burglary crimes in the City of Omaha and explore their relationship with the selected socio-economic characteristics. The location quotient of crime (LQC) was employed as an alternative measure to capture the specialization and structure of dominant crimes across census tracts. Chapter One addressed the nature of the problem, the objectives, hypotheses, and significance of this research. The major theories and previous research literature on crime mapping and crime analysis were reviewed in Chapter Two. Chapter Three presented the methodology of the thesis, and both the approaches of GIS visualization and statistical analysis were included in this research. Three kinds of mapping methods (point, grid cell analysis, and choropleth map) were used to display the location of crime incidents, the hot spots distribution, and the spatial variation of crimes across census tracts. For the statistical analysis, both factor analysis and multiple regression models were used to explore the crime-causation relationship. Chapter Four presented the results and analysis of the map interpretation and statistical models.

5.2 Major Findings of Research

Through this research, the distribution pattern of the four types of crimes and their relationship with socio-economic characteristics were explored. The major findings of this research include:

(1) Through the mapping of the crime incidents, the analysis of hot spots and the areal differentiation, the major profile of crime in Omaha is that crimes are unevenly distributed in the city and all the four types of crimes show a high concentration in the eastern part of the city, especially North Omaha and the downtown area. Specifically, assault and robbery exhibit a more disproportionate distribution pattern than property crime and is mainly dominated by the North Omaha and downtown areas, while property crime is spread throughout the whole city.

(2) The LQC has the advantage of highlighting the relative specialization of crime across geographical areas and can be successfully used as an important alterative to the conventional measures for crime mapping. The LQC maps of each of the four types of crimes and the structure map of dominant crimes in each census tract show that east Omaha has a higher occurrence of violent crime and diversified crime structure while the western part of the city is dominated by property crime and has relatively specialized structure of crimes. This finding is not only helpful for supporting police to find the dominant crimes for each area and to deploy rational resources in response to different structure of crimes, but also helps citizens determine out the prevailing crimes in their neighborhoods.

However, the LQC may also cause a misleading perception of crime distribution. Special caution needs to be exercised in the interpretation of LQCs for areas with extraordinary low or high occurrences of crime to avoid a biased conclusion. Therefore, integrating the conventional measure (count or crime rate) is advised when using LQCs for crime mapping and statistical analysis.

(3) The regression model using LQC as a dependent variable can significantly explain a modest proportion of the specialization of four types of crimes. The control model (regression model using count of crimes as dependent variables) produced similar results for the assault and robbery crimes as the LQC models, but quite different results for the auto-theft and burglary crimes. This simply reflects the difference between the LQCs and the count of the property crimes in Omaha.

Social tress variables such as PBLK, PHISP, PFEM, PM1.01, PDEN, and PMF had the expected signs (positive) for both LQC and count models, separately or in combination, for the assault and robbery crimes. But, PM1.01, PUEM, PMFP, PHISP, PFEM, and PCMP had negative coefficients for the auto-theft and burglary crimes in Model-2, which is contrary to the second hypothesis. This finding has an implication in enriching the application of LQCs for conducting multiple regression analysis and explaining the prevailing situation of property crime in the affluent areas (west Omaha) of the city. Control variables such as MHV and POWN had the expected negative coefficients to the occurrence of property crime in the count model.

The two kinds of statistical models (LQC model and count model) had distinctive advantages in accounting for the different aspects of the crime (relative specialization or absolute occurrence of crime) and can be used to justify the general spatial patterns of crime in the corresponding LQC maps and count maps.

(4) Factor analysis is an effective method for reducing the multicollinearity that exists in the predictor matrix but did not necessarily improve the predictability in the regression analysis by using the principal components as independent variables. Although

factor analysis does not lead to a higher Adjusted R^2s than Model-2, Model-3 exhibits some particular compensation in determining a better combination of predictor variables and provides more reasonable explanation of the variance of crimes than using the original variables. For example, low social status, commercial land use, and apartment & density had positive coefficients on LQC_Robbery. This finding clarified the citizen's common view that apartment and commercial areas attract more crimes.

5.3 Future Work

More research is needed to focus on various aspect of crime analysis that could not be addressed in this thesis. The multiple regression models used in this research, could only explain about one third of the variation of the change in the dependent variable. Therefore further research is needed to improve the geographical predictability of crime. Specifically, five aspects are possible for future study in crime mapping and crime analysis.

(1) Focus on a specific type of crime to explore its spatial pattern and causation. The major purpose the research presented here was to examine the general profile of crime in the City of Omaha. For future studies, choosing an individual crime to conduct in-depth analysis is essential.

(2) Use finer spatial units, like block groups or blocks. Although census tracts can be successfully used to study the variations of crimes, using a finer unit of observation may greatly increase the accuracy of both the crime and demographic data and achieve a higher level of explanation.

(3) Including more detailed variables, such as the number of bars, number of entertainment center for youth, number of gas stations and 24-hour stores, may account for a higher proportion of variance of crimes over time and across space.

(4) Focus on crime hot spots. Using location quotients to analyze the concentration and extent of dominant crimes in risk areas (hot spots) or examining the distribution pattern of crime over time would be interesting areas of research.

(5) Examine longer periods of crime data. The common practice is to use several years (usually three years) of crime data for statistical analysis to reduce the annual fluctuations and enlarge the possibilities of crime incidents for some low-crime areas. Furthermore, including time-series analysis of crime along with sector analysis is also helpful in revealing the nature of crime over time and space.

(6) The spatial autocorrelation needs to be taken into consideration. Because of the limitation of time and software, spatial autocorrelation was not examined when conducting the multiple regression analysis. Spatial autocorrelation has been addressed by previous researchers in recent years when conducting regression analysis based on small areal units (i.e., census tracts and blocks) (Brown 1982; Mencken and Barnett 1999; Messener et al. 1999; Murray et al. 2001; Rice and Smith 2002; Roncek and Maier 1991; Rosenfeld et al. 1999; Weatherburn and Lind 2001). Therefore, checking the existence of spatial autocorrelation among observations and adding a specific variable reflecting the spatial autocorrelation to control the neighborhood effects is essential for the future studies. Software package such as SpaceStat can be used for the spatial autocorrelation analysis (Vania et. al., 2002).

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Appendix I-1: Crime Data

Tract	Count _S	Count_R	Count _A	Count _B	LQC-Types	LQC_S	LQC_R	LQC_ A	LQC_ B
2	3	14	34	21	R/A	0.62	1.98	1.04	0.76
3	26	18	46	45	S/R	2.88	1.36	0.75	0.87
4	6	3	27	35	S/B	1.26	0.43	0.84	1.29
5	4	3	58	44	A/B	0.55	0.28	1.18	1.06
6	8	8	47	42	S/B	1.14	0.77	0.99	1.05
7	7	10	33	50	S/R/B	1.05	1.02	0.73	1.31
8	8	10	31	32	S/R/B	1.48	1.26	0.85	1.03
9	1	9	17	21	R/B	0.31	1.91	0.78	1.15
10	11	12	24	34	S/R/B	2.03	1.51	0.65	1.1
11	9	17	40	52	S/R/B	1.14	1.47	0.75	1.15
12	13	19	62	43	S/R	1.42	1.41	1	0.82
16	6	6	60	24	A	0.93	0.64	1.38	0.65
18	15	23	93	44	S/R/A	1.28	1.34	1.17	0.66
19	4	7	40	34	A/B	0.7	0.84	1.04	1.05
20	11	22	75	30	S/R/A	1.19	1.62	1.2	0.57
21	3	5	45	18	A	0.63	0.72	1.4	0.66
22	1	0	17	11	A	0.52	0	1.29	0.99
23	2	0	30	17	A	0.61	0	1.35	0.91
24	11	7	44	40	S/B	1.61	0.7	0.95	1.03
25	3	2	34	27	A/B	0.68	0.31	1.14	1.07
26	3	5	50	28	A	0.52	0.59	1.28	0.85
27	11	14	46	34	S/R	1.57	1.36	0.97	0.85
28	4	3	55	30	A	0.65	0.33	1.32	0.85
29	20	12	80	47	S/A	1.88	0.77	1.11	0.77
30	2	2	39	13	A	0.53	0.36	1.54	0.61
31	6	6	76	39	A	0.71	0.48	1.32	0.8
32	5	4	50	14	S/A	1.02	0.56	1.51	0.5
33	2	6	32	25	A/B	0.46	0.94	1.09	1.01
3401	2	1	27	24	A/B	0.55	0.19	1.1	1.16
3402	2	1	12	20	B	0.85	0.29	0.76	1.5
35	5	9	19	40	S/R/B	1.02	1.25	0.57	1.43
36	2	5	15	18	R/B	0.75	1.27	0.83	1.18
37	0	2	7	11	R/B	0	1.02	0.77	1.44
38	6	9	47	47	B	0.82	0.84	0.95	1.13
39	24	27	54	49	S/R	2.33	1.78	0.77	0.83
40	7	11	34	43	S/R/B	1.1	1.18	0.79	1.19
41	2	13	25	28	R/B	0.44	1.94	0.81	1.08
42	1	6	20	22	R/B	0.3	1.25	0.9	1.18
43	7	24	44	49	R/B	0.84	1.97	0.78	1.03
44	2	15	36	24	R/A	0.39	1.98	1.03	0.82
45	1	4	9	10	R/B	0.62	1.69	0.83	1.09
46	0	0	6	15	B	0	0	0.63	1.87
47	0	0	5	12	B	0	0	0.65	1.85
48	3	22	74	45	R/A	0.31	1.55	1.13	0.82

49	12	33	91	91	R/B	0.79	1.48	0.89	1.05
50	8	21	45	58	R/B	0.91	1.62	0.75	1.15
51	6	13	39	47	R/B	0.85	1.26	0.82	1.17
52	21	20	44	41	S/R	2.49	1.61	0.77	0.85
53	12	11	55	46	S	1.45	0.9	0.98	0.97
54	14	9	42	48	S/B	1.85	0.81	0.82	1.11
55	2	4	31	35	B	0.42	0.56	0.95	1.27
56	1	6	48	33	A	0.17	0.69	1.2	0.98
57	1	18	31	33	R/B	0.18	2.21	0.82	1.04
58	10	11	57	64	S/B	1.05	0.79	0.89	1.18
5901	12	14	34	42	S/R/B	1.76	1.4	0.74	1.08
5902	11	6	50	26	S/A	1.77	0.66	1.19	0.73
60	30	26	90	62	S/R	2.15	1.27	0.96	0.78
6101	17	6	29	36	S/B	2.89	0.69	0.73	1.07
6102	8	9	37	49	S/B	1.16	0.89	0.79	1.25
6202	10	14	61	48	S/R/A	1.12	1.07	1.01	0.95
6301	2	4	40	28	A	0.4	0.55	1.19	0.99
6302	8	5	51	32	S/A	1.25	0.53	1.17	0.87
6303	6	4	28	22	S/A	1.49	0.68	1.03	0.96
64	3	6	28	32	B	0.65	0.88	0.9	1.21
6501	2	7	46	42	A/B	0.31	0.73	1.05	1.13
6502	1	6	31	29	A/B	0.22	0.91	1.02	1.13
6601	5	21	77	46	R/A	0.5	1.43	1.14	0.81
6602	2	9	18	18	R	0.64	1.95	0.85	1
6701	6	21	53	35	R/A	0.78	1.86	1.02	0.8
6702	2	6	37	15	R/A	0.5	1.02	1.36	0.65
6801	3	5	41	32	A/B	0.55	0.63	1.12	1.03
6802	1	0	8	13	B	0.68	0	0.8	1.55
6901	3	3	29	23	A/B	0.77	0.53	1.1	1.04
6902	2	2	9	16	S/B	1.03	0.7	0.69	1.44
7001	2	4	53	40	A/B	0.3	0.41	1.18	1.06
7002	2	1	9	22	B	0.88	0.3	0.58	1.69
7003	0	0	22	28	B	0	0	0.97	1.47
71	13	7	89	58	S/A	1.16	0.43	1.18	0.91
7304	0	0	4	5	B	0	0	0.98	1.45
7305	3	7	22	21	R/B	0.85	1.34	0.92	1.04
7306	2	5	17	9	R/A	0.91	1.54	1.14	0.71
7403	4	3	31	31	B	0.87	0.44	0.99	1.18
7404	1	5	17	12	R/A	0.43	1.45	1.07	0.9
7405	1	1	3	3	S/R	1.87	1.27	0.83	0.98
7406	0	1	15	21	B	0	0.27	0.9	1.49
7407	1	3	7	10	R/B	0.71	1.45	0.74	1.25
7408	3	1	18	16	S/A/B	1.18	0.27	1.05	1.1
7409	4	11	82	76	A/B	0.35	0.65	1.05	1.15
7411	1	1	10	3	A	1	0.68	1.47	0.52
7415	4	11	58	41	A	0.52	0.98	1.12	0.94
7418	0	0	21	12	A	0	0	1.41	0.95

