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**EVALUATING THE EFFECTS OF CLOSED-CIRCUIT
TELEVISION ON CRIME IN PUBLIC HOUSING: AN
APPLICATION OF GIS AND SPATIAL STATISTICS**

by

Douglas A. Williamson

**A dissertation submitted to the Graduate Faculty in Earth and
Environmental Sciences in partial fulfillment of the requirements for
the degree of Doctor of Philosophy, The City University of New York**

2003

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This manuscript has been read and accepted for the Graduate Faculty in Earth and Environmental Sciences in satisfaction of the dissertation requirement for the degree of Doctor of Philosophy.

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Abstract

EVALUATING THE EFFECTS OF
CLOSED-CIRCUIT TELEVISION ON
CRIME IN PUBLIC HOUSING: AN
APPLICATION OF GIS AND
SPATIAL STATISTICS

by Douglas A. Williamson

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In recent years, the use of Closed Circuit Television (CCTV) as tool for crime prevention has been on the rise. While there has been some research, primarily in Great Britain, on the effectiveness of CCTV in reducing crime many of the studies show mixed results. These studies have looked at the spatial and temporal components of crime change caused by CCTV, but the robustness of the analyses has been a source of debate.

Nowhere is crime prevention more of a concern than in the nation's public housing developments. Here, residents and police have teamed to address the problem of crime reduction through a number of preventive measures, including the use of CCTV. Several cities including Boston, Mass., Camden, N.J., and Garfield, N.J. have already installed CCTV in select public housing projects to

reduce the rates of crime. While CCTV is present in a variety of locales, its presence in certain New York City public housing is particularly noteworthy. Considering the expense of installing and operating a large scale CCTV system, the attention given to other crime prevention strategies in New York City, and the importance of resident safety in public housing, it certainly is useful to examine the effects, if any, of CCTV on crime.

The purpose of this research is to examine the impacts of CCTV on crime for a large public housing development in New York City that recently acquired CCTV and a matched 'control' project that does not have CCTV. This research explores the effects of CCTV on crime incidence in and around public housing. It utilizes a number of statistically robust space-time techniques to assess the geographical patterns of crime change near the two housing projects. For each method, the results are discussed and strengths and weaknesses are compared. The techniques included in the analyses are inferential statistics based on count data, density estimation and segmented regression, local indicators of spatial autocorrelation (LISA), raised incidence models and animation. The analyses are performed for different categories of crime including major felonies, violations, and misdemeanors, as well as for different categories of arrests.

From these methods, a number of conclusions can be drawn. It appears that CCTV has had an effect on crime at and near public housing communities, but the patterns of change are mixed. That is, some areas show significant decreases, while others close by show significant increases. This is particularly apparent from the results of the segmented regression analysis, where felony complaints increase in areas near the CCTV cameras but have a more 'patchy' pattern of decrease/increase further away. In contrast, for violation complaints and arrests, most areas show a decreasing trend in response to CCTV. The results from the

buffer count analysis also have a mixed pattern of change. Of note here is the absence of statistical significance in these results. The LISA methods show signs of spatial dependence in the difference in crime counts after CCTV and may indicate displacement at some locations. The true random nature of crime, and the difficulties associated with isolating one variable, namely CCTV, from the many other factors that affect crime incidence, is evident in the animation section. Animation files are included as AVI files on a CD-ROM at the end of the document. Finally, the raised incidence models do not provide an adequate statistical explanation of crime density based on distance to public housing.

ACKNOWLEDGMENTS

The author wishes to acknowledge a number of people, without which, this research would not have been possible. First, the distinguished members of the committee, Dr. John Mollenkopf, and Dr. Charles Ehlschlaeger whose applied critical thinking were invaluable and made the research come alive through thoughtful questions and answers. Also, Dr. Victor Goldsmith who has been more than just a scholarly advisor, but rather a mentor. His lessons extend far beyond the academic realm. Finally, Dr. Sara McLafferty, whose patience and fortitude has been immeasurable, and her advice and guidance has been incalculable. Over the years, she has been more than a teacher and sage, but a close friend as well.

On a personal level, the author wishes to acknowledge his friends and family, particularly his parents, whose support and confidence never wavered. Above all, the author wishes to thank his loving wife, Adina. Her inner strength and resolve have taught more than all the research in the libraries of the world. For certain, without her love, and gentle guidance in all other matters, this work would never have reached fruition.

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LIST OF FILES

The following is a list of files included on the enclosed CD-ROM at the end of this document. The files are stored in the Windows Audio Video Interleave (AVI) format. They are viewable in most media players, including the Windows Media Player and the RealOne Player.

<u>Name</u>	<u>Size (MB)</u>
ALL_ARR.AVI – All arrests, month by month (1997-1999)	~19
ALL_COM.AVI – All complaints, month by month (1997-1999)	~19
DIF_ALL_ARR.AVI – Month by month differences, All arrests (1997-1999)	~2
DIF_ALL_COM.AVI – Month by month differences, All arrests (1997-1999)	~2
DIF_FEL_ARR.AVI – Month by month differences, All arrests (1997-1999)	~2
DIF_FEL_COM.AVI – Month by month differences, All arrests (1997-1999)	~2
DIF_IND_COM.AVI – Month by month differences, All arrests (1997-1999)	~2
DIF_MAJ_COM.AVI – Month by month differences, All arrests (1997-1999)	~2
DIF_MIS_ARR.AVI – Month by month differences, All arrests (1997-1999)	~2
DIF_MIS_COM.AVI – Month by month differences, All arrests (1997-1999)	~2
DIF_VIO_COM.AVI – Month by month differences, All arrests (1997-1999)	~2
FEL_ARR.AVI – Felony arrests, month by month (1997-1999)	~19

FEL_COM.AVI – Felony complaints, month by month (1997-1999)	~19
IND_COM.AVI – Indicator complaints, month by month (1997-1999)	~19
MAJ_COM.AVI – Major felony complaints, month by month (1997-1999)	~19
MIS_ARR.AVI - Misdemeanor arrests, month by month (1997-1999)	~19
MIS_COM.AVI – Misdemeanor complaints, month by month (1997-1999)	~19
RATIO.AVI – Ratio of arrests versus complaints, month by month (1997-1999)	~19
VIO_COM.AVI – Violation complaints, month by month (1997-1999)	~19

Chapter 1: Introduction

In recent years, the use of Closed Circuit Television (CCTV) as tool for crime prevention has been on the rise. While there has been some research on the effectiveness of CCTV in reducing crime, namely in Great Britain, many of the studies show mixed results. These studies have looked at the spatial and temporal components, but the robustness of the analyses has been a source of debate.

Nowhere is crime prevention more of a concern than in the nation's public housing developments. Here, residents and police have teamed to address the problem of crime prevention through a number of preventive measures, including the use of CCTV. Several cities including Boston, Mass., Camden, N.J., and Garfield, N.J. have already installed CCTV in select public housing projects to reduce the rates of crime. While CCTV is present in a variety of locales, its presence in certain New York City public housing is particularly noteworthy. Considering the expense of installing and operating a large scale CCTV system, the attention given to other crime prevention strategies in New York City and the importance of resident safety in public housing, it would certainly be useful to examine the effects, if any, of CCTV on crime.

The purpose of this research is to examine the impacts of CCTV on crime for a large public housing development in New York City that recently acquired CCTV and a matched 'control' project that does not have CCTV. This research explores

the effects of CCTV on crime incidence in and around public housing. It utilizes a number of, in some cases new, statistically robust space-time techniques to assess the effect. For each method, the results are discussed and strengths and weaknesses are compared.

Background

Since 1994, the New York City Police Department (NYPD) has increasingly used geographic information systems (GIS) and spatial statistics to determine crime control tactics and allocate resources within and across the city's police precincts. During this period, all major crimes, except rape, have declined significantly in the city. The NYPD has deployed PC-based mapping technology to most of the NYPD's 76 precincts as well as many of its specialized units. One unit in particular, is the Housing Bureau. The Housing Bureau was created in April 1995 when the Housing Authority Police Department merged with the New York City Police Department. This newly formed division is responsible for overseeing the safety and well-being of the estimated 425,000 residents in its 345 public housing developments across the city (Mayor's Management Report Fiscal Year 2002, downloadable at:

http://www.nyc.gov/html/ops/pdf/2002_mmr/0902_mmr.pdf

The Housing Authority has initiated a wide variety of programs to reduce the amount of crime in its developments, including the Housing and Urban Development Agency's Public Housing Drug Elimination Program (PHDEP), the Lobby Monitoring Program, the Tenant Patrol Program and various physical improvements such as increased lighting and new locks and intercoms. A significant drop in crime in the city's public housing developments, 21 percent between 1994 and 1995, has been attributed to the implementation of such programs. One program, in particular, is being credited for a great deal of the reduction, namely Video Interactive Patrol Enhanced Response (VIPER). The VIPER unit is responsible for the installation, maintenance and monitoring of Closed Circuit Television (CCTV) systems in selected public housing communities.

Personnel assigned to the VIPER unit review complaint reports, gather information on wanted persons, probation/parole violators and crime conditions. They also assist detectives in performing in-depth post incident investigations. Video produced by the VIPER unit has been instrumental in the apprehension of individuals wanted for murder, assault, robbery and rape. The VIPER unit has also been 'witness' to murders, assaults and robberies, all of which have been closed by arrest as a direct result of reaction by the unit.

A further benefit of CCTV in public housing is the decrease in quality of life crimes. In developments equipped with CCTV, the New York City Housing

Authority (NYCHA) report: that the incidence of graffiti, littering and vandalism have decreased significantly. According to the Housing Bureau's Strategic Plan for 2002, "although, the decreases in index crimes and quality of life crimes are noteworthy, it is important to note that residents of developments where CCTV systems are installed have overwhelmingly expressed their satisfaction with the system. Furthermore, at several community meetings many residents who live in developments that are not equipped with CCTV have requested for both the NYPD and NYCHA that their development be the next scheduled for installation." (page 5, NYPD – Housing Bureau Strategic Plan, 2002) As a result, NYCHA and the NYPD are evaluating methods by which to expand the program. Unfortunately, to date, researchers outside the Housing Bureau and NYCHA have not closely scrutinized the effects of CCTV on crime in public housing. In addition, the effects on crime in neighboring areas have not been assessed.

One large-scale CCTV initiative is currently under way in the Albany public housing projects in Brooklyn, New York. This CCTV installation comprises approximately 105 cameras, which monitor the project's nine buildings. Camera locations include, but are not limited to, all elevators, lobbies and roofs, as well as common areas and building water tanks. Uniformed officers of the New York City Police Department (NYPD) monitor the cameras 24 hours a day, seven days a week from a remote location. The Albany projects are similar to many other projects in New York City. However, compared to public housing developments

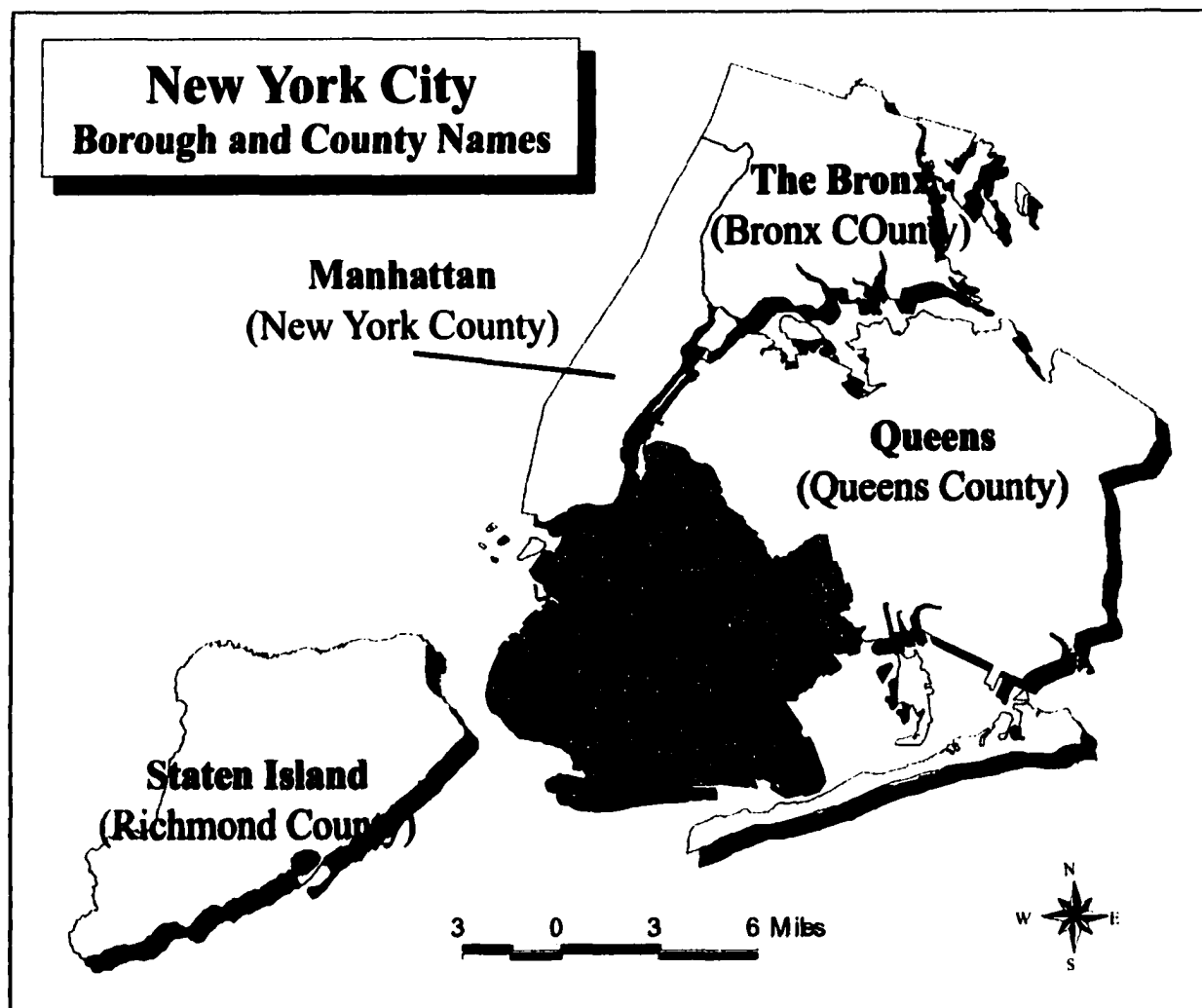


FIGURE 1:1 New York City

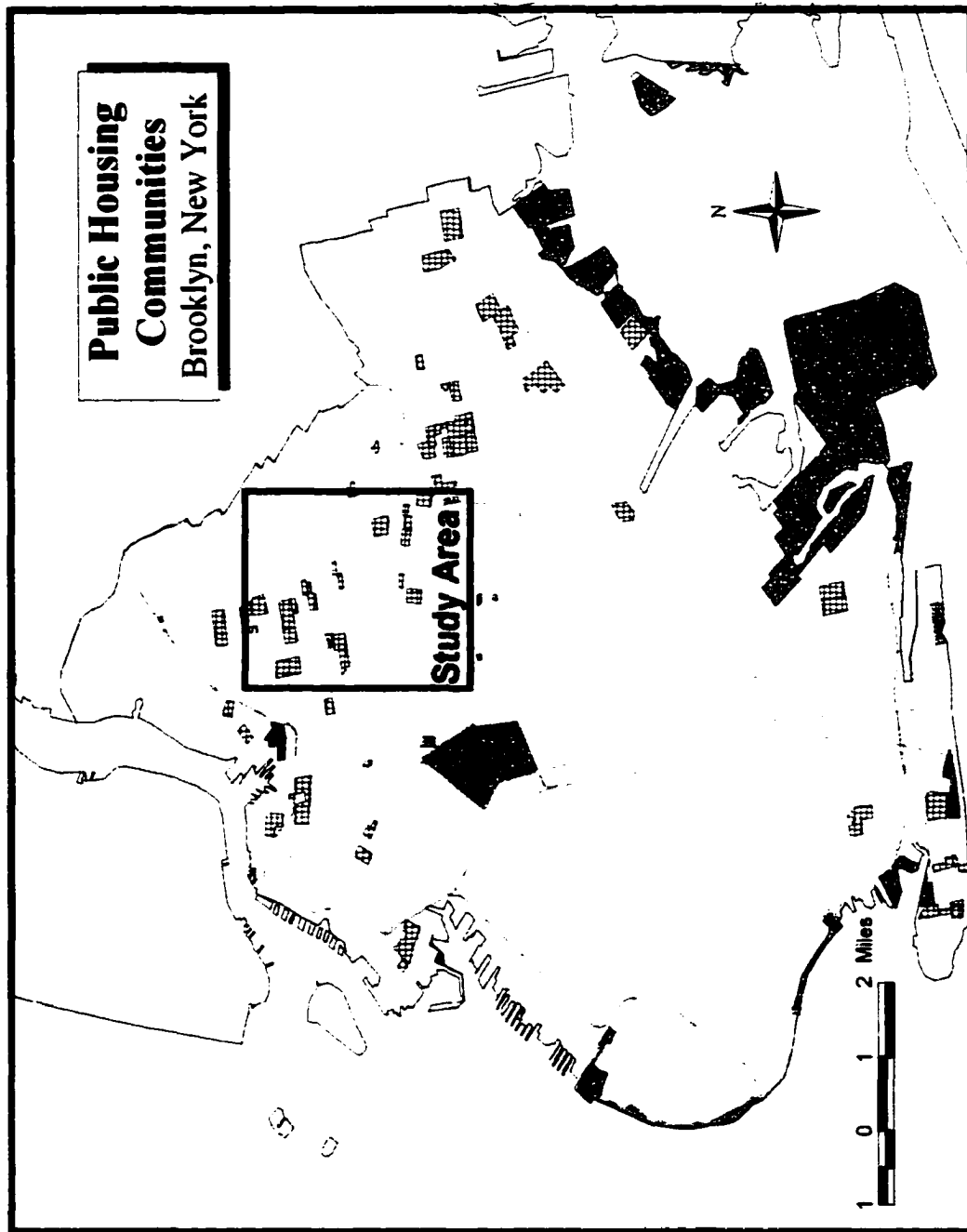


FIGURE 1:2 Brooklyn, New York

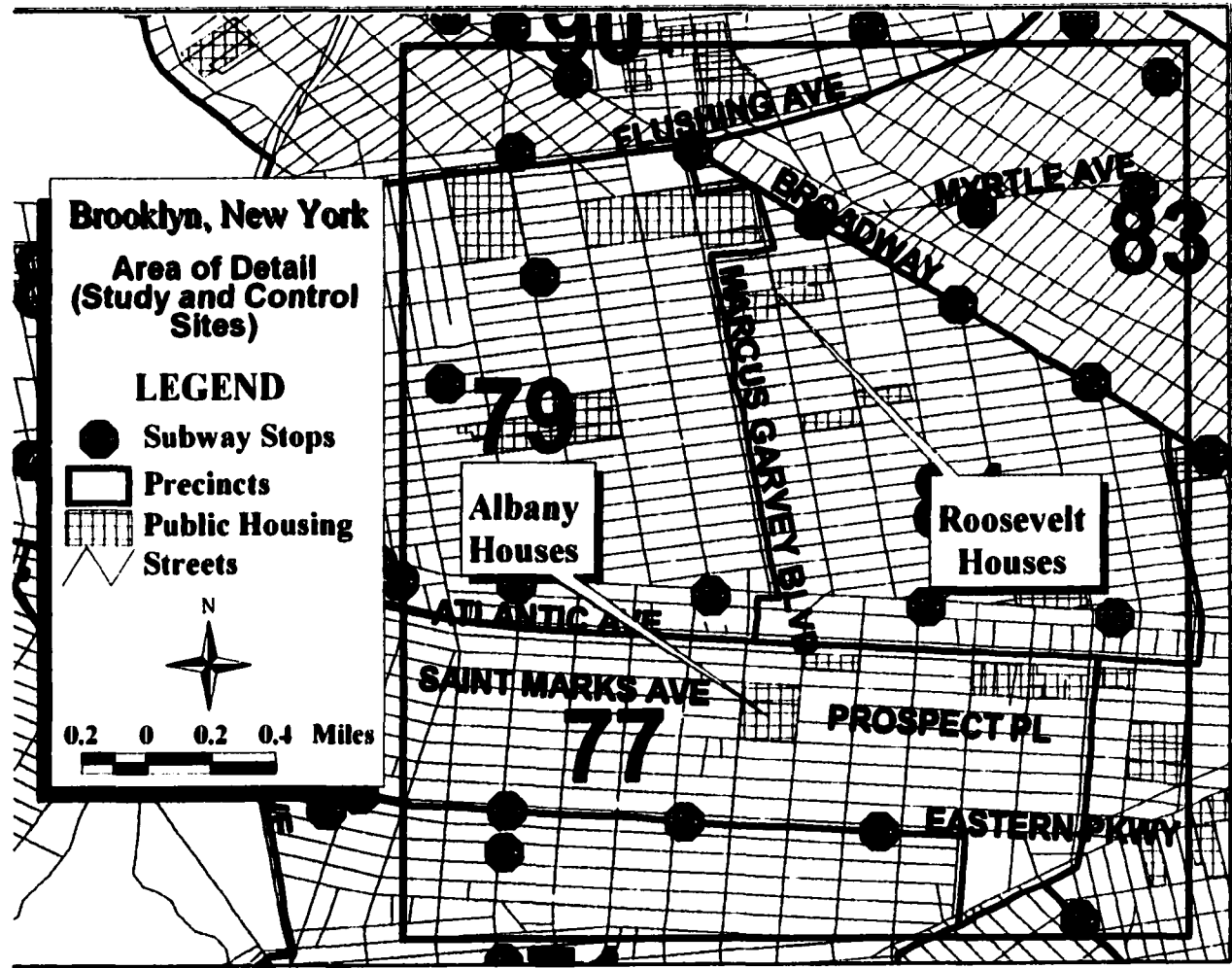


FIGURE 1:3 Study Area - Brooklyn, New York

outside New York City, they are extremely large, equivalent to roughly one census tract. The Albany projects include 1,220 apartments housing an estimated 3,014 people. The complex spans roughly 14 acres, of which buildings cover approximately 27 percent. The installation phase of CCTV in the Albany complex was completed in the fall of 1998.

The Albany housing complex is a prime site for an evaluation of CCTV not only because of its size, but for other reasons as well. First, it is one of several housing projects to have CCTV installed and second, observers feel that there are virtually no other 'effective' prevention strategies currently under way in the Albany complex. If this assertion is true then, any changes in crime incidence can be attributed primarily to the installation of CCTV.

For the purpose of this evaluation, it is necessary to select a control site that will be used for comparative purposes. The control public housing development should be similar in all aspects to the study site (Albany), except for the glaring difference that the control site will not have CCTV present. It is hoped that by comparing another site that does not have CCTV and is similar in most other characteristics, the effects of CCTV can be isolated and the evaluation will be more scientifically rigorous. For this study the Roosevelt Houses, which are also located in Brooklyn was selected as a control site. The Roosevelt houses are a little over a mile away from the Albany Houses, therefore the neighborhood characteristics are similar. As for other characteristics, such as demographics the

two projects are very comparable (see Table 1:1). The two housing projects are almost identical in population size, number of families and average family size. The Roosevelt site contains a somewhat smaller proportion of families on welfare; however average income levels are comparable.

	1997		1998		1999	
	Albany	Roosevelt	Albany	Roosevelt	Albany	Roosevelt
Number of Families	1124	1077	1132	1092	1126	1099
Population	2912	2795	2936	2801	2883	2818
Average Family Size	2.6	2.6	2.6	2.6	2.6	2.6
Average Gross Income	\$11,698	\$11,085	\$11,486	\$11,762	\$11,712	\$12,188
Number of Welfare Families	426	336	422	313	369	283
Number of Major Felonies	92	87	66	67	55	63
Average Number of Years in Public Housing	19.2	16.2	19.0	16.2	18.9	16.4

TABLE 2:1 - Housing Development Characteristics

Overall, the neighborhoods surrounding the two projects are very similar. Census information on population, race, ethnicity, housing characteristics, etc., indicates that the areas surrounding the two communities are comparable (see Figures 1:4 – 1:7). Both communities are in densely populated urban areas. The Albany Houses are in the Crown Heights neighborhood, and the Roosevelt Houses are in the Bedford-Stuyvesant neighborhood. The residents in these neighborhoods are predominantly African-American. There is a large percentage of people living below the poverty level, particularly near the Roosevelt Houses.

Also, in each area, there are a large proportion of female-headed households with children.

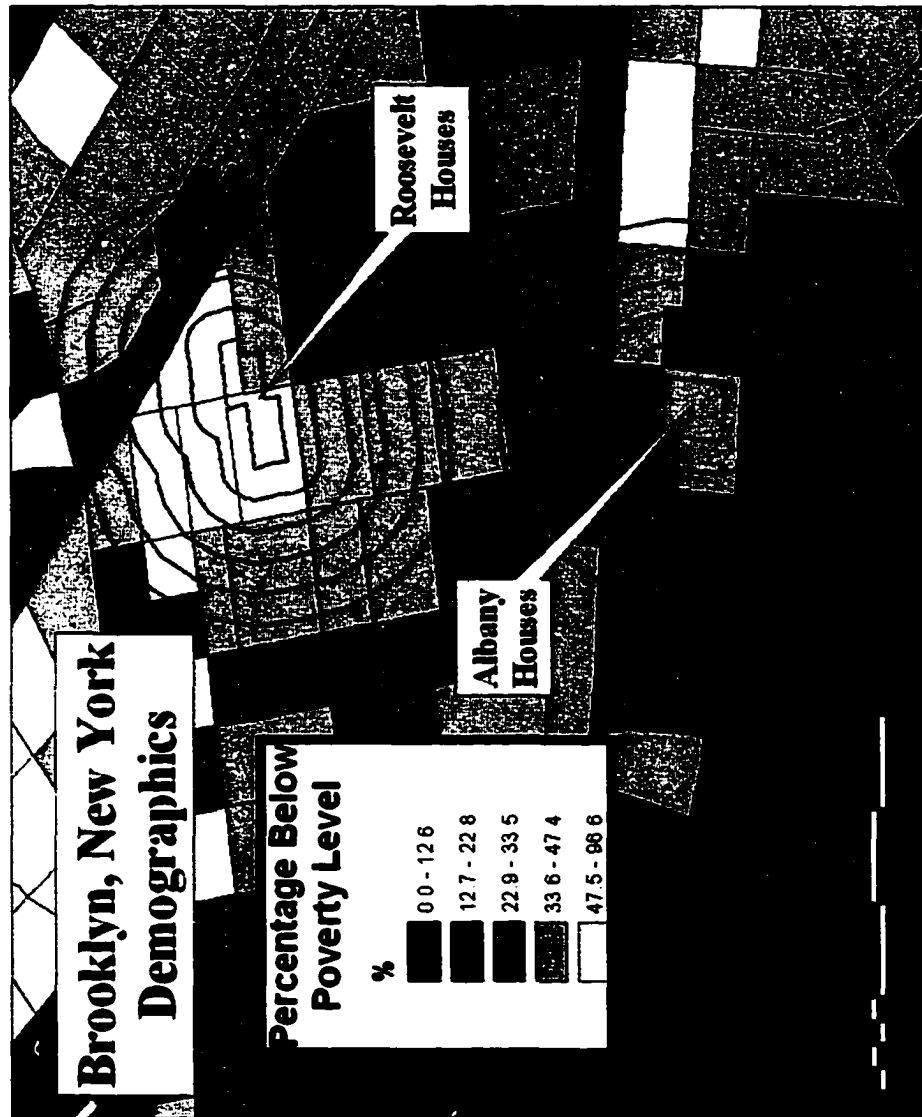


FIGURE 1:4 -- Study Area Demographics, Percentage Persons Below Poverty Level

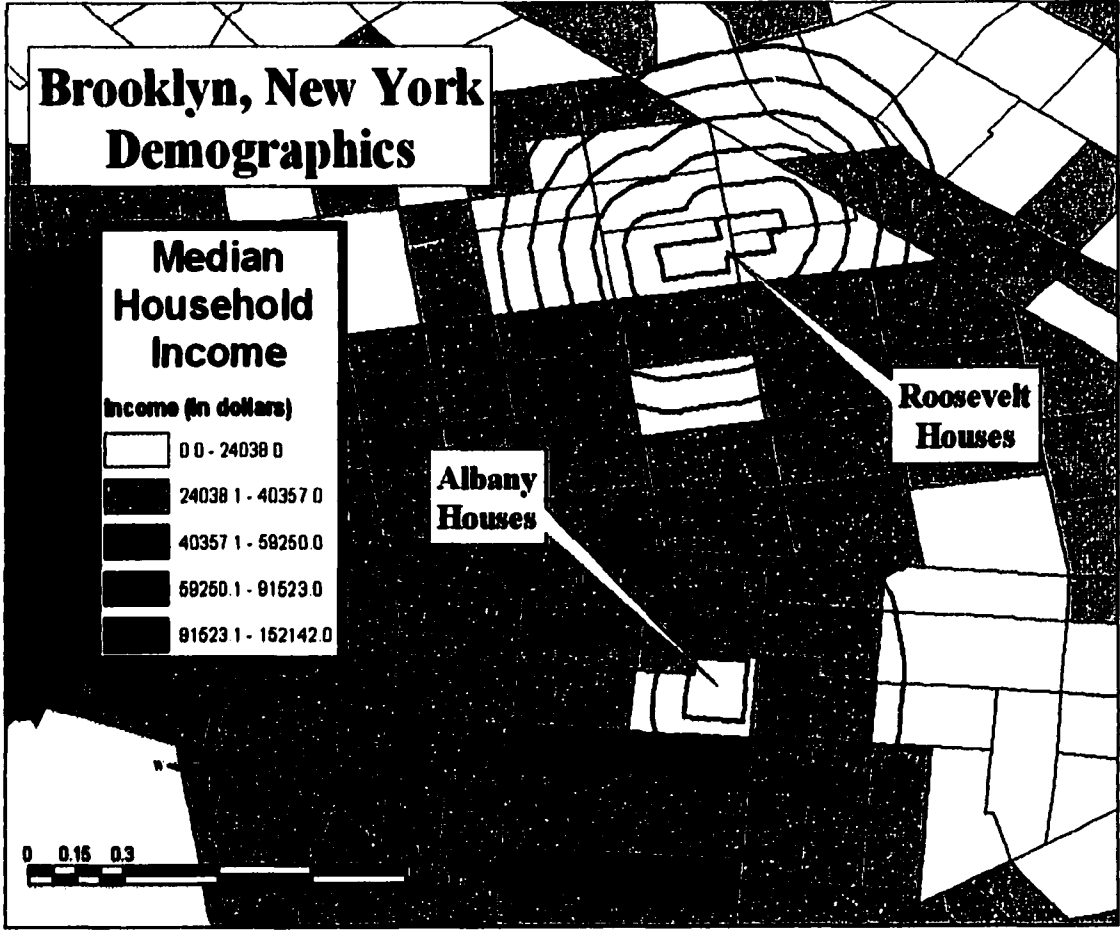


FIGURE 1:5 – Study Area Demographics, Median Household Income

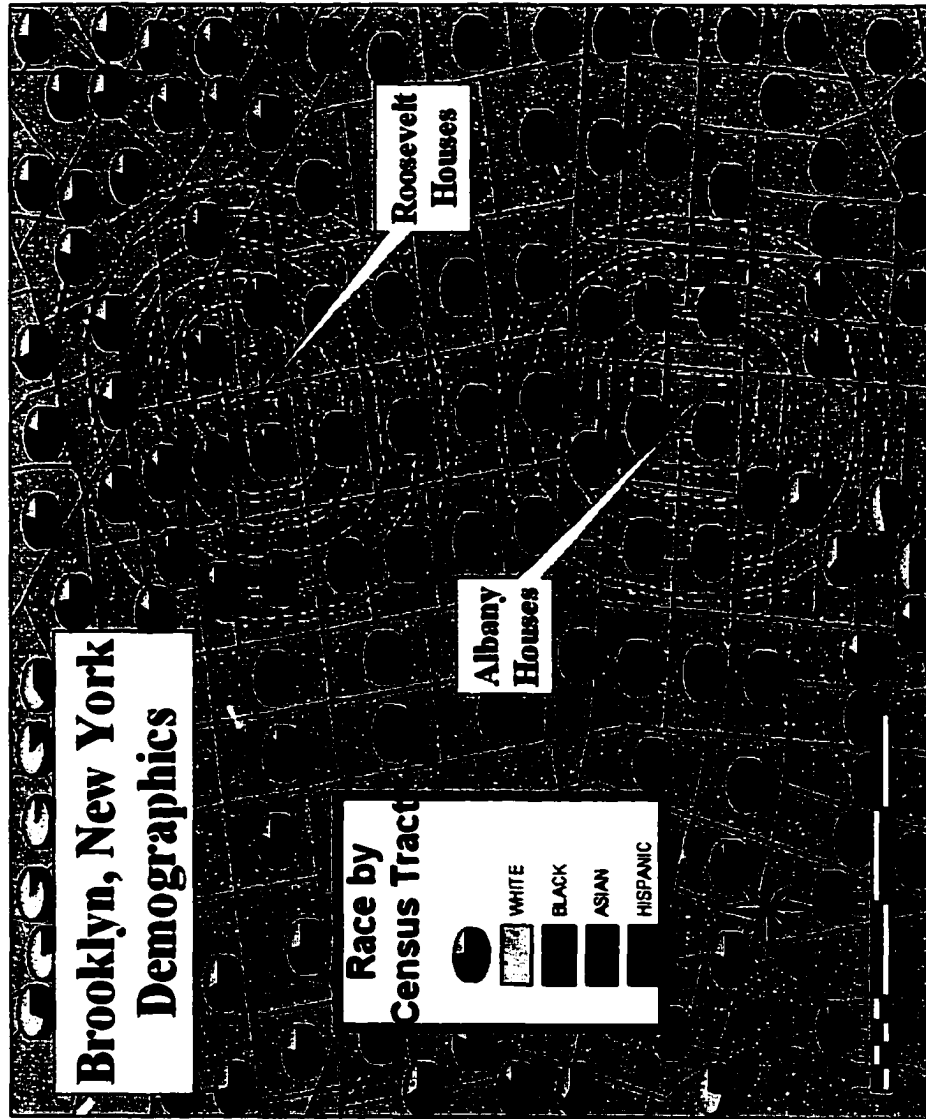


FIGURE 1:6 – Study Area Demographics, Race characteristics

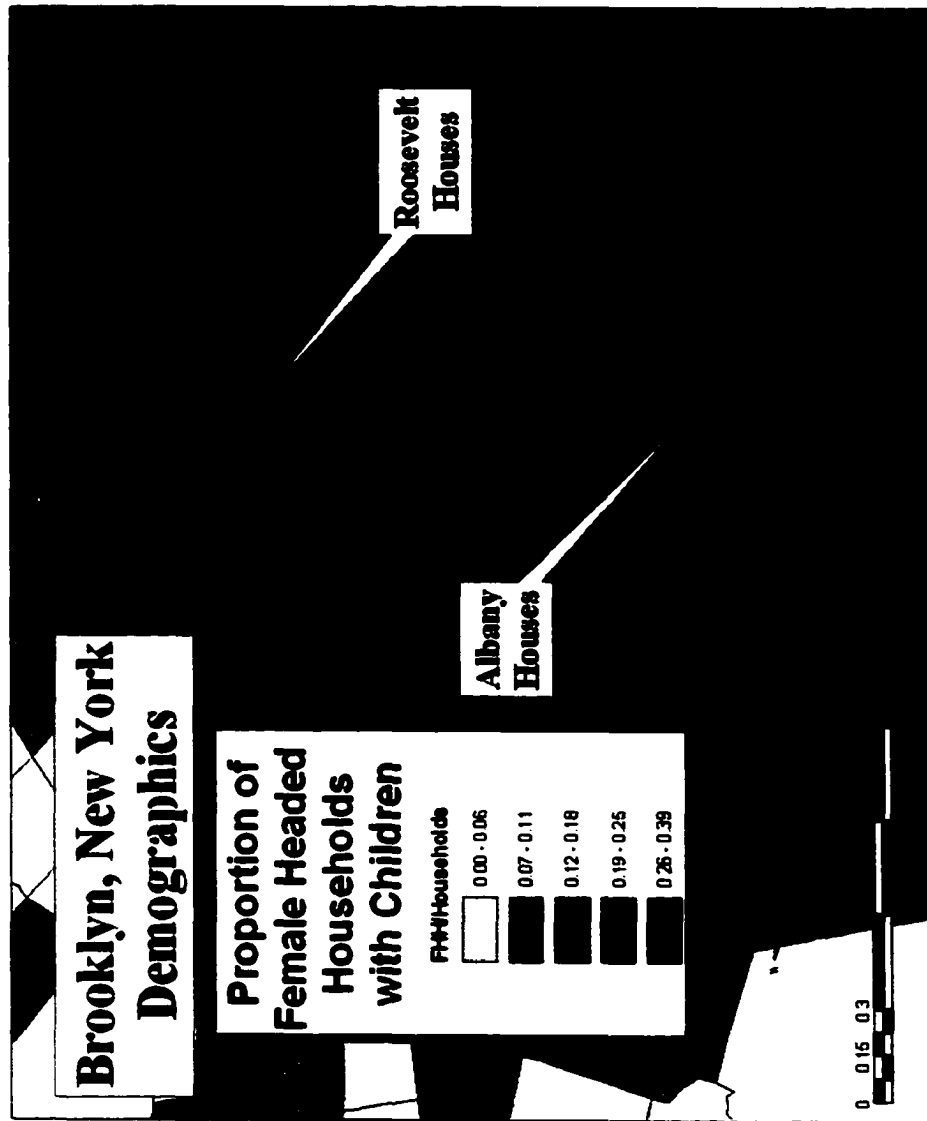


FIGURE 1:7 – Study Area Demographics, Proportion of Female Headed Households

Goals and Objectives

The goals and objectives of the proposed research project can be classified into two groups. The primary goal is to conduct a comprehensive evaluation of the effects of the installation of CCTV on crime rates in and near the Albany public housing development. This study uses a scientifically rigorous methodology involving spatial statistics and geographic information systems (GIS) to determine the overall effects of CCTV as well as any indirect effects such as displacement. A case-control study design is used so that changes potentially related to CCTV can be compared with trends occurring in a similar housing development without CCTV. In addition, crime data are disaggregated by crime type for arrests along with complaints, so that differences in CCTV effectiveness for various categories of crime can be detected.

The second goal is to strengthen and enhance the set of GIS and spatial statistics tools that exist for monitoring and analyzing spatial and temporal changes in crime and related social issues. The past few years have witnessed an explosion in the use of GIS in these areas. This research uses a mix of existing and new tools for analyzing spatial and temporal changes in crime patterns. The tools include: local spatial autocorrelation analysis, buffer analysis, raised incidence modeling, animation, and a new method based on segmented regression analysis. An

important component of the research is to evaluate each tool and compare the tools' strengths and weaknesses. The tools evaluated in this project are useful for analyzing complex spatial and temporal processes and thus may be applicable to other policy contexts as well.

Research Significance

This study makes several contributions to our understanding of geographical changes in crime in relation to CCTV and the development of spatial statistical methods for evaluating crime prevention programs. First, this study contributes to our understanding of the impacts of CCTV. Although several recent studies investigate the effects of CCTV on crime, most do not examine the detailed geographical patterns of crime change in nearby areas (Welsh and Farrington 2002). In addition, many recent CCTV evaluations do not include a control site so the impacts are difficult to assess. By using advanced spatial analysis methods and adopting a case-control design, this research provides a rigorous assessment of the effects of CCTV on crime in the context of public housing.

Secondly, this research contributes to the development of GIS-based methods for visualizing and analyzing crime patterns. Although methods for analyzing spatial point patterns have existed for decades, methods for analyzing changes in point patterns through time and space are just now being developed (Bailey and Gatrell 1995, Openshaw et al 1994). In this study, a new method based on segmented regression analysis is proposed for analyzing the spatial and temporal

trends in crime incidents before and after a crime intervention. In addition, existing methods such as animation and raised incidence modeling are used to explore these same spatial and temporal patterns. Using and comparing different spatial statistical methods provides an opportunity to evaluate the robustness of the research findings and to comment on the strengths and limitations of each method for assessing crime change in response to CCTV.

Finally, this research is important from a policy standpoint. Considering the size and scope of the Albany CCTV project, the findings should be of interest to the New York City Housing Authority (NYCHA), which oversees the operation of the project, and the NYPD, which polices the project. According to the Mayor's Management Report (MMR), which serves as a public report card about the way City services affect the lives of City residents, CCTV does and will continue to be an important crime prevention tool. "In conjunction with the New York City Police Department (NYPD), NYCHA has installed 3,100 closed circuit television (CCTV) cameras in 15 developments over the last five years. Crime in developments with CCTV dropped by 24 percent compared to an 11.9 percent reduction in developments without CCTV" (MMR, 2002). The CCTV initiative also weighs heavily in the NYPD Housing Bureau's Strategic Plan for 2002, which describes CCTV as "an intelligence gathering/analysis center and proactive crime prevention and apprehension system" (NYPD, 2002). Although significant investments in CCTV in New York City public housing projects are likely to continue, no comprehensive evaluation of an ongoing CCTV project has

been conducted. This study performs such an evaluation for one of the largest existing CCTV developments and thus provides

Organization

Following this introduction, this document contains seven chapters. A literature review chapter outlines and briefly describes the research to date on relevant topics such as crime prevention, the use of CCTV, crime mapping and evaluation research. A chapter describing the methods used, literature related to these methods, and the data used in the methods follows this. The following five chapters describe in detail the results obtained using each method for analyzing CCTV impacts. The individual chapters cover buffer analysis, segmented regression, local indicators of spatial autocorrelation, raised incidence and animation. Included in each section is a discussion of the method and a review of relevant literature as it relates to that method. In addition, the results and findings from each method are described in detail. Finally the results are summarized in the conclusion and the strengths and limitations of each method are compared. Future considerations, limitations and policy implications are discussed in this section as well.

Chapter 2: Relevant Literature Review

Introduction

For as long as people have been victims of crime, they have been developing ways to prevent it. Over the past decades, a vast amount of research has accumulated dealing with issues of crime prevention. Traditionally, crime prevention programs and research focused on the broad societal aspects of crime, analyzing the underlying causes of crime such as unemployment or drug abuse. For a review of macro level ecological studies see Schwatz (2000). These types of prevention strategies are said to be 'corrective' (Legins, 1965). Advocates of this theory believe that crime can be avoided if the conditions under which crime is thought to flourish are alleviated. An example of this is the 'Weed and Seed' program from the United States Department of Justice, which aims to revitalize and prevent, control, and reduce violent crime, drug abuse, and gang activity in communities by partnering residents (to seed) and law enforcement (to weed). Other examples include after-school programs for juveniles, literacy programs, home-ownership programs, and small business incentives for neighborhood residents.

More recently, however, the trend in prevention has been to address the attractiveness of certain settings for crime. These types of programs are known

as 'situational' crime prevention (Clarke, 1997), and are based on the often-quoted work, "Broken Windows" (Wilson 1982). This comes from the observation that if one window is broken on a building and remains unrepaired, other windows will be broken soon after. It relates to crime in the sense that if minor criminal infractions are tolerated, other more serious offenses will soon follow. Therefore, rather than attempting to reduce criminal tendencies, these situational crime prevention programs try to eliminate the opportunity for crime through environmental change. In addressing crime in public housing projects, the development of situational crime prevention was greatly stimulated by the pioneering work on 'defensible space' by Newman (1972). Newman argued that the architectural design of public housing strongly affects criminal activity. The large scale of buildings in a public housing project can create anonymity among residents, and the large number of unprotected entrances and public areas invites criminals to the developments. The concept is further outlined by Housing Secretary Cisneros (1995). Evaluating the effects of defensible space characteristics on crime in public housing using GIS are discussed by Hyatt. & Holzman, (1999). Skeptics argue that defensible space can only be effective if there is a strong preexisting social fabric in the community (see Merry, 1981).

Defensible space has been furthered to a new approach in prevention known as CPTED (Crime Prevention Through Environmental Design). "Basic principles of CPTED include target hardening (controlling access to neighborhoods and buildings and conducting surveillance on specific areas to reduce opportunities

for crime to occur) and territorial reinforcement (increasing the sense of security in settings where people live and work through activities that encourage informal control of the environment)” (NIJ 1996). For an overview of CPTED see Crowe (1991), Gardiner (1978), Wallis and Ford (1989) and Sarkissian Associates (2000).

Situational crime prevention seeks to increase the risk to perpetrators of engaging in criminal activity, increase the difficulties of criminal activity, and reduce the rewards from criminal activity by modifying environmental characteristics. There has been an abundance of research in the area of situational crime prevention, particularly relating to opportunity-reducing techniques. These include studies in banks, parking facilities, public transportation and hospitals to name a few (Laycock, et al 1992, Poyner 1991, Ramsay 1991, Hannan 1982, Hemingway 1989, Van Andel 1989, Gandjean 1990, and Meredith, et al 1992).

Clarke (1997) describes sixteen types of opportunity-reducing techniques, many of which attempt to create defensible space. Two, in particular, focus on the problem of large numbers of unprotected entrances and public areas in public housing. They are ‘formal surveillance’ and ‘surveillance by employees’. The aforementioned surveillance techniques attempt to deter crime through monitoring of space either by public or private authorities. The purpose then of surveillance is to prevent crime by increasing the risk of apprehension. The topic of surveillance is discussed in detail in “Surveillance of Public Space: CCTV, Street Lighting and Crime Prevention” (Painter and Tilley, eds 1999).

CCTV and Crime Prevention

Recently, the task of surveillance has been greatly enhanced by the development of Closed-Circuit Television or CCTV. This advancement in technology has allowed authorities to monitor potential crime settings remotely, instead of *in situ*. The police have used CCTV since the late 1960s, but only recently has it been accepted as a useful tool in crime prevention. Nieto (1997) provides an overview of the use of CCTV in public housing and other environments. He discusses legal issues of public surveillance, gives a history of public surveillance and provides examples of how specific cities are using CCTV.

Several studies mention the use of CCTV in prevention (Poyner 1988, Poyner 1991, Mayhew et al. 1979, LaVigne 1997, Chainey 1997 and Chainey 1999); yet the use of CCTV in these cases comes within the broad context of crime prevention and is discussed along with a variety of other techniques.

More recently, researchers have begun to evaluate the use of CCTV in crime prevention and the impacts of CCTV on crime incidence. Based on surveys, interviews and crime incident data Brown (1995) examined the effectiveness of CCTV as a tool for crime prevention in three town centers in the UK. Tilley (1993) evaluated the use of CCTV in parking facilities, again in the UK, finding that, in certain circumstances, CCTV can be an effective tool for crime

prevention. Using statistical methods, Chatterhorn et al (1994) found a reduction in burglaries by 79% in adult communities that utilized CCTV. Other studies focus on the effectiveness of CCTV based on the perceptions of CCTV by the general public (Honess et al 1992) and the criminals themselves (Short et al 1996). From surveys, Holmes et al found a positive reception to the use of CCTV from the general public. The respondents also believed CCTV was an effective crime prevention tool. Short et al examined the perceptions of CCTV from the perspective offenders who revealed, in general, that they are aware of the CCTV systems. In some cases, these offenders have made 'adjustments' to their routines based on the presence of CCTV. For a more detailed review of CCTV evaluations see Phillips (1997) and Welsh and Farrington (2002). From the evaluations, no clear answer arises on the effectiveness of CCTV on crime. A large portion of the evaluations reveals that CCTV has had a positive effect, but still others reveal mixed results. While these reviews of CCTV evaluations are useful, they are limited in their treatment of the spatial component of crime. Many of them deal with counts of crimes and do only address the location component in a general, descriptive way.

Crime and Public Housing

The relationships between crime and public housing have also been the focus of numerous studies. Kamber, et al (1999) performed a number of analyses on the relationship between crime and socio-economic variables in public housing in New York City. The authors suggested that there is no correlation between crime

rates and the rates of assisted housing in Brooklyn, New York. They further suggest that the most consistent and significant predictor of crime rates is the number of residents. Fagan, et al (2000) studied the effects of crime diffusion around public housing. They found that rates of violent crime in public housing project in the Bronx were only weakly tied to the social and structural characteristics of the public housing sites; however there was a strong relationship between the levels of violent crime in the housing project and in the immediate surrounding area. McNulty et al (2001) examine the relationship between race, crime and public housing, finding that predominantly black neighborhoods have similar crime rates as white neighborhoods, unless public housing is present.

One crime prevention initiative, the Public Housing Drug Elimination Program (PHDEP) was the focus of research by Popkin et al (1995). They found favorable results due to new strategies that aimed at removing opportunities for drug sales in and around public housing projects. In the United Kingdom, several studies were done studying the effects of crime preventions strategies on crime in a housing development known as Kirkholt (Pease 1991, Forrester et all 1990, Forrester et all 1988 and Tilley 1993). The target hardening strategies at Kirkholt resulted in significant decrease (75%) in residential burglaries. In a different study, Roncek et al (1981), report that the presence of public housing significantly increases both property and personal crime rates, and that presence of public housing may affect the crime rates in surrounding blocks that are nearby but not adjacent to public housing.

These findings on crime in public housing are important for several reasons. First, they reveal a complex association between crime and public housing. Although in some cases crime rates are higher in public housing than in similar residential areas with different types of housing; this is not always true. The design of public housing and presence of crime prevention programs have important impacts on crime. Second, crime in public housing is connected in complex ways to crime in neighboring areas. These spatial relationships are poorly understood , and they may be influenced by crime prevention strategies such as CCTV.

Many researchers and policy-makers have asserted that CCTV does in fact have a positive effect on crime, leading to a decrease in the areas immediately surrounding the CCTV systems (Brown 1995). However, other effects need to be examined, particularly spatial and temporal displacement and 'free-rider' effects. Spatial and temporal displacement are two of the six types of crime displacement as defined by Reppetto (1976). Gabor (1986) revisits the concept of multi-mode displacement. Spatial displacement refers to the movement of crime from one location to another after a prevention technique is employed. Temporal displacement describes a similar shift in the timing of crime incidents. 'Free-rider' effects and diffusion of benefits refer to the reduction in crime in nearby areas that may occur after a prevention technique is employed. Very often, areas adjacent to the location of the prevention strategy will notice a decrease in

criminal activity, simply due to their proximity. No strategies are employed at these places, they merely benefit from the efforts at another location (Cornish 1987, Eck 1994, and Clarke 1997).

Several efforts have been made to analyze the effects of crime prevention strategies as they relate to these phenomena. Meithe (1994) found limited existence of displacement or free rider effects when examining target hardening and community based crime prevention programs. Clarke, et al (1994) identified displacement in the use of one of two types of subways slugs (inexpensive replications of legitimate tokens) in the London Underground. Diffusion of benefits was found when evaluating the effects target hardening strategies on drug hotspots (Green, 1995) and retail (merchandise) loss (Masuda, 1992).

As was stated earlier, little work has been done in evaluating CCTV as a tool in crime prevention, and the primary work in this area lacks rigorous tests of significance.

Several studies have shown mixed results in the effects of CCTV on crime reduction. For example, Skinns (1998) found decreases in certain types of crime and increases in others. He also observed displacement in neighboring areas as well as diffusion of benefits. Tilley (1993) found that there was an initial decrease in auto crime in car parks with CCTV, but it was not sustained over time. It was

also observed that auto crimes increase in neighboring areas, suggesting displacement.

Some evaluations have indicated more promising results. Brown (1995) provides strong evidence, consistent with Poyner (1992), that crime prevention programs deploying CCTV have generally led to reductions in various categories of car crime. Short and Ditton (1998) showed dramatic decrease in crimes in two town centers in Great Britain. Chatterhorn and Frenz (1994) found significant decreases in crime in a senior citizens community after the installation of CCTV. Finally, Armitage, et al (1999) showed areas covered by CCTV had dramatic decreases in crime, with little to no displacement observed in another town center

Still other research shows little to no impact of CCTV on crime. Brown (1995) was unable to prove CCTV had any effect on the reduction of burglary or vehicle theft in a town center. Relevant to this research study, Musheno (1978) was unable to link CCTV with a reduction in crime in a public housing development in New York City

From this it is clear that there is a need for a comprehensive evaluation of the use of CCTV as a tool for crime prevention in public housing. The evaluation should focus not only on the raw numbers of crime, but also on the geographical and temporal patterns of crime. To this end, Geographic Information Systems (GIS) and spatial statistics are important tools for the evaluation

Chapter 3: Data and Methods

Methodology

Geographic Information Systems (GIS) and spatial statistics are vital tools for mapping, analyzing, and visualizing crime data. Police departments across the United States are using these methods to pinpoint hot spots of criminal activity and to allocate law enforcement resources to areas where they are most needed (Block, et al 1995, Goldsmith, et al 2000, Hirshfeld, et al 2001, and Harries 1999). However, very little research has been done using these tools in the evaluation of intervention strategies or crime prevention programs, in particular closed circuit Television (CCTV). Much of the evaluation work on CCTV has been done in Great Britain, where CCTV has been in place for a number of years (Brown, 1995 and Chainey, 1997). However, since the technology of CCTV and developments in crime mapping and spatial statistics are relatively new, the evaluations are limited at best. The United States Department of Housing and Preservation (HUD) publishes a manual "A Guide to Evaluating Crime Control Programs in Public Housing", but it is of limited use for research and designed more for policy makers and planners.

To evaluate the impact of CCTV on crime in public housing, a quasi-experimental study design is utilized in which crime patterns in housing projects with and without CCTV programs are compared, before and after the installation

of CCTV. The projects are matched in terms of size, demographics, and neighborhood location but differ in whether or not they have CCTV (see Fagan et al 1998). Spatial and temporal patterns of crime surrounding the two projects are compared for two time periods – before CCTV and after CCTV. The goal is to uncover any differences in crime trends between the two sites that might be related to CCTV.

Choice of Public Housing Developments

The Albany House, which has CCTV serves as the experimental site. Another housing development without CCTV, the Roosevelt Houses, is used as a control for comparison. This control housing development is similar in size and demographic characteristics to the Albany Project based on data provided by the New York City Housing Authority (NYCHA), which oversees the developments. The control site, like the Albany Houses, had few other crime prevention programs initiated over the study period. Otherwise such programs could confound the estimation of CCTV impacts.

The specific type of research method employed in this study falls under the category of ‘quasi-experimental design’ (Campbell and Stanley 1963). “A quasi-experimental design is one that looks a bit like an experimental design but lacks the key ingredient – random assignment” (Trochim 2002). A quasi-experiment is a type of quantitative research design conducted to explain relationships and/or clarify why certain events happen. The purpose of quasi-experimental

designs is to examine causality. Causality attempts to explain the relationship between two variables where one variable (independent variable) is thought to cause or determine the presence of the other variable (dependent variable). Quasi-experimental designs facilitate the search for knowledge and examination of causality in situations in which complete control is not possible. These designs were developed to provide alternate means for examining causality in situations not conducive to experimental controls.

Methods

Analyzing the impacts of CCTV is complex because it involves monitoring changes in crime incidence over time and space. Regarding time, we need to measure the level of crime before and after CCTV installation and account for seasonal and secular trends in crime. Geographical patterns include changes in crime within the housing project itself, possible beneficial effects on crime in areas surrounding the CCTV cameras, and potential displacement of crime to neighboring areas. For a general overview of spatial analyses see Anselin, et al (1997) and Bailly and Gatrell (1995) for statistical techniques. There is no single best methodology for analyzing these space-time patterns. Therefore, a range of methods is used and the consistency of results will be evaluated among the different methods.

Spatial Smoothing Methods

These methods generate a smooth, color-shaded map that shows the density of events (i.e. crimes) at different locations. In particular, although crimes occur at discrete locations, the risk of crime exists almost everywhere. Thus, crime density can be viewed as a spatially continuous variable with peaks representing areas of high crime and valleys representing areas of low crime (LeBeau 1995). Spatial smoothing methods (SSM) are used to generate such a continuous surface from point data.

Simple spatial smoothing methods, like quadrat mapping, have existed for many years, but have well known limitations (Bailey and Gatrell 1995). A superior approach is kernel estimation, a new and robust procedure for smoothing point data that has increasingly been applied in geographical epidemiology (Gatrell et al. 1996). Kernel estimation moves a circular window across the study area and computes the density of events within this window. Events near the center have a greater weight than those distant from the center. After computing kernel estimates for regularly spaced grid points in the study area, one can generate a smooth map of density using standard map contouring procedures. The results may be displayed as a standard contour map, a 3-dimensional surface (see LeBeau 1995), or a continuously shaded map with gray- or color-tones representing density levels data (Williamson, et al 1999)

Smoothed density maps created by kernel estimation offer several potential advantages for the display and visualization of crime. Unlike the widely used procedures for hot-spot mapping (Block 1995), kernel estimation represents crime density as a surface. Features such as subways, abandoned buildings, schools and public housing can also be overlaid on the crime surface to depict spatial associations (Hicks and Wilson 1995). Finally, the smoothed maps can be used to analyze changes in crime density over time periods. One can create smoothed maps of crime density for each time period and compute a 'difference map' that displays the change in crime over time. These difference maps can be used to gauge the impacts of law enforcement interventions and to display displacement of criminal activity from one location to another (Rossmo 1995). Alternatively, they can be used as input into regression models, specifically, segmented regression models and raised incidence models (see below). Finally, they can be utilized in the creation of cartographic animations (see below).

Difference maps are estimated to describe the change in crime between the time periods before and after CCTV installation for both housing projects. If the cameras are effective, we should see a significant drop in crime density in and near the Albany housing project, with no similar drop for the control project. Given the large size of the housing projects, there should be no problem in identifying these effects with our tools and experience in this type of analysis. Displacement will be visible on the map as emerging hotspots of criminal activity in nearby surrounding areas.

Spatial Autocorrelation Methods

Spatial autocorrelation methods are used to determine the geographic association between data values at adjacent locations. In the context of crime analysis, spatial autocorrelation analysis measures the extent to which the crime rate in a given area is correlated, either positively or negatively, with the rates in nearby areas. The concept of spatial autocorrelation is not entirely new to crime analysis. Wasserman and Stack (1995) have analyzed the effects of spatial autocorrelation on regression analyses of crime data. However, most researchers have considered the overall level of spatial autocorrelation for a study area, rather than local variation in crime rates. A more relevant concept for crime mapping is the concept of local spatial autocorrelation (Anselin 1995), namely local Moran's I.

Anselin's local indicator of spatial autocorrelation (LISA) statistic measures the correlation between the data value at a given location and values at neighboring locations (Anselin 1995). The correlation can be positive or negative. Positive LISA scores indicate areas with high values (i.e. high crime rates) surrounded by high values or areas with low values surrounded by low values. These LISA scores can be plotted on a map to show where distinct groupings of high-crime and low-crime areas are located. In contrast, a negative LISA score shows either a high-value area surrounded by low values, or vice versa. In crime analysis, this can occur if high-crime areas act as a local magnet for crime, attracting criminals

and thus depleting surrounding areas of criminal activity, or where some other barrier segments an area. When displayed on a map, these local indicators of spatial autocorrelation offer a potent summary of the relationships among crime rates in adjacent areas.

LISA statistics are scale dependent. If the two zones were next to each other, which would be true for two adjacent blocks for example, then the pair of observations would have a very high weight, sufficient to distort the I value for the entire sample. Further, there is a scale problem which alters the value of the weight. If the zones are police precincts, for example, then the minimum distance between precincts will be a lot larger than the minimum distance between a smaller type of geographical unit, such as blocks. We need to take in to account these different scales. Although beyond the scope of this research, one possibility to alleviate this problem of scale is to incorporate Lagrange Multipliers into the autocorrelation analysis.

Raised Incidence Models

Raised incidence or elevated risk models assess clustering around particular points. These models have been used in epidemiology to study clustering of disease around hazardous sites such as cancer around nuclear installations or incinerators (Bithell, et al. 1989 and Diggle, et al. 1990) and extended by Gatrell

(1994). These models can be applied to understand the variation of crime with distance around particular locations, namely housing projects. In general, the models test to see if events are more likely to occur near certain point features. For example, it would be hypothesized that the likelihood of crime occurrence increases the closer one gets to public housing. From this, one can apply a distance decay function that describes how the incidence varies with distance from the suspected source.

In the case of CCTV, two patterns may emerge. Before the installation of CCTV, clustering of crime may occur near the project. Then, after the installation of CCTV, instead of events clustering around the housing project, they would be dispersed away from the project or reduce in number at and nearby the development. These hypotheses can be tested using raised incidence models. The input to these models would be smoothed density maps, as described above, and distance maps around the developments.

Segmented Regression

Up to this point, the focus has been primarily on mapping, with before and after comparisons. An alternative approach is to analyze trends in crime over time, at various locations. The temporal data consists of two segments -- data from before the CCTV installation, and data from after the CCTV installation. Because of this, a useful approach is to evaluate crime trends before and after

CCTV using segmented or two-phase regression. According to Gillings et al. (1981), this method is appropriate when the response variable (in this case, crime incidence) has a linear or nonlinear trend over a certain range of the independent variable, time, followed by another trend over a succeeding range. Seber (1977) suggests using segmented regression in situations where a function exists over time, and at time t_c a treatment is applied that may possibly affect the slope or intercept of the regression line either immediately or after a time lag. Selke (1982) uses the pre and post intervention segments with crime prevention programs by analyzing slopes and intercepts of resulting trend lines and Hilton (1984) found little impact of drinking and driving laws on fatal accidents using similar interrupted time series analysis.

One important test that results from segmented regression is the Chow Test (Chow 1960). This test, using a standard F-ratio, compares the difference of error terms of two regression segments to the entire segment to determine significance. From this, it can be determined if the two segments are significantly different.

An important benefit of segmented regression is the flexibility of data that can be input into the model. For analyzing crime, several different inputs can be used depending on the desired level of detail in space and time. First, density values from kernel estimation (see above) can be used as input, and the changes over time analyzed via segmented regression for specific locations. One can vary the

time period to focus on monthly, weekly or daily trends. Another approach is to use census blocks or street segments as geographic units, again with varying time periods. To measure displacement, these approaches are used to model crime at various locations to see if crime has shifted from place to place. This is visible in the output from the models, namely maps of slope and maps of critical F-Values (Chow Test). The maps of slope indicate the change in crime density over time, while the critical F-Values show which areas have changed significantly over time, statistically speaking.

Animation

Exploratory Data Analysis (EDA) has been one of the leading visualization techniques in social statistics. EDA, and its extension in geography, Exploratory Spatial Data Analysis (ESDA), are inductive approaches to statistical analysis, and can be extremely useful for investigating complex relationships within datasets. “Exploratory data analysis is the process of seeking important information in sets of data. An analyst strives to gain understanding of the data, i.e. to penetrate into relationships, patterns, and trends hidden inside the data volume, without having any prior theories or assumptions. This differentiates exploratory analysis from the more traditional techniques of statistics that typically consist of checking a priori selected hypotheses and may therefore be characterized as ‘confirmatory’” (Andrienko, 1999)

ESDA has developed into a new research field: "Geovisualization". Geovisualization can be defined as a field on the use of visual geospatial displays - including Virtual Environments - to explore data and through that exploration to answer questions, generate a hypothesis, develop problem solutions, and construct knowledge (Kraak 1999). Dykes (1996) suggests that cartographic visualization systems, including animation, may represent the principal technology for the scientific visualization of digital spatial information.

Animation in cartography is not an entirely new idea. In fact it has been around for approximately 30 years. Campbell, et al, documents the milestones in animated cartography in the 1991 article "Animated Cartography: Thirty Years of Scratching the Surface". He mentions examples from well know cartographers like Thrower (1959), Tobler (1970) and Moellering (1980).

There have been a few attempts at research in the field of animated cartography, but not enough to be considered substantial. Battenfield et al (1994) utilized animated/interactive cartography in their research on radial growth in trembling aspens. The work was based on previous research, but updated to include the use of computers and animation. MacEachren et al (1992) examined climate change in Mexico via animation. Monmonier (1990) attempts to describe methods of examining time-series data of which animation plays a strong role. Finally, Slocum et al compares traditional and sequential

displays of choropleth maps (i.e., paper versus animated). Animation has become such an important aspect of geovisualization Michael Peterson authored the first textbook devoted to animated cartography in 1995. In the book, he recommends a variety of geo-spatial data that would be suitable for animation. It appears that virtually all maps could be animated in one form or another.

Animation may prove to be an extremely useful way of visualizing the results of other analytic techniques. In the past, animation has been used with limited success (Campbell 1990) because the sequencing of maps has required large scale computing power not generally available. However, new software and advances in desktop computing power now put these techniques within reach. Time can now be considered the third dimension of two-dimensional maps, with obvious relevance to the mapping of crime. In epidemiology, animated maps have been made of AIDS data (Stephenson 1995), while animated maps have also been added to multimedia encyclopedias (DiBiase 1994), and LeBeau has produced animated maps of calls for police service (LeBeau 1995).

For the purpose of studying the effects of CCTV on crime over time, animated maps for the study area that encompass both the Albany and Roosevelt housing developments will be generated. The animated maps are useful for visualizing changes in crime intensity around both housing projects and for exploratory analysis of issues like displacement and spillover effects. The animations will be based on the smoothed density maps resulting from kernel estimation. Each

frame in the animation will represent a months worth of crime incidents. The data for this study spans three years, so there will be 36 frames in the animation, 18 before CCTV installation and 18 after CCTV installation.

Data Input

Geocoding

Typically, in any large-scale geographic analysis of crime patterns the issue of geocoding must be addressed. Geocoding or more accurately, address matching, in its simplest terms, is the process by which a GIS package takes an address from a data table, and assigns a location, i.e., a geographic coordinate (X, Y), to it. Fundamentally, the process is quite simple. The software takes the address from tabular data, and compares it to all the addresses in a base map. If the addresses match, then the software assigns the location from the base map to the record in the data table. Unfortunately, addresses in a table do not necessarily match those on the map because of errors in the address information or errors in the base map and its associated address information. Most GIS packages account for this by assigning probabilities to how close the match may be. Therefore, the user can interactively decide which address on the map should be assigned to a particular address in the table. For example, an address in a table may have been misspelled as 777 Mian Street. The software will only locate a number of streets beginning with the letter M. The user can then select the appropriate street.

In the case of this research, the address matching issues were very complicated. Raw, un-geocoded crime data from the NYPD was used to assure quality control and quality assurance in address matching. Therefore, all the complaints, 763,715 incidents, needed to be address matched. Some major issues crept up during the address matching of the complaints. One prime example was the newly renamed streets. For example, in the data utilized, an address occurred on Thomas S. Boyland Street. However, on older base maps, the street was known as Hopkinson Avenue. To overcome this and many other problems, a simple 'find and replace' operation was performed in a text editor to correct the known changes in street names.

The process we used to address match the data was three-fold. First, the addresses in the raw data were 'scrubbed' using the find and replace method. Second, the addresses were address matched to a commercial base map from Geographic Data Technology, Inc. (GDT). Finally, any addresses that were not matched to the GDT base map were run through the TIGER files from the U.S. Census. The results for this 'multi-phase' geocoding were quite impressive. From Tables 3:1-3:3 below, an average match rate of over 99 percent was achieved. Considering the sheer number of complaints per year, approximately 250,000 per year, the 99 percent match rate is very significant. It should also be noted from these tables, that the number of complaints decreased over the three year time period (1997 – 260254 incidents, 1998 – 255,667 incidents and 1999 – 247,794 incidents).

The geocoding process does present some potential limitations despite the very high match rate. For example, there may be unmatched crimes that actually occurred in the study area. This could potentially underestimate the effects of CCTV on crime. Overall, unlike many studies, very little error is introduced via geocoding process.

Year	Month	TOTAL		GDT			TIGER			
		Matched	Difference	Match (75-100)		Match (<75)		Unmatch		
				No.	(%)	No.	(%)	No.	(%)	
1997	January	21246	20312	934	185	19.80	520	55.67	229	24.51
1997	February	19409	18205	1204	281	23.33	683	56.72	240	19.93
1997	March	21090	20124	966	183	18.94	615	63.66	168	17.39
1997	April	20838	19832	956	188	19.66	589	61.61	179	18.72
1997	May	22244	21227	1017	182	17.89	593	58.30	242	23.79
1997	June	22061	21047	1014	188	18.54	611	60.25	215	21.20
1997	July	23047	22043	1004	206	20.51	557	55.47	241	24.00
1997	August	22901	21854	1047	198	18.91	617	58.93	232	22.15
1997	September	22924	21881	1043	207	19.84	608	58.29	228	21.86
1997	October	22830	21425	1405	327	23.27	785	55.87	293	20.85
1997	November	20779	19795	984	147	14.93	618	62.80	219	22.25
1997	December	20885	19942	943	140	14.84	631	66.91	172	18.23
		260254	247737	12517	2432	19.21	7427	59.54	2658	21.24

TABLE 3:1 Geocoding Results for Complaints, 1997

Year	Month	TOTAL GDT		Match (75-100)			TIGER		Unmatch	
		Matched	Difference	No.	(%)		Match (<75)		No.	(%)
1998	January	21901	20848	1053	196	18.61	679	64.48	178	16.90
1998	February	19278	18391	887	181	20.40	555	62.57	151	17.02
1998	March	21743	20735	1008	225	22.32	571	56.64	212	21.03
1998	April	20202	19202	1000	214	21.4	595	59.5	191	19.1
1998	May	21418	20374	1044	222	21.26	605	57.95	217	20.78
1998	June	21696	20722	974	202	20.73	566	58.11	206	21.14
1998	July	22977	21936	1041	239	22.95	620	59.55	182	17.48
1998	August	22287	21253	1034	222	21.47	573	55.41	239	23.11
1998	September	21628	20637	991	227	22.90	591	59.63	173	17.45
1998	October	21772	20779	993	194	19.53	594	59.81	205	20.64
1998	November	20462	19577	885	174	19.66	523	59.09	188	21.24
1998	December	20303	19350	953	168	17.62	614	64.42	171	17.94
		255667	243804	11863	2464	20.74	7086	59.76	2313	19.49

TABLE 3:2 Geocoding Results for Complaints, 1998

Year	Month	TOTAL GDT		Match (75-100)			TIGER		Unmatch	
		Matched	Difference	No.	(%)		Match (<75)		No.	(%)
1999	January	19911	18939	972	154	15.84	636	65.43	182	18.72
1999	February	18335	17457	878	158	17.99	574	65.37	146	16.62
1999	March	20954	19923	1031	223	21.62	611	59.26	197	19.10
1999	April	20023	19062	961	227	23.62	595	61.91	139	14.46
1999	May	21212	20210	1002	243	24.25	573	57.18	186	18.56
1999	June	21779	20638	1141	251	21.99	624	54.68	266	23.31
1999	July	22191	21077	1114	246	22.08	626	56.19	242	21.72
1999	August	22100	21058	1042	208	19.96	619	59.40	215	20.63
1999	September	20828	19829	999	225	22.52	600	60.06	174	17.41
1999	October	20861	19880	981	195	19.87	623	63.50	163	16.61
1999	November	20174	19250	924	209	22.61	550	59.52	165	17.85
1999	December	19426	18460	966	164	16.97	621	64.28	181	18.73
		247794	235783	12011	2503	20.78	7252	60.56	2256	18.64

TABLE 3:3 Geocoding Results for Complaints, 1999

Types of Crime

For the purposes of this research, certain types of crimes are to be examined to assess whether or CCTV had an effect on the specific crime types. That is, does CCTV have an effect on serious crimes such as robbery and assault and less effect on minor infractions such as vandalism and graffiti, or vice versa? CCTV might affect different crimes based on the fact that by introducing formal surveillance, the potential for apprehension for 'quality of life' crimes will be increased. If the perceived risk for getting caught for these non-opportunistic crimes increases, offenders will be less likely to commit them in the first place. On the other hand, CCTV may not have any effect on crimes of opportunity such as robbery and burglary since the perpetrators will act if the opportunity presents itself, regardless of the surroundings. Therefore, a number of subsets needed to be created. From the two primary categories, complaints and arrests, querying the data tables created nine sub-categories. Complaints are defined as any conduct that, as defined by law, can result in imprisonment or fine, while arrests are the formal holding by the police of such persons who are suspected of committing a complaint. For the complaint data the address used in geocoding refers the location of where the incident occurred. For the arrest data, the address refers to the location where the arrest physically took place. That is, the place where the suspect was taken into custody. It does not refer

specifically to the victim or perpetrator residence address, unless that address is where the arrest took place. This is important geographically because a large number of arrests may have occurred at a police precinct, therefore, that may show up as a hot spot of arrests. Clearly the use of the complaint data is a good indicator of criminal activity. Arrests are also a reasonable indicator of illegal activity, but also as an indication of police activity. In areas that there is little criminal activity, little police activity would be required. However, the location of arrests may be problematic at a specific location, namely a police precinct. A large proportion of arrests 'officially' take place there, so this location will show up as a hotspot on the maps, and therefore may 'skew' the results

The sub-categories utilized in this study are briefly outlined below:

All Complaints – Includes all complaints

Major Felony Complaints – Includes the seven major felony categories as defined by the Federal Bureau of Investigations Uniform Crime Report (Murder, Rape, Aggravated Assault, Robbery, Burglary, Larceny, and Auto Theft).

Felony Complaints – Includes the Seven Major Felonies and all other felonies such as arson, serious drug offenses, sex crimes etc.

Misdemeanor Complaints – Includes less serious, non-felony crimes, such as criminal mischief, gambling, minor drug offenses, petty larceny, etc.

Violation Complaints – Includes minor infractions such as loitering, disorderly conduct etc.

Indicator Complaints – Includes 18 crime types that constitute approximately sixty-seven percent, or the majority of complaints. They are indicative of any

illegal activity. Different felonies, misdemeanors and violations are grouped together including but not limited to, assault, burglary, criminal trespass and criminal mischief.

All Arrests - Includes all arrests.

Felony Arrests – Includes the Seven Major Felonies and all other felonies such as arson, serious drug offenses, sex crimes etc.

Misdemeanor Arrests – Includes less serious crimes, such as criminal mischief, gambling, minor drug offenses, petty larceny, etc.

These crime subsets were used as input in the creation of density grids, which were then used in the segmented regression analysis, the cartographic animations, and the raised incidence analysis. The point subsets were also used in the LISA analysis and the buffer analysis.

Density Estimation

Once the geocoding process was complete and point datasets had been created for both complaints and arrests, another technique was used to derive estimates of the density of crime incidents at various locations in the study area. The technique used, kernel estimation, falls under the category of spatial smoothing methods and provides information about the intensity of incidents at a particular location. In short, spatial smoothing methods create continuous surfaces from discrete point

locations. The basis for this is that although crimes do occur at discrete locations, the risk of crime exists throughout the area. Therefore, crime can be seen as a spatially continuous variable.

The goal of kernel estimation is to estimate how the density of events varies across a study area based on a point pattern. “Kernel estimation was originally developed to obtain a smooth estimate of a univariate or multivariate probability density from an observed sample of observations...” (Bailey and Gatrell, 1995). In the spatial case, kernel estimation creates a smooth map of density values in which the density at each location reflects the concentration of points in the surrounding area See Figures 3:1 and 3:2).

Kernel estimation begins by laying a fine grid across the study area. A circular window with a constant radius or *bandwidth* is moved across the study area, centered at each grid point (Figure 3:3). The density of events is computed within this circular window. Events within the window are weighted according to their distance from the center of the window, the point at which density is being estimated (Gatrell et al. 1996). Events located near the center have a greater weight than those distant from the center. In this way, kernel estimation reflects the underlying geographic locations of events within each window.