7419	1	1	16	27	B	0.33	0.23	0.79	1.57
7420	0	2	13	10	A/B	0	0.81	1.15	1.05
7421	6	5	75	56	A/B	0.63	0.36	1.17	1.03
7422	4	4	53	49	A/B	0.54	0.37	1.06	1.17
7423	1	10	31	35	R/B	0.19	1.32	0.89	1.19
7424	3	6	17	18	S/R/B	1.02	1.39	0.85	1.07
7425	2	2	20	21	B	0.66	0.45	0.98	1.22
7426	0	0	3	2	A/B	0	0	1.32	1.05
7427	0	1	5	7	B	0	0.78	0.85	1.41
7428	2	0	9	9	S/B	1.49	0	0.99	1.18
7429	0	0	2	3	B	0	0	0.88	1.57

Appendix I-2: 1997 Socio-Economic Data

TRACT	AREA	TPOP	PBLK	PHISP	PYM	PNHD	PFEM	MHV	PM1.01
2	1.1881	3537	20.53	1.47	9.16	17.44	41.16	45000	1.32
3	0.45609	2472	67.56	1.46	10.11	23.84	56.63	27000	5.42
4	1.53201	2212	6.69	4.34	8.86	41.89	39.64	35000	5.39
5	7.7268	913	31.54	0	7.56	33.45	48.02	35000	7.91
6	0.3697	1459	66.35	2.74	9.12	36.8	45.79	28500	5.86
7	0.35849	1407	86	1.63	13.43	32.68	50.1	30000	4.16
8	0.60555	2216	93.68	0.41	11.51	28.16	44.52	39000	4.38
9	0.18845	1174	97.87	0	15.5	22.76	58.89	35000	3
10	0.25796	1039	87.87	5.2	5.2	39.95	61.82	25000	1.42
11	0.45318	1501	76.68	2.8	3.86	26.24	67.29	39000	7.8
12	0.5474	1839	71.56	4.79	7.18	35.53	59.64	25000	7.52
16	0.66653	620	27.42	2.26	7.58	20.39	49.15	40000	7.23
18	0.87386	1330	10.68	8.12	7.97	6.24	39.32	25000	4.56
19	0.19189	1484	12.53	14.02	10.98	19.56	29.33	53000	1.97
20	0.6586	2633	1.75	36.84	8.13	37.03	38.25	40000	5.8
21	0.29159	2451	2.77	25.13	5.92	26.73	39.38	45000	1.9
22	0.30638	1198	4.67	31.14	8.43	24.63	45.99	50000	4.01
23	0.70264	2247	3.92	14.64	3.29	26.37	31.22	45000	5.81
24	0.51568	3073	7.91	21.87	6.7	27.85	37.17	42000	3.22
25	1.50173	2238	1.07	16.13	9.43	24.88	29.21	45000	2.45
26	0.32916	1721	0	42.53	7.03	43.79	38.97	51900	12.76
27	0.70642	1886	2.76	49.31	7.85	40.06	27.02	45000	6.23
28	0.76712	2752	5.85	29.11	4.54	24.79	29.79	50000	4.52
29	1.00978	4136	20.99	35.28	5.25	35.41	47.8	45000	5.56
30	0.96029	5204	1.31	12.8	6.8	21.98	34.28	55000	0.59
31	1.49069	3271	2.23	16.14	6.73	24.26	33.36	54000	2.48
32	0.53714	1963	5.65	36.78	10.09	43.64	40.98	40000	3.7
33	0.53581	1983	0	22.19	8.98	35.2	34.92	45000	4.9
3401	0.56205	3115	3.02	7.58	5.87	13.57	37.56	60000	0
3402	0.39951	2322	0.82	8.61	5.56	7.61	26.57	65000	0.7
35	1.11788	3961	2.12	2.37	5.02	14.45	30.23	70000	0
36	0.69746	3962	1.06	2.5	3.05	7.32	36.33	70000	0.35
37	0.37735	2744	0.73	2.22	5.25	8.68	25.97	77500	1.38
38	0.72768	4099	4.29	17.69	9.59	18.05	30.61	76000	3.31
39	0.18537	2920	10.99	29.08	9.42	22.15	34.83	35000	14.85
40	0.21627	1584	13.76	13.64	4.86	28.45	36.29	42500	1.58
41	0.15757	619	6.3	20.52	10.34	29.66	48.37	39000	5.98
42	0.19042	1667	2.1	7.98	14.16	16.99	29.45	55000	4.51
43	0.37099	2387	3.02	2.6	13.95	3.05	45.51	75000	0.52
44	0.50403	1474	0	10.31	7.94	12.19	43.92	68000	1.06
45	0.38867	3125	4.42	0.22	3.49	4.72	42.2	85000	0
46	0.73562	2240	1.38	3.13	11.52	3.51	24.49	100000	3.43
47	0.91877	2247	0	0.27	4.14	0.39	16.47	209000	0

48	0.45582	4832	8.03	4.24	7.35	6	41.89	95000	1.33
49	0.65695	4441	19.43	6.06	12.54	9.53	43.11	50000	2.44
50	0.38607	4331	16.49	9.1	10.69	11.12	41.78	63000	4.18
51	0.31104	2342	35.74	2.69	12.38	21.27	45.3	40000	2.16
52	0.28824	1407	90.85	0.47	5.54	40.57	57.96	35000	10.4
53	0.69081	2098	75.6	0.71	6.67	27.23	52.49	38000	3.58
54	0.4442	3035	39.01	2.54	9.65	19.89	44.97	40000	1.65
55	0.79452	4832	3.95	1.14	6.6	4.46	33.83	85000	0.95
56	1.15083	4425	7.1	3.21	6.42	11.54	37.26	53000	4.74
57	0.6815	4115	12.39	3.4	5.42	13.22	45.58	47000	2.25
58	0.70573	4645	39.46	1.68	3.85	11.39	43.21	50000	2.24
5901	0.51851	2561	82.16	0	8.08	24.26	60	40000	0
5902	0.60502	2270	85.51	0	10.57	28.9	58.55	35000	0.57
60	0.65223	3809	64.95	4.94	7.53	31.49	55.18	36000	4.07
6101	0.59367	2470	68.54	1.62	6.4	22.35	52.2	40000	3.01
6102	0.97042	4151	64.39	2.67	7.4	27.14	46.01	40000	4.76
6202	1.16487	5100	39.63	2.69	8.41	19.53	44.87	45000	0.81
6301	1.1938	2562	52.62	1.52	4.25	17.12	51.78	70000	0.53
6302	0.91583	4012	61.59	1.92	7.33	14.83	40.37	58000	3.33
6303	0.37568	3078	29.08	1.07	5.72	14.8	35.54	50000	1.7
64	1.04588	4795	2.31	2.4	6.59	8.58	35.04	67000	1.92
6501	2.8463	6557	7.15	0.87	6.97	9.25	28.62	85000	0.26
6502	2.04332	4640	29.63	0.88	8.06	10.67	37.85	62000	1.18
6601	1.51059	6579	6.32	4.24	7.81	7.75	35.39	75000	1.91
6602	1.21799	4858	1.52	4.32	5.25	9.96	45.08	80000	0
6701	2.00944	3565	0	1.37	5.95	1.86	33.98	150000	0.3
6702	2.00074	4640	3.62	1.27	6.66	4.01	39.02	140000	0.27
6801	2.27173	5727	0.8	0.96	6.48	3.02	34.44	140000	0.55
6802	1.76936	3880	0	1.31	6.08	2.82	16.69	160000	0
6901	1.48869	4974	0.28	1.05	5.33	5.35	33.07	80000	0.66
6902	1.92115	6701	1.31	1.12	9.01	1.42	23.63	118000	2.08
7001	1.45747	3013	1.03	5.54	6.6	14.39	41.48	65000	2.18
7002	0.67842	3260	0.18	1.72	7.27	14.44	33.54	75000	2.97
7003	1.86518	2198	0.32	3.87	4.91	26.3	35.06	55000	0.74
71	3.60787	5745	1.57	5.31	7.31	19.21	28.06	66000	1.9
7304	3.00492	1512	6.75	2.78	2.12	5.41	15.13	120000	0
7305	3.84906	4199	10.12	2.74	7.5	3.97	29.22	85000	0
7306	9.00846	7555	5.15	1.93	6.5	4.47	25.66	95000	1.37
7403	1.98616	5806	5.06	1.07	9.61	2.7	40.12	95000	0.95
7404	1.99224	6717	3.29	0.48	7.12	3.53	27.94	150000	1.07
7405	2.5053	1138	0.7	2.9	3.51	1.45	8.28	300000	0
7406	1.01023	5818	1.58	2.34	7.84	3.75	24.02	110000	0.93
7407	1.01088	3589	0.47	5.54	6.1	8.17	30.45	100000	3.32
7408	0.88236	4576	5.27	3.17	6.82	7.46	38.29	80000	1.2
7409	4.97988	2590	0.35	0.39	6.41	5.02	21.02	90000	0

7411	1.49768	5215	0.59	3.53	6.77	8.38	24.2	80000	0
7415	2.63804	9633	7.18	1.33	8.03	3.53	29.17	100000	1.34
7418	6.34043	20306	1.05	1.15	6.54	1.8	10.98	120000	0.48
7419	1.55066	6598	1.33	3.18	7.76	9.43	21.04	85000	2.22
7420	1.96497	5239	1.43	2.29	7.96	5.17	32.31	88000	0.32
7421	2.4792	12363	0.78	2.64	7.63	4.76	22.6	95000	1.49
7422	1.47588	8467	2.76	3.41	10.04	5.63	31.66	92000	1.93
7423	1.54918	8695	5.32	1.44	8.34	6.35	29.46	80000	1.52
7424	0.61532	2664	3.08	0.38	6.16	7.26	48.51	90000	1.39
7425	8.1491	17274	2.68	2	4.62	4.19	17.49	116000	1.11
7426	2.01906	8204	0.78	2.52	6.46	1.39	9.82	130000	1.03
7427	1.49119	7542	0.4	1.47	7.78	1.42	15.38	138500	0.29
7428	4.07637	9444	0.95	1.49	6.96	2.87	15.27	110000	0.19
7429	1.22987	3455	1.07	0	6.77	4.47	8.37	130000	0.67