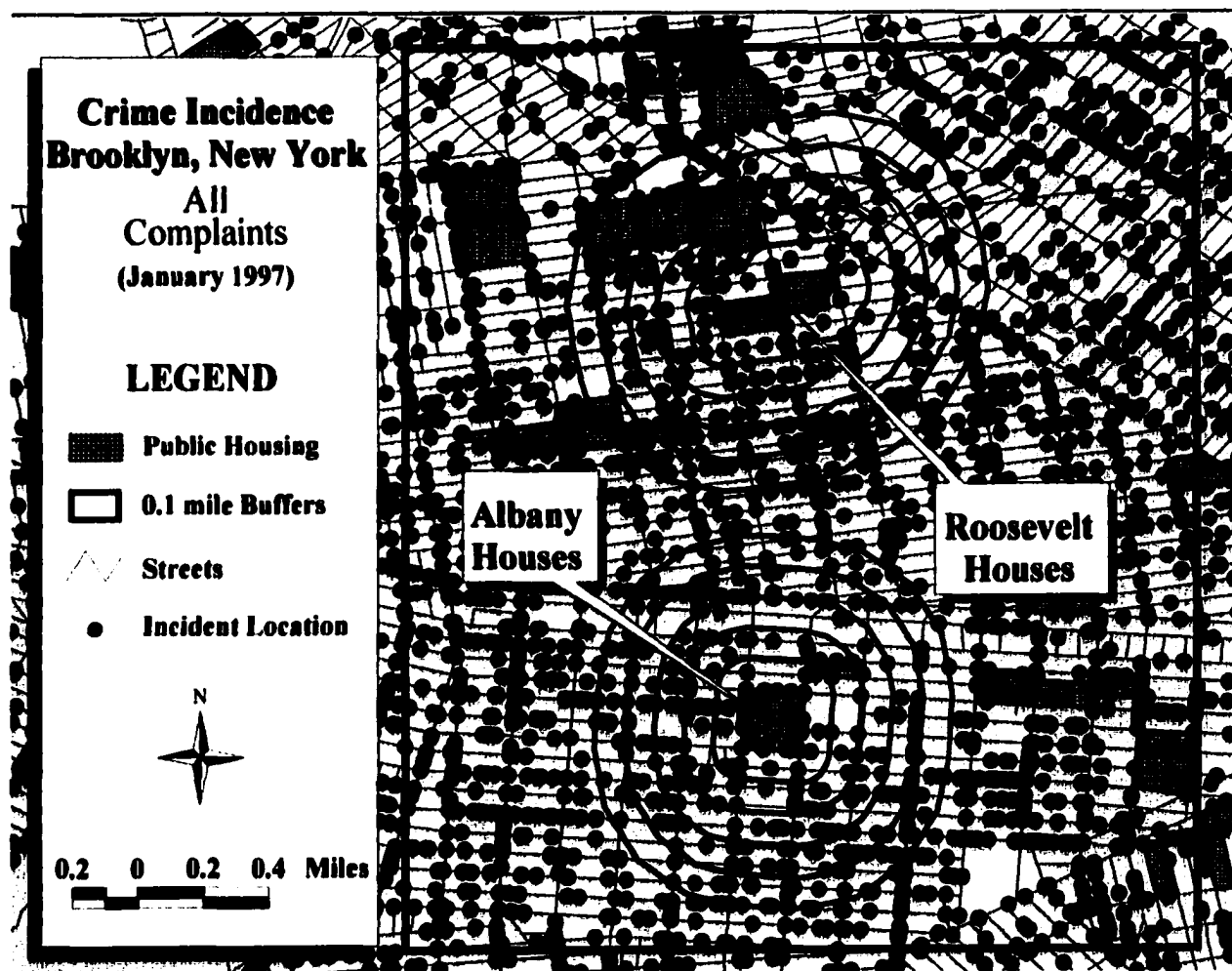


FIGURE 3:1 – Distribution of points, crime incidents

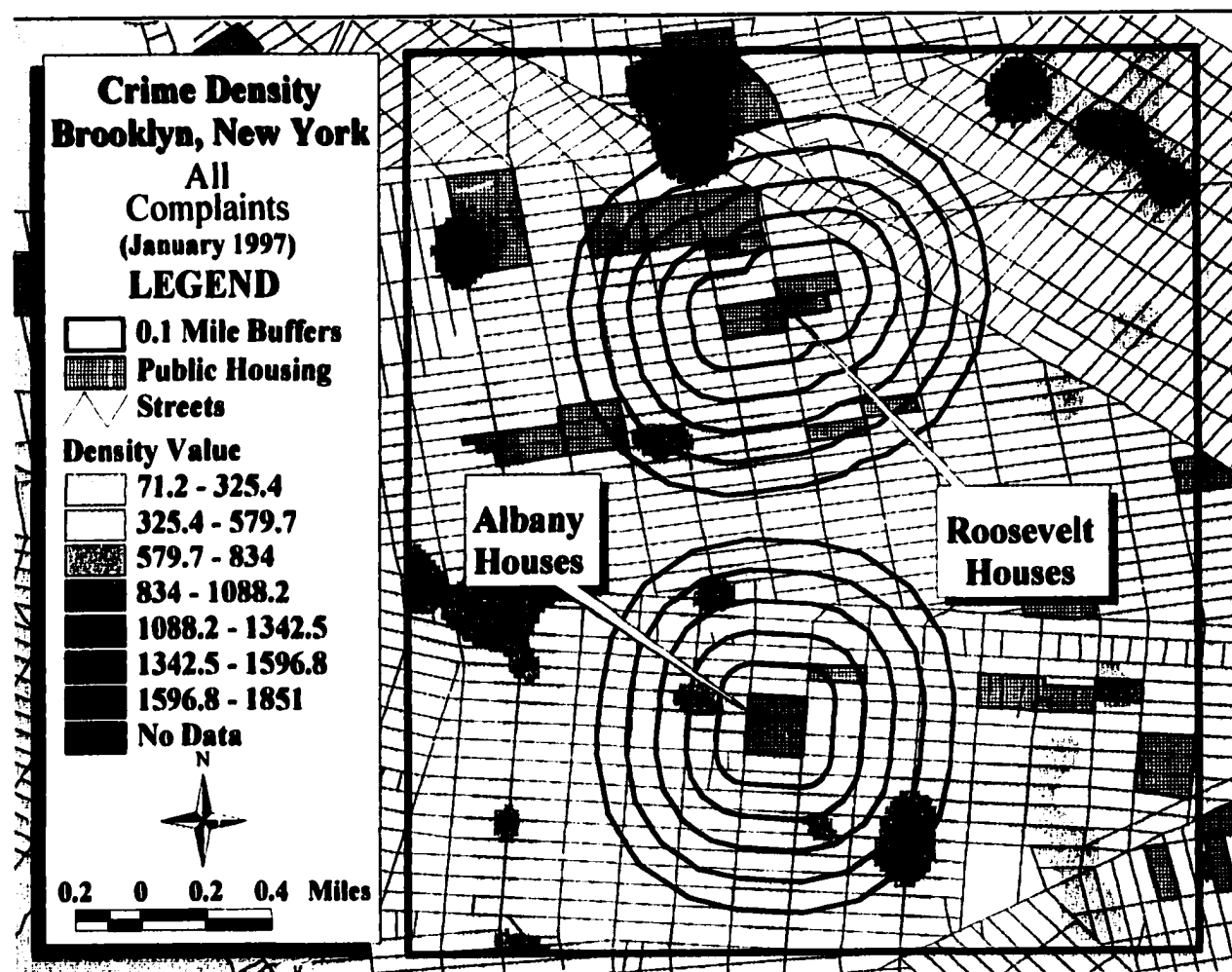


FIGURE 3:2 – Smoothed density map of Distribution of points incidents

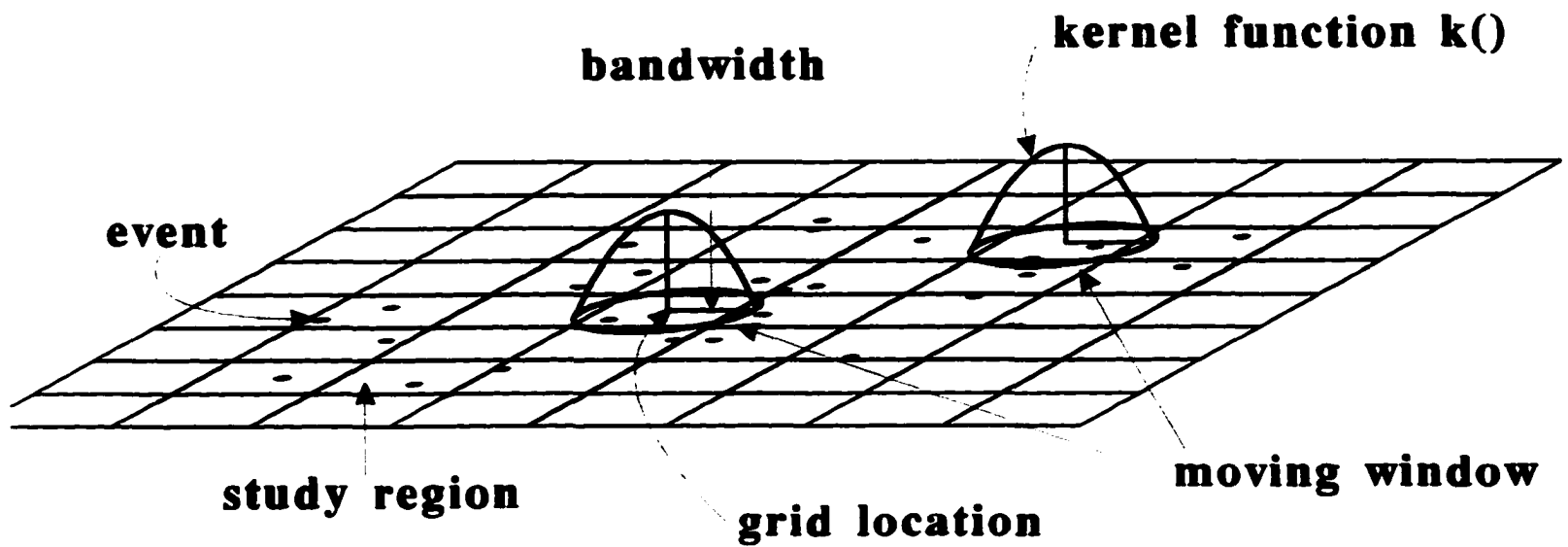


FIGURE 3:3 – Visual interpretation of kernel density estimation

Let s refer to a grid point location. The density of crime events at grid point s , $\lambda(s)$, is estimated as:

$$\lambda(s) = \sum_{d_i < \tau} 1/\tau \cdot k(d_i/\tau)$$

Where:

$\lambda(s)$ = estimated density at grid point s
 d_i = distance from point i to grid point s
 τ = bandwidth

The bandwidth, τ , defines the radius of a circle, centered on s , within which density is being estimated. The kernel function, $k()$, describes mathematically the weight assigned to points (crime events) within the circle in calculating density.

Weight varies inversely with distance so that the weight assigned to any crime event decreases as its distance (d) from s increases. Thus, nearby events are given more weight in the density calculation than those farther away.

This means that density depends on both the number of crimes within a circle and their spatial configuration. Even if two grid points have the same numbers of crimes within their respective circles, if the spatial patterns of crimes differ, density will differ. A grid point with crimes clustered nearby will be assigned a much higher density than one with crimes more widely dispersed. In this respect, kernel smoothing differs from more traditional density methods that simply count the number of events within regularly spaced circles, hexagons, or squares.

After computing kernel estimates of crime density for each regularly spaced grid point, one can generate a smooth map of density values. The results may be displayed as a standard contour map, a 3-dimensional surface, or as a continuously shaded raster map with gray- or color-tones representing density levels (see LeBeau, 1995).

The result from kernel estimation method is a simple, aesthetically pleasing image from which users can identify hotspot areas based on density. Under kernel smoothing, the hotspots encompass a uniquely defined area, and are not limited to any jurisdiction, or any man-made boundary for that matter. The

hotspots may cover several separate geographic entities like police precincts or sectors, representing the fact that crime often cuts across political boundaries

Another strength of kernel estimation is its usefulness in analyzing change over time. Hot spots are not static. Rarely will the densities stay the same over time. Because of this, density maps from multiple time periods can be overlaid and/or compared. This is useful in understanding the movements of crime over time within an area.

Before generating a density surface from the data it was necessary to create an analysis mask of the study area. An analysis mask is a derived data layer that specifies the extent of cells that are included in an analysis. By creating this layer it is possible to exclude crimes that will not be used in the density estimation and define the area of interest or study area. In short, the mask assigns values of 'no data' to points outside the study area, even though it is possible for them to have values. The analysis mask minimizes, however, it does not prevent what Bailey and Gatrell (1995) refer to as the "edge effect" from occurring. The edge effect refers to the effect of the study area boundary, or edge, on density estimates. Specifically, for border or "edge" cells, only a portion of the bandwidth area contains data but the algorithm uses the entire area in the calculation. Essentially what happens is that when a grid point is visited that lies on the border, only a portion of the cells will contain values but the entire area of the bandwidth is used in the calculation. This has the effect of over smoothing or "washing out" the

density estimates of edge cells. For this research, this was dealt with by performing the analysis for a larger area, then limiting the display to a user defined study area window. Therefore, actual data was used in the calculation of density outside the boundary of the study window, it was not however, used in any further analyses, or displayed in any maps.

The cell size for the density grids is set to 0.0003 decimal degrees, or at the latitude of Brooklyn, approximately, 110 feet. This cell size is appropriate for showing the local variation in density and for creating aesthetically pleasing map displays. Anything larger would hide local variation and appear too coarse in the display. Smaller grid cell sizes might appear better, but would not necessarily reveal any more variation. Smaller cell sizes would also result in much larger grid sizes on disk thus greatly increasing the speed and time of data processing. The density values returned indicate the number of incidents per unit area. In this case, although the data are unprojected, the output units are square miles.

Although kernel estimation holds great potential for visualizing and analyzing crime patterns, there are several challenges, specifically the choice of a radius, or bandwidth, for the region of influence can be problematic. Selecting an appropriate bandwidth is a critical step in kernel estimation. The bandwidth determines the amount of smoothing of the point pattern. The bandwidth defines the radius of the circle centered on each grid cell, containing the points that contribute to the density calculation. In general, a large bandwidth will

result in a large amount of smoothing and low-density values, producing a map that is generalized in appearance. In contrast, a small bandwidth will result in less smoothing, producing a map that depicts local variations in point densities. Using a very small bandwidth, the map approximates the original point pattern and is spiky in appearance.

In this study, the bandwidth is selected based on the context of the analysis, namely the evaluation of CCTV, and on the variations of different bandwidth from a psuedo-sensitivity analysis. A number of simulations of the Chow Test (see below) were performed using different bandwidths (see figures 3:2-3:6). The results show the extremes of using a small bandwidth, 0.0625 miles, overemphasize local variation and a large bandwidth, 1.0 mile underemphasizes local variation. It appears that at some point between 0.125 mile bandwidth and 0.25 mile bandwidth the results begin to be 'washed out' and local variations can no longer be examined. It is at this distance, 0.1875 miles, that the bandwidth is selected for use in the following analyses. This bandwidth is also valid in the context of the evaluation of CCTV. The range of CCTV cameras is in some cases, as far as several miles, for example, the Verrazano-Narrows Bridge is clearly visible miles away from the rooftop cameras, but the effective range of most CCTV cameras near the ground is approximately 1000 feet. Therefore, the selection of 0.1875 mile bandwidth is reasonable for this evaluation, because it reflects the typical CCTV camera range.

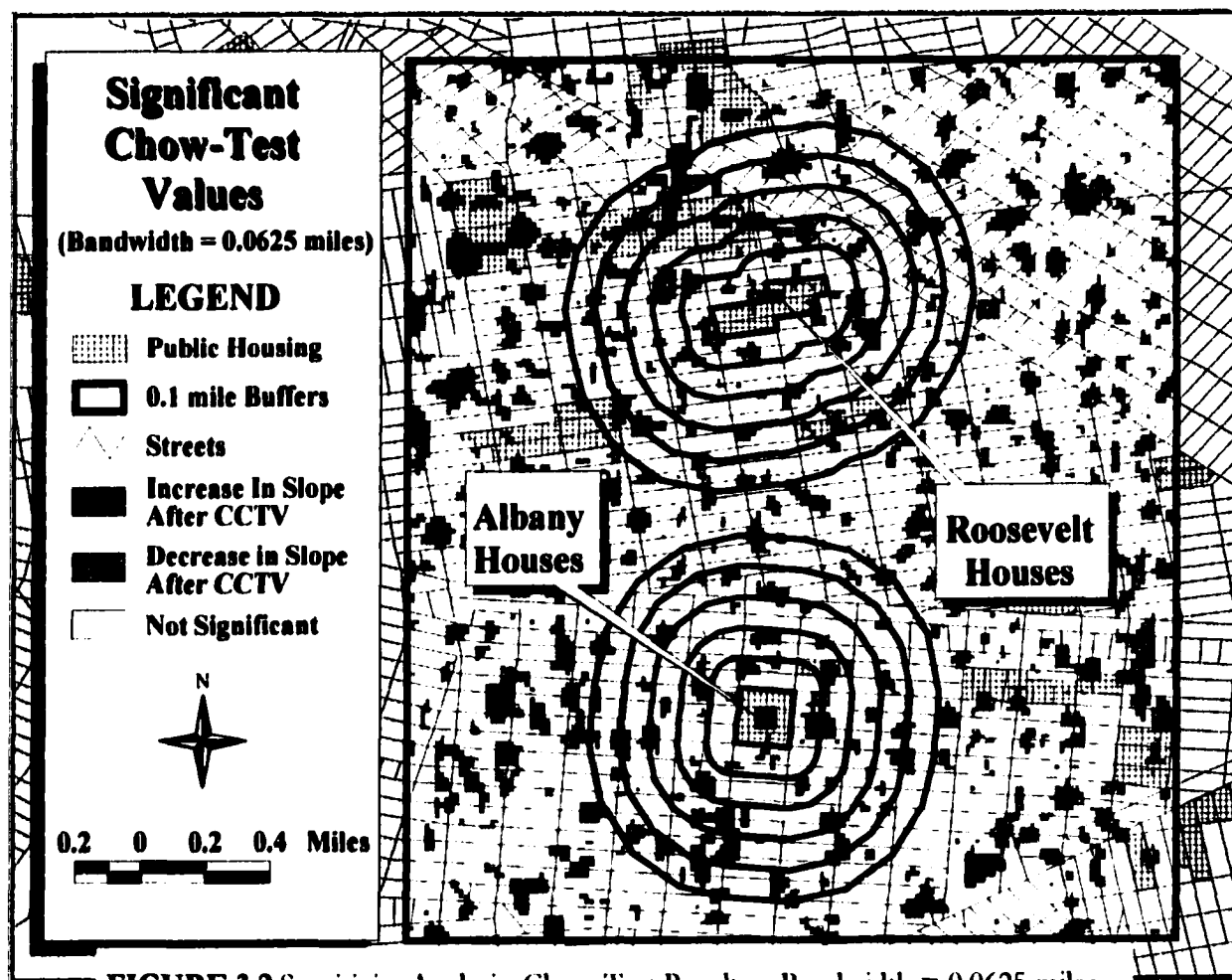


FIGURE 3:2 Sensitivity Analysis, Chow Test Results – Bandwidth = 0.0625 miles

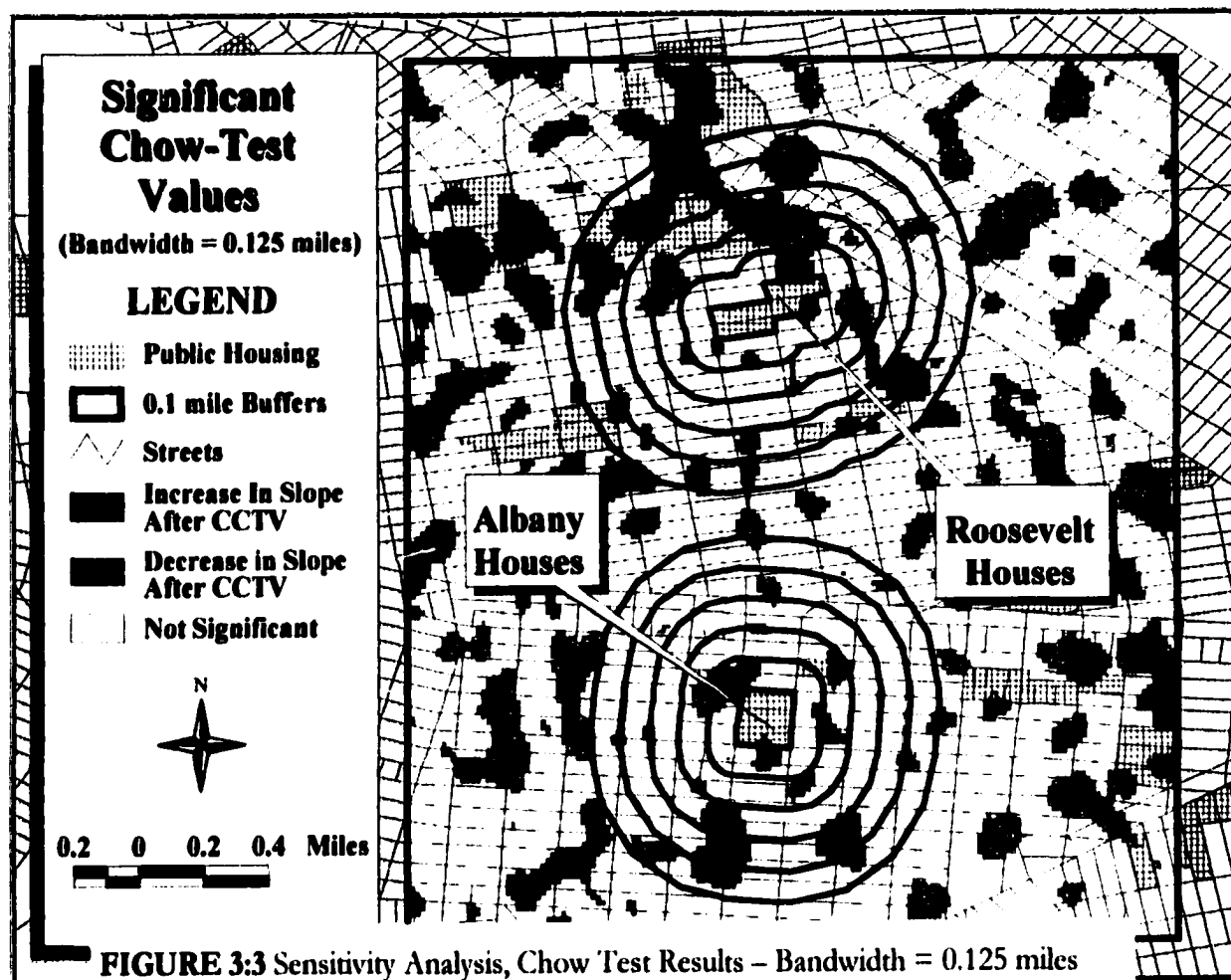


FIGURE 3:3 Sensitivity Analysis, Chow Test Results – Bandwidth = 0.125 miles

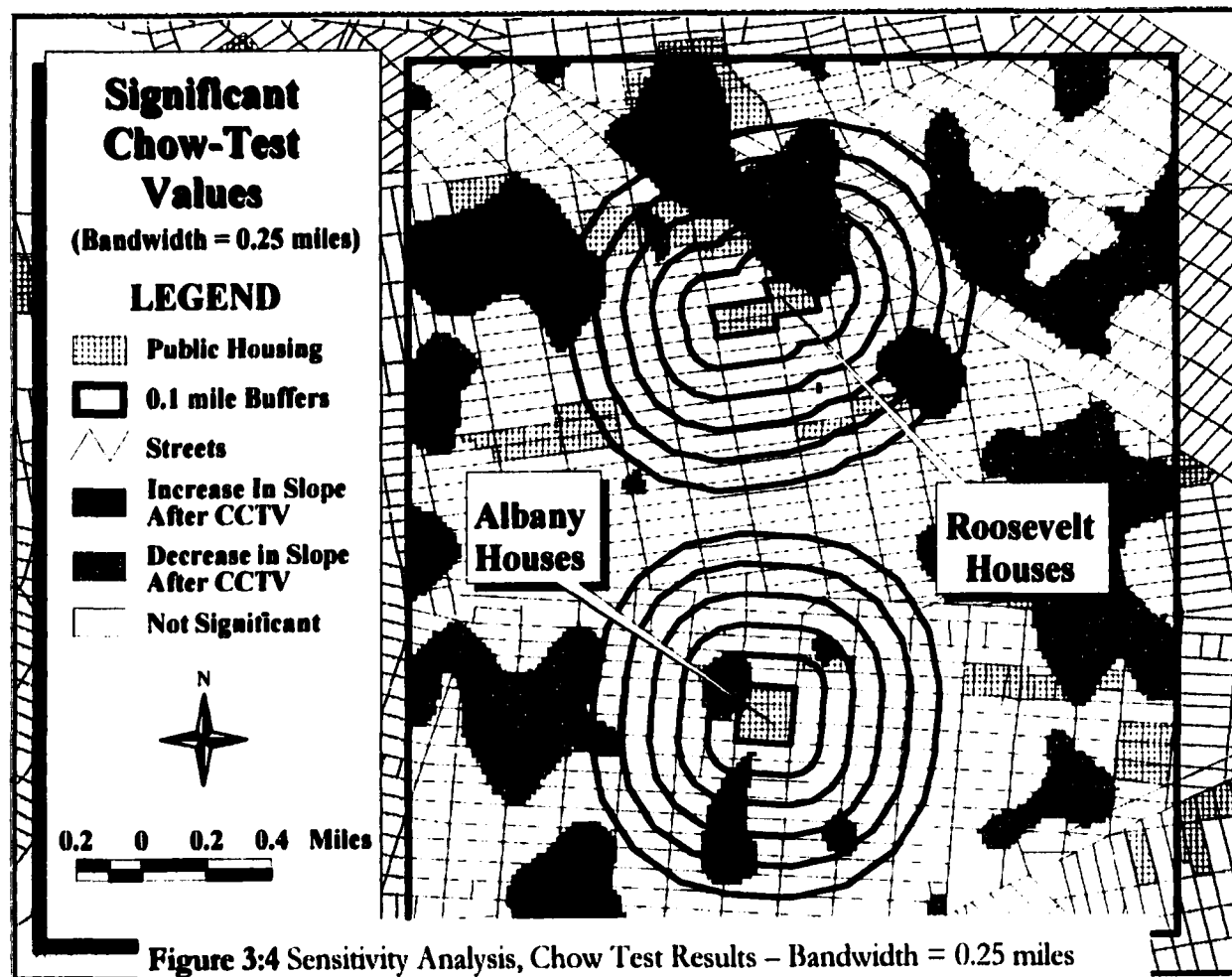


Figure 3:4 Sensitivity Analysis, Chow Test Results – Bandwidth = 0.25 miles

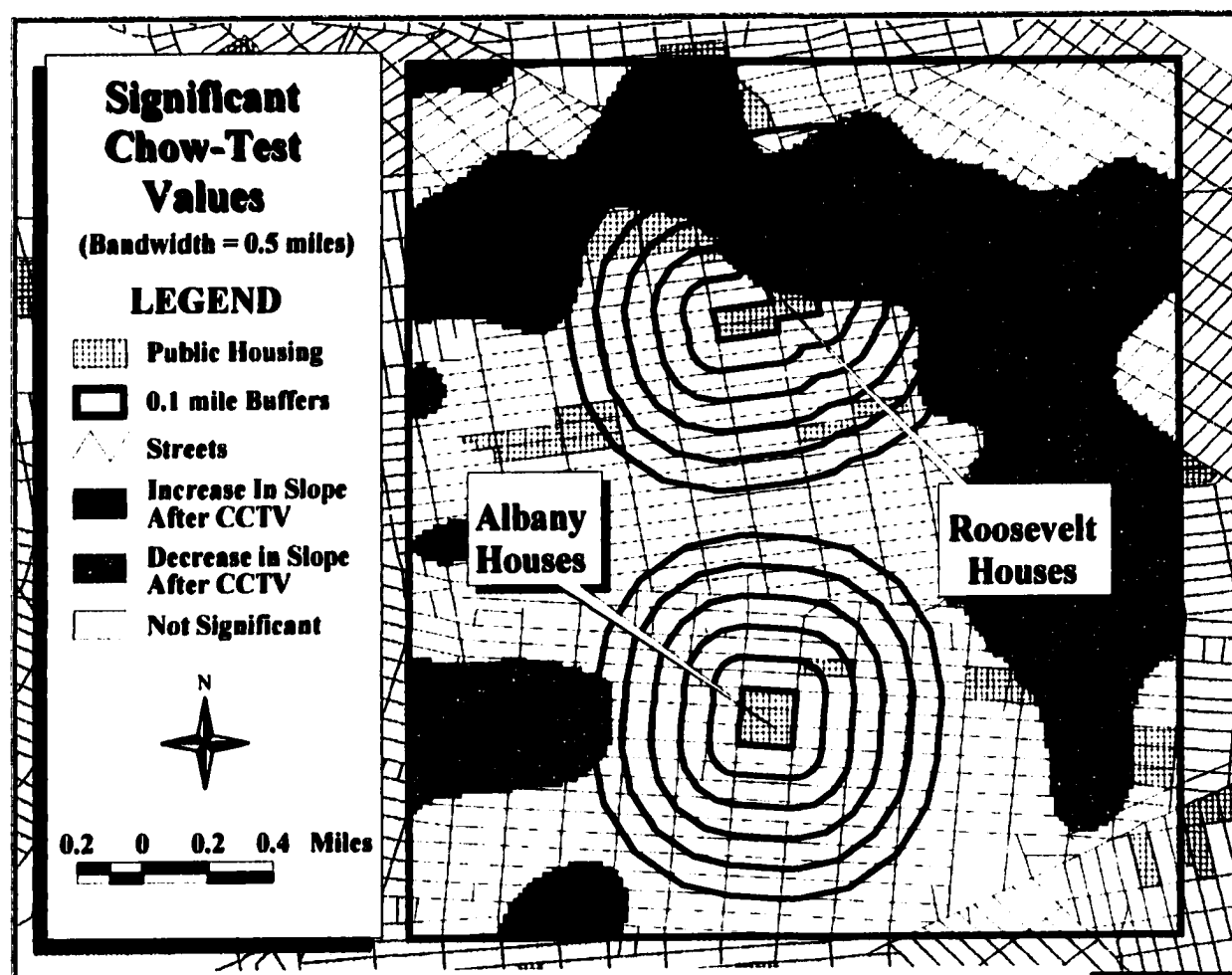


Figure 3:5 Sensitivity Analysis, Chow Test Results – Bandwidth = 0.5 miles

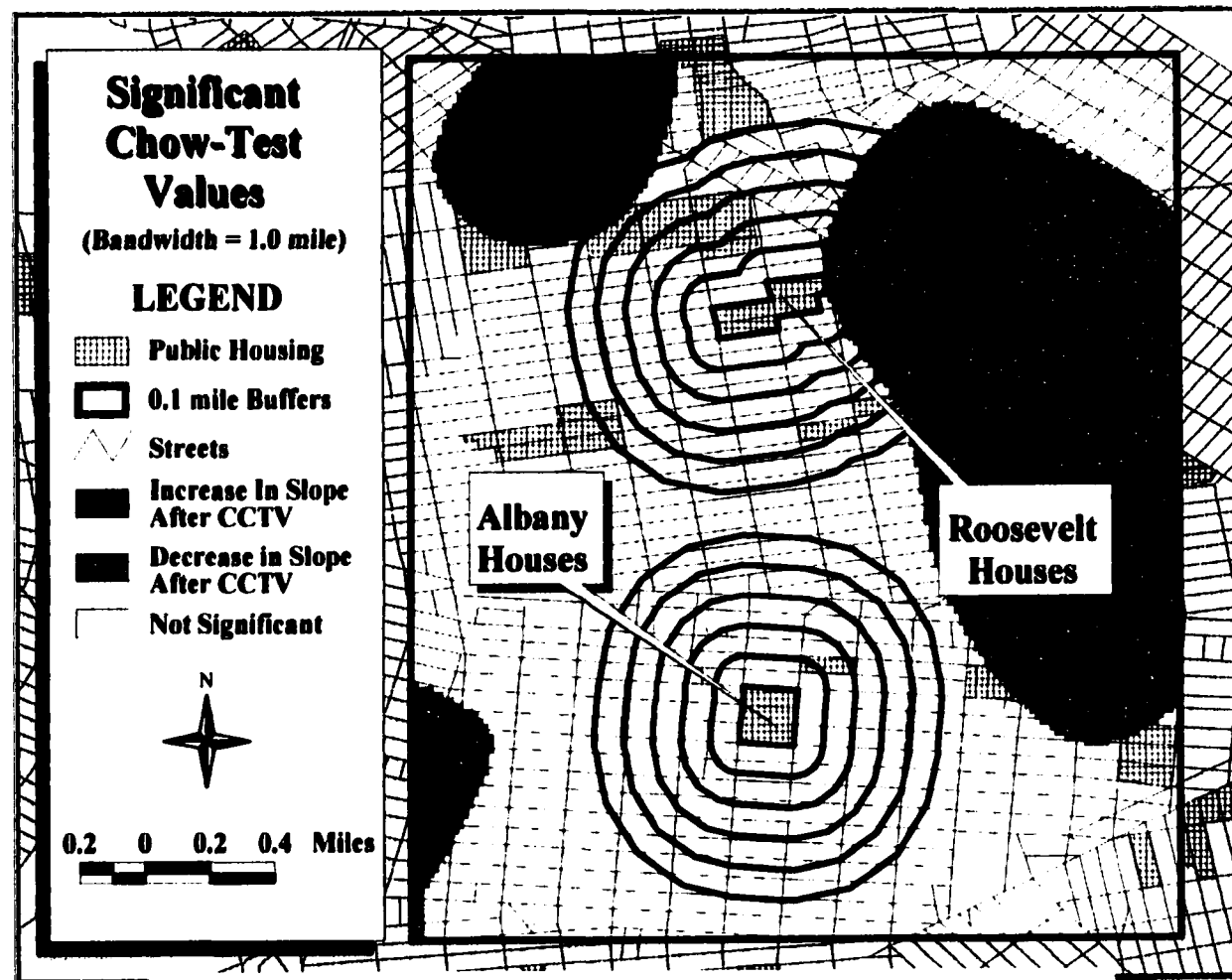


Figure 3:6 Sensitivity Analysis, Chow Test Results – Bandwidth = 1.0 miles

Once the parameters for kernel estimation have been defined, the grids of crime density can be created. These grids were then used in the segmented regression analysis, the raised incidence analysis and the cartographic animations.

Chapter 4: Buffer Analysis

This section explains the data and methods used in performing the buffer analysis. The analysis involves a number of relatively simple statistical methods to compare the counts of crime incidents around the housing developments within different distance rings around the developments. As the name suggests, there are two elements to this method, the creation of buffers around the Albany and Roosevelt developments and determining counts of geocoded crime incidents within the buffers during the before and after time periods. The data were created and manipulated primarily in the ArcView GIS, through out of the box functionality and statistical analysis was performed in SPSS version 11 for Windows.

Data

Five buffer rings were generated around each development, Albany and Roosevelt in ArcView. The five concentric rings are at equal distances of 0.1 miles. Therefore, the last ring is at a distance of 0.5 miles from the respective development. The decision to use 0.1 mile rings was fairly arbitrary. Other studies have used 50 and 100 meters, but this distance seemed too small in this context. The distance between Albany and Roosevelt is a little over 1 mile, so by using 0.1 mile buffers up to 0.5 mile there would be no overlap between the two

sets of rings, and any influence each housing project has on its immediate surrounding could be taken into consideration. Other housing developments near or within these rings may influence these results. Specifically, crimes may be counted and attributed to a certain development, when in fact they are attributable to some other development. This is less important around Albany where there are fewer neighboring developments, but there are several neighbors around Roosevelt.

The geocoded crime incidents described in Chapter 2 were used to calculate the counts of crimes within each ring for the before and after time periods. The different crime types and categories were used for the analysis as well. To find the count per ring, a point in polygon analysis, or spatial join was done in Arcview. In short, this assigns the number of points that fall within each ring to the corresponding record in the buffer polygon data table. From the counts, the before and after difference in crime count and percent change in crime count were computed and populated in the tables. These tables were then used in SPSS for the statistical analyses.

Methodology

It is hypothesized that public housing will act as a 'magnet' for crime. That is, crime will tend to occur closer to housing developments than other public facilities. It is further hypothesized that after the installation of CCTV, public housing will act in the opposite fashion. That is, developments with CCTV will

repel crime occurrences in the buffer rings closest to the housing development. For the developments without CCTV, no equivalent change in crime occurrence by buffer ring is expected. By examining the buffer rings and the changes in their respective crime counts, the developments can be compared before and after CCTV installation to test these hypotheses.

Specifically, in this analysis, it is expected that around the Albany Houses, before the installation of CCTV, the number of crimes will decrease as the distance from Albany increases. That is, the number of crimes is inversely proportional to distance. However, in the period after the installation of CCTV, the number of crimes will increase as the distance increases. This is the hypothesized pattern for the Albany development. In the case of the control site, the Roosevelt Houses, there are different expectations. Specifically, in both periods, before and after the installation of CCTV, crime counts would be inversely proportional to buffer distance. That is, as the distance increases away from Roosevelt, the crime counts will decrease. It is expected that, that Roosevelt will act as a 'magnet' for crime, regardless of the time period.

To test whether the crime changes were statistically significant for the crime counts, a number of statistical test are performed in SPSS for Windows, namely the Paired Samples t-Test, and the Wilcoxon Signed Ranks Test. The Paired Samples t-Test compares the means of two variables for a matched set of observations. In this case, the counts of crimes for Albany (or Roosevelt) before

and after the installation of CCTV are compared. The test computes the differences between values of the two variables for each case and tests whether the average differs from 0. The Wilcoxon Signed Ranks Test is a nonparametric procedure that is equivalent to the paired t test.. This test takes into account information about the magnitude of differences within pairs and gives more weight to pairs that show large differences than to pairs that show small differences. The test statistic (Z) is based on the ranks of the absolute values of the differences between the two variables and makes no assumptions about the shapes of the distributions of the two variables. The Wilcoxon test is more appropriate for this analysis because the sample size (number of distance rings) is very small.

Results

The analysis is performed on all the crime sub categories for Albany before and after, before and after difference counts between Albany and Roosevelt and before and after percent change values between Albany and Roosevelt. The charts (see Appendix A), Chart A:1- A:27 and maps, Figures A:1—A:18) do not indicate a consistent pattern of decreasing crime counts after the installation of CCTV.

Below in Table 4:1, is a summary of the patterns which emerge from the buffer counts.

Crime Type	Albany	Roosevelt
All Complaints	Decrease in inner rings, increase in outer rings	Decrease in all but one area
Major Felony Complaints	Decrease in all areas	Decrease in all areas
Felony Complaints	Mixed pattern of increase and decrease	Mixed pattern of increase and decrease
Misdemeanor Complaints	Alternating between increase and decrease	Decrease in all areas
Violation Complaints	Increase at Albany, followed by decrease, then increasing in outer rings	Increase at Roosevelt, followed by decrease, then increasing in outer ring
Indicator Complaints	Decrease in inner rings, increase in outer rings	Decrease in all but one area
All Arrests	Alternating between increase and decrease	Increase in inner rings, decrease in outer rings
Felony Arrests	Mixed pattern of increase and decrease	Increase at Roosevelt, followed by decrease, then increasing in outer ring
Misdemeanor Arrests	Increase in all but one areas	Mixed pattern of increase and decrease
Ratio of Arrests to Complaints	Increase in all but one areas	Increase in inner rings, decrease in outer rings

TABLE 4:1 – Summary of patterns in maps resulting from buffer count analysis

For the all complaints category, there is a decrease in crime counts within a distance of 0.2 miles of Albany and an overall decrease (or no change) within 0.5 miles of Roosevelt. This decreasing trend at Roosevelt may suggest that something other than the CCTV installation alone is responsible. It may simply be a result of the general trend of crime reduction in the area where both housing projects are located. Since crime is decreasing close to Albany, and increasing in its outer rings, displacement may be occurring near Albany.