Appendix I-2 Socio-Economic Data (continued)

TRACT	MHIN	POWN	PVA	P5YRS	PUEM	PNSJ	PDEN	PPOV	PMFP	PCMP
2	27732	75.63	4.01	62.93	7.33	0	2977	9.61	1.08	3.37
3	18240	61.08	13.81	47.45	18.14	4.05	5420	40.13	5.16	1.01
4	20128	69.13	5.96	40.51	13.71	5.3	1443.9	28.39	0.1	3.42
5	16408	68.36	21.85	55.42	19.9	0	118.2	37.35	1.03	6.91
6	20934	52.2	6.51	48.8	10.79	6.36	3946.4	35.92	2.88	2.73
7	14653	36.04	18.68	43.5	23.1	7.48	3924.8	45.13	3.95	6.18
8	23148	60.68	7.94	45.67	8.57	0	3659.5	18.64	4.2	4.8
9	17718	54.27	5.25	43.36	15.41	18.06	6229.8	44.72	11.18	4.19
10	8981	31.05	26.11	29.55	45.09	0	4027.8	73.24	4.63	4.8
11	10241	29.32	14.49	38.04	21.14	0	3312.1	56.56	2.02	7.35
12	16132	43.3	3.32	29.09	18.95	0	3359.5	50.08	7.87	13.39
16	9800	2.34	20.74	27.26	0	0	930.2	44.84	5.79	56.61
18	28583	7.99	12.52	18.2	1.75	0	1522	22.03	6.66	46.93
19	17115	5.02	26.85	21.09	8.97	11.86	7733.6	24.73	17.9	26.07
20	20129	47.49	13.37	52.6	8.07	0	3997.9	23.36	5.41	6.62
21	22606	44.19	12.15	38.64	14.09	0	8405.6	16.2	6.34	11.76
22	24722	37.98	12.23	35.81	8.33	9.09	3910.2	19.45	7.49	7.49
23	22666	74.38	5.01	53.54	4.09	31.19	3197.9	16.15	2.81	3.4
24	22020	48.91	8.74	40.12	12.36	5.83	5959.1	20.21	7.23	6.06
25	25299	69.94	3.6	50.31	6.55	0	1490.3	9.52	2.07	1.62
26	29738	65.34	17.61	45.44	4.61	0	5228.5	12.96	4.92	1.27
27	20129	61.19	12.62	46.87	5.08	6.02	2669.8	25.72	1.87	6.68
28	26370	68.17	1.74	49.85	1.52	0	3587.4	12.25	2.55	2.37
29	18182	50.51	7.7	35.64	6.91	0	4095.9	39.46	1.88	5.91
30	28459	82.24	5.23	60.88	2.98	0	5419.2	8.84	1.28	1.75
31	31095	71.99	1.75	59.58	3.13	0	2194.3	11.77	1.59	5.57
32	15070	24.89	11.37	27.66	6.71	0	3654.5	32.25	4.99	14.11
33	27182	59.92	4.21	41.4	6.89	0	3700.9	14.47	8.42	4.08
3401	27493	60.4	6.44	48.12	1.44	0	5542.2	14.64	3.63	1.32
3402	39022	82.79	4.01	66.02	3.73	5.66	5812.1	5.17	4.5	1.39
35	31550	66.4	3.12	63.87	1.62	0	3543.3	3.61	3.12	3.05
36	37252	81.76	5.22	54.27	2.51	8.54	5680.6	5.68	2.09	1.88
37	44804	87.94	1.9	65.82	2.73	4.61	7271.8	4.63	0.28	0.57
38	23233	36.38	9.74	38.52	7.6	4.78	5633	14.91	20.81	2.2
39	20241	24.84	14.36	27.71	2.16	0	15752.3	31.1	28.9	8.62
40	12144	8.97	22.6	35.29	14.71	23.33	7324.2	40.4	37.79	13.03
41	20988	16.85	18.4	24.23	9.3	0	3928.4	33.6	21.6	62.4
42	24154	30.33	11.82	49.31	7.83	0	8754.3	22.02	35.74	9.4
43	23233	23.8	7.29	30.04	5.75	0	6434.1	19.27	27.03	14.37
44	33118	55.17	6.93	48.37	1.38	0	2924.4	22.12	6.42	12.84
45	35000	69.93	1.96	54.14	3.07	0	8040.2	8.64	5.79	3.37
46	43125	71.79	5.64	60.54	2.21	0	3045.1	11.88	3.82	1.01

47	97174	97.39	0	69.51	1.86	0	2445.7	1.56	0.52	0.79
48	28106	33.44	2.12	39.74	3.42	0	10600.7	14.07	25.07	6.29
49	22758	32.46	7.7	36.03	5.75	13.41	6760	20.9	17.6	7.17
50	21384	24.35	5.95	28.65	6.32	0	11218.2	29.32	33.18	2.93
51	17172	28.67	19.64	30.32	7.78	0	7529.6	34.16	14.54	2.99
52	18175	38.22	24.4	43.29	18.16	54.46	5193.6	47.29	1.84	2.76
53	18737	45.21	13.86	45.14	12.21	0	3037	37.7	1.53	3.99
54	25262	47.74	13.58	48.6	7.52	6.8	6832.5	20.92	3.63	3.47
55	42965	76.64	3.25	49.86	1.67	0	6081.7	9.11	5.4	1.34
56	30193	73.2	5.81	53.94	2.45	2.9	3845.1	13.27	3.46	2.27
57	25753	60.48	5.23	54.56	2.55	0	6038.2	19.22	5.47	6.14
58	28389	63.93	6.15	48.57	6.69	0	6581.8	19.78	3.43	0.27
5901	22102	50.1	8.15	49	20.28	11.43	4939.2	20.15	0.76	0.95
5902	17311	52.93	12.73	41.72	11.34	0	3751.9	40.09	1.38	3.25
60	19827	51.25	11.74	49.88	9.34	9.77	5840	32.92	1.49	2.45
6101	23253	57.87	7	51.38	10.98	0	4160.6	23.97	1.76	1.41
6102	26121	69.68	6.81	59.5	9.79	0	4277.5	25.63	1.64	0.88
6202	25509	71.11	3.34	55.1	7.08	0	4378.2	29.18	1.85	1.9
6301	23722	54.53	6.32	50.74	5.43	13.66	2146.1	26.78	0.8	1.3
6302	30701	67.6	2.61	48.8	14.86	22.18	4380.7	12.49	1.67	2.42
6303	29403	63.21	8.59	55.23	11.14	11.51	8193.1	23.39	5.55	1.33
64	32258	72.39	1.09	56.48	3.17	3.13	4584.7	8.15	2.69	0.82
6501	38679	75.96	5.67	62.74	3.15	2.8	2303.7	3.1	0.52	3.11
6502	32772	69.9	0	56.01	3.81	0	2270.8	11.55	1.84	2.03
6601	30723	52.84	1.94	49.07	3.9	0	4355.3	13.38	2.29	4.54
6602	32536	33.21	7.34	44.24	3.93	0	3988.5	6.71	1.76	5.45
6701	45209	62.41	4.82	56.3	5.09	0	1774.1	7.63	1.35	13.1
6702	50321	60.39	4.94	57.54	5.29	0	2319.1	2.37	1.06	5.89
6801	46465	57.73	3.13	53.73	3.38	0	2521	6.39	1.95	3.89
6802	62287	85.45	0	62.4	3.43	0	2192.9	4.02	1.03	2.58
6901	37318	76.13	0	65.26	2.6	0	3341.2	4	2.94	5.49
6902	52358	76.22	1.12	60.05	2.32	0	3488	3.7	2.44	1.1
7001	27032	29.26	4.61	21.84	1.6	3.43	2067.3	13.38	3.84	16.16
7002	33702	74.36	1.33	69.79	4.54	0	4805.3	4.75	2.46	0.63
7003	28081	75.95	2.28	58.01	2.72	0	1178.4	15.15	1.05	4.03
71	34503	77.81	8.48	59.25	3.19	0	1592.4	6.95	1.43	4.33
7304	76379	93.28	6.45	54.96	0.89	0	503.2	2.25	0	1
7305	40481	67.28	5.61	45.63	1.96	0	1090.9	3.72	0.77	3.65
7306	45564	74.2	1.52	38.91	2.84	2.19	838.7	4.13	0.52	1.6
7403	35559	28.33	2.77	32.24	2.99	0	2923.2	5.58	2.7	10.43
7404	57349	75.43	2.04	58.55	1.54	0	3371.6	3.44	0.82	1.68
7405	139553	94.38	2.59	29.35	1.73	0	454.2	6.33	0	1.1
7406	46214	61.26	1.79	56.46	0.88	0	5759.1	3.32	0.41	3.11
7407	46061	66.3	2.1	44.94	0.94	0	3550.4	6.83	2.35	4.11
7408	35993	61.6	1.18	56.32	1.23	0	5186.1	6.29	0.6	1.88

7409	49099	86.2	4.56	66.99	4.66	0	520.1	2.59	0.72	9.03
7411	40993	68.52	3.68	60.81	1.5	3.01	3482.1	3.41	2.72	6.63
7415	43786	47.62	3.22	45.33	2.7	1.24	3651.6	6.79	2.73	3.48
7418	68226	92.24	0.87	42.25	1.29	1.2	3202.6	1.57	0.26	0.87
7419	44671	68.7	2.33	51.97	2.83	0	4255	3.8	1.29	7.21
7420	50920	81.44	0.32	63.81	1.71	0	2666.2	2.12	2.61	2.19
7421	41570	43.65	3.75	41	1.71	0	4986.7	4.84	1.65	5.07
7422	38436	42.08	5.32	40.4	4.14	1.87	5736.9	6.38	1.65	2.16
7423	40548	58.85	3.56	50.98	1.76	0	5612.6	3.24	1.44	2.8
7424	29050	50.24	5.31	57.77	2.7	0	4329.5	5.86	4.42	3.56
7425	62714	93.32	1.33	38.25	2	0.95	2119.7	1.13	0.14	1.3
7426	74296	98.89	0.71	58.02	2.62	0	4063.3	0.68	0	0.86
7427	70799	82.06	0.86	46.96	2.79	0	5057.7	1.82	0.05	0.67
7428	65362	96.25	0.65	60.72	3.65	2.33	2316.8	2.98	0.46	3.4
7429	80688	98.65	1.8	58.55	2.16	0	2809.2	1.68	0	1.05

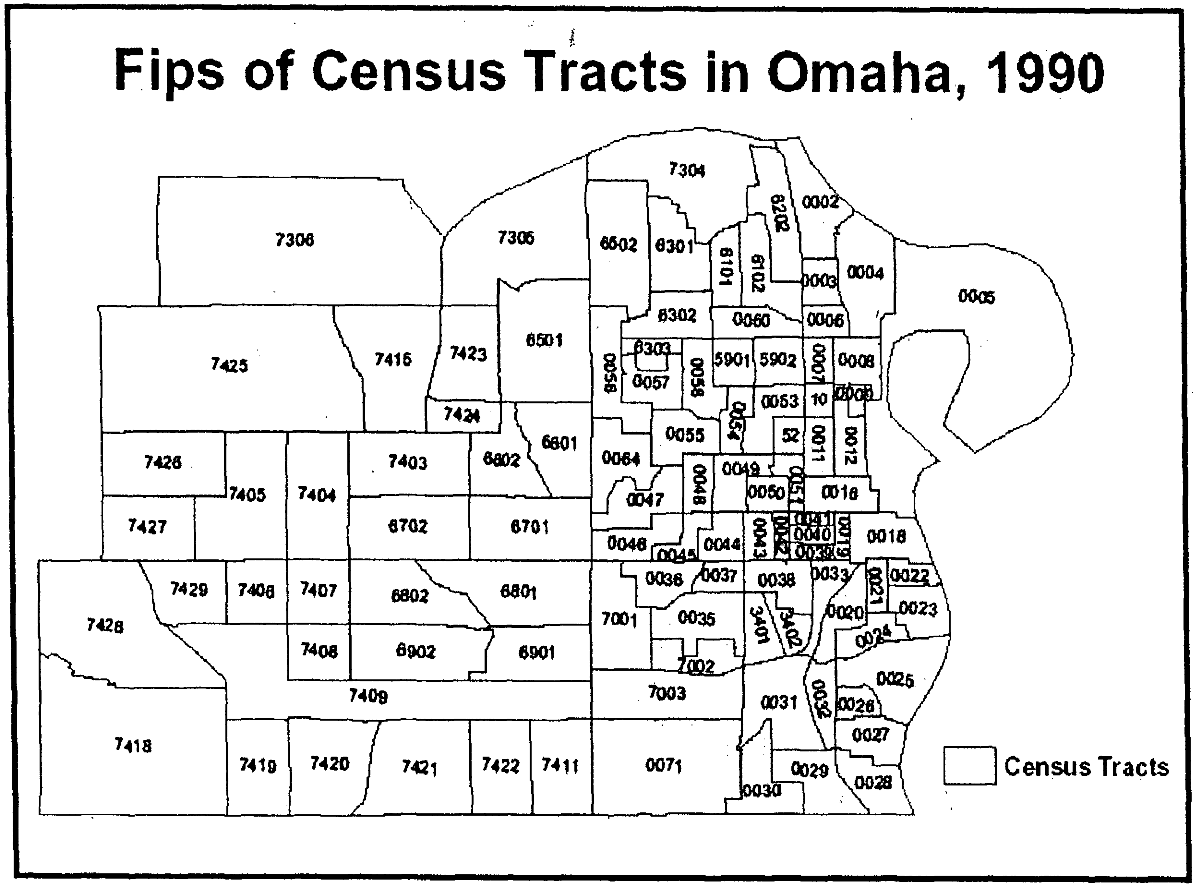
Appendix I-3: Principle Components from Factor Analysis

TRACT	Factor_1	Factor_2	Factor_3	Factor_4	Factor_5	Factor_6
2	0.59775	-0.96896	-0.29967	-0.22313	-0.30374	-1.21434
3	1.9292	-0.44285	-0.24448	0.3426	0.0707	0.13655
4	0.94822	-0.19407	1.03115	-0.91474	0.31428	-0.26836
5	1.90151	0.62503	1.03138	-2.19204	2.08456	0.02809
6	1.47659	-0.54297	0.3093	-0.1524	-0.29172	-0.00388
7	2.40099	0.39485	-0.54817	0.13208	0.19336	0.21266
8	1.54775	-0.35364	-0.41971	0.10479	0.0485	-0.81943
9	2.20984	-0.34963	-1.2593	1.42434	0.02929	0.46164
10	3.18419	1.06364	-0.62518	-1.08435	-0.12745	1.4698
11	2.12769	0.6418	-0.02409	-1.05049	-0.45442	0.53132
12	1.86531	0.6609	0.23249	-0.51549	-0.03818	-0.22908
16	0.299	4.12012	-0.09497	-1.6351	-1.11662	-1.14404
18	-0.41024	3.65618	-0.2627	-0.96753	-0.7219	-1.18712
19	-0.3646	2.69676	0.06404	1.3235	-0.28829	1.0462
20	-0.07223	-0.18514	2.60336	-0.23282	-0.31976	-0.57183
21	-0.20128	0.25617	1.14741	0.51594	-0.63843	0.05505
22	-0.19471	0.57195	1.49824	0.05029	-0.59962	0.2778
23	-0.50511	-0.87322	1.55143	-0.54631	-0.66062	2.56048
24	-0.004	-0.0324	1.21676	0.3394	-0.23113	0.34057
25	0.02003	-0.52577	0.99155	-0.50832	-0.07174	-1.15574
26	-0.58985	-0.47865	4.0644	-0.23051	-0.1972	0.32598
27	-0.52809	-0.17832	3.52723	-0.74937	-0.27575	0.01892
28	-0.65412	-0.78096	2.00686	-0.48633	-0.57752	-0.46602
29	0.28451	0.06374	2.33133	-0.57026	0.11802	-0.24696
30	-0.186	-1.23472	0.65001	0.12218	-0.25244	-0.74875
31	-0.21563	-0.72125	0.9868	-0.71946	-0.40208	-0.96882
32	0.10979	1.10367	2.21008	-0.19411	-0.15283	-0.99774
33	-0.16172	-0.2352	1.66772	0.07641	-0.27863	-0.72258
3401	-0.2718	-0.43306	-0.06227	0.25064	-0.73787	-0.47866
3402	-0.73932	-1.2389	0.02385	0.24241	-1.16406	0.23534
35	-0.41136	-0.81419	-0.20202	-0.29159	-0.72879	-0.63169
36	-0.61476	-0.851	-0.28939	-0.03926	-0.83076	0.7673
37	-0.76266	-1.47966	-0.1861	0.32153	-1.10265	0.3513
38	-0.47659	0.45434	0.63849	1.42859	0.24655	0.29402
39	-0.85616	0.48522	2.77853	3.57832	0.49953	0.89123
40	-0.25199	1.68761	0.31825	1.66525	-0.68412	3.04168
41	-0.31356	4.11589	0.69494	-0.36559	-1.108	-1.00623
42	-0.34203	0.64614	0.01782	2.89743	-0.26038	-0.43824
43	-0.13613	1.59009	-1.35619	2.20161	-0.25715	-1.05995
44	-0.27742	0.51443	-0.17508	-0.31771	-1.13249	-0.89537
45	-0.55113	-0.76559	-0.78971	0.58875	-1.20811	0.03954
46	-0.47716	-0.4221	-0.36706	0.20487	-0.4652	-0.66113
47	-1.96725	-0.50172	-1.27178	-1.23077	-1.49601	1.39342

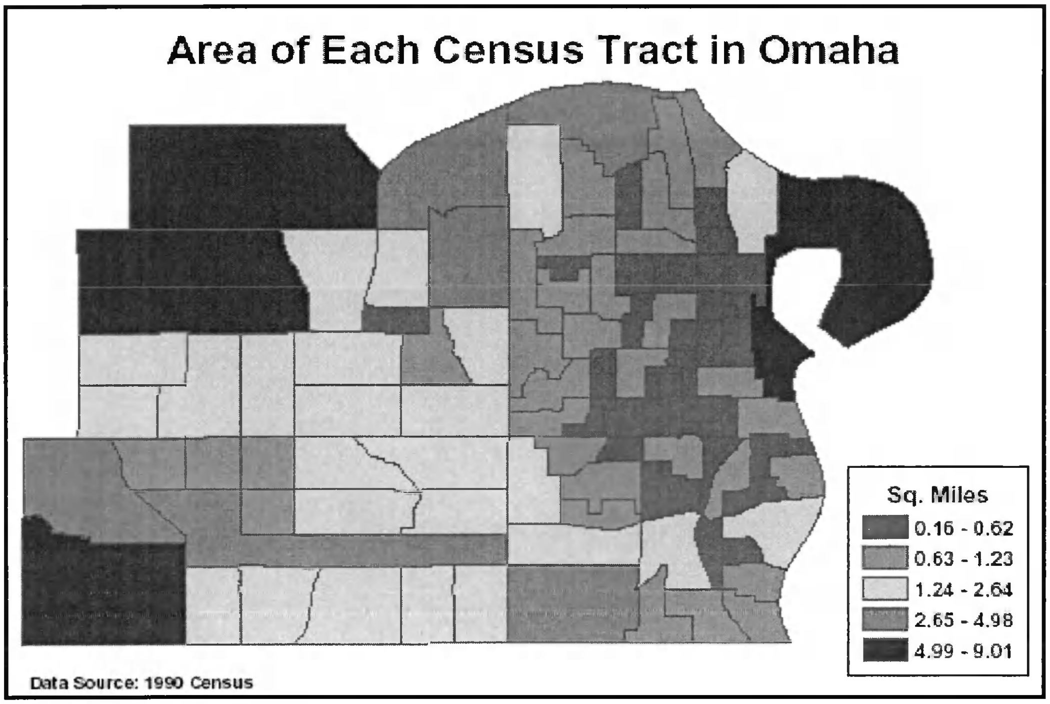
48	-0.68472	0.29082	-0.79603	2.51536	-0.29256	0.07979
49	0.19973	0.57793	-0.53059	1.96622	0.39153	0.24598
50	-0.20239	0.62659	-0.17852	3.32977	0.38466	0.09438
51	0.89629	0.84322	-0.47527	1.60917	0.12463	-0.3356
52	1.76715	-0.0132	0.64236	-0.22802	0.00097	5.81849
53	1.66001	0.09919	-0.36495	-0.69597	-0.34207	-0.12237
54	0.76558	-0.26194	-0.41569	0.7649	-0.27504	0.05967
55	-0.55494	-0.5621	-0.58237	0.56041	-0.29769	-0.14474
56	-0.07635	-0.62341	0.31787	-0.05437	-0.0732	-0.2304
57	0.08983	-0.52399	-0.11276	0.32192	-0.61382	-0.55888
58	0.38499	-0.71274	-0.34761	0.26626	-0.29485	0.14264
5901	1.89376	-0.65866	-1.1803	0.02339	-0.37362	0.56283
5902	2.10774	-0.02851	-0.94831	-0.15814	-0.14745	-0.78653
60	1.41056	-0.58191	0.13519	0.14382	-0.04874	0.53062
6101	1.31705	-0.65747	-0.4166	-0.31083	-0.50724	-0.34901
6102	1.26565	-1.07726	0.1319	-0.22452	0.02351	-0.38051
6202	0.9687	-0.85627	-0.40548	0.07196	0.10733	-0.87697
6301	0.76088	-0.29858	-0.72504	-0.8357	-0.68374	0.87577
6302	0.76404	-0.7603	-0.52253	0.09983	0.13365	1.75256
6303	0.2736	-0.85055	-0.388	0.77783	-0.5851	1.24931
64	-0.2407	-0.89429	-0.18901	0.21186	-0.23004	-0.37351
6501	-0.21795	-0.55804	-0.37719	-0.50504	0.58974	-0.34705
6502	0.37328	-0.64832	-0.55146	-0.30847	0.19856	-1.00235
6601	-0.08966	-0.18222	-0.2857	0.29852	0.43227	-0.73763
6602	-0.21864	0.38901	-0.54801	-0.14148	-0.32034	-0.44418
6701	-0.7589	0.62215	-1.06389	-1.03452	-0.59095	-0.07906
6702	-0.54307	0.14977	-1.02519	-0.67077	-0.26883	-0.12405
6801	-0.6254	0.1677	-0.90527	-0.45218	0.14269	-0.10733
6802	-1.22324	-0.37714	-0.87757	-0.80759	-0.48809	0.35035
6901	-0.45931	-0.79727	-0.48701	-0.30841	-0.46854	-0.66157
6902	-0.69588	-0.55712	-0.57292	0.15164	0.51345	-0.335
7001	-0.31296	1.62735	-0.17386	-0.51909	-0.11252	-0.50596
7002	-0.2284	-1.33958	-0.00959	0.12763	-0.77724	-0.68266
7003	0.00756	-0.61673	0.31064	-1.20449	-0.65132	-0.83322
71	-0.08649	-0.34608	0.46062	-0.82652	0.91113	-0.65524
7304	-1.36836	-0.0183	-0.40124	-1.89791	-0.57104	0.99885
7305	-0.28178	0.32464	-0.52909	-0.82006	0.76208	-0.59027
7306	-0.2051	0.58992	-0.01999	-1.172	3.38743	-0.0717
7403	-0.21119	1.16006	-1.01251	0.17419	0.61189	-0.95809
7404	-0.86322	-0.34521	-0.80091	-0.25103	0.27222	0.09596
7405	-2.94815	1.66133	-1.55605	-2.21745	-0.62154	3.20935
7406	-0.81211	-0.49198	-0.60127	0.47641	-0.09616	-0.31459
7407	-0.82081	-0.02173	-0.03409	-0.27126	-0.37532	-0.09349
7408	-0.31357	-0.72925	-0.42321	0.25199	-0.45821	-0.68953
7409	-0.50607	-0.07921	-0.46263	-1.50952	0.3823	-0.46348
7411	-0.65098	-0.42613	-0.35136	-0.14908	-0.20495	-0.34198