The grouping of all arrests again suggests a confused pattern, particularly at Albany where the crime counts alternate between decreasing and increasing trends by distance ring. At Roosevelt, the number of arrests increases dramatically near the development, but decreases in the outer four buffers. This may represent displacement from Albany to Roosevelt, or it could result from an unknown crime prevention policy at Roosevelt that caused an increase in arrests.

For violation complaints, there is an increase in the inner most ring (the developments themselves) for both Albany and Roosevelt. For Albany the next two rings show a decrease while the outer three rings show an increase. It is possible that displacement is occurring, but the evidence would have been stronger if the innermost ring shown decreasing values. Roosevelt shows a pattern similar to Albany for violation complaints, only here the outermost ring shows an increase.

A pattern similar to all arrests emerges for misdemeanor complaints with crime counts alternating between increasing and decreasing around Albany. However, in this case misdemeanor complaints decrease all around Roosevelt. The reduction in complaints around Roosevelt and the lack of a clear geographic pattern around Albany suggest that CCTV has not had a significant impact on misdemeanor complaints.

There are dramatic increases in misdemeanor arrests for all but two buffers around Albany with innermost ring showing a decrease. Roosevelt has a similar pattern, but here only three buffers show an increase. Again, the increase in the outer rings at Albany and Roosevelt may indicate displacement.

The picture for major felony complaints is a little rosier. Here all buffers indicate decreasing crime at both Albany and Roosevelt. However the fact that both housing developments experienced similar decreases in major felonies suggests that the decrease is not likely a consequence of CCTV.

Indicator complaints are decreasing in the inner three rings around Albany, but increasing in the outer rings. For Roosevelt indicator complaints are decreasing for all buffers, except the 0.3 mile ring. Displacement may again be present at Albany.

Around Albany, felony complaints are increasing in the inner two and outer two buffers and decreasing elsewhere. For Roosevelt on the other hand, felony complaints are decreasing in the innermost ring, then increasing out to the 0.3 mile buffer, then decreasing.

For felony arrests, the 0.1 mile buffer and the 0.5 mile buffer at Albany are increasing while the other buffers indicate decreases or no change. With the exception of the 0.3 mile and 0.2 mile buffers, felony arrests are decreasing around Roosevelt. Once more, displacement may be occurring for both felony complaints and felony arrests, since crimes tend to increase the outer rings.

Finally, the ratio of arrests versus complaints was compared for each buffer ring. This metric gives an indication of how police activity changes compared to criminal activity. The inner-most ring for Albany shows a decrease in the ratio from Period 1 to Period 2. This means either that the number of arrests went up, or that the number of complaints went down in this area. The opposite is true for the next three rings at Albany and the inner two rings at Roosevelt since there is a positive difference value for these areas. At Albany, this may be an indication of displacement.

While the crime counts are interesting and do reveal some interesting patterns, statistically, they are not very relevant. Unfortunately, when the appropriate

significance tests are performed for the numbers displayed in the maps, a different picture emerges. One problem with these significance tests is that they only evaluate whether or not the change in crime is significant and do not take into consideration the geographic pattern. For example, if displacement is indeed occurring, then crime goes down in the inner rings and goes up in the outer rings. In the statistical tests then, the positive and negative differences offset each other and the test shows no significant difference. Therefore, the significance test is only useful to show if there are consistent changes. That is, the test will show significance if crime increases in every ring or it decreases in every ring.

The significance values from SPSS (see Table 4:2) indicate that there are few statistically significant overall changes in crime specifically, major felonies at Albany before and after CCTV installation and between Albany and Roosevelt, and misdemeanors between Albany and Roosevelt. The results also indicate that the patterns around Albany don't differ significantly from those around Roosevelt. There may be some evidence of displacement for some crimes, indicator complaints for example, where the change in crime varies by distance ring.

Therefore, although the raw numbers indicate some decreases close to Albany, and increasing numbers in the outer rings may indicate displacement, the

statistical tests, due largely to the inherent properties of the tests, do not always show significant differences.

Crime Type	Albany Before/After (Significance Matched T)	Albany/Roosevelt Percentages (Significance Wilcoxon Z)
All Complaints	0.596	0.249
Major Felony Complaints	0.008	0.249
Felony Complaints	0.788	0.173
Misdemeanor Complaints	0.419	0.046
Violation Complaints	0.956	0.463
Indicator Complaints	0.334	0.345
All Arrests	0.675	0.753
Felony Arrests	0.633	0.753
Misdemeanor Arrests	0.475	0.6
Arrests versus Complaints	0.666	0.917

TABLE 4:2 – SPSS Results from Buffer Analysis of Crime Counts

Discussion and Conclusions

The maps and tables showing differences in counts and percent change in counts after the installation of CCTV show some interesting trends. In the cases of all complaints, violation complaints and indicator complaints, to name a few, displacement may be occurring as indicated by the increase in complaints away from the Albany housing project. Whether or not this is due purely to the installation of CCTV is not clear however, especially since most of the statistical tests are not significant.

An interesting point is the increase of counts in the inner rings for categories like violation complaints and felony complaints. Is this increase necessarily a negative thing? Perhaps this increase is due to the increase in formal surveillance, and that previously the crimes went unnoticed or unreported. If this is the case, then in the short run CCTV is having a positive effect by increasing the detection of crime. Over the long run, it is anticipated that future trends for these crime categories would go down.

Another point of interest is the possibility of the diffusion of benefits, particularly at the Roosevelt Houses. For the crime categories all complaints and misdemeanor complaints, it appears that while there is an increase around Albany, there is a decrease at Roosevelt. This may be related to the installation of CCTV at Albany in the fact that it is possible that offenders think since Albany

has CCTV, Roosevelt does as well. In short offenders are not aware that Roosevelt does not have CCTV and therefore are not committing crimes near Roosevelt.

Chapter 5: Local Indicators of Spatial Autocorrelation

This chapter discusses the results of spatial autocorrelation analysis of crime patterns around the two public housing developments. The analysis focuses on Local Indicators of Spatial Autocorrelation (LISA) that describe localized patterns of crime. The chapter begins with a discussion of LISA measures and their implementation in this research project. The next section describes the results of the LISA analysis, with an emphasis on the changes in spatial autocorrelation patterns around the two housing projects before and after CCTV.

Data

Again, the data were created and manipulated primarily in the ArcView GIS. Further analysis was performed in SpaceStat v1.80 (see Anselin, 1998). The data builds on much of the primary information described previously, specifically the geocoded crime incidents and includes other information, namely United States Census tract boundaries for Brooklyn. For the purpose of this analysis, the Brooklyn tracts were clipped to the study area. The resulting intersection is irregular in shape but contains all the tracts that cover the study area. Census tracts are a very common unit of analysis in geographic research. They were chosen as the unit of analysis here, primarily because they are approximately the size of the housing developments in question, geographically and

demographically. That is, the public housing developments studied here contain roughly the same amount of people as the standard census tract.

Methodology

Before the analysis could be undertaken in SpaceStat, several steps needed to be taken. The first step was that the counts for each crime grouping and time period had to be calculated for each census tract in which they occurred. This simple 'point in polygon' analysis is relatively easy in ArcView, but does require the joining of the incident attribute table to the census tract attribute table based on their spatial relationship. Secondly, and more importantly, a spatial weights matrix needed to be created. This matrix contains information on the contiguity of each census tract and its neighbors. This is done seamlessly through the SpaceStat extension to ArcView.

SpaceStat v1.80 is a set of tools for spatial analysis. Of particular value are the LISA statistics, which were developed by Luc Anselin and implemented in his SpaceStat software. As the name implies, LISA is a method for detecting spatial autocorrelation, typically in area (polygon) data. "Local indicators of spatial autocorrelation (LISA) allow for the decomposition of global indicators into the contribution of each individual observation. They detect clustering around a given observation rather than a pre-specified site somewhere in the sampled space" (page 425, Messner, 1999). The LISA value for each

observation gives an indication of significant spatial clustering of similar values around that observation, ie., hot-spots, or of negative clustering in which a particular value is surrounded by dissimilar values

For this study, local Moran's I (LISA) values are computed for each census tract by using the first order spatial weights matrix with the local Moran function in SpaceStat. The local Moran's I is an indicator of spatial autocorrelation. Spatial autocorrelation exists when the value on a variable of one unit is related to the value of its geographic neighbors. A high value for local Moran's I indicates that the score of the polygon is closely correlated with the value of its neighbors, while a zero score suggests no association with the values for adjacent polygons. A negative Moran's I indicates an inverse relationship: if the value of the polygon is high, adjacent polygons are likely to be low, and vice versa.

The formal expression of Moran's I is:

$$I = \frac{N \sum_{i=1}^N \sum_{j=1, j \neq i}^N w_{ij} z_i z_j}{S_0 \sum_{i=1}^N z_i^2}$$

Where:

N= the number of observations

w_{ij} = the element in the spatial weights matrix corresponding to observation pair i, j

$Z = x - \mu$

S_0 = scaling constant (the sum of all weights)

The significance test for this statistic is based on a permutation approach whereby 999 I_i statistics are generated to form a reference distribution. Each tract's I_i statistic is compared to this reference distribution for inference purposes. Like the more familiar global Moran's I statistic, this local statistic distinguishes positive from negative spatial autocorrelation, but it is calculated for each observation in the data set. LISA statistics can be mapped to reveal areas where local spatial autocorrelation is positive, negative, or close to zero.

Results

A visual inspection of resulting choropleth maps of crime counts from the point in polygon analysis for all complaints in Period 1 and Period 2 is potentially unreliable in the detection of clusters and patterns of displacement (see Figures 5:1 – 5:2). Only patterns of areas with high or low crime activity can be identified and there is no way to detect "significant" clustering. It can be seen that from these examples that there are areas of high crime activity to the west and southeast of Albany and to the north and northeast of Roosevelt. As was mentioned earlier, it would also be useful to examine the difference in counts between time periods to identify potential displacement between periods (see Figure 5:3). Again, the picture is clouded by all the information, and only general patterns can be seen, such as the apparent decrease in crimes in a tract immediately surrounding Albany, and an even larger decrease in two tracts near Roosevelt.

Therefore, it may be useful to map LISA statistics to allow for the formal assessment of the presence of clusters and the relationship of tract crime counts to the crime counts in neighboring tracts. While mapping raw Moran's I values may be an interesting exercise, it is far more valuable to map tracts with statistically significant Moran's I values and how they relate to their neighbors (see Figures 5:4 – 5:5). In these examples of all complaints for Period 1 and Period 2, it is observed that three tracts near Albany (to the east) have

significant LISA values. The exact nature of the relationship between significant tracts can also be examined (see Figures 5:6 – 5:7). For example, in the legend, high-high indicates a high average value surround by above-average value tracts. To further this analysis, the difference between Period 1 and Period 2 can be calculated and LISA values can be generated in SpaceStat for mapping. See Table 5:1 for a summary of these results.

Crime Type	Albany	Roosevelt
All Complaints	No SA*	Some positive SA with decreasing counts
Major Felony Complaints	Mixed positive and negative SA with increasing and decreasing counts	Some positive SA with decreasing counts
Felony Complaints	Some positive SA with increasing counts	Some negative SA with decreasing counts
Misdemeanor Complaints	Some positive SA with increasing counts	Some positive SA with decreasing counts
Violation Complaints	No SA	Some positive SA with decreasing counts
Indicator Complaints	No SA	Some positive SA with decreasing counts
All Arrests	Some positive SA with increasing counts	Some negative SA with decreasing counts
Felony Arrests	No SA	Some negative SA with decreasing counts, Some negative SA with increasing counts and Some positive SA with decreasing counts
Misdemeanor Arrests	Some negative SA with decreasing counts, Some positive SA with increasing counts	Some negative SA with decreasing counts, Some positive SA with increasing counts

TABLE 5:1 – Summary of patterns in maps resulting from LISA analysis
 *SA (Spatial Autocorrelation)

By using the difference values, a different pattern emerges. The three tracts described no longer have significant Moran's I values. An area in between the two housing developments, to the north of Albany and to the south of Roosevelt, has several tracts with in the low-low category. This suggests that these tracts have had considerable decreases in all complaints, and are surrounded by tracts that have had similar decreases. This is the pattern expected around Albany, where CCTV was expected to cause a localized reduction in crime. Unfortunately the low-low cluster occurs at some distance from Albany, which suggests that it is unrelated to the installation of CCTV.

The difference between Period 1 and Period 2 is calculated for all crime groupings and LISA values are generated in SpaceStat. The results are mapped in Appendix B (see Figures B:1 – B:8). From these it can be seen that with the exception of misdemeanor arrests, none of the crime groupings have statistically significant tracts adjacent to Albany. In the case of misdemeanors, the tract adjacent to Albany has a value of high-high, indicating that the number of misdemeanor arrests increased in that tract and neighboring tracts also experienced an increase in misdemeanor arrests. This may be related to the installation of CCTV, but based on the distances away from Albany it is unlikely.

Interestingly, for felony arrests, there is a high-low tract near Roosevelt suggesting a tract with a high number of arrests surrounded by tracts with lower numbers. A pattern similar to the one described above for all complaints emerges for misdemeanor, indicator and violation complaints. Again, it is hypothesized that this decreasing trend after CCTV installation would emerge in the areas including or immediately surrounding Albany. A number of groupings, all arrests, misdemeanor arrests, major felony complaints, felony complaints and misdemeanor complaints have tracts that fall in the high-high category at some distance from the Albany. This may be an indication of displacement, although the spatial pattern seems to differ from one type of crime to another. For example for the pattern of high-high values for all arrests occurs southwest and east of Albany. For misdemeanor arrests and misdemeanor complaints the same pattern occurs to the west of Albany. Other directional differences appear in felony complaints in which the pattern appears to the northwest of Albany and for major felony complaints, which occurs to the southeast of Albany. Since these patterns do not occur at similar locations and the distance is considerable, usually well beyond the 0.5 mile buffer it is unlikely that displacement is due solely to the installation of CCTV at Albany. Similarly, for violation complaints, which has a high-high pattern, and again occurs at some distance, it is unlikely this is due to the installation of CCTV alone, but rather in conjunction with some other factors such as increased opportunities in the tracts in question.

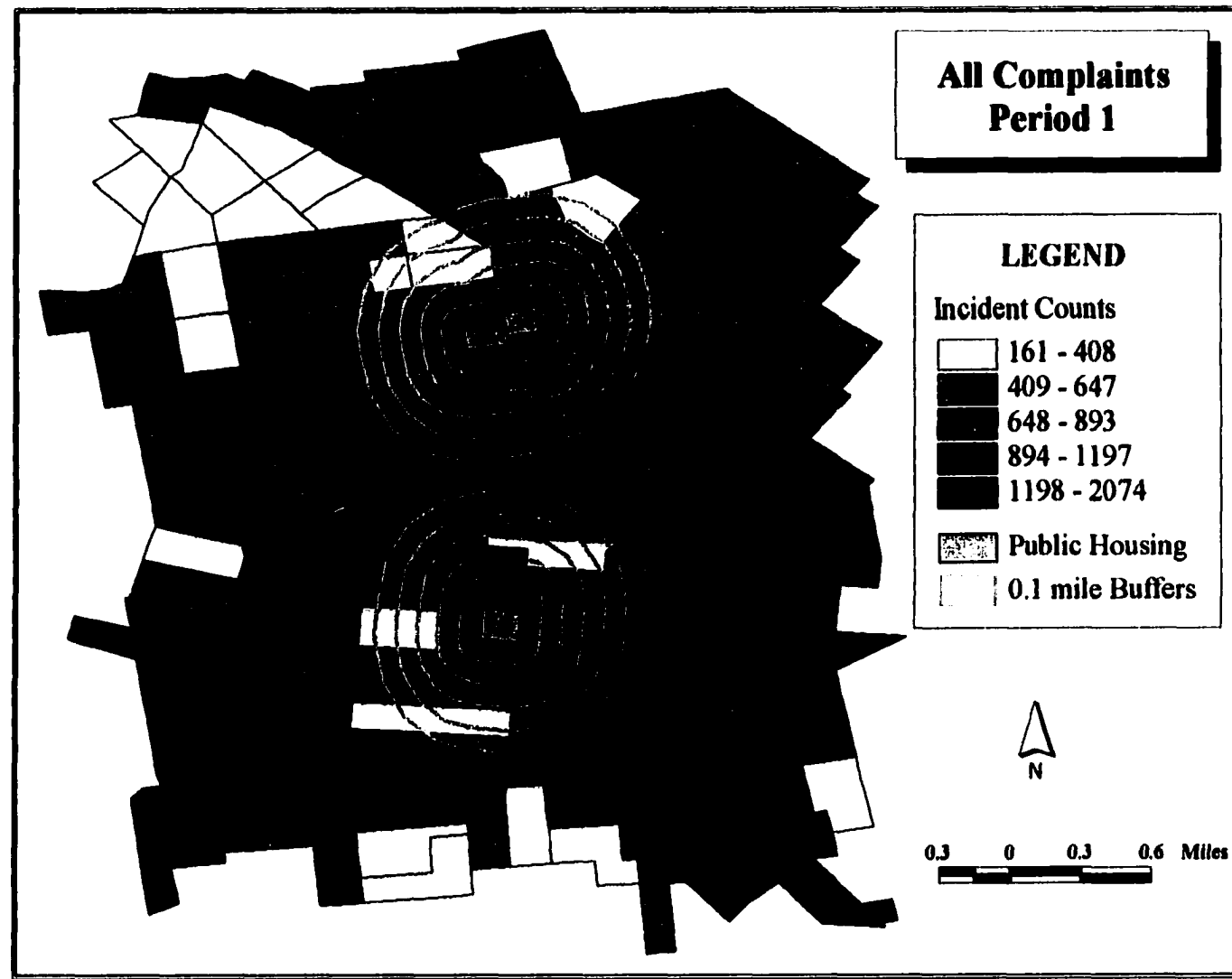


FIGURE 5:1 Counts by Tract (All Complaints)

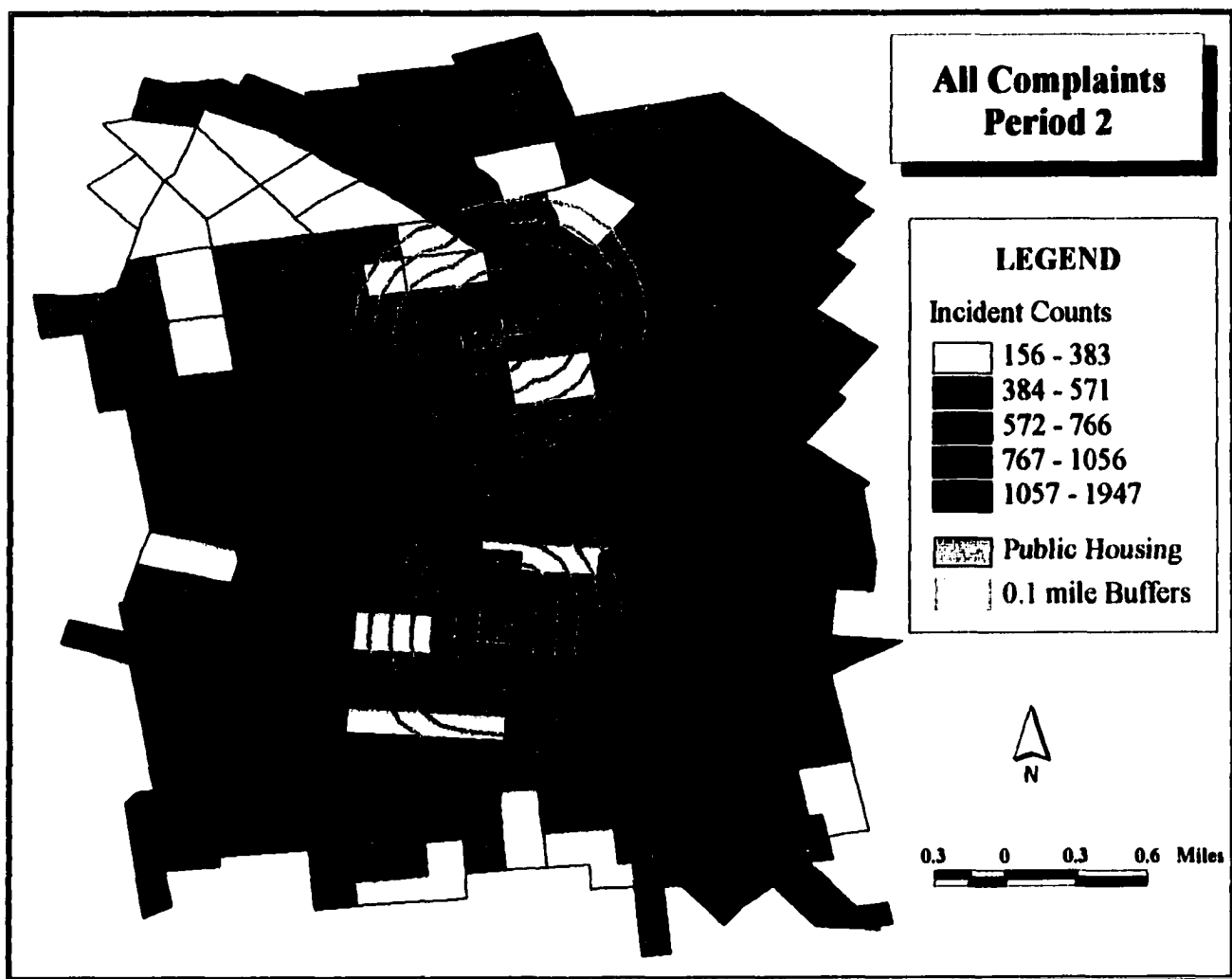


FIGURE 5:2 Counts by Tract (All Complaints)

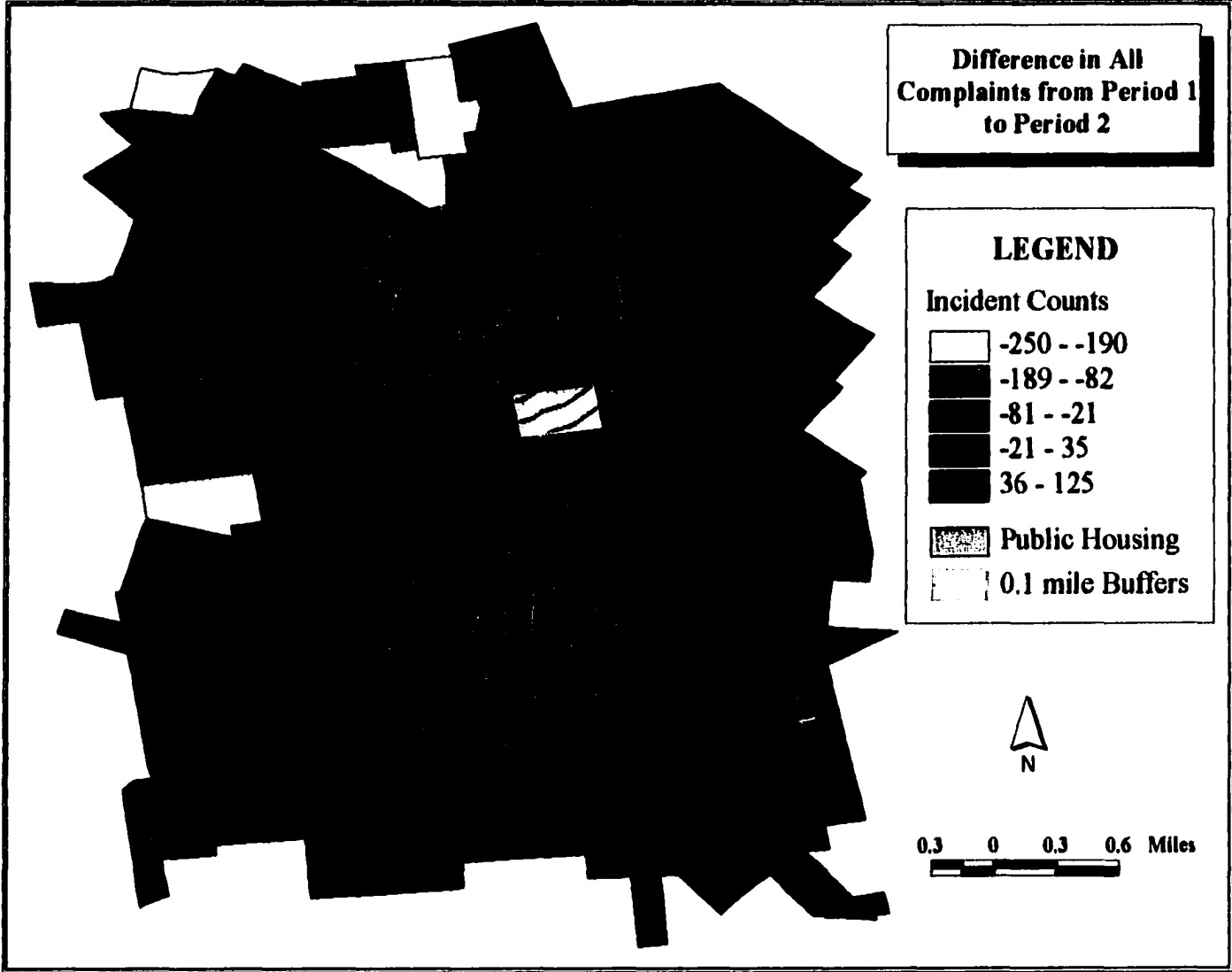


FIGURE 5:3 Difference in Counts by Tract (All Complaints)

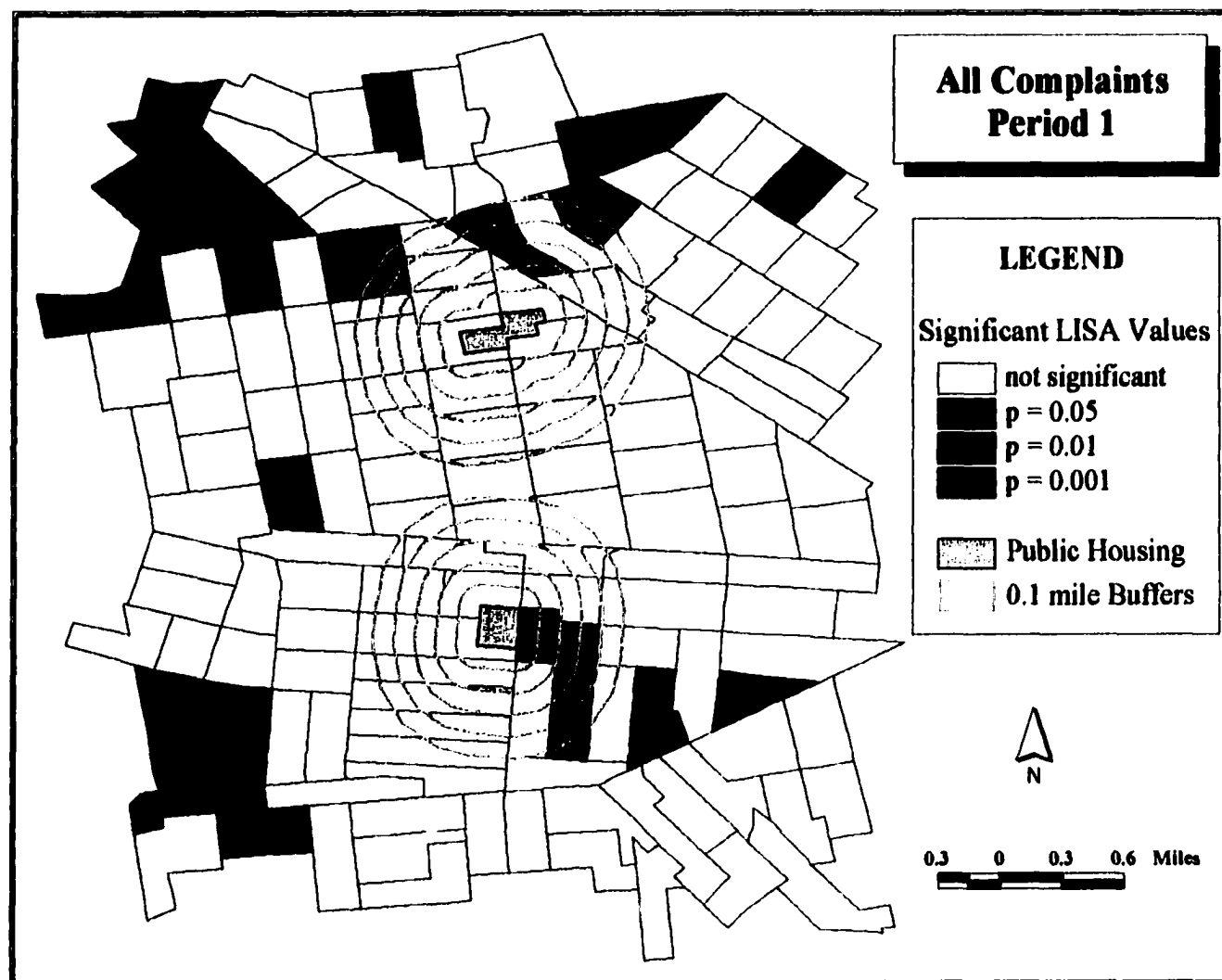


FIGURE 5:4 Significant LISA Values by Tract (All Complaints)

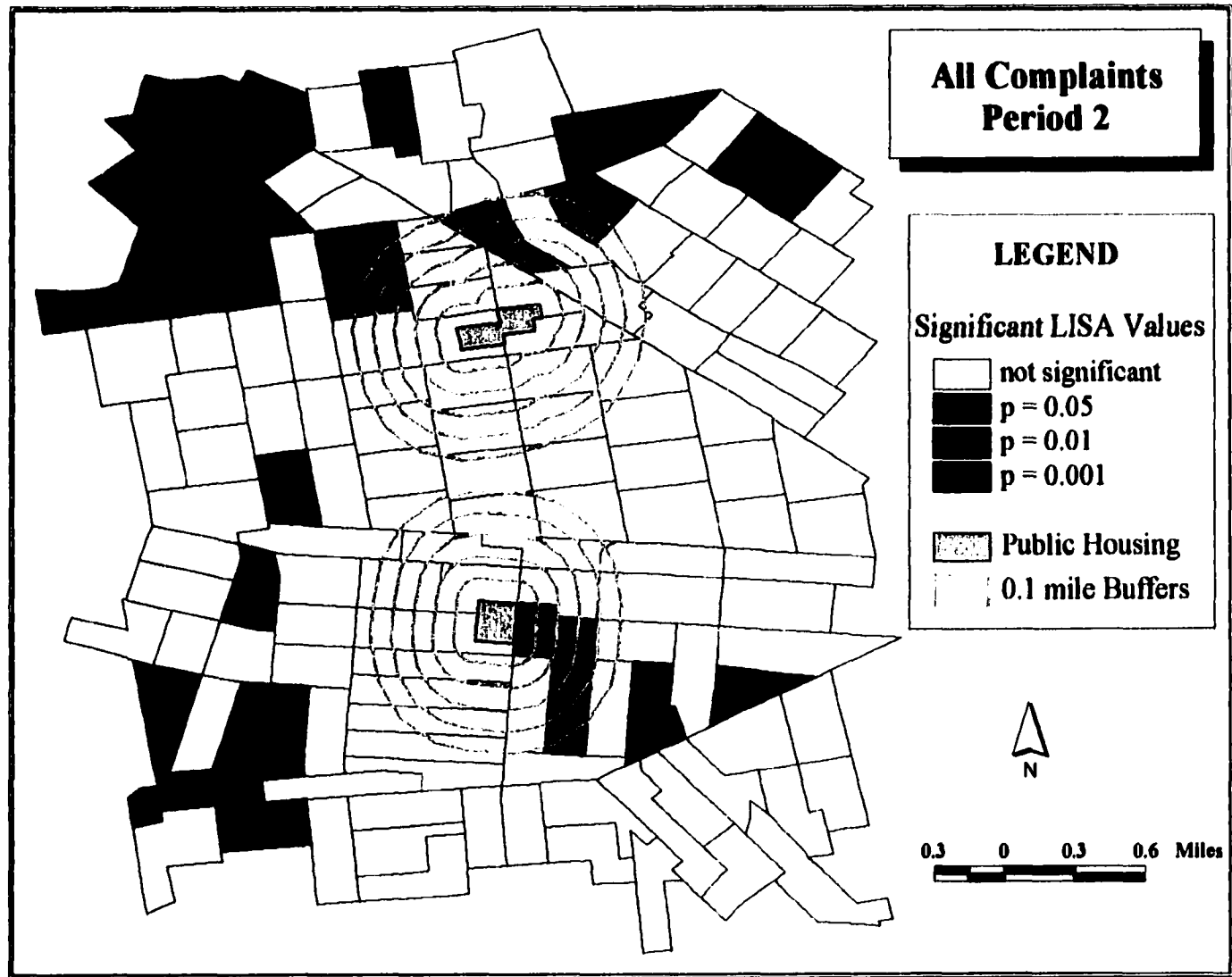


FIGURE 5:5 Significant LISA Values by Tract (All Complaints)

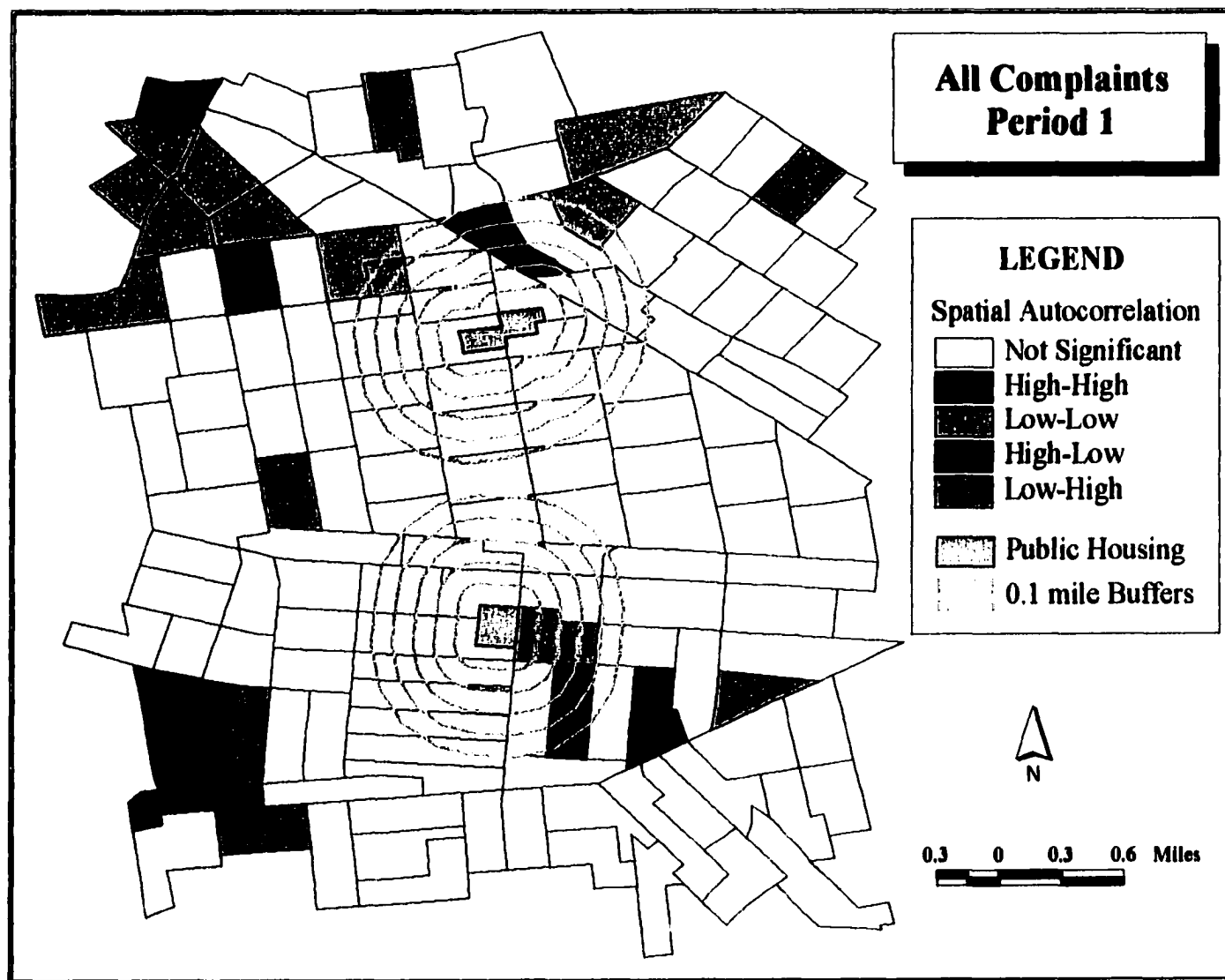


FIGURE 5:6 Significant LISA Values and Relationships by Tract (All Complaints)