7415	-0.37076	0.23686	-0.60143	0.32182	1.46324	-0.27418
7418	-0.79155	-0.07846	-0.10852	0.11842	4.86736	0.4678
7419	-0.65051	-0.23796	-0.10851	0.07277	0.43641	-0.41329
7420	-0.46951	-0.78373	-0.57322	-0.22921	-0.02546	-0.75026
7421	-0.57525	0.30335	-0.2984	0.68734	2.00521	-0.29433
7422	-0.28094	0.15074	-0.45834	0.97292	1.13175	-0.3507
7423	-0.35717	-0.42216	-0.39289	0.70824	0.86946	-0.56177
7424	-0.18079	-0.31421	-0.71949	0.05294	-1.08638	-0.62325
7425	-0.64234	0.21735	0.14718	-0.64892	4.8459	0.55955
7426	-1.31439	-0.71738	-0.43758	-0.19678	0.72134	0.56064
7427	-1.21805	-0.27182	-0.80568	0.23376	0.60043	0.45611
7428	-0.80752	-0.52666	-0.43181	-0.56104	1.6227	0.19461
7429	-1.41272	-0.53464	-0.67636	-0.69414	-0.4809	0.59653

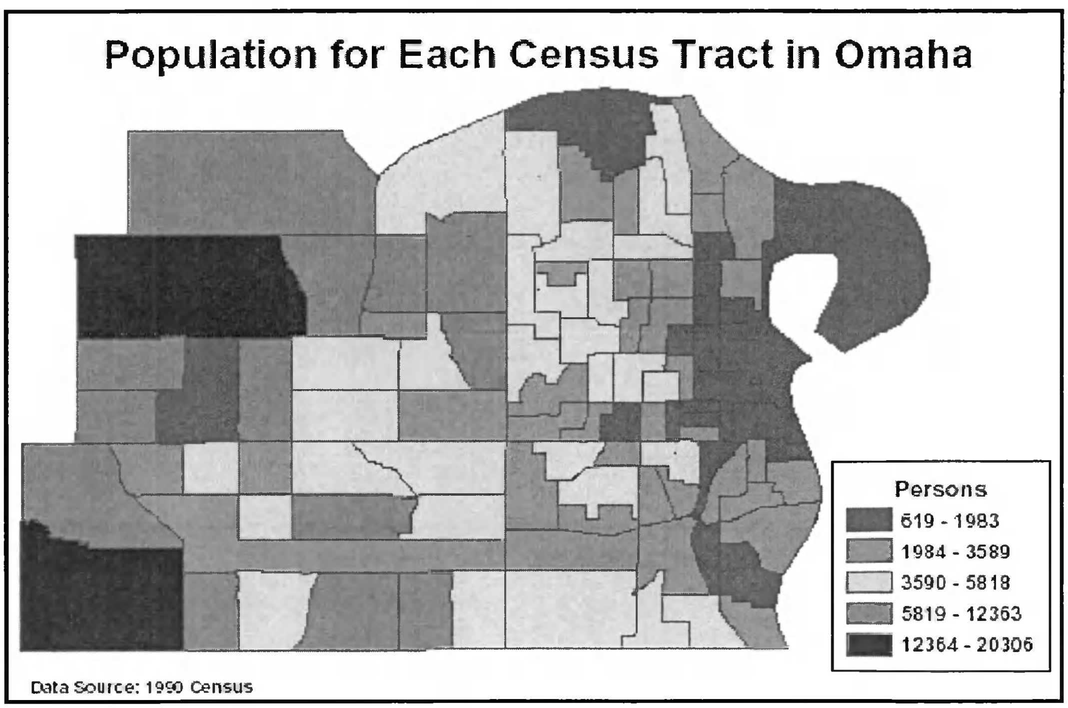
Appendix II Fips of census tracts in Omaha, 1990



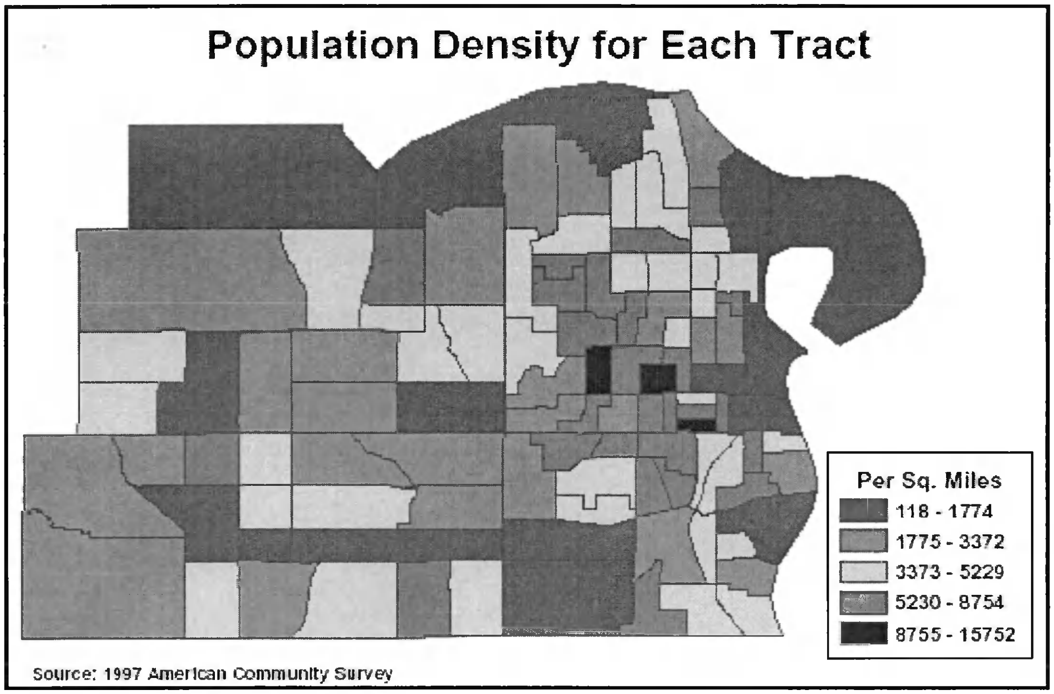
Appendix III-1: Map of area for each census tract



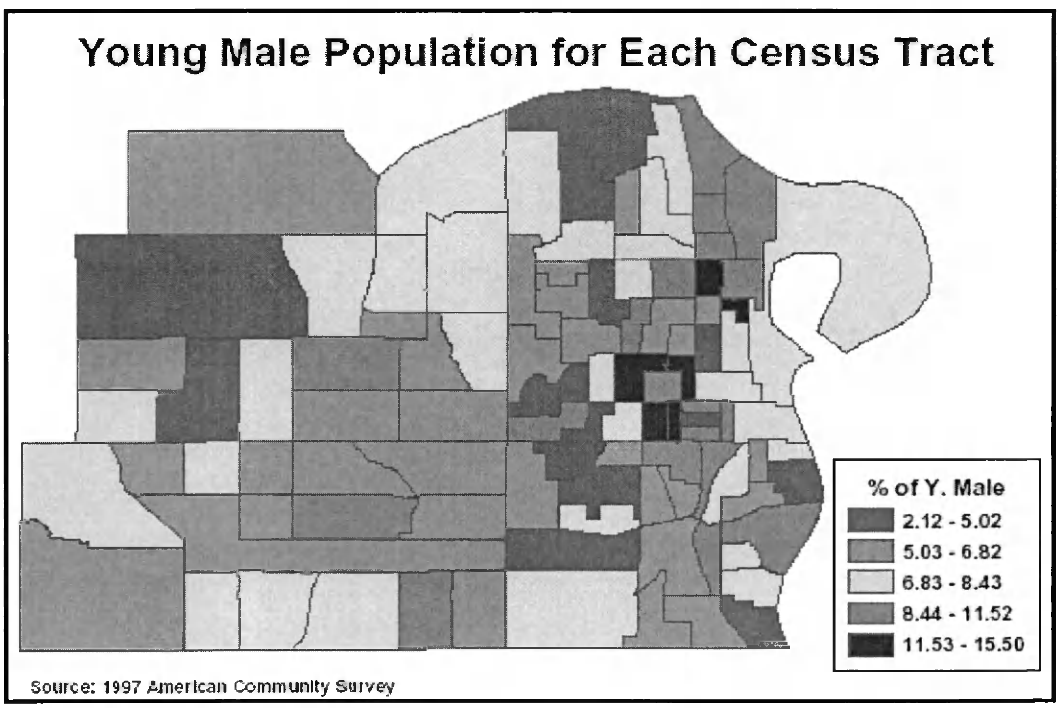
Appendix III-2: Map of the total population for each tract