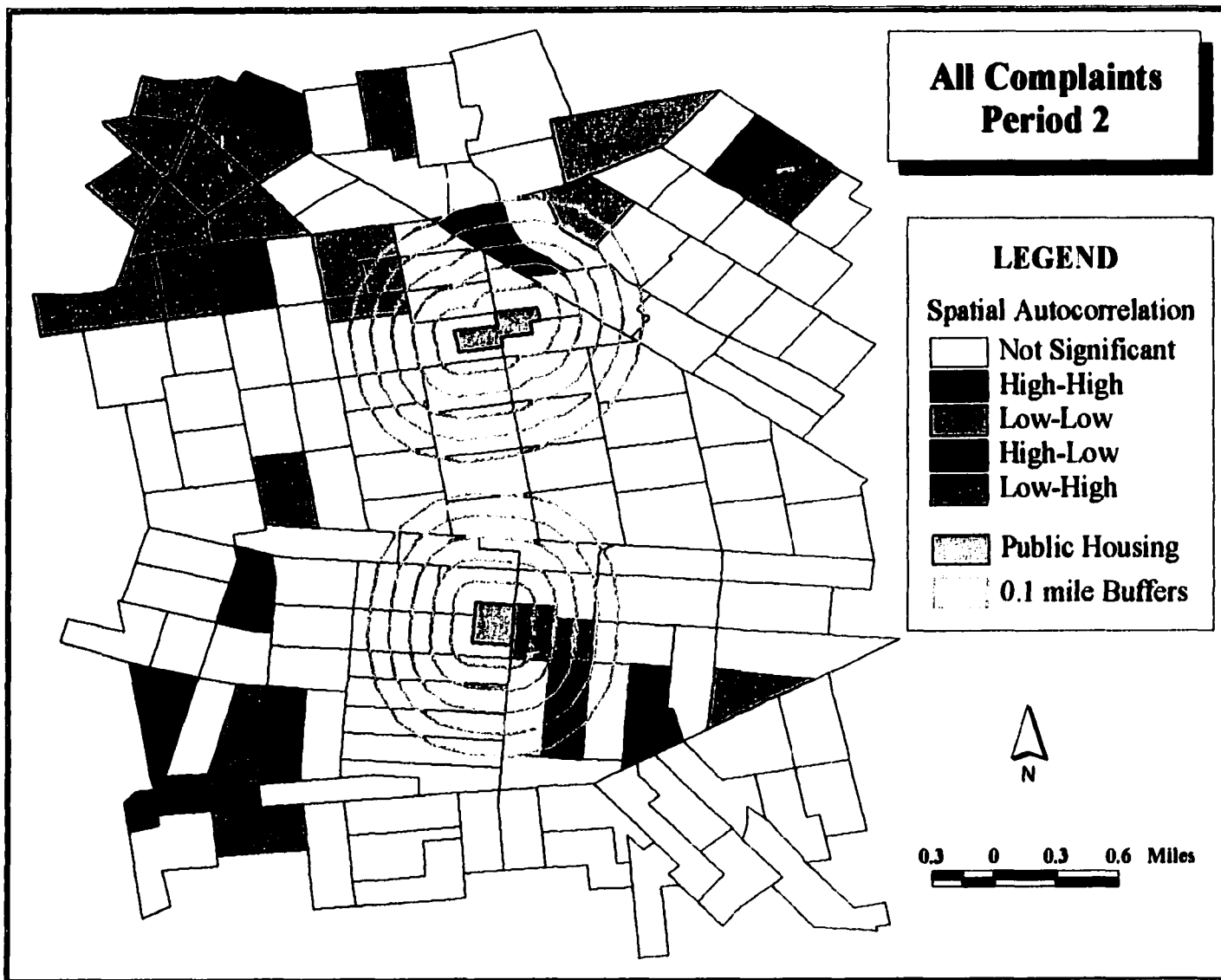


FIGURE 5:7 Significant LISA Values and Relationships by Tract (All Complaints)

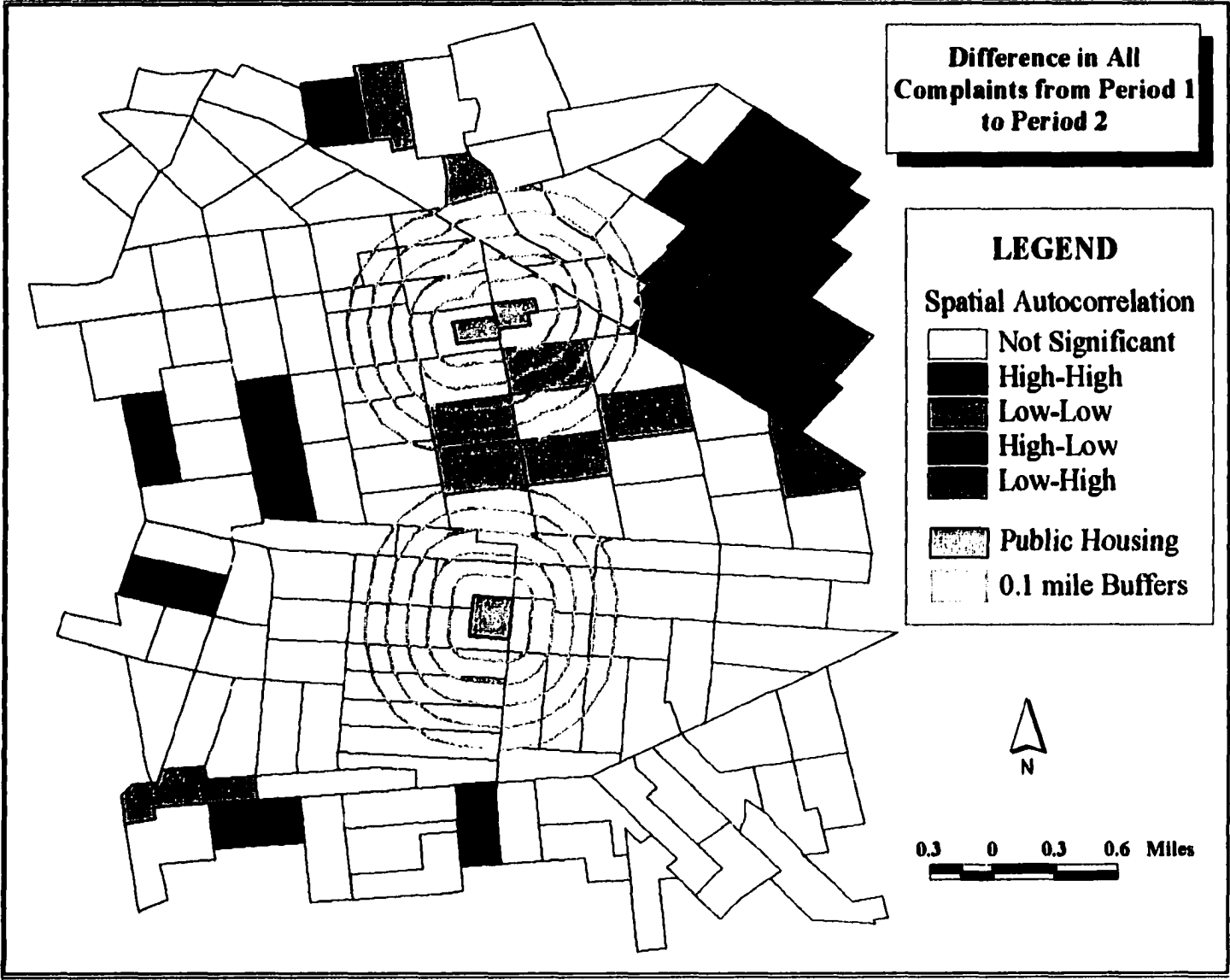


FIGURE 5:8 Significant LISA Values and Relationships for Difference by Tract (All Complaints)

Conclusions and Discussion

It is hypothesized here that after CCTV installation around the Albany Houses, a pattern would emerge showing tracts near Albany would have large decreases (low values) based on the differences between Period 1 and Period 2 and would be surrounded by tracts with comparably large decreases. Unfortunately, this hypothesis is not supported by the LISA maps. It is further hypothesized that displacement would occur after the installation of CCTV in the areas at some distance from Albany. This phenomenon may be occurring in certain crime types such as all arrests, felony complaints, misdemeanor arrests and misdemeanor complaints. However since the patterns occur at considerable distances from Albany it is unclear if the displacement is solely a function of CCTV installation and not some other factors. Also, due to large number of housing projects near Roosevelt it is difficult to remove the 'noise' from the analysis and thus attribute any decrease solely to CCTV installation.

Chapter 6: Segmented Regression

This section explains the data and methods used in analyzing the effect of CCTV in the context of segmented, or two-phase regression. The spatial information used in this research spans two time periods, or segments, specifically the period before the installation of CCTV at the Albany Houses and the period after the installation of CCTV. The results of segmented regression analysis indicate whether or not two temporal segments are significantly different. Since one of the primary goals of this research is to evaluate the effectiveness of CCTV over time as well as space; therefore the use of segmented regression is a logical extension.

Data

The data utilized in this section is derived from the primary datasets described previously, specifically the geocoded crime incidents. Again, the data were created and manipulated primarily in the ArcView GIS, through out of the box functionality as well as some custom scripting.

The point locations of crime incidents were used to create density grids of crime as described above in the kernel estimation section. Specifically, one density grid is created for each month for each crime type, for the eighteen-month period

before the installation of CCTV in the Albany Houses and for the eighteen-month period after CCTV installation, for a total of thirty-six grids for each crime type. The time frame encompasses the period beginning January 1997 and ending December 1999. Another set of grids was also created to serve as the independent variable, time. There is one grid for each time period or month in the analysis. The values at each location in these grids correspond to the month number (1-36). Therefore, the grids contain only constant values – all of the grid cells have the same value within each grid. All these grids were created in ArcView's Spatial Analyst.

Methodology

The underlying concept behind segmented regression is simple. Assuming a collection of samples gathered over consecutive time periods, and a point in time at which a change or intervention occurred, are the models for the periods before and after that point in time significantly different? Segmented regression analysis provides a statistical method for determining if the trends over time changed significantly after an intervention. In the case described here, the collection of samples is the crime density values for each monthly period for each crime subtype. The point in time, which is known in this case, is the installation of CCTV at the Albany Houses (July 1998). The segmented regression method allows us to

determine if, at a particular location, the trend in crime density over time changed significantly before and after CCTV installation.

This study is significant because it is not limited to one location. The models are calculated at all grid cell locations throughout the study area, or more specifically, at 25398 unique locations. Therefore, unlike other studies that look at one area, this one looks at every discrete location within the area, creating a continuous surface of segmented regression model results.

The input into the regression equation is similar to standard regression analysis, however, instead of the standard columns of independent and dependent variables, two matrices for the independent and dependent variables (See Figure 6:1) are used. The matrices correspond to the geographic grid locations. The dependent variable is the crime density at each location, for each month, for each crime type. The independent variable is the time of the event, or this case, the month. The output is the standard slope and intercept coefficients, the R-Squared values and the error terms (See Figure 6:2).

Sample Input Into Segmented Regression

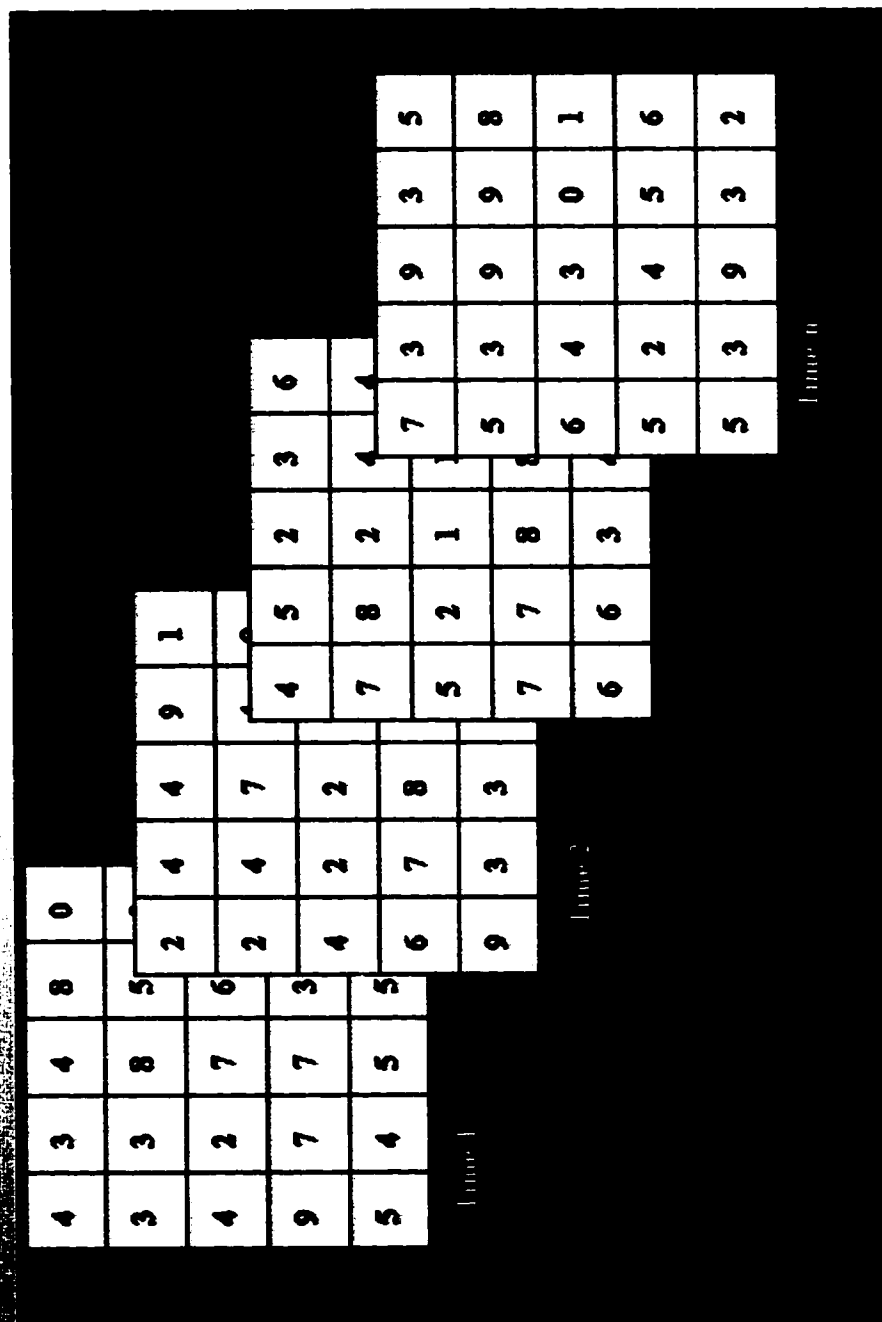


FIGURE 6:1 Hypothetical Input into Segmented Regression

Sample Output From Segmented Regression

Intercept Values					Slope Values				
4	3	4	8	0	2	4	4	9	1
3	3	8	5	0	2	4	7	4	0
4	2	7	6	0	4	2	2	0	0
9	7	7	3	0	6	7	8	0	0
5	4	5	5	0	9	3	3	0	0
R Squared Values					F Values for R Square				
7	3	9	3	5	4	5	2	3	6
5	3	9	9	8	7	8	2	4	4
6	4	3	0	1	5	2	1	1	0
5	2	4	5	6	7	7	8	8	0
5	3	9	3	2	6	6	3	4	0

FIGURE 6:2 Hypothetical Output from Segmented Regression

Because the input for the analysis is in matrix form, standard statistical packages could not be used to calculate the output. Also, the goal was to create maps of the output, so that one could visualize areas where significant changes in crime trends occurred. In this case, custom scripts were written for ArcView's Spatial Analyst to perform the segmented regression analysis on a cell by cell basis. Several locations were picked at random, and the results from the custom scripts were verified against regression analyses in Microsoft Excel and SPSS to ensure validity. The scripts use the standard regression formulas to perform the analysis:

$$b = \frac{N \sum XY - (\sum X)(\sum Y)}{N \sum X^2 - (\sum X)^2}$$

$$a = \frac{(\sum Y)(\sum X^2) - (\sum X)(\sum XY)}{N \sum X^2 - (\sum X)^2}$$

The value of r^2 can be computed using the following:

$$r^2 = \frac{\sum (\hat{Y}_i - \bar{Y})^2}{\sum (Y_i - \bar{Y})^2} \quad \text{or} \quad r^2 = \frac{RSS}{TSS}$$

Where:

$$\text{Regression (explained) Sum of Squares (RSS)} = \sum (\hat{Y}_i - \bar{Y})^2$$

$$\text{Total Sum of Squares (TSS)} = \sum (Y_i - \bar{Y})^2$$

By computing the slope, intercept and coefficient of determination at each point in the study area, maps for each parameter can be made to examine trends in the area (see Figures 6:3 – 6:5). As useful as the basic regression analysis is, further operations need to be performed to run the segmented regression which checks the equality of the trends (as reflected in the regression slopes) for the two regression segments. The test for equality of regression slopes is the Chow test (Chow, 1960). Again, this analysis was done in ArcView's Spatial Analyst using custom scripts and takes advantage of the error terms generated in the standard regression analysis. The equation for the Chow Test is :

$$\frac{(ESS_{\text{Overall}} - ESS_{\text{Period 1 + Period 2}})/k}{ESS_{\text{Period 1 + Period 2}}/(N+M + 2k)}$$

Where:

$$\text{Error (unexplained) Sum of Squares (ESS)} = \sum (Y_i - \hat{Y}_i) \text{ or TSS - RSS}$$

In short, the Chow Test is a special case of the F Test, which checks the equality of the coefficients. It uses the sum of the sum of errors in each separate model compared to the sum of the errors for the combined (overall) model (see Figure 6:6). Since the test is based on the F distribution, critical values for the F Test can be obtained from a statistical table and location (points) where the F test exceeds the appropriate critical value can be identified. These points are isolated in ArcView using a standard query. Locations where the Chow test is rejected are

places where the trend in crime density over time changed significantly before and after CCTV. Thus, these are locations where CCTV may have had a significant impact on crime.

Another important aspect of the segmented regression analysis is that locations can be isolated based on the sign of their change in slope (change in crime trend over time), and the significance of the Chow Test. That is, points can be isolated that have a negative change in slope (decreasing crime) and have significantly different model coefficients. The same can be done for positive slopes (increasing crime). This makes it possible to distinguish locations that may have experienced an increase or decrease in crime density over time as a result of CCTV.

Results

There are a number of preliminary results derived, before the significance tests of the Chow Test are computed. Namely, the standard regression coefficients of intercept, slope and the coefficient of determination (r^2) are calculated (see Figures 6:3 – 6:5). The intercept maps show the estimated crime density at each location for time period zero, or in others words, the estimated initial density. The slope maps are very useful in establishing the trend of crime density for a specific time period at each location. These maps indicate at what rate crime is increasing, decreasing or remaining constant at each point. The r^2 or coefficient of determination maps reveal how much of crime density (dependent variable)

can be explained by time (independent variable), or how correlated, if at all, the two variables are.

Extending the analysis further, The Chow Test can be performed on the datasets derived to compute the above maps, slope, intercept, and r^2 . These Chow test maps indicate if the two segments for the periods before and after CCTV installation are significantly different and what the sign (positive or negative) of the change is. See Table 6:1 for a summary of these results.

Crime Type	Albany	Roosevelt
All Complaints	Mixed patches of increase and decrease	Majority of significant areas are decreasing
Major Felony Complaints	Large area of increase near Albany then, mixed patches of increase and decrease	Large area of increase near Roosevelt then, mixed patches of increase and decrease
Felony Complaints	Pattern of increase and decrease at Albany, some patches of increase and decrease at some distance	Mixed patches of increase and decrease
Misdemeanor Complaints	Mixed patches of increase and decrease	Majority of significant areas are decreasing
Violation Complaints	Majority of significant areas are decreasing	Mixed patches of increase and decrease
Indicator Complaints	Large area of decrease near Albany then, mixed patches of increase and decrease	Mixed patches of increase and decrease
All Arrests	Majority of significant areas are decreasing, particularly at Albany	Majority of significant areas are decreasing
Felony Arrests	Majority of significant areas are decreasing	Majority of significant areas are increasing
Misdemeanor Arrests	Majority of significant areas are decreasing	Majority of significant areas are decreasing
Ratio of Arrests to Complaints	Majority of significant areas are decreasing, particularly at Albany	Mixed patches of increase and decrease

TABLE 6:1 – Summary of patterns in maps resulting from segmented regression analysis

By querying the Chow Test maps for significant values and overlaying that result with the slope maps conclusions can be drawn on the effectiveness of CCTV. This is evident when examining the resulting maps in Appendix C (see Figures C:1 – C:9), which show significant F values for the Chow test and the corresponding sign (positive or negative) of the slope at each location. For each of the different categories of complaint data, a general pattern is that much of the area surrounding Albany and Roosevelt do not have statistically significant Chow Test values. That is, there are large areas, indicated in light yellow, which, based on the pre- and post- CCTV installation segmented regression models, are not significantly different. This is contrasted by the different categories of arrest data, which shows larger areas of significantly significant Chow Test values.

There are several small areas with negative slopes and significant F values near Albany, particularly in all complaints, indicator complaints and violation complaints. This indicates, that for these crime categories, crime was decreasing after the installation of CCTV. This is especially true at the northwest corner of the Albany complex. Anecdotally, it was reported that this area has a corner store, or 'bodega' that was a source of criminal activity. Coincidentally, this area was encompassed in the range of the CCTV cameras at Albany and resulted in more police activity at that location. This can be seen then as a diffusion of benefits since the location is not within the confines of the Albany development but it benefits from the effects of CCTV at Albany. Both positive and negative

slopes straddle Albany with significant F values for felony complaints, indicating that on the northwest side of Albany there was an increasing trend of felony complaints while the southeast side had a decreasing trend. An increase in slope with significant F values is observed for major felonies around Albany. This unexpected result may be due to the fact that after CCTV is installed, these serious crimes are not only captured on film, but reported as incidents as well, resulting in a significant increase. Previously, they may have gone unreported.

Roosevelt shows negative slopes and significant F values for all complaints, indicator complaints, felony complaints and misdemeanor complaints, particularly to the north of the development. This suggests that these crime types were decreasing significantly around Roosevelt after the installation at Albany. It is difficult to explain these decreases at Roosevelt. Roosevelt is in close proximity to other housing projects and it is relatively close in distance to the subway to the north. Also, other factors, namely police department initiatives, may be taking place in these areas.

The pattern for arrests shows large areas with significant F values. Large areas with negative slopes can be seen at and to the southeast of Albany for all arrests and to the southeast of Albany felony arrests. Negative slopes can also be seen for misdemeanor arrests at some distance from Albany particularly to the east and southeast. These areas with significant values, specifically for all arrests, indicate that after CCTV installation there was a dramatic decrease in arrests. This does

not necessarily suggest that criminals were not getting caught, but perhaps that the crimes were not being committed. This is most likely due to the fact that with the presence of CCTV and increased surveillance, criminals feared being caught, and therefore didn't operate in these areas anymore.

Interestingly, for felony arrests, there is an increasing trend to the west and southwest of Albany. This may suggest that the criminals moved from the other areas to these new locations.

The patterns are less clear for arrests around Roosevelt. Here both negative and positive slopes punctuate the surrounding areas. There are areas of significant decreases at Roosevelt on the south side and to the north for the arrest categories, all arrests, felony arrests, and misdemeanor arrests. Interesting, there are increasing trends to the west and to the south. The pattern to the south is particularly interesting because it is an area directly between Albany and Roosevelt, which may be indicative of displacement.

The segmented regression analysis was also performed on a derived data set, namely the ratio of all arrests to all complaints. It was expected that this would give an indication of how police activity changed in response to a change in criminal activity, if at all. This is displayed in Figure C:9. From this map, it appears that the density of arrests compared to the density of complaints went down at and to the east of Albany after the installation of CCTV. This does not

necessarily imply that there is less police activity after CCTV, but rather that there is less criminal activity. Interestingly, the area in between Albany shows an increase in the ratio of arrest densities and complaint densities. This may be an indication of displacement.