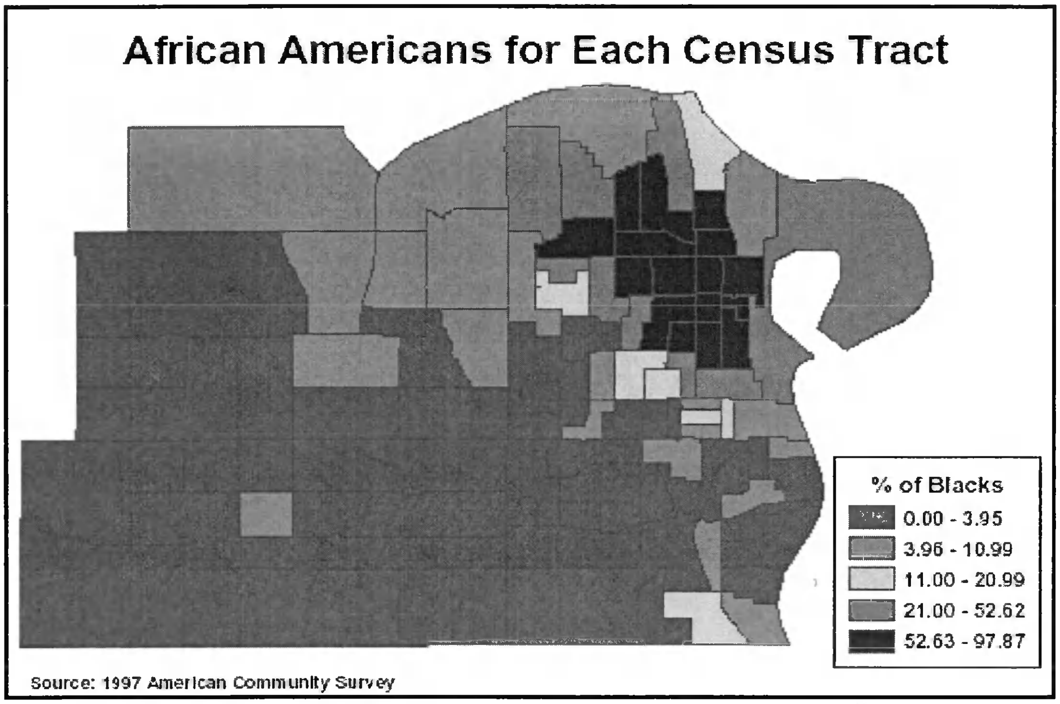
Appendix III-3: Map of population density for each census tract



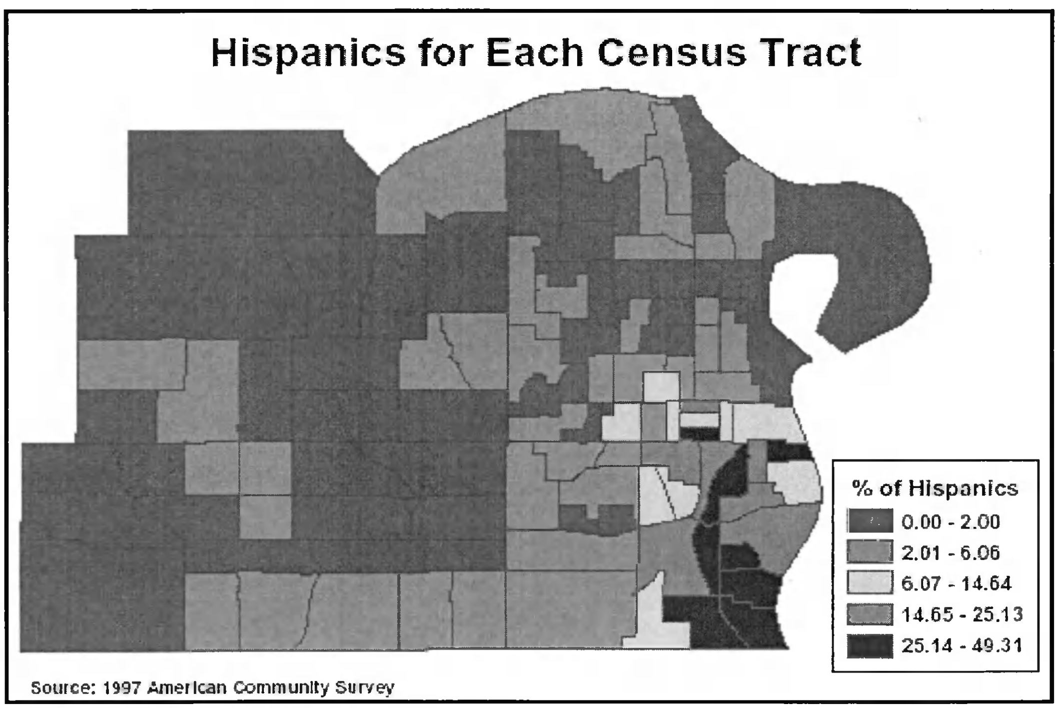
AppendixIII-4: Population of young males at age of 15-24



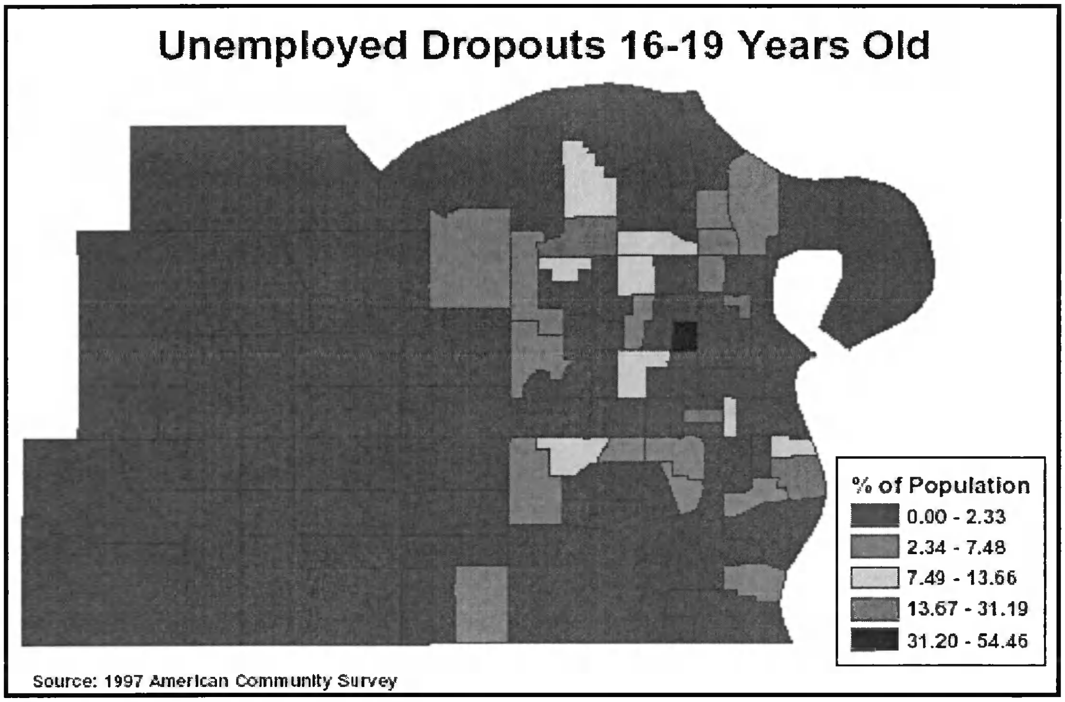
Appendix III-5: Map of the percentage of African Americans for each tract



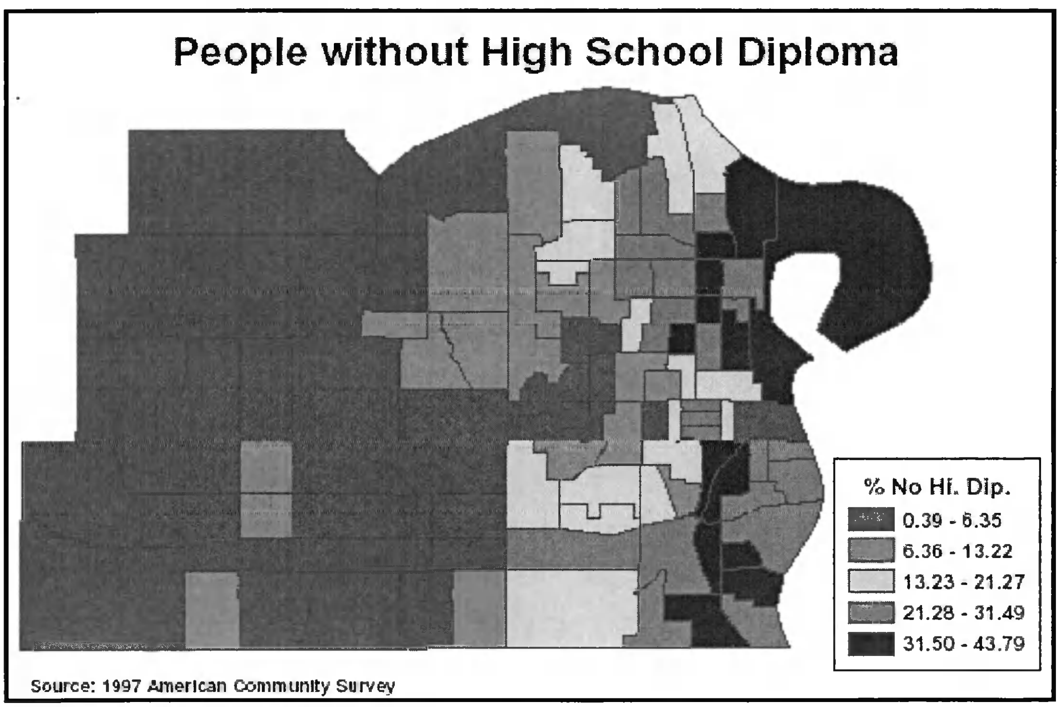
Appendix III-6: Map of Hispanics population



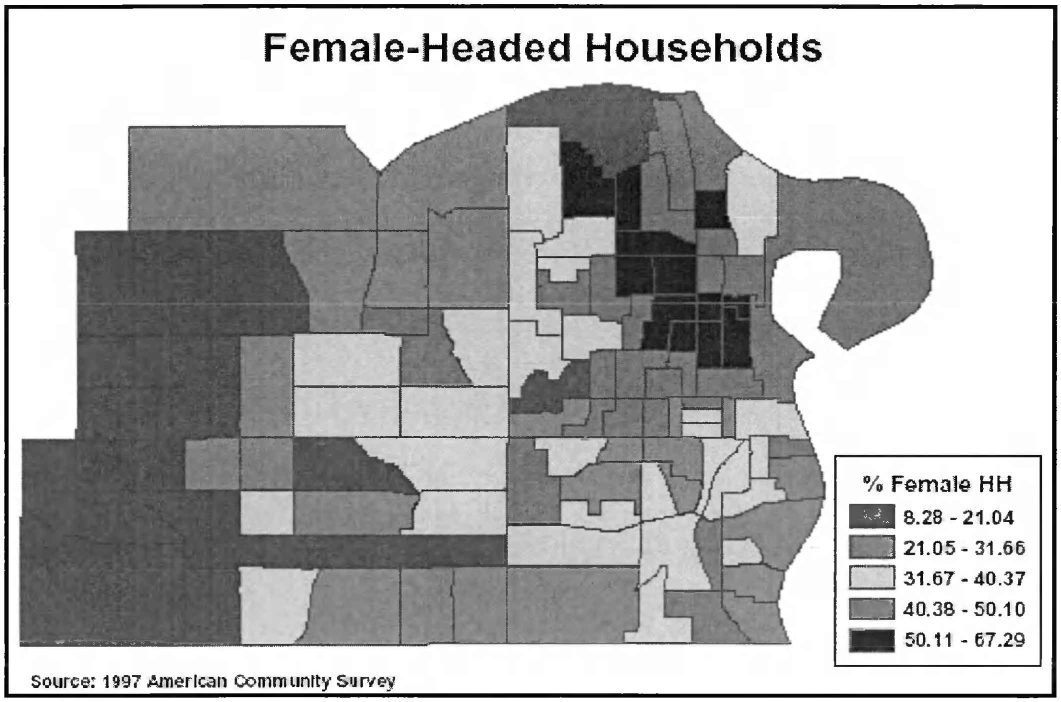
Appendix III-7: Map of unemployed dropouts at age of 16-19