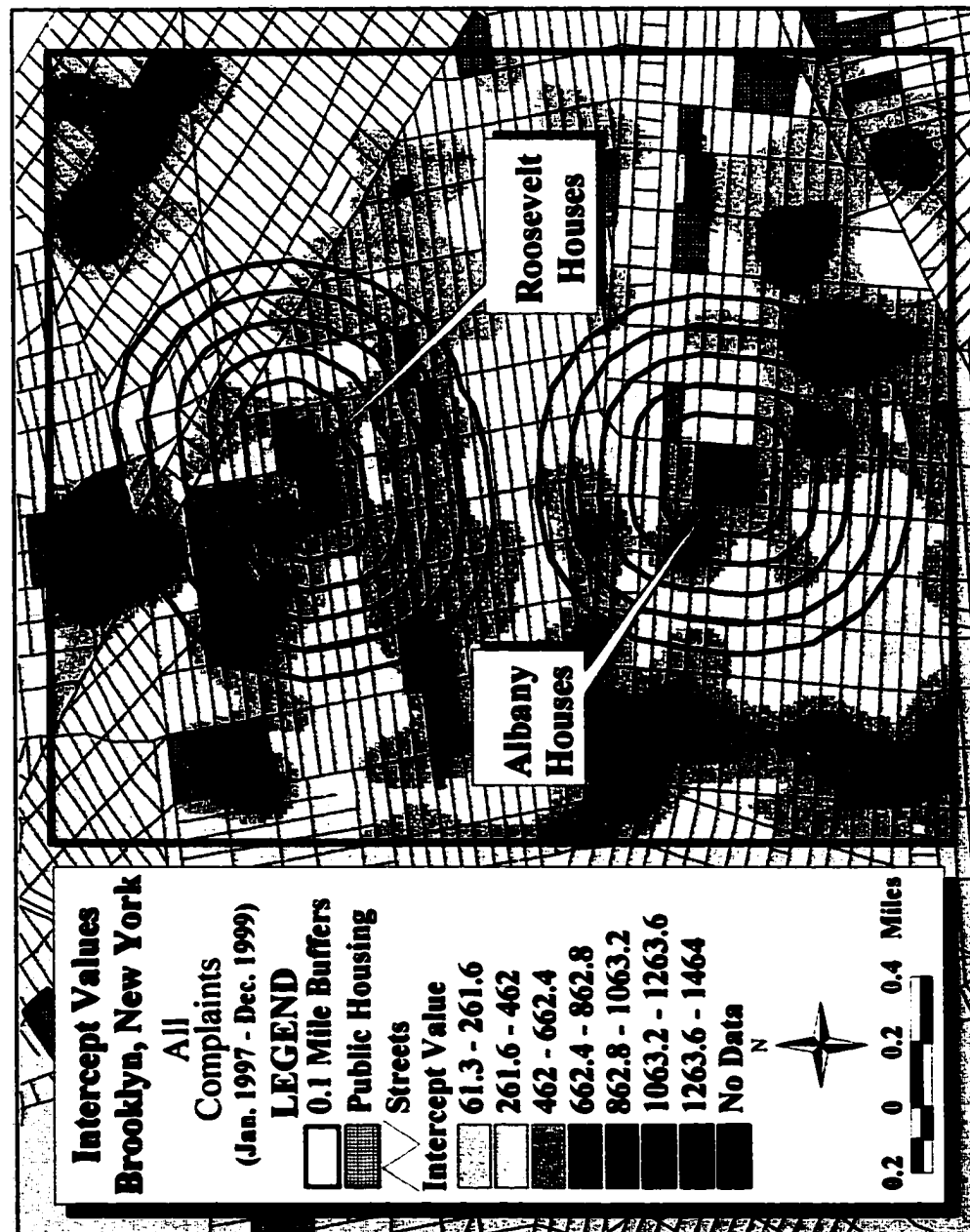


FIGURE 6:3 Intercept Values, All Complaints

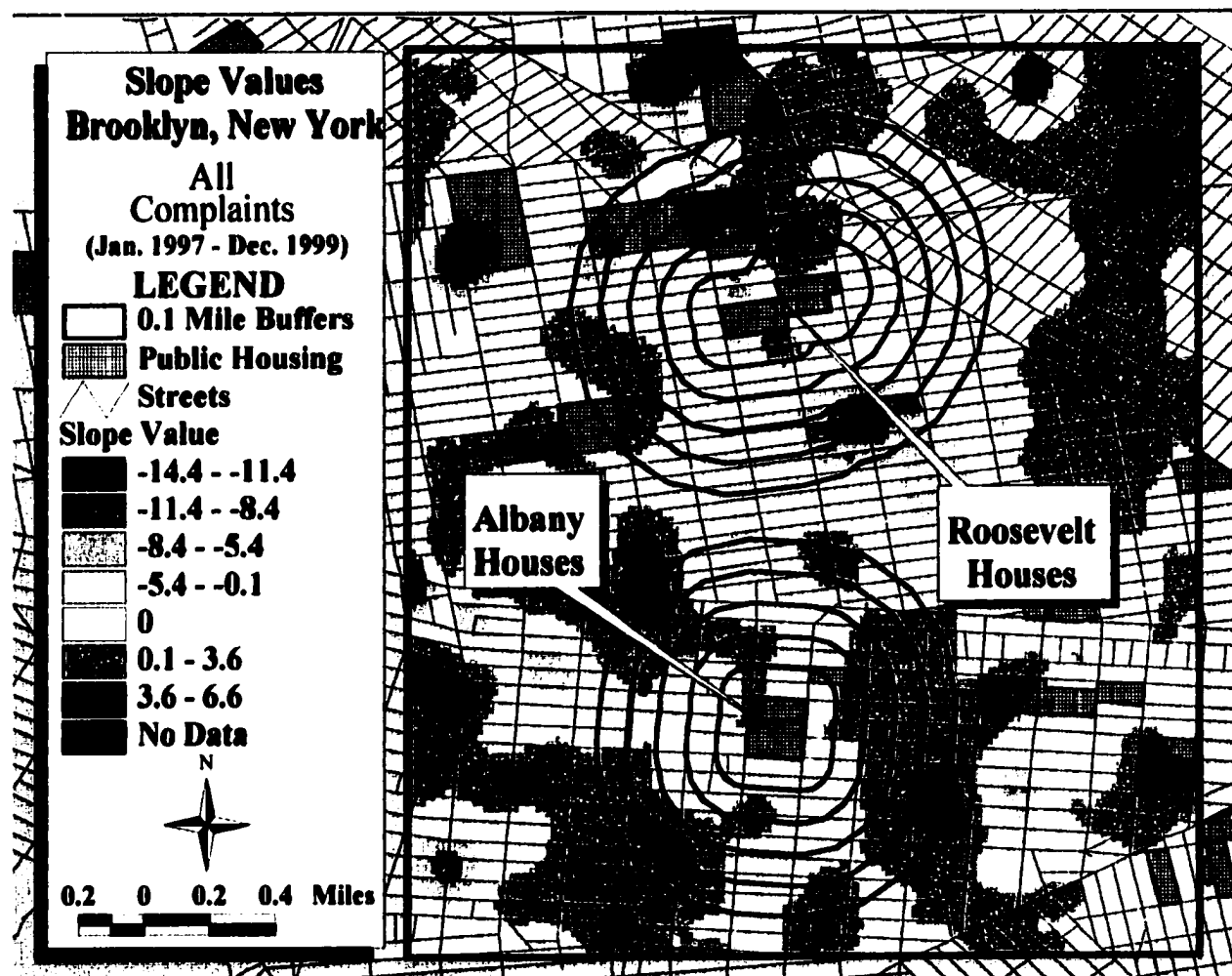


FIGURE 6:4 Slope Values, All Complaints

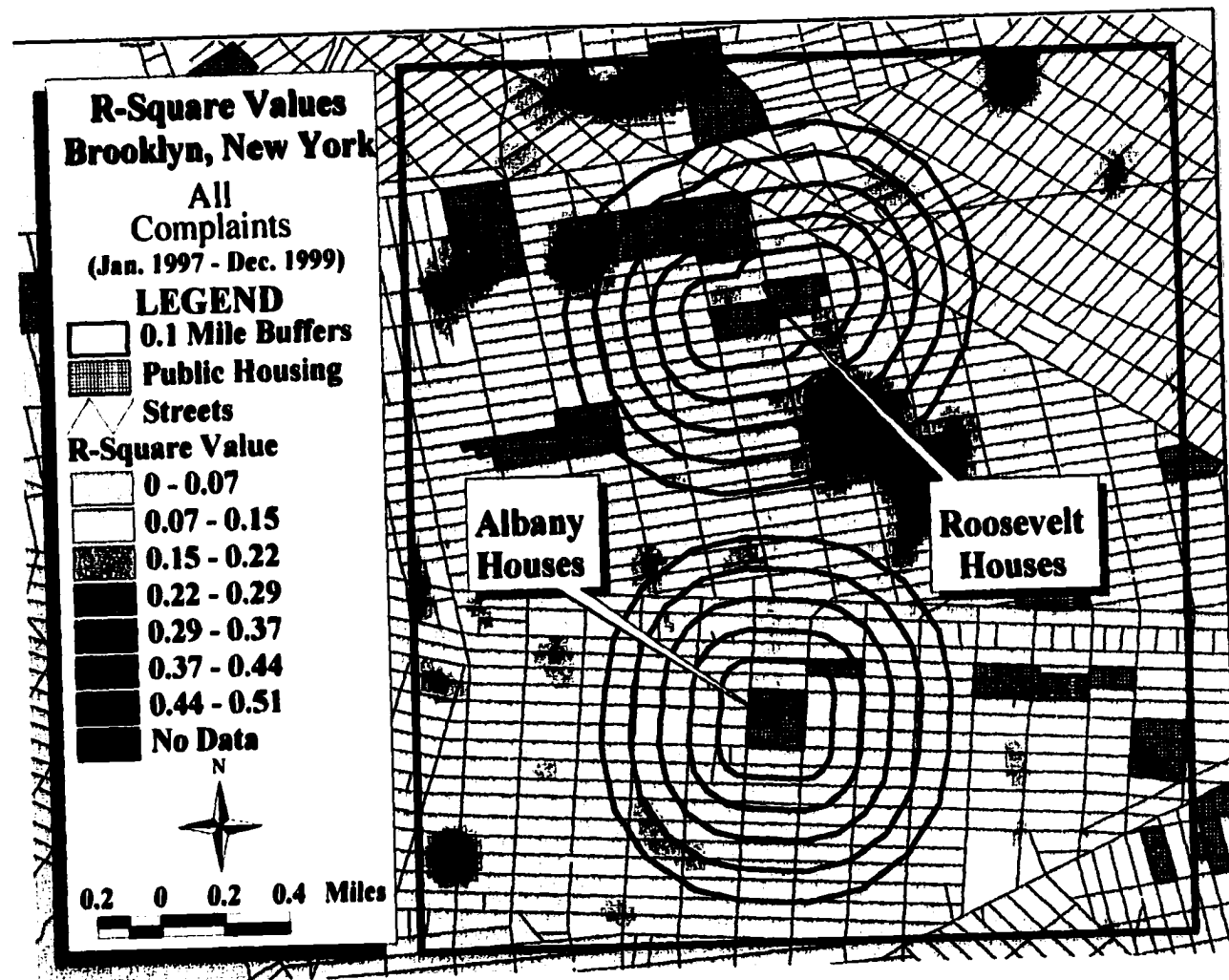


FIGURE 6:5 R^2 Values, All Complaints

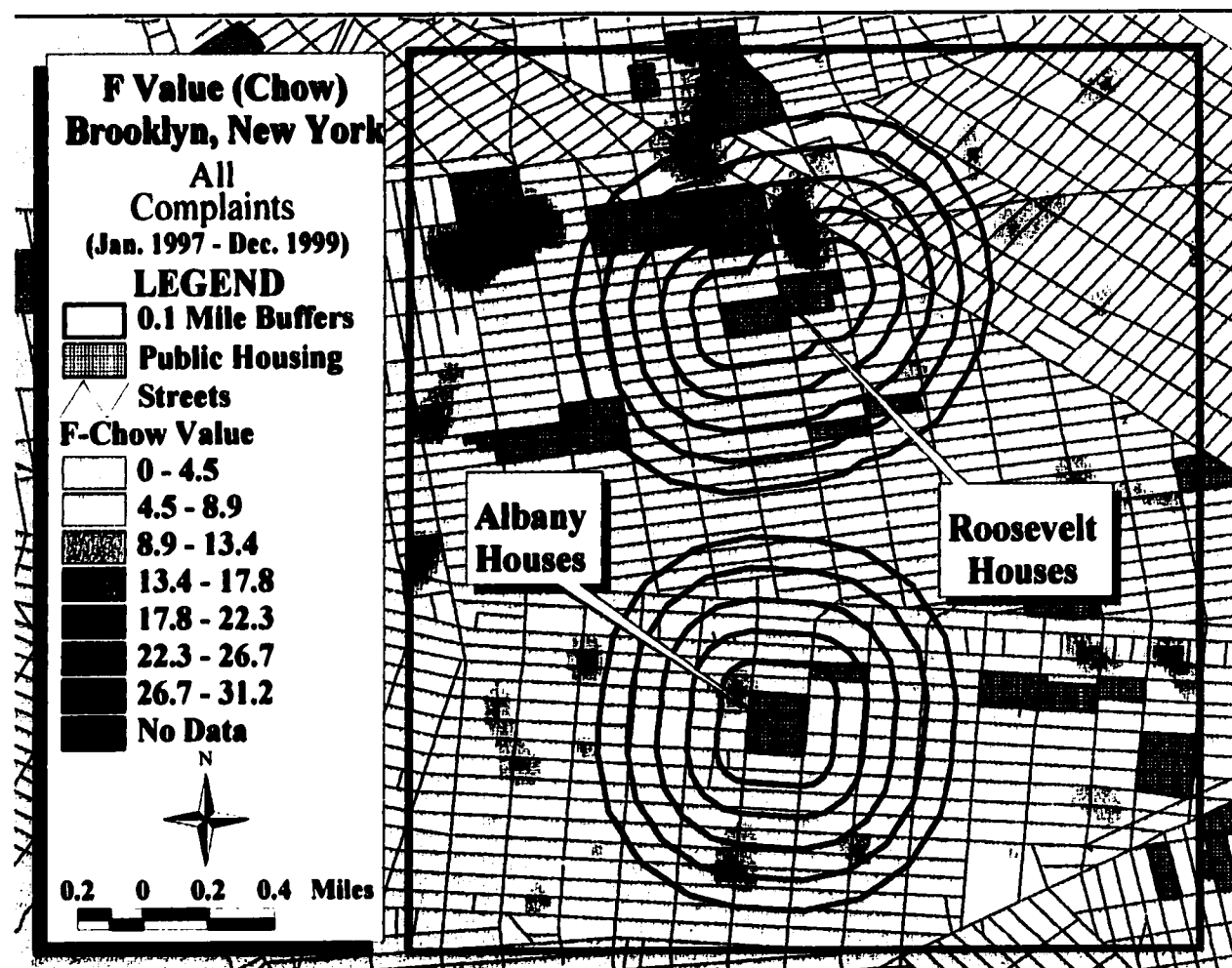


FIGURE 6:6 F (Chow) Values, All Complaints

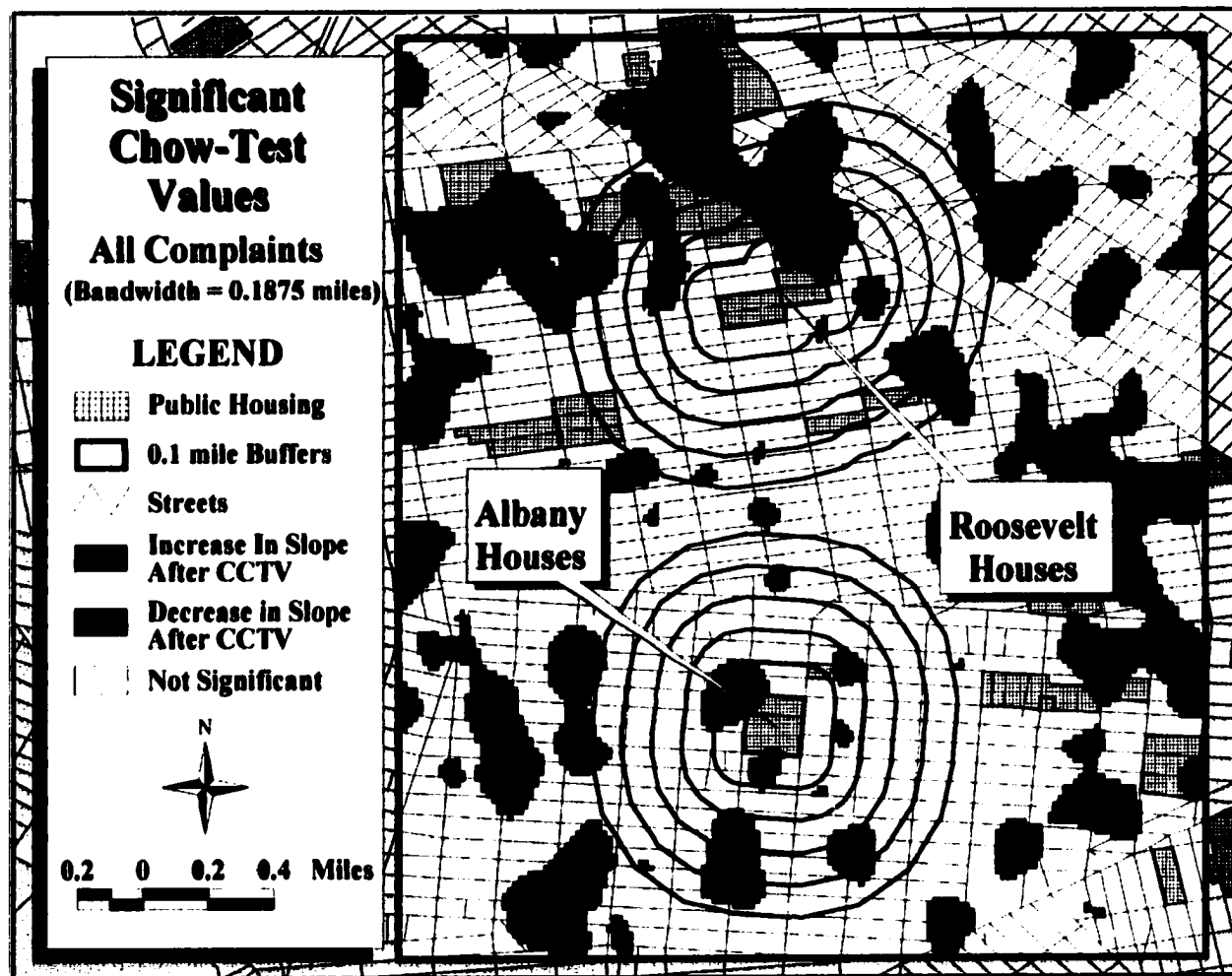


FIGURE 6:7 Significant F Values and Trend of Slope Values, All Complaints

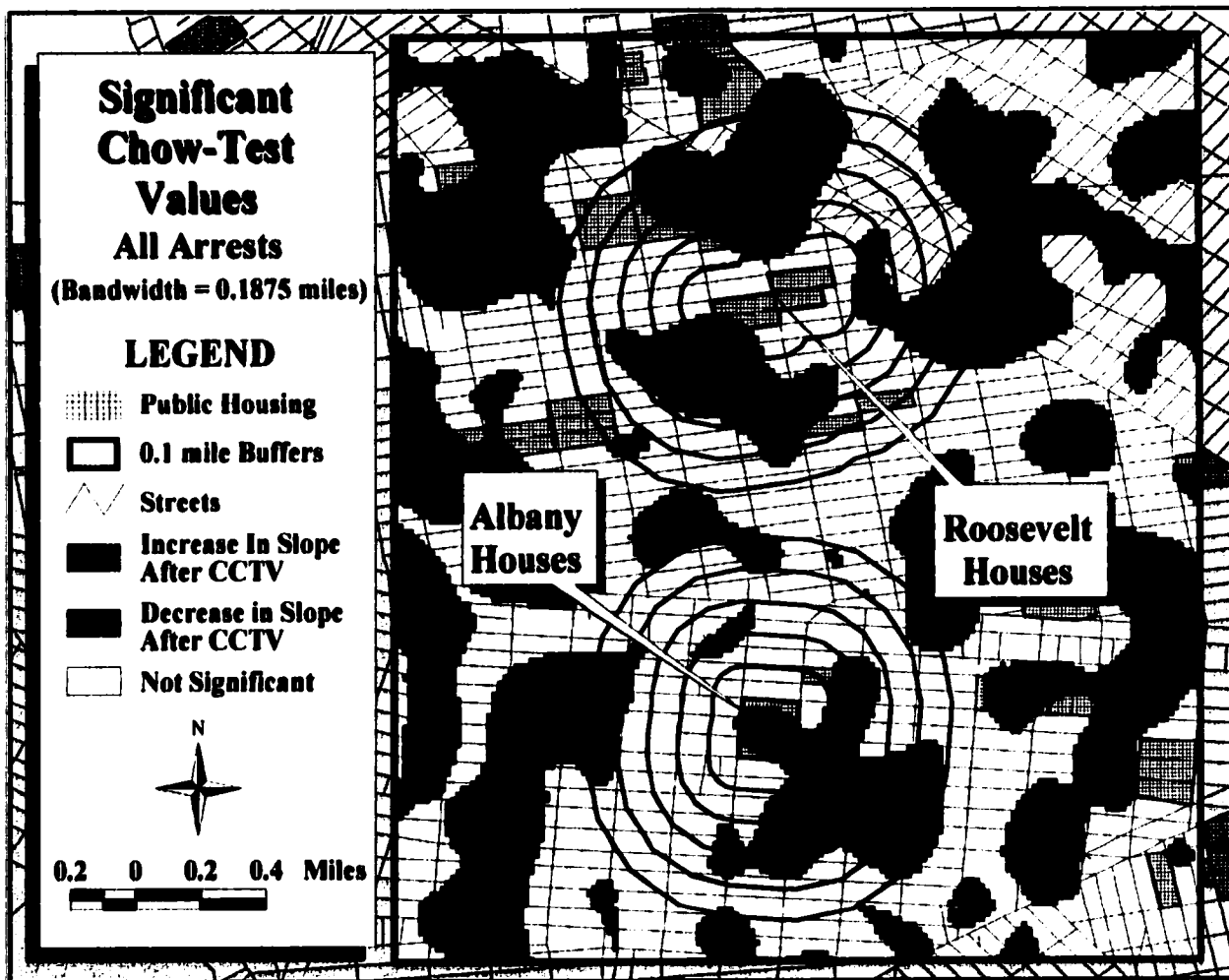


FIGURE 6:8 Significant F Values and Trend of Slope Values, All Arrests

Discussion and Conclusions

Segmented regression builds on the standard regression model. It is particularly useful in evaluation studies with its ability to compare the equality of before and after scenarios via the error terms of the respective regression models. In the case of CCTV installation at certain Brooklyn public housing sites, there appear to be significantly different trends in some small areas near the study site for certain crime complaint types. Complaints in general have smaller uniform areas of increasing or decreasing trends. Larger uniform areas are observed for arrests. The decreasing trends for all complaints, indicator complaints and felony complaints immediately at and adjacent to the Albany Houses may be attributed to the installation of CCTV. The large areas of decreasing arrests are also significant as they may be related to CCTV. A diffusion of benefits may be seen at some distance from the study site, particularly at the bodega, a known location for criminal activity across the street. Increasing trends in the area between Albany and Roosevelt may indicate displacement.

Chapter 7: Animation

A recent trend in spatial analysis is the development of methods for exploratory spatial data analysis (ESDA). ESDA methods allow one to start without hypotheses about the geospatial data and then explore the data to search for patterns and generate hypotheses. Geovisualization tools, ie spatial statistical methods, optimization methods, etc., assist in an interactive, undirected search for structures and trends. Maps and visualization techniques such as animation provide a basis for formulating hypotheses about patterns and processes. Therefore, the entire process of ESDA begins with an idea about the data and develops into a goal-oriented examination of an hypothesis, where geovisualization (animation) should lead to confirmation or rejection.

Uses of animated cartography and GIS traditionally, have been to visualize the spatial aspect of the data, particularly when a there is a priori knowledge about the presence (or absence) of some phenomenon such as urban sprawl or deforestation. Recently, advanced visualizations have been done with respect to error visualization (Ehlschlaeger et al 1997 and Cockings et al. 1997). In these examples, animation is used to confirm existing hypotheses, as well as develop new ones. For the purpose of this research, hypotheses already exist about the data. Specifically, it is expected that crime will decrease in the areas in and around public housing directly following the installation of CCTV. It is further

hypothesized that areas in and around public housing developments without CCTV may show an increase of crime incidence directly following the installation of CCTV at the other development. It is hoped that animation will clearly reveal these patterns.

Data

This section explains the data and methods used in creating and analyzing the cartographic animations. Again, the data were created and manipulated primarily in the ArcView GIS, through out of the box functionality as well as some custom scripting. The animations are viewed in the Windows Media Player, but could be viewed in any software that supports the AVI file type, including Microsoft PowerPoint.

The point locations of crime incidents were used to create density grids of crime as described above. These density grids used as input are the same as the grids used in the segmented regression section. That is, one density grid is created for each month for each crime type, for the eighteen-month periods, before the installation of CCTV in the Albany Houses (January 1997 through June 1998), and after the installation of CCTV (July 1998 through December 1999), for a total of thirty-six grids for each crime type (See Figures 7:1 – 7:6). Another set of grids is also used for input into the animations. These grids are derived from the original crime density grids and represent the difference in crime density from one period to the next. For example, the density from January 1997 would be

subtracted from the density of February 1997 (see Figures 7:7 – 7:12), resulting in a new grid of difference values. The result here is thirty-five difference grids.

Methodology

All the grids were created in ArcView's Spatial Analyst extension. Since the grids encompass such a large time period, the range of density values is extremely large, even for a single type of crime. Because of this, and to ensure consistency of the maps in the animations, legends had to be created that would span the entire range of possible values, and could be used for each grid. To do this, the minimum and maximum density values for each grid were determined over the entire time period and then used as the starting and ending values for the data classes in the legends. Intermediate classes were then extrapolated based on these values. After the density grids and associated legends were ready, they were used to create monthly density maps, which also show the locations of the Albany and Roosevelt Houses, the 0.1 mile buffers and the street network. These maps were then exported as Windows BitMaps (BMP). To automate this process, an Avenue script was created for preparing the layout and exporting the image. Once generated, each image is input into a shareware product known as VFD (Video for DOS). This software streams each image into a video file. The result is an animation file that can be viewed by most multimedia systems. Each AVI file contains thirty-six frames (thirty five for the difference maps), playing at one

frame per second, for a total of 36 (or 35) seconds. While there has been some research on the optimum number of frames per second, one frame per second was chosen here. Although it was arbitrary, several other values were tested, namely 0.5 frames per second and 2 frames per second. However, these rates seemed to over or underestimate the rates of change, and no patterns could be discerned. Also, the total length of the animations resulting from one frame per second, 36 seconds, seemed a more reasonable amount of viewing time for each series.

Results

As stated earlier, the goal of animation is primarily exploratory data analysis, or scientific visualization. Therefore, the analysis is less formal and more ad hoc compared with the other spatial statistical methods used in this thesis. There are no statistical tests or significance values. Instead, the analyst views the animation and searches for unusual or interesting patterns. In this research, we are searching for patterns that might reflect the differential impacts of CCTV on crime patterns around the two housing sites. The animations or visualizations do provide interesting information about such impacts, although there are no formal hypothesis tests.

First, and most surprising, there is no glaring change in crime densities around the Albany Houses after CCTV was installed (see AVI files). This is particularly obvious in the animations for all complaints (all_com.avi) and all arrests (all_arr.avi). It was expected that the values would decrease significantly after the installation in areas adjacent to the Albany Houses, however, this never really occurs. From the animation of all complaints animation we see the areas to the northwest stay relatively constant even after the installation of CCTV occurs. Another phenomenon that is expected is displacement. If displacement occurred, one would expect areas of higher crime density to appear at some distance from the Albany Houses where the density had been lower previously. Again, this never materializes in the animations. This is seen in the animation for misdemeanor arrests. Although there are occasional 'spikes' of crime in outlying areas, these spikes do not persist over time, and they are present both before and after installation of CCTV. They appear to represent normal 'random' occurrences of high crime density, rather than displacement related to CCTV.

An unexpected characteristic of all the animations is the wide variation in densities from month to month. Geographic variation is expected within each month individually: that is, there will be areas with high density, and other areas with low density. However, in the animations, the density values vary considerably at the same location from month to month. This appears to be true for all crimes, not just those with small initial values as would be expected. This

illustrates the truly random nature of crime and reiterates the fact that at very small temporal and spatial scales, crime is very unpredictable.

This becomes extremely clear when looking at the difference map animations. At certain locations, the differences in density values switch from positive (higher density minus lower density) to negative (lower density minus higher density) then back to positive. This suggests that at one point in time the density value was relatively high, the next, the value was lower then finally, the value increases again. This pattern is clearly seen in the difference of all complaints and difference of all arrests where the values appear to alternate back and forth between high and low. All this indicates that at any given location the density of crime can vary greatly from one point in time to the next.

Additional information may be gleaned from the 'difference' animations (animations based on change in crime density over time) than was evident in the standard animations. For example, in the difference animation of major felony complaints, the month of CCTV installation, July 1998, shows a dramatic drop in density near the Albany Houses. This is difficult to see, if at all, in the standard animation for the same crime type. Unfortunately, this decrease is not sustained, and the values increase shortly thereafter. Similar patterns emerge in the difference animations for felony arrests and all complaints, where a temporary

decrease in density is observed followed by an increase to higher values. Interestingly, the reverse pattern occurs for felony complaints. For this crime type, it appears that the density increased when CCTV was first installed then stabilized immediately after. For indicator complaints, the differences vary around Albany when CCTV is installed, one area shows a decrease, while other nearby areas show an increase.

Conclusions

Although animation is not a formal statistical technique, it is a useful tool in visualizing data, particularly spatial-temporal data. From the animations, it is inferred that there is no obvious change in crime densities around the Albany Houses after CCTV was installed. The animations of difference maps, from one time period to the next, reveal subtle changes in crime density over time. It appears that crime density varies widely, not only within individual time periods, but also between time periods. This may be due to the random nature of the crimes themselves, or it may be an effect of policing efforts such as the reactionary Compstat process. Compstat's weekly and monthly meetings may have a short-term impact on crime, but these benefits may be short-lived as seen in the animations. In summary, the animations do not show any clear geographical impact of CCTV on crime yet they do reveal some interesting patterns in the variable nature of crime.

Chapter 8: Raised Incidence

This section explains the data and methods used in analyzing the raised incidence models. As with the other methods, the data were created and manipulated primarily in the ArcView GIS, through out-of-the-box functionality as well as some custom scripting. Further analysis was performed in SPSS version 11 for Windows. The data consists of the crime incident information described previously, specifically the geocoded crime incidents, along with other 'derived' information, including distances from the Albany and Roosevelt developments.

Data

The point locations of crime incidents were used to create density grids of crime as described in Chapter 2. These grids differ from the previous grids in several ways. The extent, cell size and bandwidth are the same. The grids however, are not broken down into monthly time periods. The time periods in this case are the period before the installation of CCTV in the Albany Houses, January 1997 through June 1998 and the period after CCTV installation, July 1998 through December 1999. Therefore each time period contains 18 months of incident data. Kernel estimation was used to compute smoothed estimates of total crime density before CCTV and after CCTV by grid cell. These before- and after-grids were created for all the crime groupings as described above. Once the grids were

created, they were converted into point datasets so they could be used as input into SPSS. That is, each density grid cell was transformed into a point (X, Y) with its associated density value. One record in the SPSS data table was created for each grid cell location on the map. This was done using an Avenue script custom written for this purpose.

Information on distance to public housing was required for each point as input into the raised incidence models. To do this, distance grids were created in ArcView. The distance grids have, as an attribute, the distance values to features as defined by the user. In this case, the features are public housing sites. The process to create these distance grids is trivial, as it is included within ArcView's Spatial Analyst extension. After the distance grids were created, they were converted to points using the same script mentioned above. Once the two point themes were created, they were joined into one table containing both density and distance values. This was a spatial join based on location.

The last step in preparing the data was the 'clipping' of the point files. The resulting point files contain only those points that are within a distance of 0.5 miles of either the Albany Houses, or the Roosevelt Houses. This was done for two reasons. First, and foremost, by limiting the distance to 0.5 miles, effects from other public housing communities will not be a factor, since typically developments are located at some distance greater than 0.5 miles from on

another. Second, by analyzing only these areas, other non-modeled factors such as varying demographics and different neighborhood characteristics will not be a factor. For the purpose of this analyses, the areas are considered homogeneous.

Methodology

It is hypothesized that public housing will act as a 'magnet' for crime. That is, the incidence of crime will be higher close to housing developments than far away. It is further hypothesized that after the installation of CCTV, public housing will act in the opposite fashion. That is developments with CCTV will repel crime occurrences. From these principles, a regression model can be developed that uses the intensity of crime as the dependent variable, and the distance from public housing as the independent variable. Models can be estimated before and after CCTV to assess changes in spatial relationships.

There are a number of expected patterns that may emerge when examining the density of crime and the distance to public housing. First, it is expected that around the Albany Houses, crime density would be inversely proportional to distance before the installation of CCTV. Here, as the distance increases away from Albany, the crime density would decrease. In other words, the slope of the regression line would be negative. Second, in the period after the installation of CCTV, crime density would be proportional to the distance. In this case, crime

density would increase as the distance away from Albany increased, or the slope of the regression line would be positive. For the entire period of the study, it would be expected that the two periods would offset one another, and the result would be that distance has no effect on crime density and the slope of the regression line would be zero.

In the case the Roosevelt Houses, there would be different expectations. Specifically, in both periods, before and after the installation of CCTV, crime density would be inversely proportional to distance. That is, as the distance increases away from Roosevelt, the crime density will decrease. It is expected that, that Roosevelt will act as a 'magnet' for crime, regardless of the time period.

The regression analysis was performed in SPSS. Initially, it was anticipated that Ordinary Least Squares (OLS) would provide reasonable explanation of the model. However, after further investigation, it was realized that the data did not meet the requirements of OLS. Specifically, the data indicate heteroskedasticity. That is, the variance of the errors is not normal. Initially, weighted least squares was used to correct for heteroskedasticity, however the correction had no impact on the findings, and given the overall lack of explanatory power, the correction was not continued.

Results

The regression coefficients from SPSS indicate that the model fits for the data are extremely poor. In other words, the incidence of crime doesn't conform to a distance model. The distance to housing developments does not affect crime density. From Table 8:1 and 8:2, it can be seen that values for r^2 are extremely small, typically ranging from 0 to 0.1, which suggests a poor 'goodness of fit' for the models, or little explanation of the variation of crime density. Although the r^2 values were extremely low, most of the categories had significant F values. Although this implies that the r^2 values are significantly different from zero, the significant F values are due in large part to the large number of observations.

Regression Results - ALBANY						
PERIOD 1 (PRE-2004)						
Incident Type	Constant	Age	Age ²	Age ³	Age ⁴	Age ⁵
Complaints						
All	1.148	0.284	0.000	-31141.346	-1.072	0.284
Felonies	0.212	0.645	0.001	-1015.135	-0.460	0.645
Major Felonies	9.355	0.002	0.003	25130.020	3.059	0.002
Indicators	5.511	0.019	0.002	-44838.432	-2.347	0.019
Misdemeanors	55.674	0.000	0.020	-65028.558	-7.461	0.000
Violations	17.428	0.000	0.006	18905.216	4.175	0.000
Arrests						
All	1.056	0.304	0.000	22921.463	1.028	0.304
Felonies	55.564	0.000	0.020	-59981.042	-7.454	0.000
Misdemeanors	17.239	0.000	0.006	74794.470	4.152	0.000
Violations	29.974	0.000	0.011	3418.408	5.475	0.000
PERIOD 2 (POST-2004)						
Incident Type	Constant	Age	Age ²	Age ³	Age ⁴	Age ⁵
Complaints						
All	9.266	0.002	0.003	88165.027	3.044	0.002
Felonies	14.599	0.000	0.005	-7504.972	-3.821	0.000
Major Felonies	59.282	0.000	0.021	52694.116	7.700	0.000
Indicators	15.643	0.000	0.006	79188.025	3.955	0.000
Misdemeanors	15.912	0.000	0.006	-39913.604	-3.989	0.000
Violations	136.349	0.000	0.047	47847.918	11.677	0.000
Arrests						
All	0.035	0.852	0.000	-4003.555	-0.187	0.852
Felonies	8.921	0.003	0.003	-23388.169	-2.987	0.003
Misdemeanors	3.780	0.052	0.001	28702.087	1.944	0.052
Violations	48.281	0.000	0.017	-5144.582	-6.948	0.000
PERIOD 3 (2005-2009)						
Incident Type	Constant	Age	Age ²	Age ³	Age ⁴	Age ⁵
Complaints						
All	0.976	0.323	0.000	57023.681	0.988	0.323
Felonies	4.970	0.026	0.002	-8556.108	-2.229	0.026
Major Felonies	27.945	0.000	0.010	77824.137	5.286	0.000
Indicators	0.783	0.376	0.000	34349.592	0.885	0.376
Misdemeanors	32.780	0.000	0.012	-104942.164	-5.725	0.000
Violations	64.591	0.000	0.023	66753.134	8.037	0.000
Arrests						
All	0.191	0.662	0.000	18917.906	0.437	0.662
Felonies	28.634	0.000	0.010	-83369.208	-5.351	0.000
Misdemeanors	10.226	0.001	0.004	103496.556	3.198	0.001
Violations	2.044	0.153	0.001	-1726.174	-1.430	0.153

TABLE 8:1 Regression results for Raised Incidence - Albany

RAISED INCIDENTS - ROOSEVELT						
PERIOD 1 (BEFORE CCV)						
Incident Type	Count	Rate	Rate	Rate	Rate	Rate
All	109.978	0.000	0.033	-221619.391	-10.487	0.000
Felonies	0.511	0.475	0.000	-1394.699	-0.715	0.475
Major Felonies	236.255	0.000	0.068	-84993.333	-15.371	0.000
Indicators	156.320	0.000	0.046	-188264.000	-12.503	0.000
Misdemeanors	183.349	0.000	0.054	-116508.701	-13.541	0.000
Violations	245.823	0.000	0.071	-63432.215	-15.679	0.000
All	108.35939	0	0.03256	-194684.3238	-10.41	0
Felonies	30.20491	0	0.00929	-57566.73173	-5.496	0
Misdemeanors	239.62037	0	0.06926	-133517.9723	-15.48	0
Violations	390.2863	0	0.1081	-13217.6788	-19.756	0
PERIOD 2 (AFTER CCV)						
All	132.541	0.000	0.040	-236752.222	-11.513	0.000
Felonies	13.565	0.000	0.004	-7193.417	-3.683	0.000
Major Felonies	358.435	0.000	0.100	-90759.405	-18.932	0.000
Indicators	195.093	0.000	0.057	-198278.817	-13.968	0.000
Misdemeanors	120.337	0.000	0.036	-97991.937	-10.970	0.000
Violations	454.365	0.000	0.124	-74025.610	-21.316	0.000
All	236.344	0.000	0.068	-264469.768	-15.373	0.000
Felonies	172.317	0.000	0.051	-111802.556	-13.127	0.000
Misdemeanors	328.756	0.000	0.093	-153717.000	-18.132	0.000
Violations	255.343	0.000	0.073	-14157.082	-15.979	0.000
PERIOD 3 (AFTER CCV)						
All	126.100	0.000	0.038	-458371.613	-11.229	0.000
Felonies	5.319	0.021	0.002	-8588.116	-2.306	0.021
Major Felonies	306.415	0.000	0.087	-175752.738	-17.505	0.000
Indicators	183.648	0.000	0.054	-386542.954	-13.552	0.000
Misdemeanors	164.924	0.000	0.049	-214500.637	-12.842	0.000
Violations	367.472	0.000	0.102	-137457.826	-19.170	0.000
All	170.116	0.000	0.050	-459154.093	-13.043	0.000
Felonies	82.188	0.000	0.025	-169369.000	-9.066	0.000
Misdemeanors	308.315	0.000	0.087	-287235.971	-17.559	0.000
Violations	384.427	0.000	0.107	-27374.761	-19.607	0.000

TABLE 8:2 Regression results for Raised Incidence - Roosevelt

All of the F values for period 1 around Albany are statistically significant (at 95% confidence) except for felony complaints and all arrests. For period 2, all categories have significant F values except all arrests. All complaints, indicator complaints and all arrests do not have significant F values, while the remaining categories are statistically significant. For Roosevelt, only felony complaints for Period 1 and Period 2 are not significant. All other groups have significant F values.

In spite of the poor fit of the models, it is useful to examine the slope values for each crime type. For Albany complaints, only major felonies and violations had positive slopes during Period 1. This suggests, in general, those densities decrease as one moves away from public housing. During Period 2 however, only two types had negative values, namely, felonies and misdemeanors. That is, for these crime types, the density decreases as one moves away from public housing. Interestingly, only the B values for all complaints and indicators are negative for Period 1 and positive for Period 2, suggesting that crime decreases away from public housing before CCTV installation and increases afterwards. All of the complaint types, except felonies and misdemeanors have positive slopes for the entire study period. This implies that, overall, the density for these crimes increases as you move away from the development, which goes against the hypothesis that public housing developments are a magnet for crime

For arrests around Albany, only felonies had a negative slope for Period 1. All arrests and misdemeanors both had positive slopes. For Period 2, however, all arrests and felony arrests had a negative slope while misdemeanor arrests are positive. Therefore, none of the arrest categories follow the expected pattern of having a negative slope during Period 1 and a positive slope during Period 2. Interestingly though, only felonies have a negative slope for the overall study period. Suggesting that for this type of arrest, the density decreases as one moves away from public housing.

The patterns around the Roosevelt development are considerably different. For all time periods, for all complaint and arrest categories, the slopes are negative. This signifies that in all cases, the crime density decreases as one moves away from the Roosevelt development, implying at least anecdotally that Roosevelt is a magnet for crime. Of importance also, are the significance values of T for the slopes around Roosevelt. With the exception of felony complaints, all the T values are statistically significant. This is not the case with Albany.

It is possible that crime density around public housing may have a directional component. Similar to the way a plume model will follow the prevailing wind direction, crime density may 'move' between locations or follow a specific

directional trend. To test this, traditional aspect maps were created for the periods before and after the installation of CCTV for the all complaints category (see figures 8:1 and 8:2). Unfortunately, based on these two figures, there is no prevailing directional component. It does appear that crime density does follow the street network, which is of no surprise, since the points were geocoded to the street grid. This is particularly clear when looking at the western edge of the study area, where there is a long north-south running swath of westward facing densities (shown in royal blue).

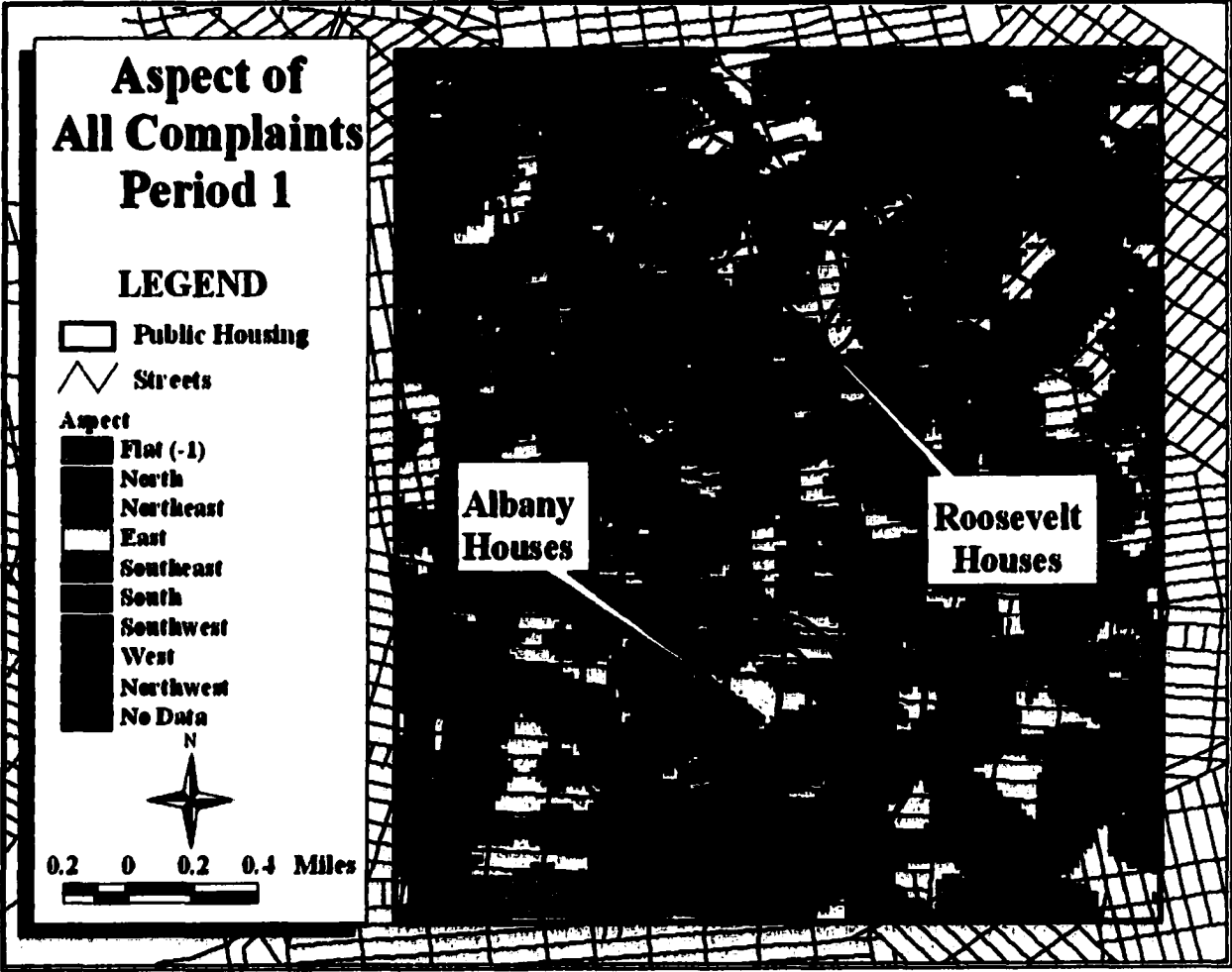


FIGURE 8:1 Direction (Aspect) of Crime Density Surface, All Complains Period 1

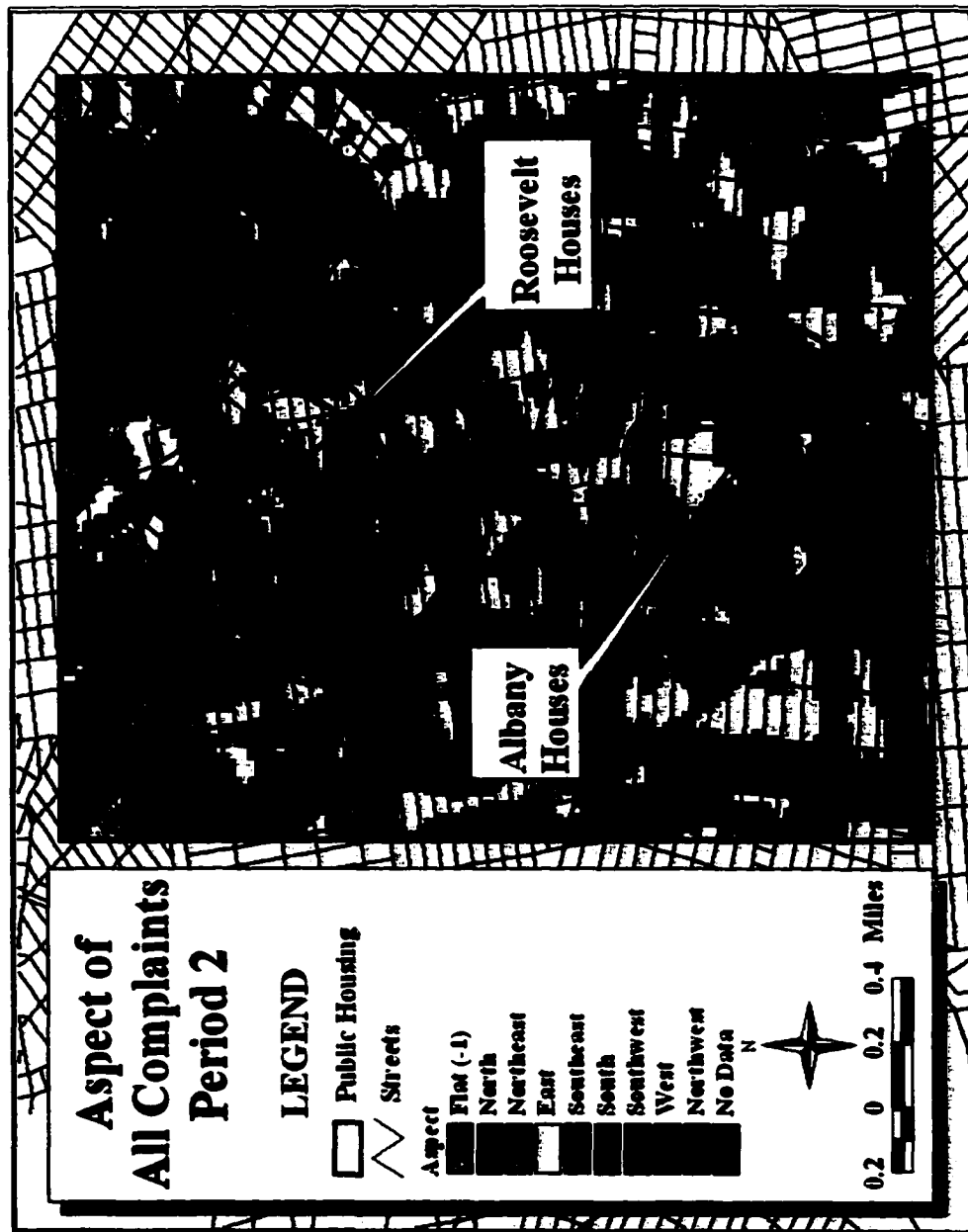


FIGURE 8:2 Direction (Aspect) of Crime Density Surface, All Complaints Period 2

Discussion and Conclusions

Contrary to initial hypotheses, crime density is poorly explained by the distance to public housing, particularly around the Albany Houses. In virtually all cases, the extremely low r^2 values indicate models that fit poorly. The significant F values indicate that r^2 is significantly different from zero. However, this may be misleading because of the very large sample size. Most of the r^2 values are very close to zero, indicating that only a tiny fraction of the variation in crime density is related to distance to public housing.

In short, the models are poor because crime, unlike many environmental phenomena that fit the distance decay model, tends to vary locally. That is, crime density varies widely from place to place, even though public housing developments are nearby. This may be due to a number of non-modeled factors including demographics (population, age, etc), activity specific locations such as transit stations, nightclubs and bars, and schools, or local police activity such as neighborhood watches.

Examining the slopes of the trend lines before and after CCTV installation proved to be an interesting exercise. The negative slopes around Roosevelt for all

time periods suggest that this development is indeed a magnet for crime., which in part supports the initial hypotheses. The Albany Houses, on the other hand, had a more complicated pattern of slopes, some negative, some positive. Of the different categories, all complaints and indicator complaints had negative slopes for Period 1 and positive slopes for Period 2. For these types, the initial hypothesis that Albany will act as a magnet for crime before CCTV installation, and will act as a repellent after CCTV installation, is supported. Unfortunately, the other groupings do not support this.

Chapter 9: Conclusion

The research presented here explains a number of spatial analytic techniques, which can be used in evaluation research for a variety of intervention strategies. While this research is focused on crime, specifically in public housing, this research is useful in any crime prevention program, particularly those in which spatial data plays a key role. These techniques are not limited to crime and crime prevention, and could be extended to virtually all evaluation research studies that use a quasi-experimental design and spatial data including epidemiology, environmental management, conservation, natural resources, sustainable development and business. The focus on the statistical significance of before and after comparisons is relatively new in a geographical context, but as shown here is extremely useful. By using a variety of techniques, variations in results can be identified and possible outcomes explained such as displacement and diffusion of benefits.

Results

Although mixed, the results of this research have proven interesting. While none of the results suggest definitively that CCTV alone has had positive impact on crime reduction, it does appear that there is a strong relationship. While each of the methods is not free from problems, they are all useful in the evaluation of CCTV as an effective tool in crime reduction.

The buffer count analysis, which utilized differences in counts and percent change in counts after the installation of CCTV shows some interesting trends. In the several cases, displacement may be occurring as indicated by the increase in complaints away from the Albany housing project. Whether or not this is due purely to the installation of CCTV is not clear since the statistical tests are not significant. Another point of interest is the possibility of the diffusion of benefits, particularly at the Roosevelt Houses. Certain crime categories indicate an increase around Albany, and a decrease at Roosevelt. Again, this may be a coincidence and not a result of the installation of CCTV at Albany.

The significance tests performed on the buffer counts evaluate whether or not the change in crime is significant. One limitation though is that unfortunately, they don't examine the geographic distribution. In reality, if displacement is present, then crime goes down in the inner rings and goes up in the outer rings. In the statistical tests however, the positive and negative values cancel each other out and the test shows no significant difference. So the significance tests are only useful to show if there are consistent changes.

While this is a significant limitation the technique is still useful, not only for those situations where there is a consistent changes in the rings, but it is also useful as an exploratory spatial data analysis tool. The researcher is easily able to discern

patterns of displacement or possible diffusion of benefits through by examining the values in the various rings between the study and control sites.

Measuring local indicators of spatial autocorrelation, although interesting, did not reveal as much information as was originally anticipated. While it does allow for the examination of spatial dependence in areas surrounding the study and control sites, its difficulty in interpretation does not clearly indicate the exact relationships between neighbors or the presence or absence of displacement.

It is hypothesized here that after CCTV installation around the Albany Houses, a pattern would emerge showing tracts near Albany would have large decreases (low values) based on the differences between Period 1 and Period 2 and would be surrounded by areas with comparably large decreases. Unfortunately, this hypothesis is not supported by the LISA maps.

Unfortunately, there are a number of difficulties associated with LISA measures, particularly in explaining the negative values. While the actual counts for certain tracts may be high in number (positive) the LISA values may be negative if the neighbors are significantly lower. This implies no association, not decreasing crime and thus can be confusing for many readers.

The application of segmented regression in the evaluation of CCTV proved to be an extremely useful exercise. The method is an extremely rich and robust

technique, which gleaned an abundance of information. Based on the results, there appears to be significantly different trends in some small areas near the study site for certain crime complaint types. Larger areas are seen near the sites for arrests. There are both increasing and decreasing trends near the sites. The decreasing trends immediately at and adjacent to the Albany Houses may be attributed to the installation of CCTV, but the possibility exists that it is coincidental. A diffusion of benefits may be seen at some distance from the study site, particularly at a known location for criminal activity across the street. Increasing trends may indicate displacement, but may just be natural occurring spikes that coincide with the installation of CCTV.

Contrary to initial hypotheses, crime density is poorly explained by the distance to public housing, particularly around the Albany Houses. The models are poor because crime, unlike many environmental phenomena that fit the distance decay model, tends to vary locally. This is an obvious limitation of the raised incidence method. The significant F values indicate that r^2 is significantly different from zero. This may be misleading because of the very large sample size and as such can be considered a limitation as well.

This is not to say however that the raised incidence method is not without merit. This technique is useful especially when examining the slopes of the trend lines before and after CCTV installation. The negative slopes around Roosevelt for suggest that this development is indeed a magnet for crime, which in part

supports the initial hypotheses. The Albany Houses, on the other hand, had a more complicated pattern of slopes, some negative, some positive. Potentially there may be a directional component to the incidence of crime, but based on a limited examination, this does not appear to be the case.

Cartographic animation is a useful tool in visualizing data, particularly spatial-temporal data. While the results from the animation study are more subjective than the other analyses and not statistical in nature, certain trends are exhibited. First, it was expected that the values would decrease significantly after the installation in areas adjacent to the Albany Houses, however, this rarely occurs. The animations do not show an obvious change in crime densities around the Albany Houses after CCTV was installed.

Another phenomenon that is expected is displacement. If displacement occurred, one would expect areas of higher crime density to appear at some distance from the Albany Houses where the density had been lower previously. Although there are occasional 'spikes' of crime in outlying areas, these spikes do not persist over time, and they are present both before and after installation of CCTV. They appear to represent normal 'random' occurrences of high crime density, rather than displacement related to CCTV.

In summary, some of the techniques proved to be valuable than others. The segmented regression approach was extremely valuable in pinpointing exact areas

that had significantly different trends before and after CCTV installation. This method could be valuable in any evaluation concerned with change over space and time. Although unsupported statistically, the animations also prove to be useful in visualizing the changes over time. Further refinements need to be made to make them more productive. The LISA analysis is useful for examining spatial variation between areas and is also useful for indicating potential displacement, however, the complicated nature of the statistics and the difficulties involved in interpreting the results make the technique rather cumbersome. The buffer analysis is useful, but the inherent properties of the statistical tests are not necessarily suitable for this geographic data. Similar problems exist with the assumptions in raised incidence models, which assume a uniform pattern in the distribution. For crime analysis, this is known to be untrue.

Comparison to Other Results

The results from this research may not support a clear relationship between the reduction of crime and the presence of CCTV, however they are comparable to other research findings. The recent literature on CCTV and crime prevention shows mixed results. Some studies find a reduction in crime associated with CCTV installation; others find no impact; while a handful of studies suggest that CCTV increases crime in neighboring areas. None of these studies evaluated the impacts on geographical patterns of crime that can arise through displacement and spillover effects.

Issues and Limitations

Much of this variation in the results can be attributed to the diversity of techniques and their associated assumptions and limitations. This research is not attempting to answer the simple question, “does CCTV work?” CCTV is not a cure-all to crime in public housing, and does not exist within a vacuum. In reality, CCTV is part of a number of crime prevention strategies. One glaring difficulty with this and other studies is the problem isolating CCTV from other prevention strategies and measures. Due to the complex nature of crime, that is the large number of causes of crime, it is difficult to isolate or attribute any change in crime levels to one strategy of prevention. When a number of measures are present, it can be difficult to separate any individual element and point to it as a source of success, and so in this case simply installing cameras is no guarantee that crime will reduce in the long term.

It is also difficult, on the basis of the available data, to explain exactly how CCTV had an effect in the context displacement. While some broad geographic patterns of displacement are observed, they are not sustained over time, making it difficult to attribute them to CCTV alone. It is also impossible to estimate if other forms of displacement occurred, such as type offenses or time of occurrence. The problems estimating displacement are clear in the buffer analysis. The statistical tests performed may ‘wash out’ any indication of displacement.

Another issue or limitation is present in the data used for the analysis, specifically the smoothed density maps in the raised incidence section. Because of the large number of sample points, the statistical test indicates significance, when in fact this is attributed to the sample size. In this case, it may be more useful to not create the density maps, but use the initial points and their distances instead.

Related to this is the selection of time categories for the data. This is an issue in the animation section where the monthly breakdowns may not have been sufficient in clearly representing the data. Weekly or daily breakdowns may have been more useful, or perhaps moving averages of time would have been a better representation.

Policy Implications

A number of issues emerge from this and other studies, which have looked at the effect of CCTV on crime. The first is that CCTV seems to work best when it is one of a number of crime prevention measures. It is important that CCTV be used as part of an overall strategy for policing and crime reduction, which in this case would be CompStat, a general command and control strategy. Secondly, as is common with many crime prevention efforts, the effectiveness of policies that include CCTV may wear off over time. Although not addressed here, in order to have a sustained effect, the cameras must play a part in the apprehension of offenders, and other institutional/organizational conditions must be altered to improve the potential of CCTV to have this effect. Camera successes should be

publicized, reinforcing the message for offenders that there is an increased risk of being caught.

The police use CCTV in a number of ways to tackle criminal and anti-social behavior. The primary use of CCTV within public housing is as a tool to 'patrol' these areas effectively and discover incidents as they occur. The police use the information provided by the cameras to coordinate responses to these incidents, and concurrently gather evidence that can direct the investigation of an offense and secure the conviction of an offender. Although camera footage is used in helping to detect an offender after an event has occurred, this is a less common and less effective way of impacting on crime. From this and other studies it appears that CCTV may be best suited for dealing with conspicuous anti-social and criminal behavior, most notably various small scale public order problems, such as criminal mischief, loitering etc. Even though many of these offenses may appear trivial in nature, following the 'Broken Windows' theory, they can be a significant problem especially in public housing communities. If problems such as littering, vandalism and loitering within public housing are not addressed quickly and effectively, they may get worse. The information provided by camera systems is also very useful in helping the police to manage their resources more effectively. Depending on the incident, CCTV can give some indication as to whether or not a police response is required.

Future Considerations

While the classification of incidents into sub-categories such as felony and misdemeanor was useful, further information could have been gleaned had the categories been more specific. It may have been more fruitful had the crimes been grouped either as property crime or personal crime. Since the etiology of personal crimes and property crimes are different, it is expected that different geographic patterns would emerge, particularly around public housing communities. Further still, individual or specific crime types may have been useful, such as robbery, assault, burglary, etc. Finally, if possible, it may have been useful to normalize the data, based on population for example. This would have been interesting specifically in the raised incidence, segmented regression and LISA.

As discussed earlier, effects of crime prevention strategies are often unsustained over time. It would be useful to continue this study with data after 1999. Related to this, it might be useful comparisons similar to the CompStat process based on 'same period'. That is compare the same time periods after CCTV installation to the same time period before CCTV installation, ie., August 1998 compared to August 1997. By using these comparisons, the differences revealed if any, might have more validity from a policing standpoint.

Another approach might be to create a Cox process model of crime using data before CCTV was installed. The Cox process would allow for the accounting of distances to subway stations, housing projects, and other known crime locations. Then, the post-CCTV data could be applied to a Monte Carlo simulation process to determine whether any of the crime hot spots are significantly different than random chance.

APPENDIX A

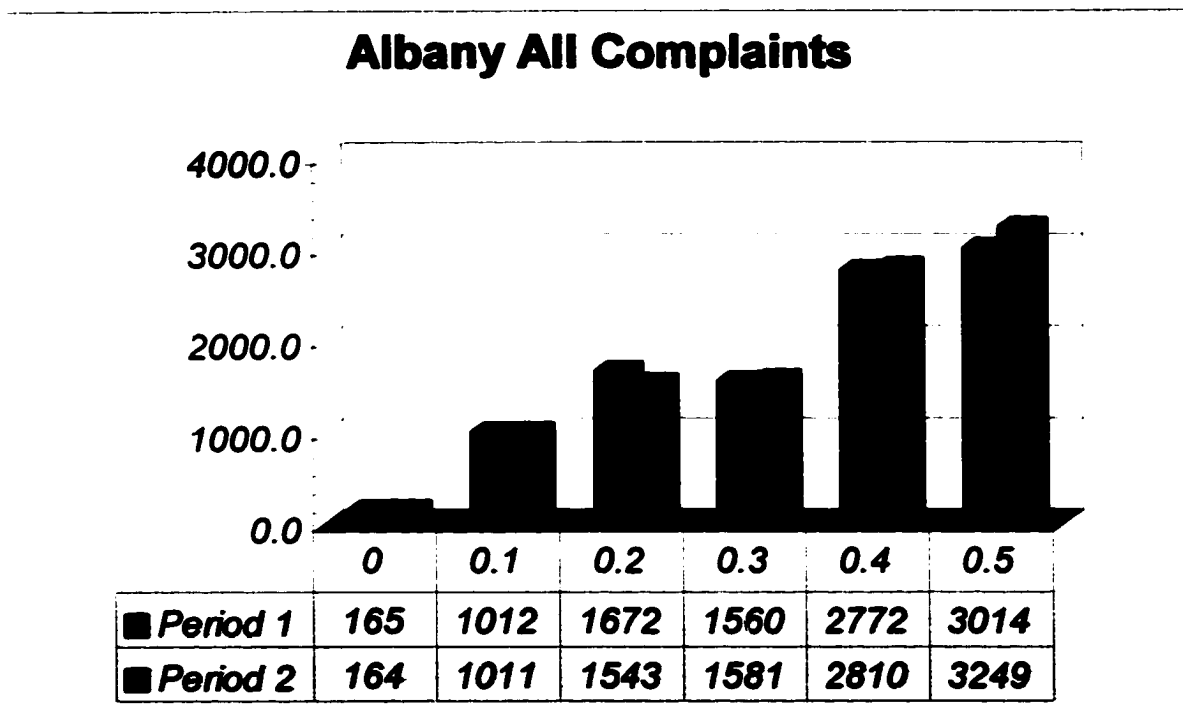


CHART A:1 Counts by Buffer, All Complaints (Albany)

Differences in All Complaints (P2-P1)

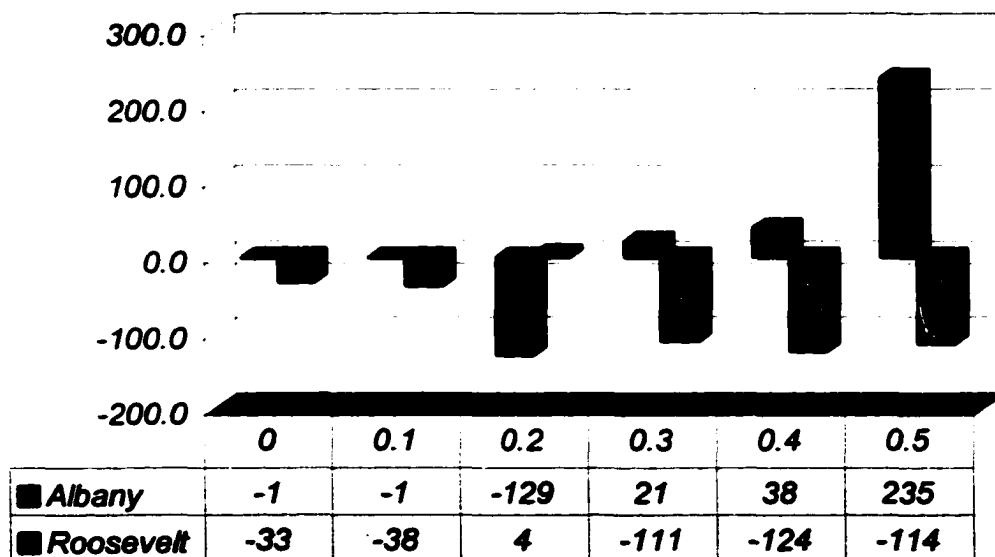


CHART A:2 Difference in Counts by Buffer, All Complaints (Period 2 – Period 1)

Percentage Change (P2 vs. P1)

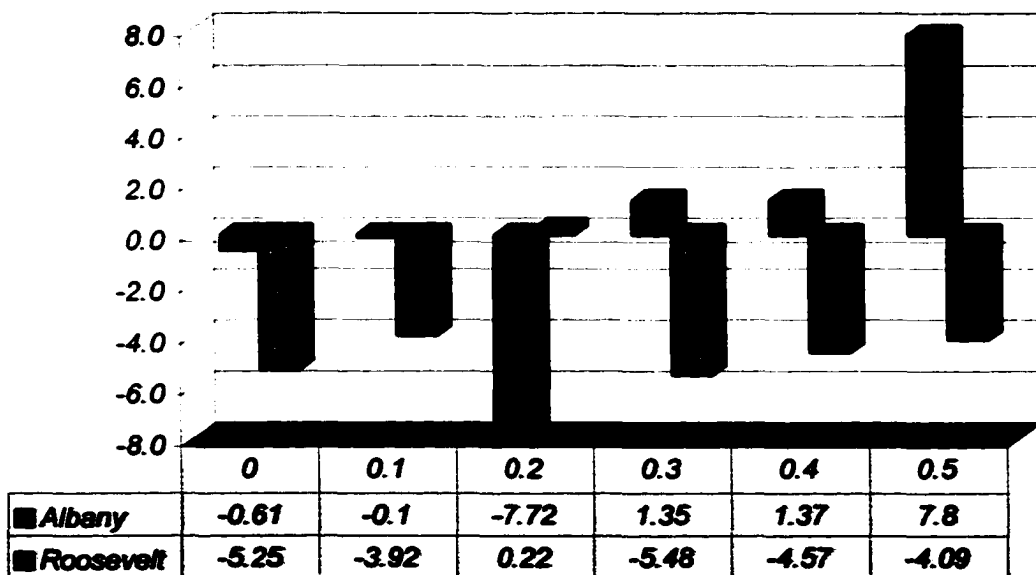


CHART A:3 Percent Change in Counts by Buffer, All Complaints (Period 2 – Period 1)

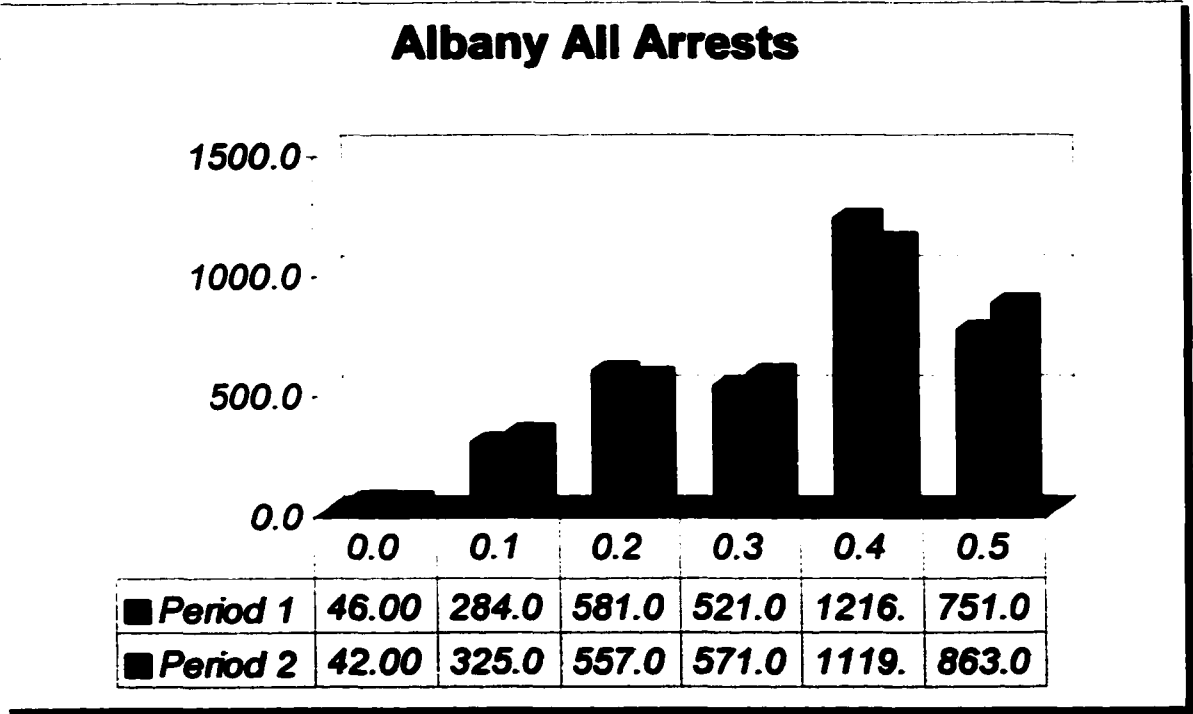


CHART A:4 Counts by Buffer, All Arrests (Albany)

Differences in All Arrests (P2-P1)

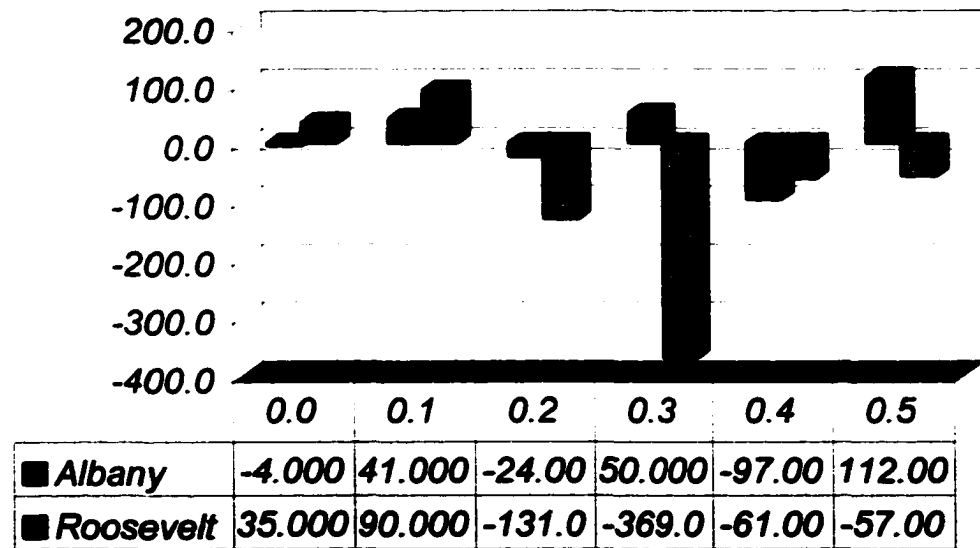


CHART A:5 Difference in Counts by Buffer, All Arrests (Period 2 – Period 1)

Percentage Change (P2 vs. P1)

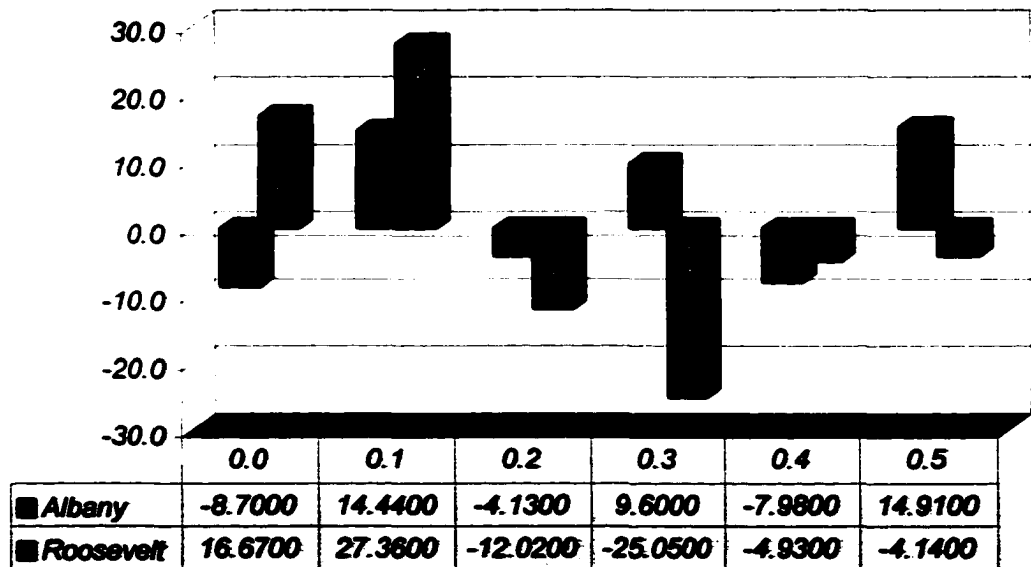


CHART A:6 Percent Change in Counts by Buffer, All Arrests (Period 2 – Period 1)

Albany Violation Complaints

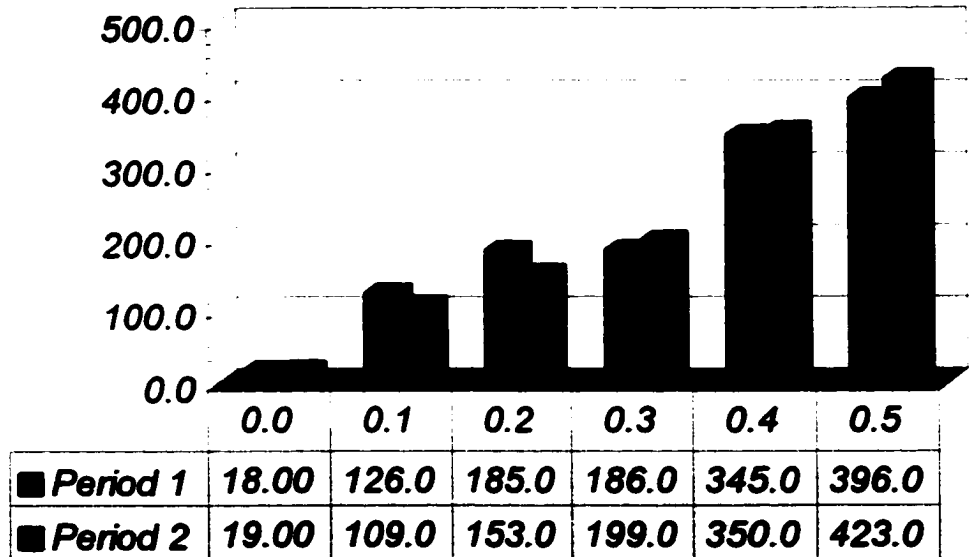


CHART A:7 Counts by Buffer, Violation Complaints (Albany)

Differences in Violation Complaints (P2-P1)

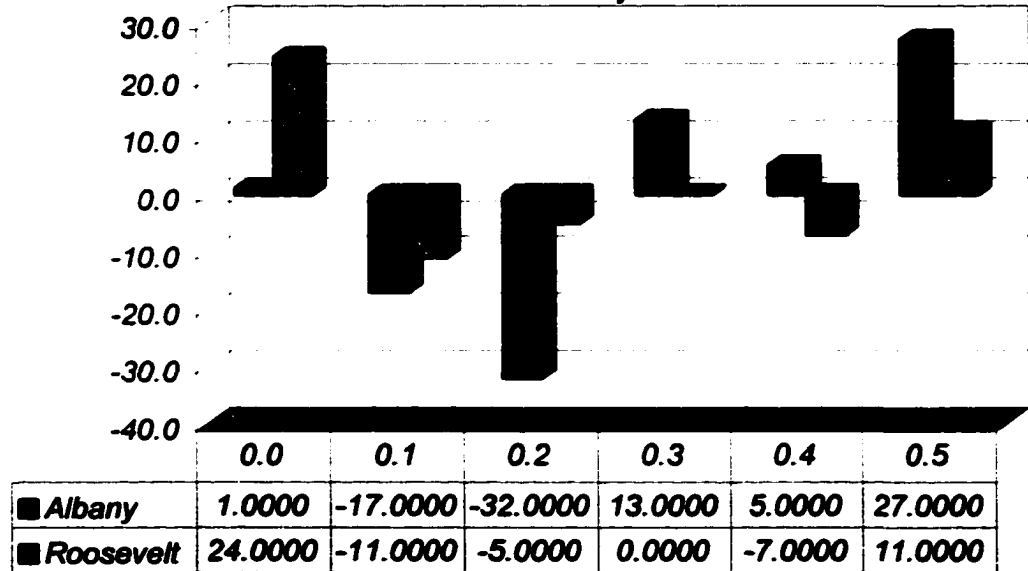


CHART A:8 Difference in Counts by Buffer, Violation Complaints (Period 2 – Period 1)

Percentage Change (P2 vs. P1)

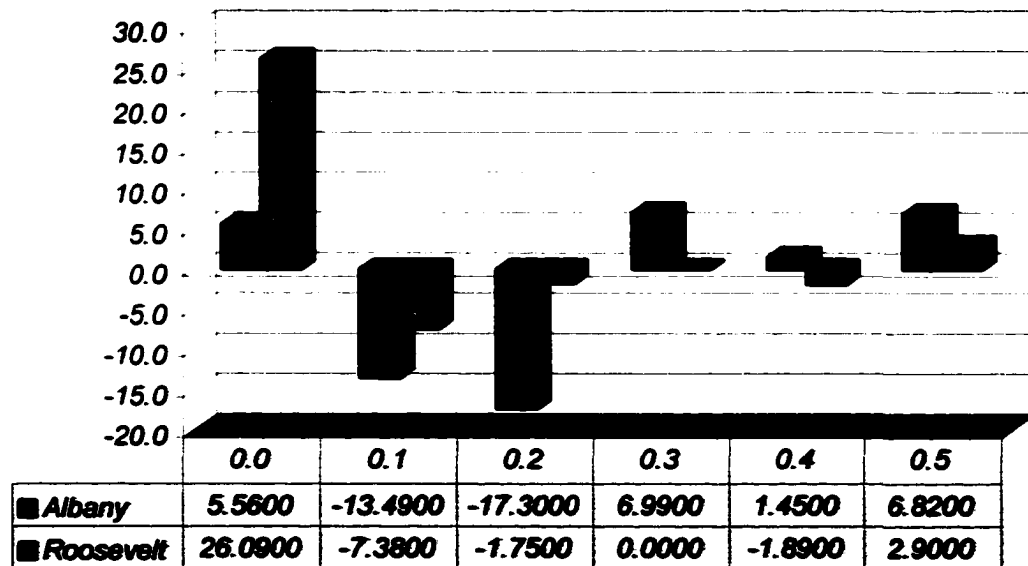


CHART A:9 Percent Change in Counts by Buffer, Violation Complaints (Period 2 – Period 1)

Albany Misdemeanor Complaints

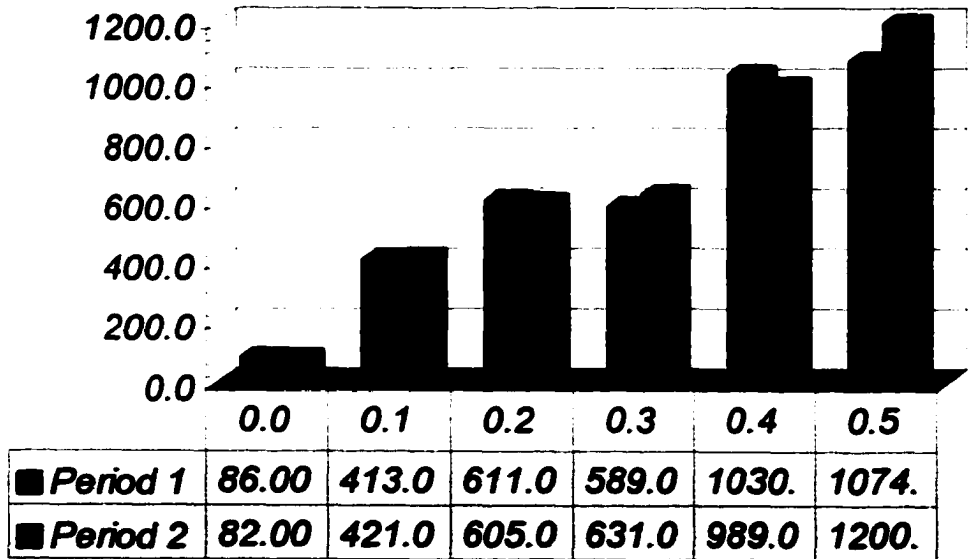


CHART A:10 Counts by Buffer, Misdemeanor Complaints (Albany)

Differences in Misdemeanor Complaints (P2-P1))

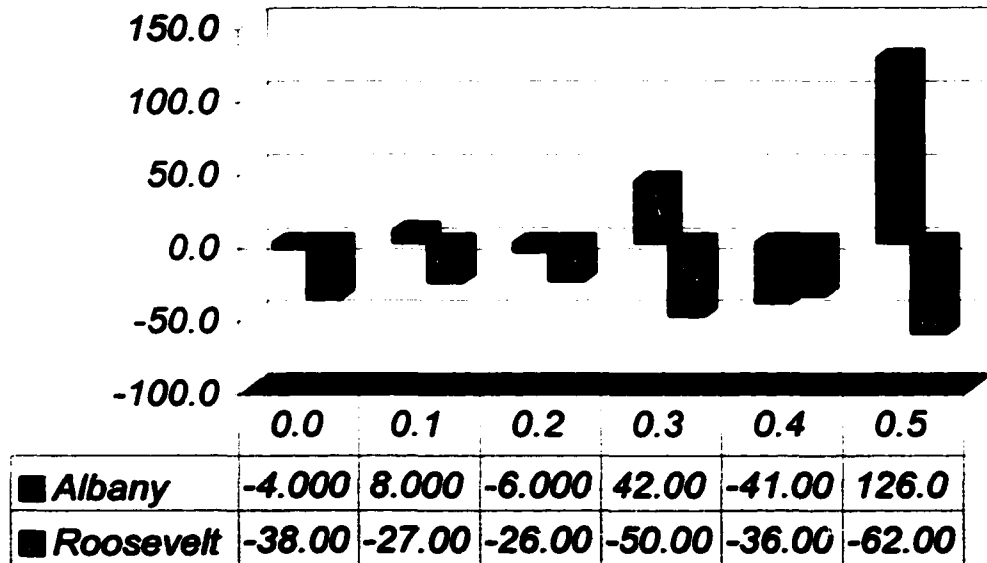


CHART A:11 Difference in Counts by Buffer, Misdemeanor Complaints (Period 2 – Period 1)

Percentage Change (P2 vs. P1)

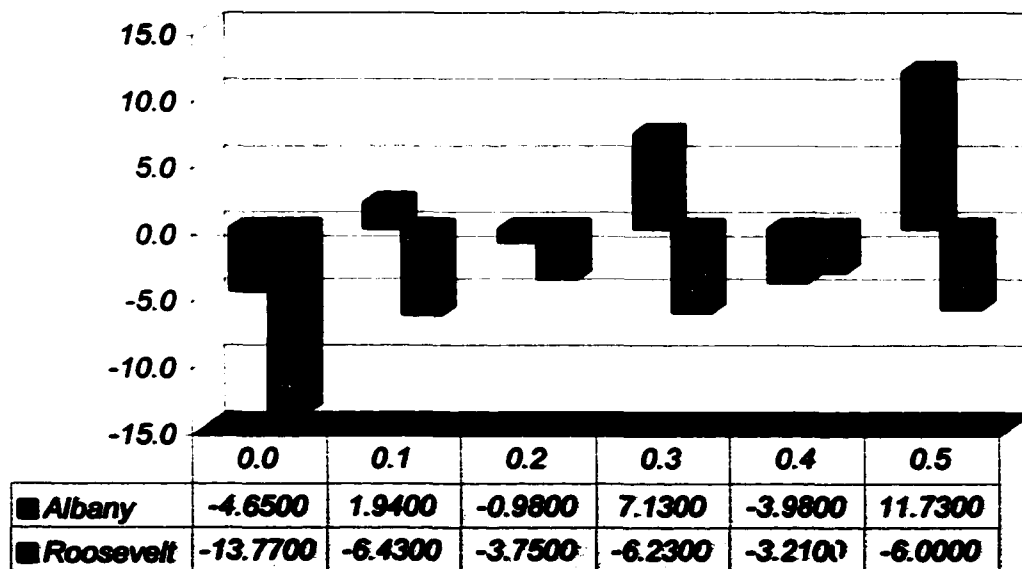


CHART A:12 Percent Change in Counts by Buffer, Misdemeanor Complaints Arrests (Period 2 – Period 1)

Albany Misdemeanor Arrests

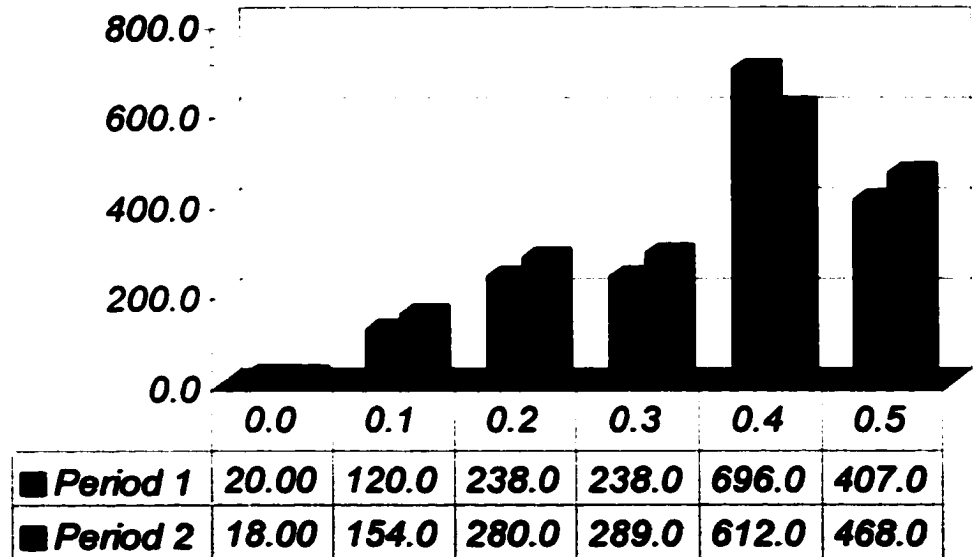


CHART A:13 Counts by Buffer, Misdemeanor Arrests (Albany)

Differences in Misdemeanor Arrests (P2-P1)

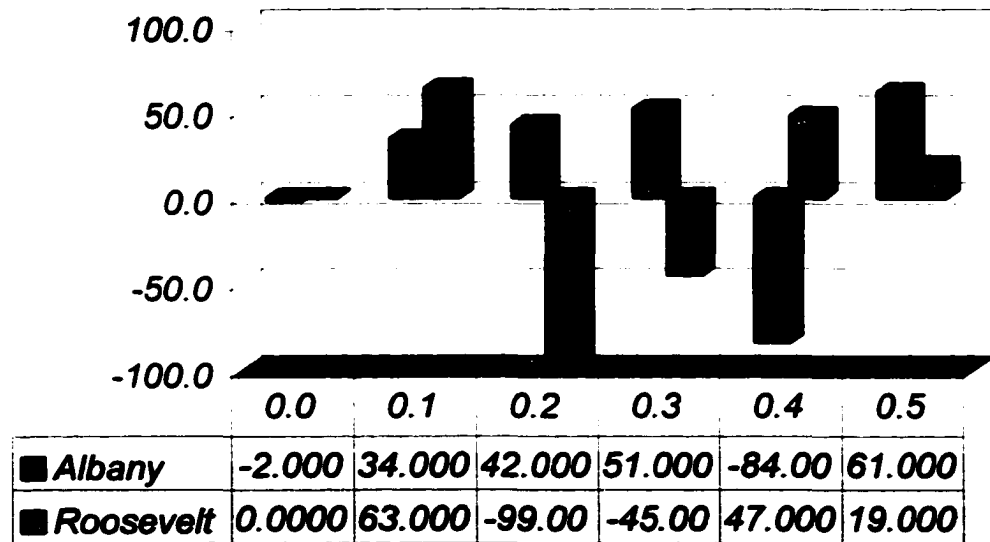


CHART A:14 Difference in Counts by Buffer, Misdemeanor Arrests (Period 2 – Period 1)

Percentage Change (P2 vs. P1)

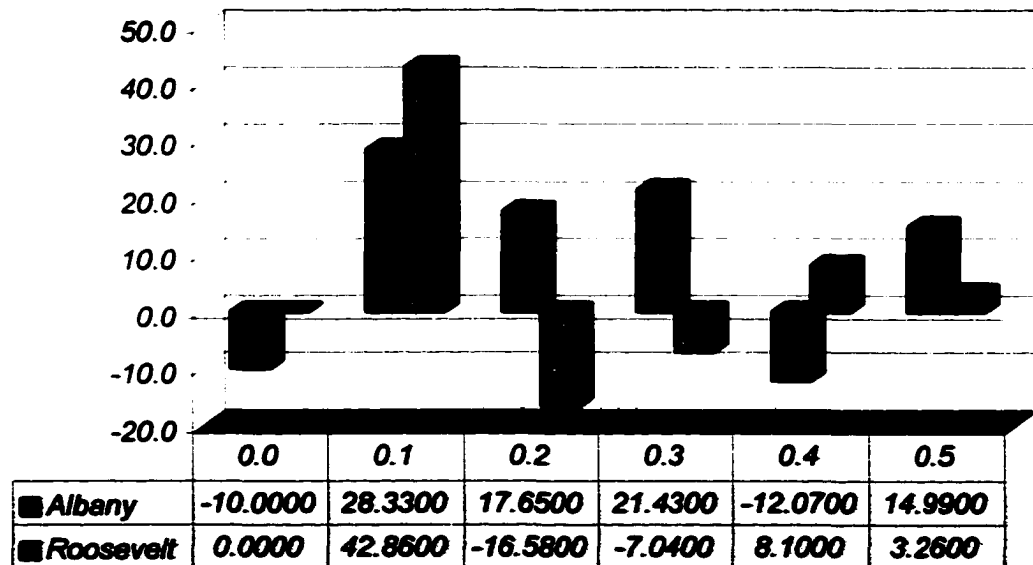


CHART A:15 Percent Change in Counts by Buffer, Misdemeanor Arrests (Period 2 – Period 1)