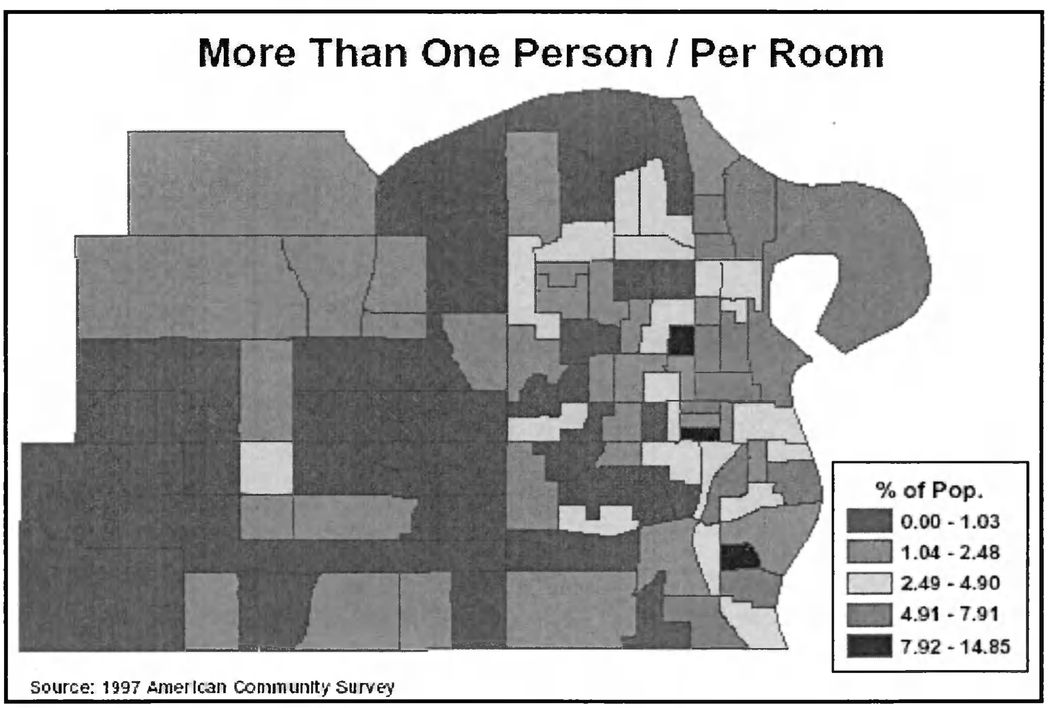
Appendix III-8: Map of the adults without high school diploma



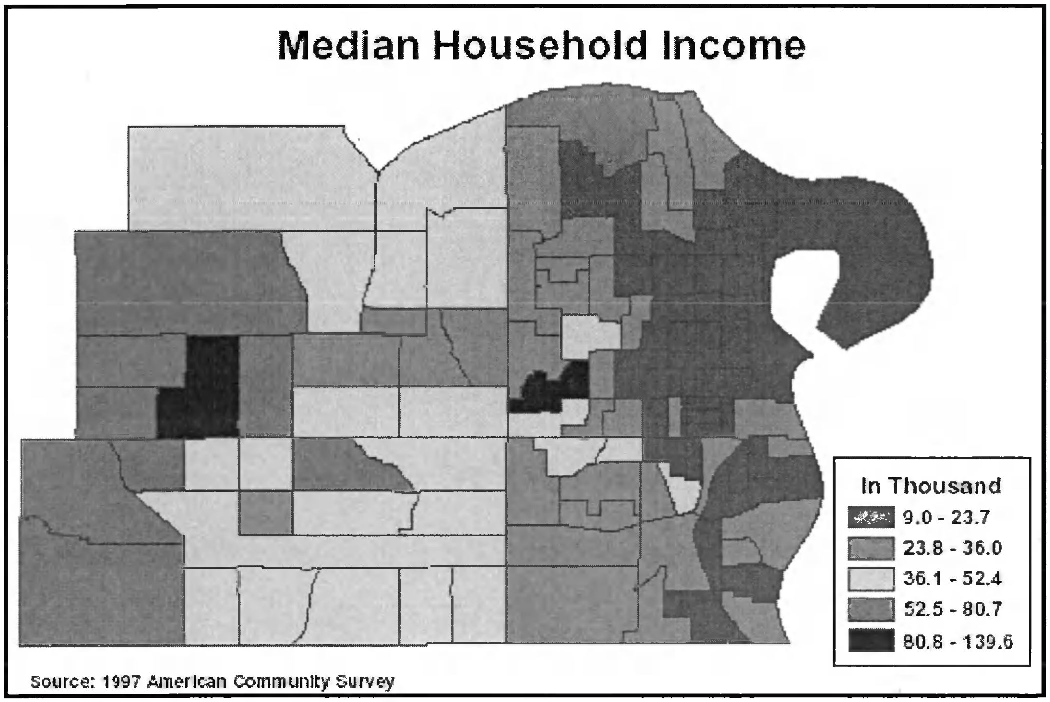
Appendix III-9: Map of female-headed households



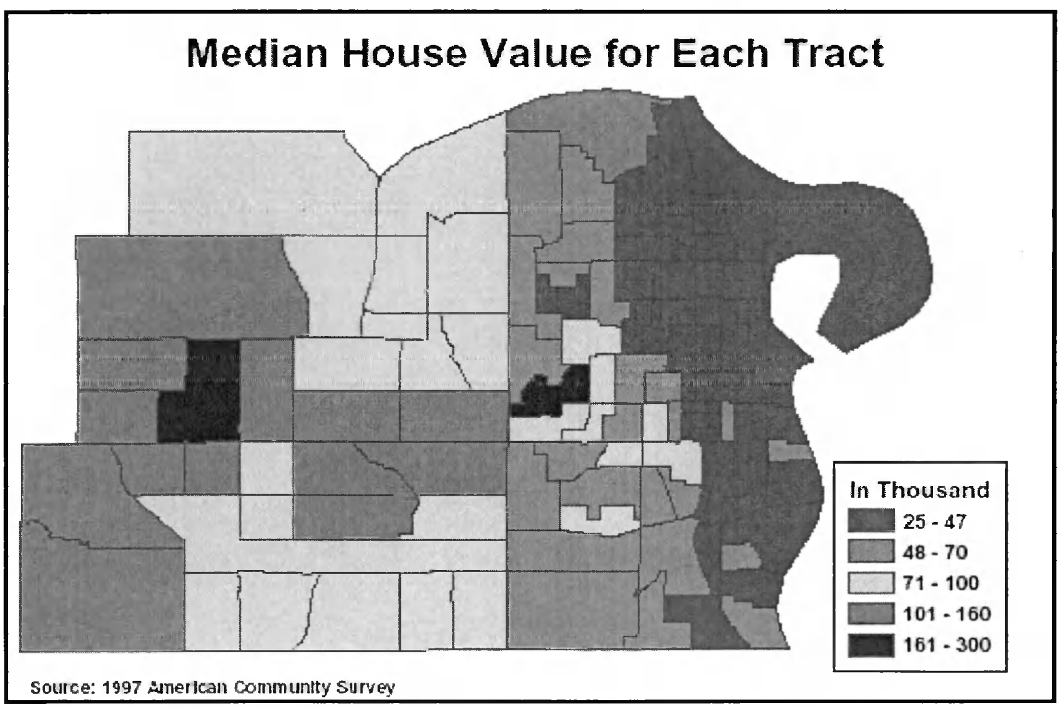
Appendix III-10: Population living in housing with 1.01 or more per room



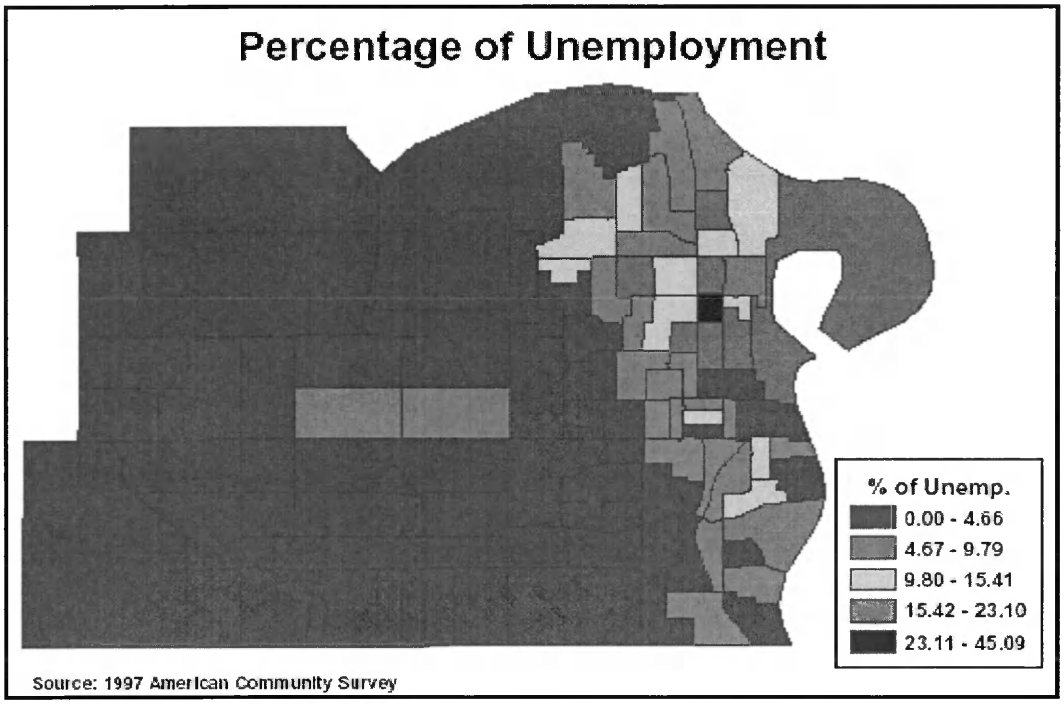
Appendix III-11: Median household income



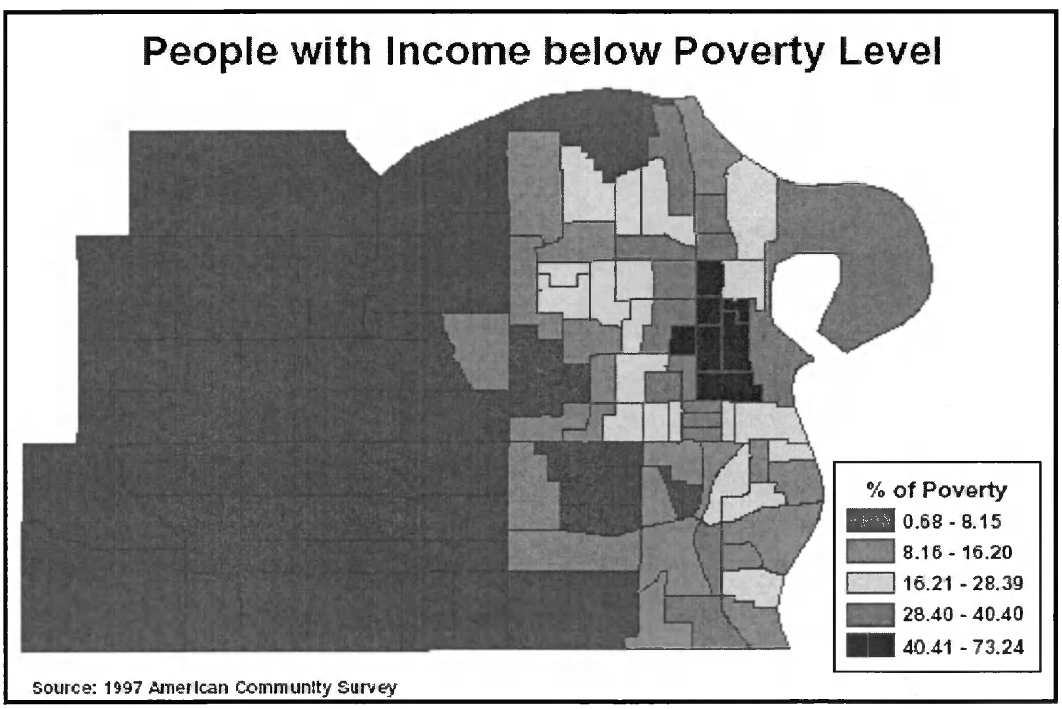
Appendix III-12: Median house value for each census tract



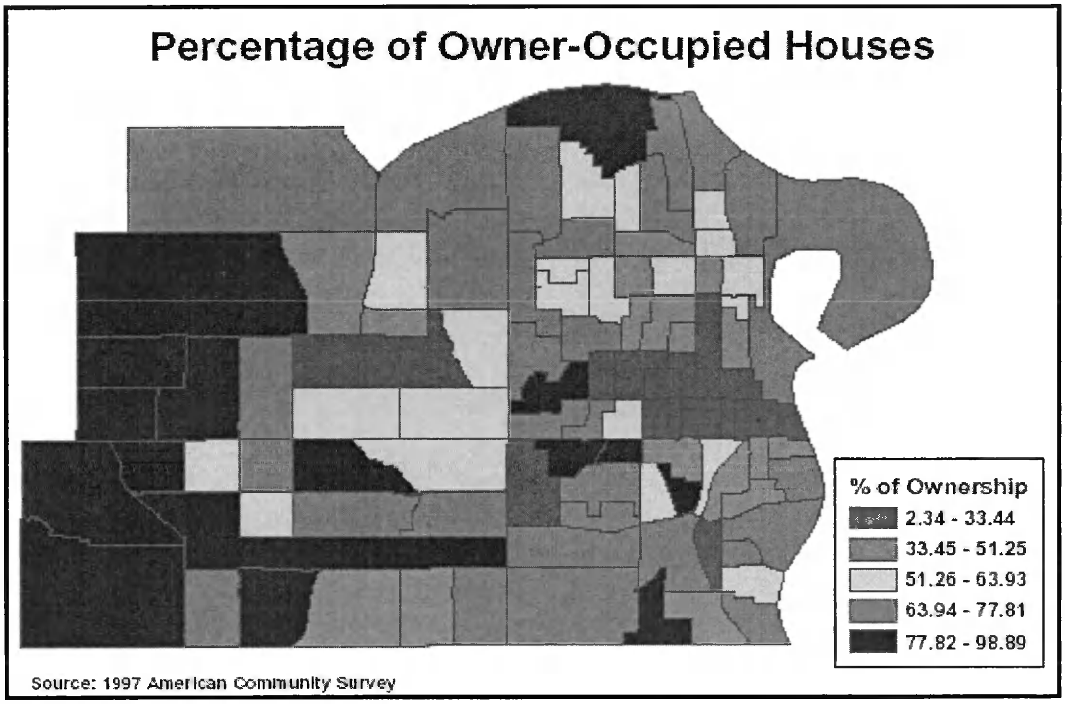
Appendix III-13: Map of percentage of unemployment



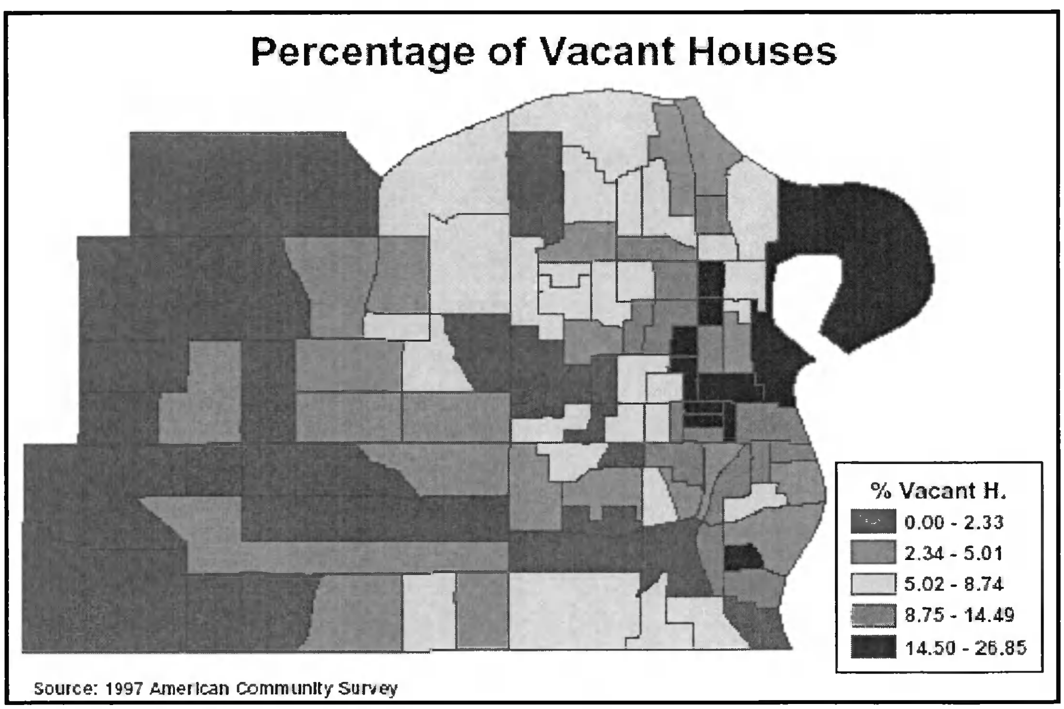
Appendix III-14: Percentage of people with income below poverty



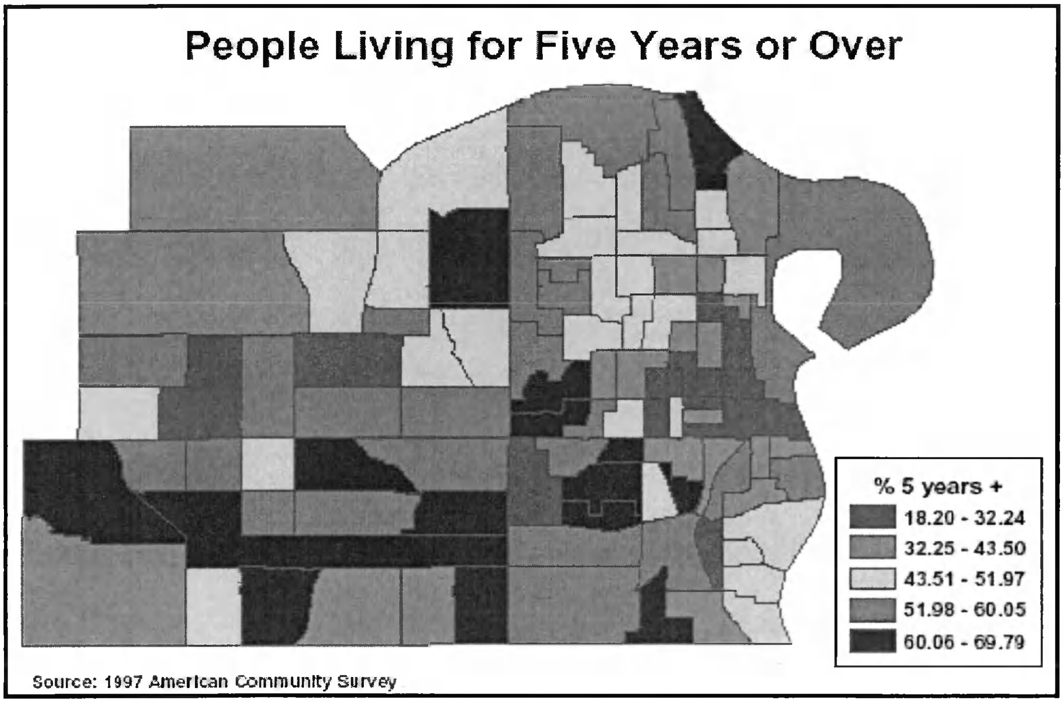
Appendix III-15: Map of Owner-occupied houses



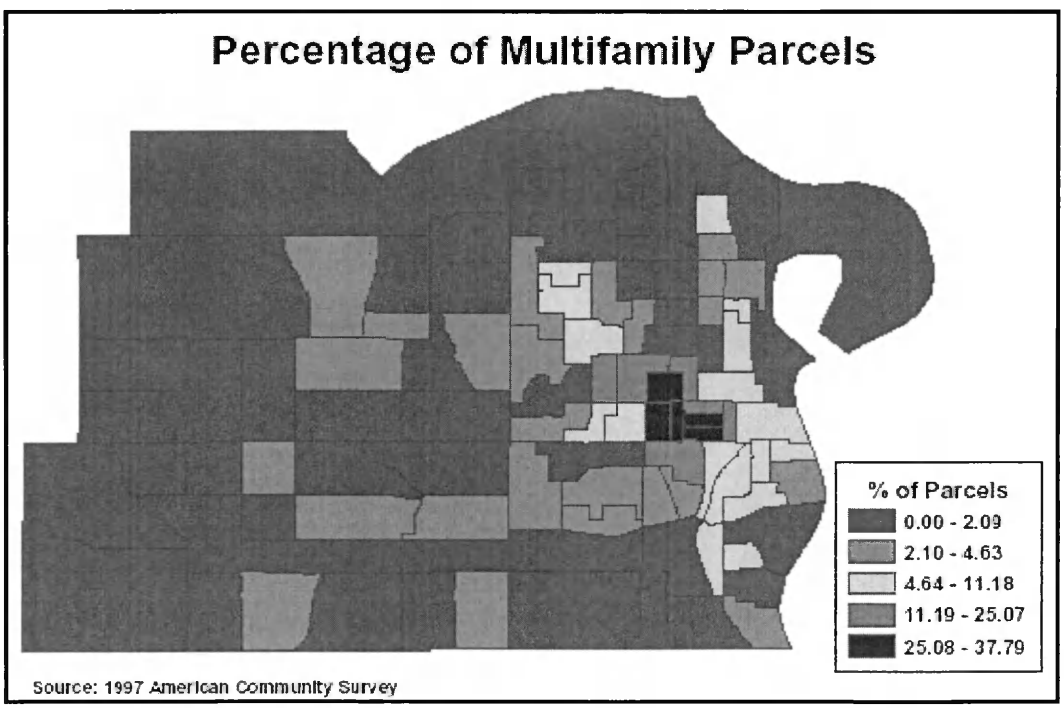
Appendix III-16: Percentage of vacant houses



Appendix III-17: Percentage of persons who live in the same house over 5 years



Appendix III-18: Percentage of multifamily parcels



Appendix III-19: Percentage of commercial parcels