Albany Major Felony Complaints

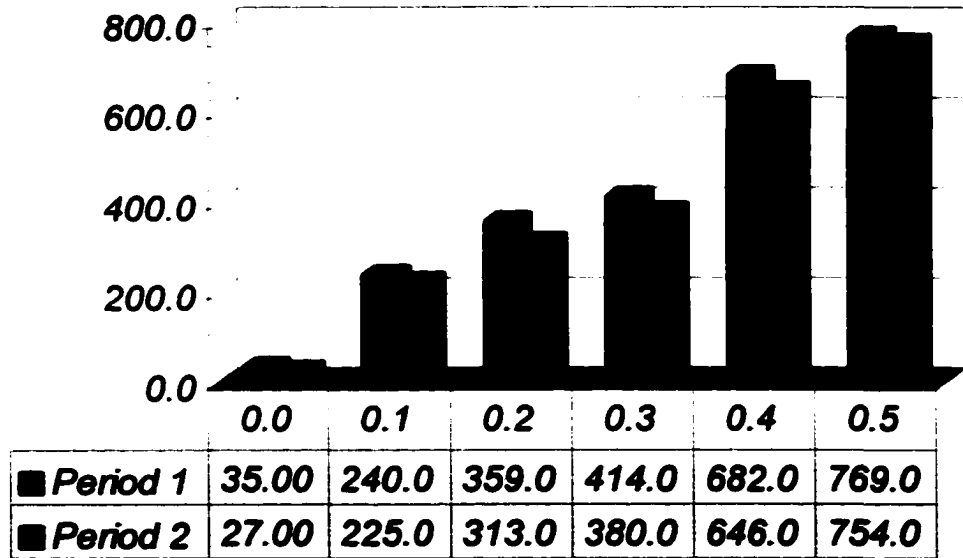


CHART A:16 Counts by Buffer, Major Felony Complaints (Albany)

Differences in Major Felony Complaints (P2-P1)

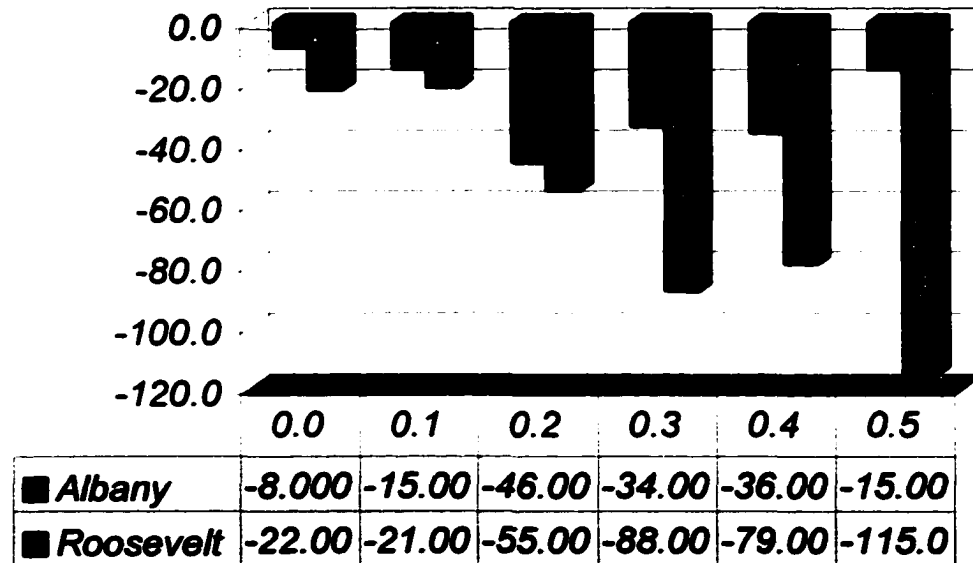


CHART A:17 Difference in Counts by Buffer, Major Felony Complaints (Period 2 – Period 1)

Percentage Change (P2 vs. P1)

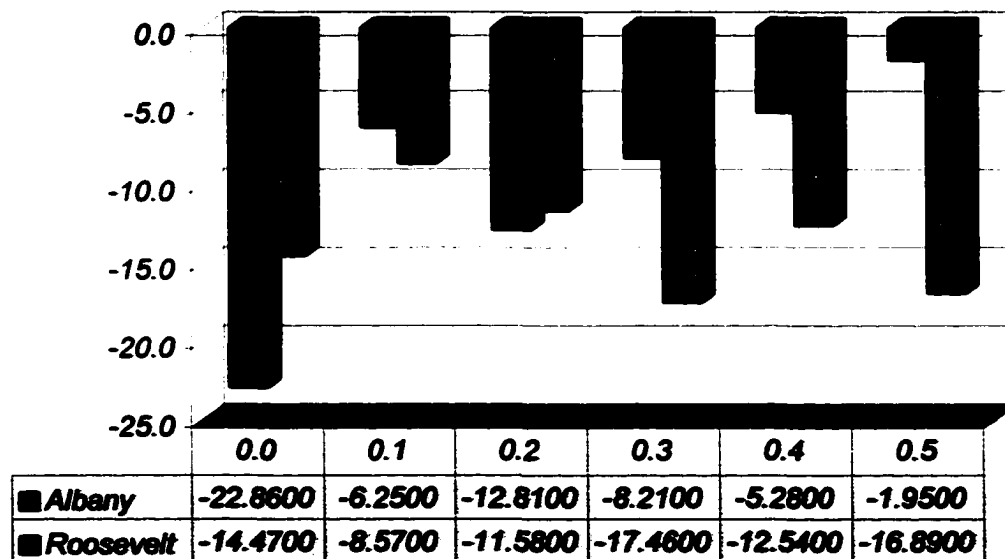


CHART A:18 Percent Change in Counts by Buffer, Major Felony Complaints (Period 2 – Period 1)

Albany Indicator Complaints

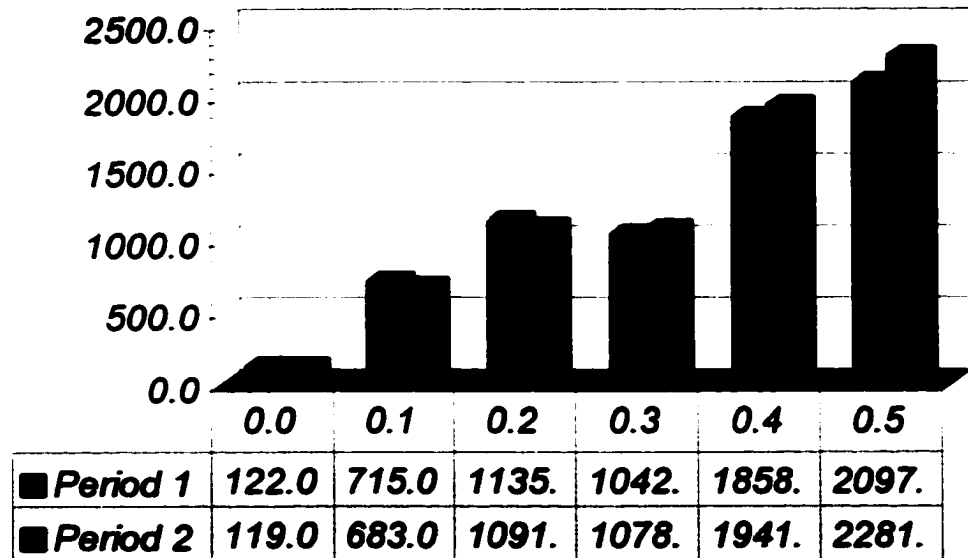


CHART A:19 Counts by Buffer, Indicator Complaints (Albany)

Differences in Indicator Complaints (P2-P1)

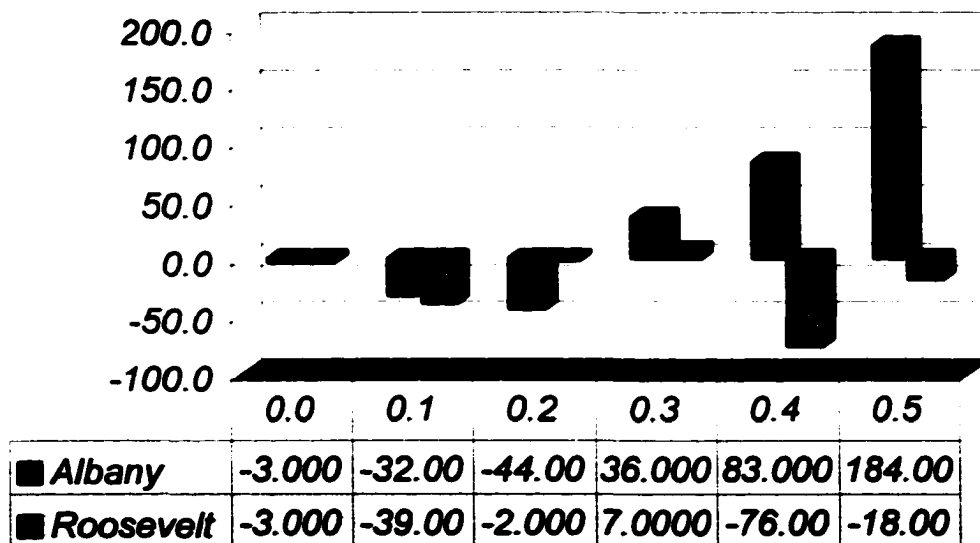


CHART A:20 Difference in Counts by Buffer, Indicator Complaints (Period 2 – Period 1)

Percentage Change (P2 vs. P1)

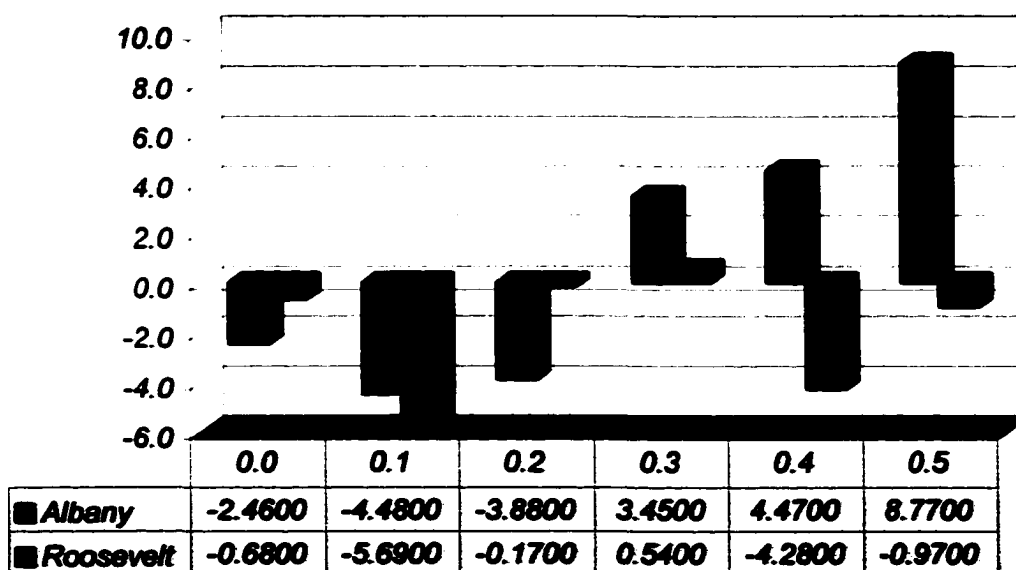


CHART A:21 Percent Change in Counts by Buffer, Indicator Complaints (Period 2 – Period 1)

Albany Felony Complaints

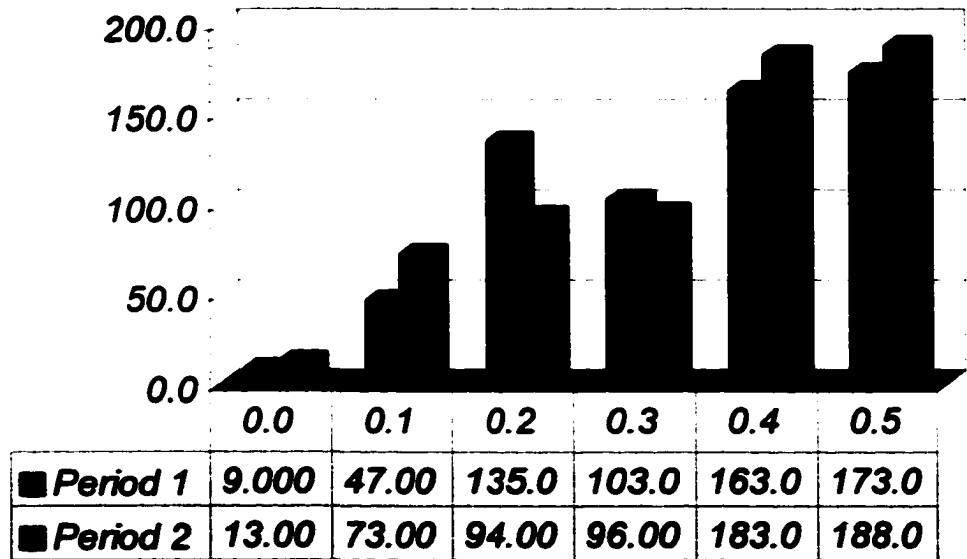


CHART A:22 Counts by Buffer, Felony Complaints (Albany)

Percentage Change (P2 vs. P1)

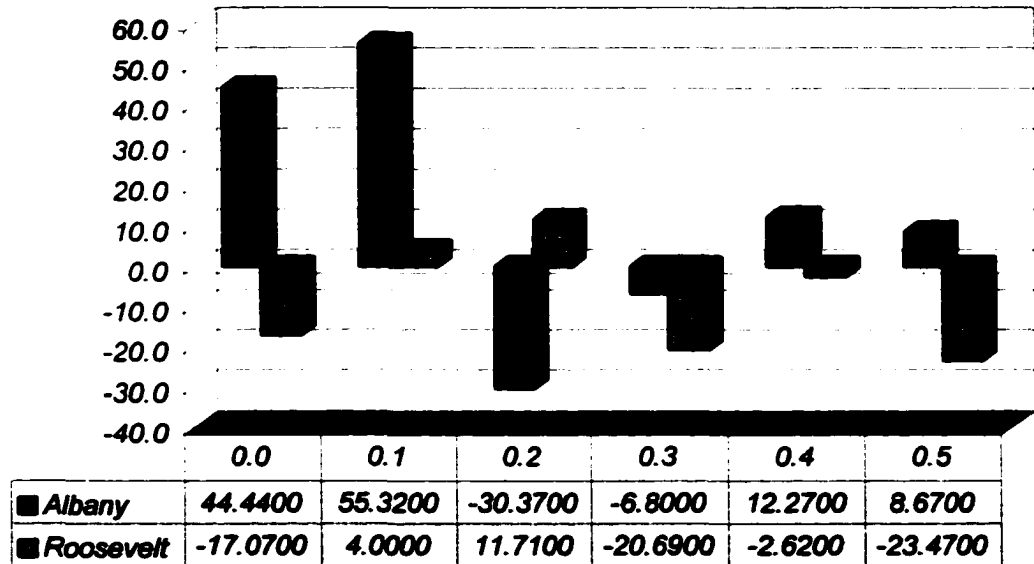


CHART A:23 Difference in Counts by Buffer, Felony Complaints (Period 2 – Period 1)

Differences in Felony Complaints (P2-P1)

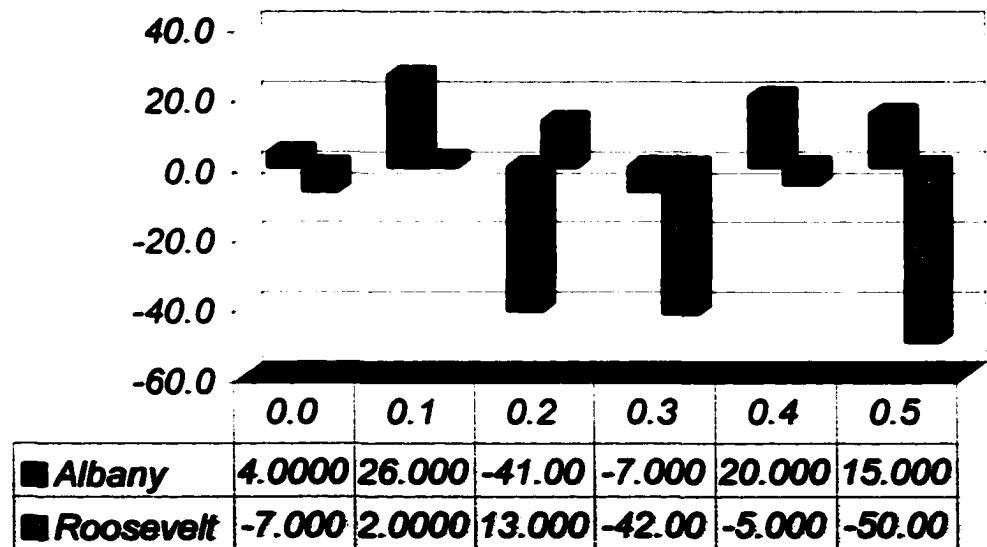


CHART A:24 Percent Change in Counts by Buffer, Felony Complaints (Period 2 – Period 1)

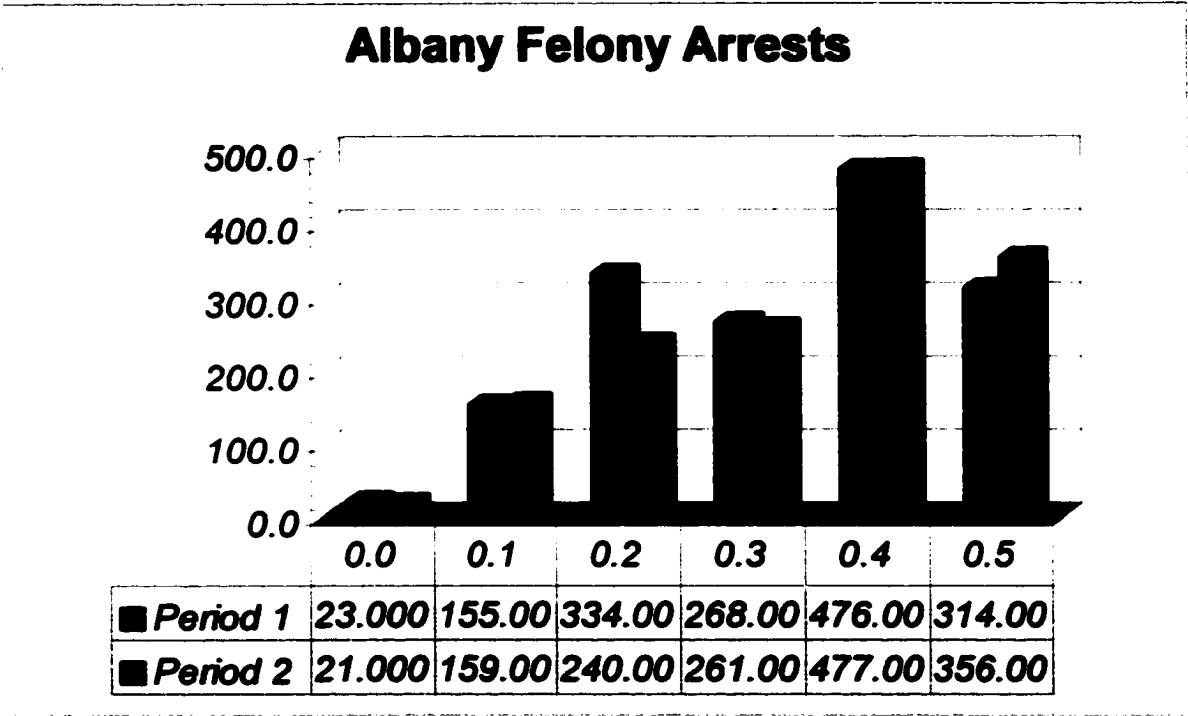


CHART A:25 Counts by Buffer, Felony Arrests (Albany)

Differences in Felony Arrests (P2-P1)

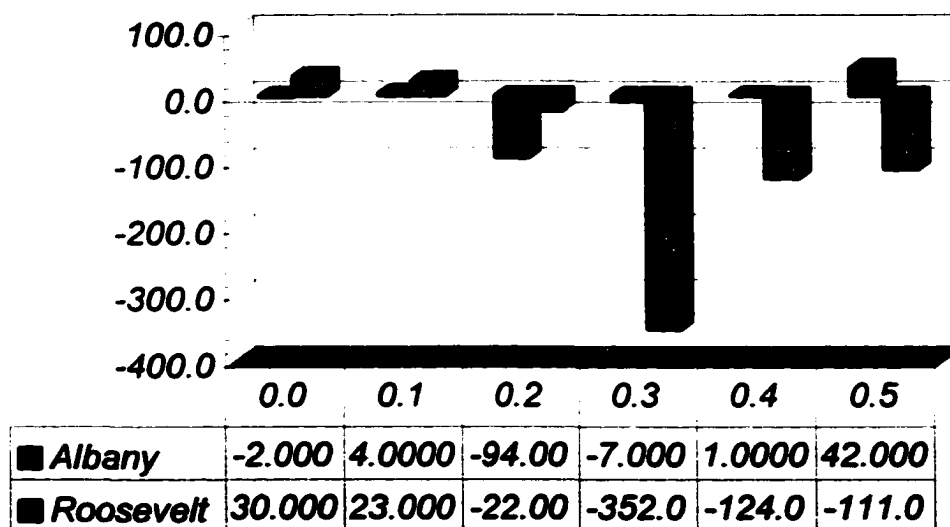


CHART A:26 Difference in Counts by Buffer, Felony Arrests (Period 2 – Period 1)

Percentage Change (P2 vs. P1)

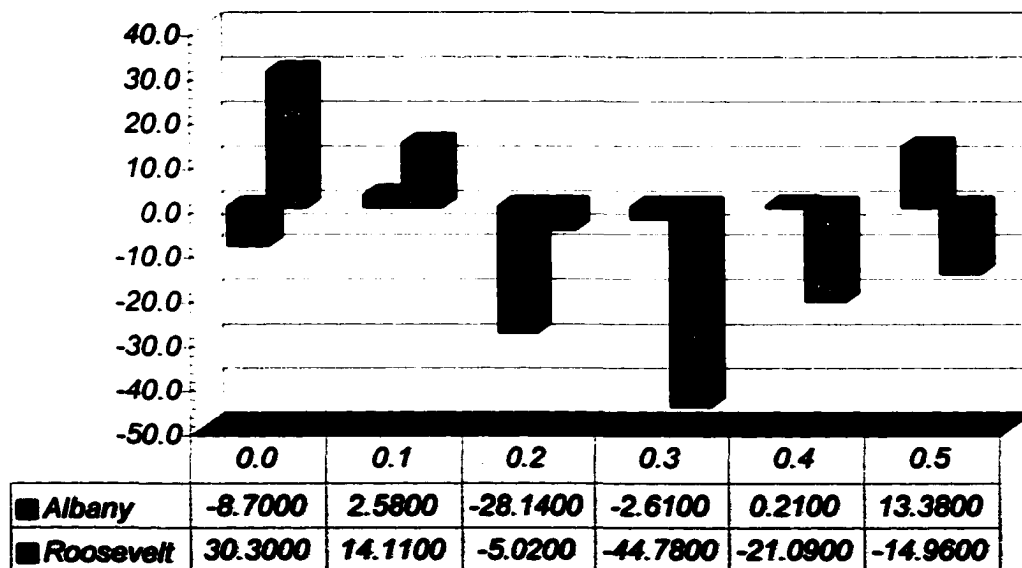


CHART A:27 Percent Change in Counts by Buffer, Felony Arrests (Period 2 – Period 1)

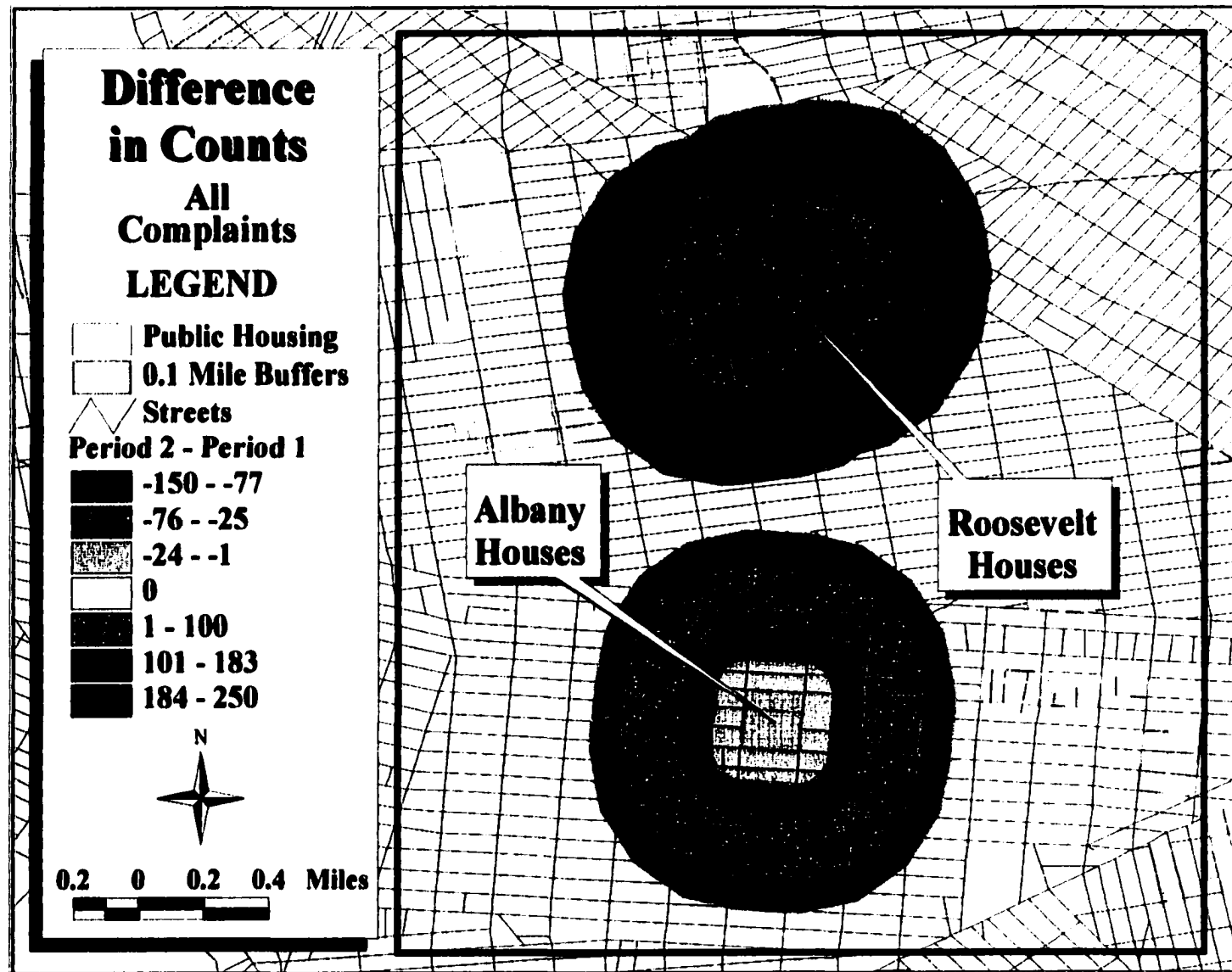


FIGURE A:1 Difference in Counts by Buffer, All Complaints (Period 2 – Period 1)

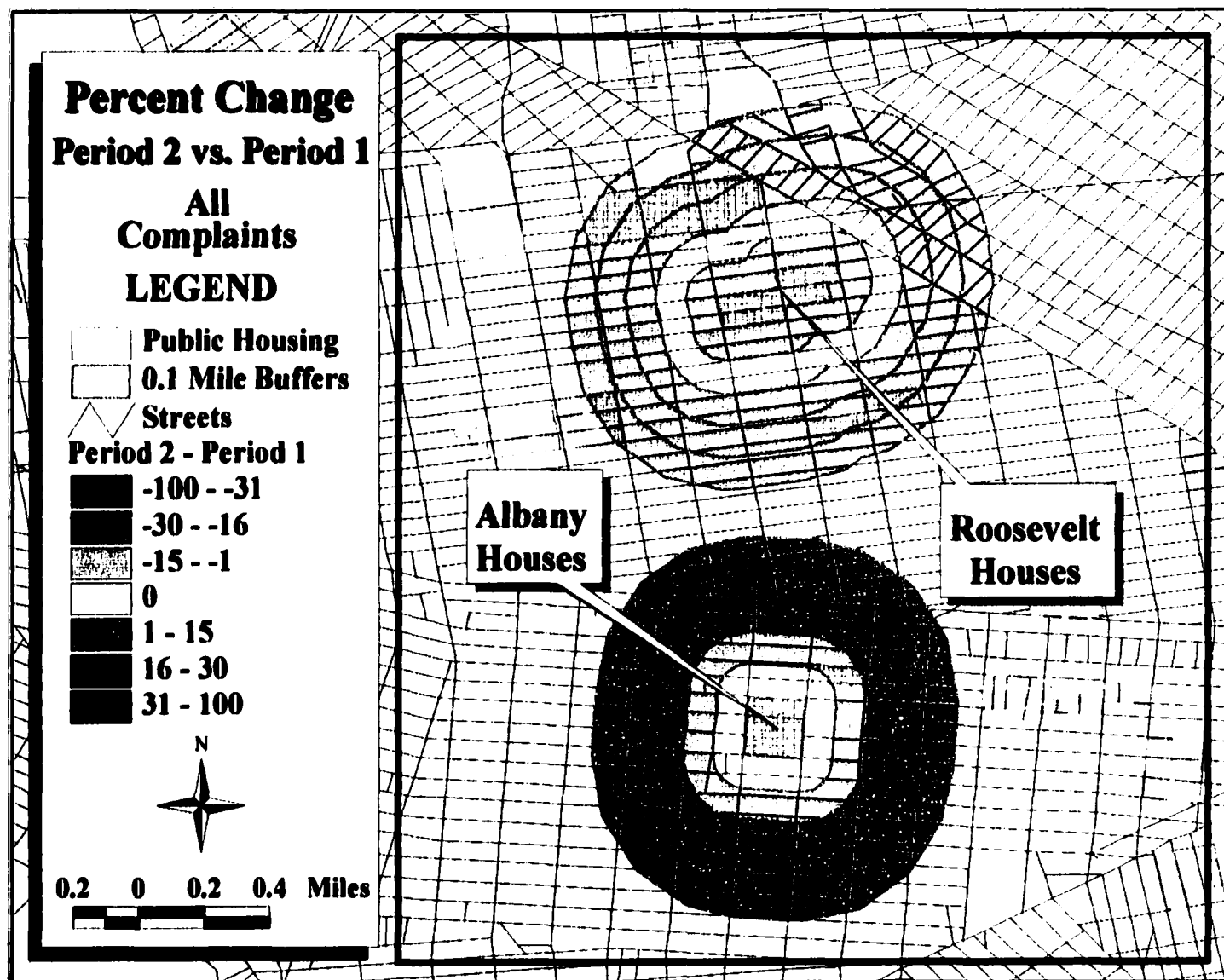


FIGURE A:2 Percent Change in Counts by Buffer, All Complaints (Period 2 – Period 1)

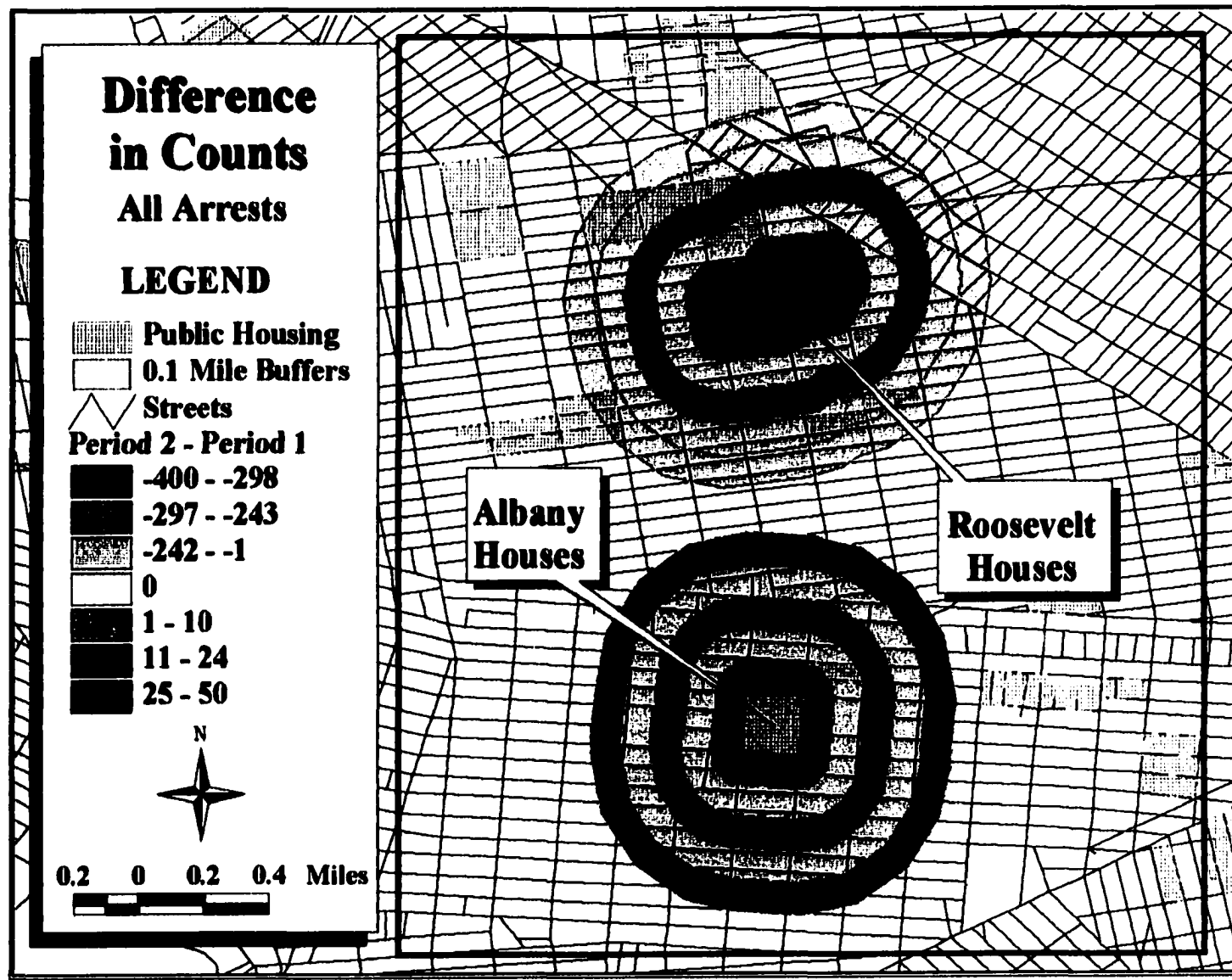


FIGURE A.3 Difference in Counts by Buffer, All Arrests (Period 2 – Period 1)

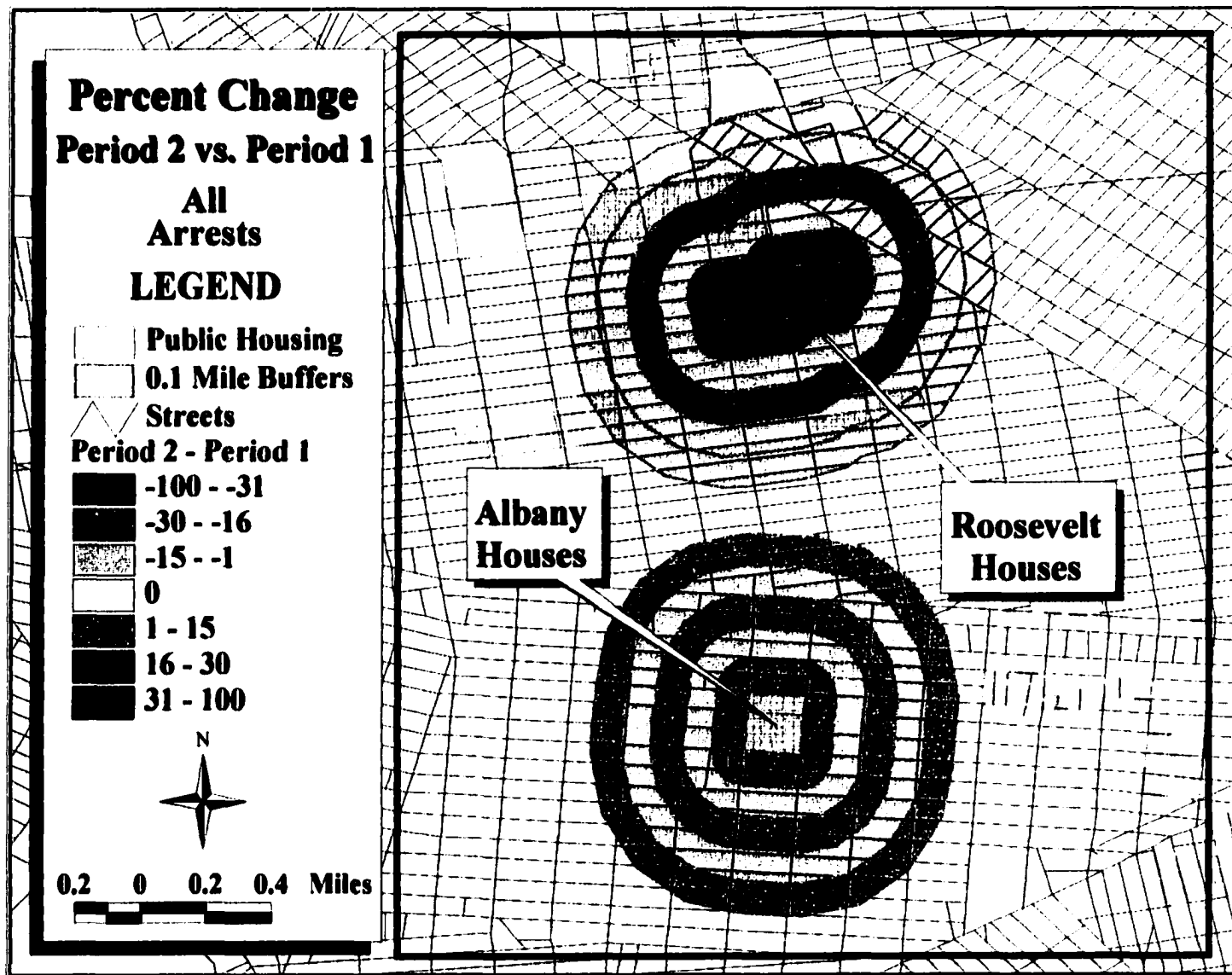


FIGURE A:4 Percent Change in Counts by Buffer, All Arrests (Period 2 – Period 1)

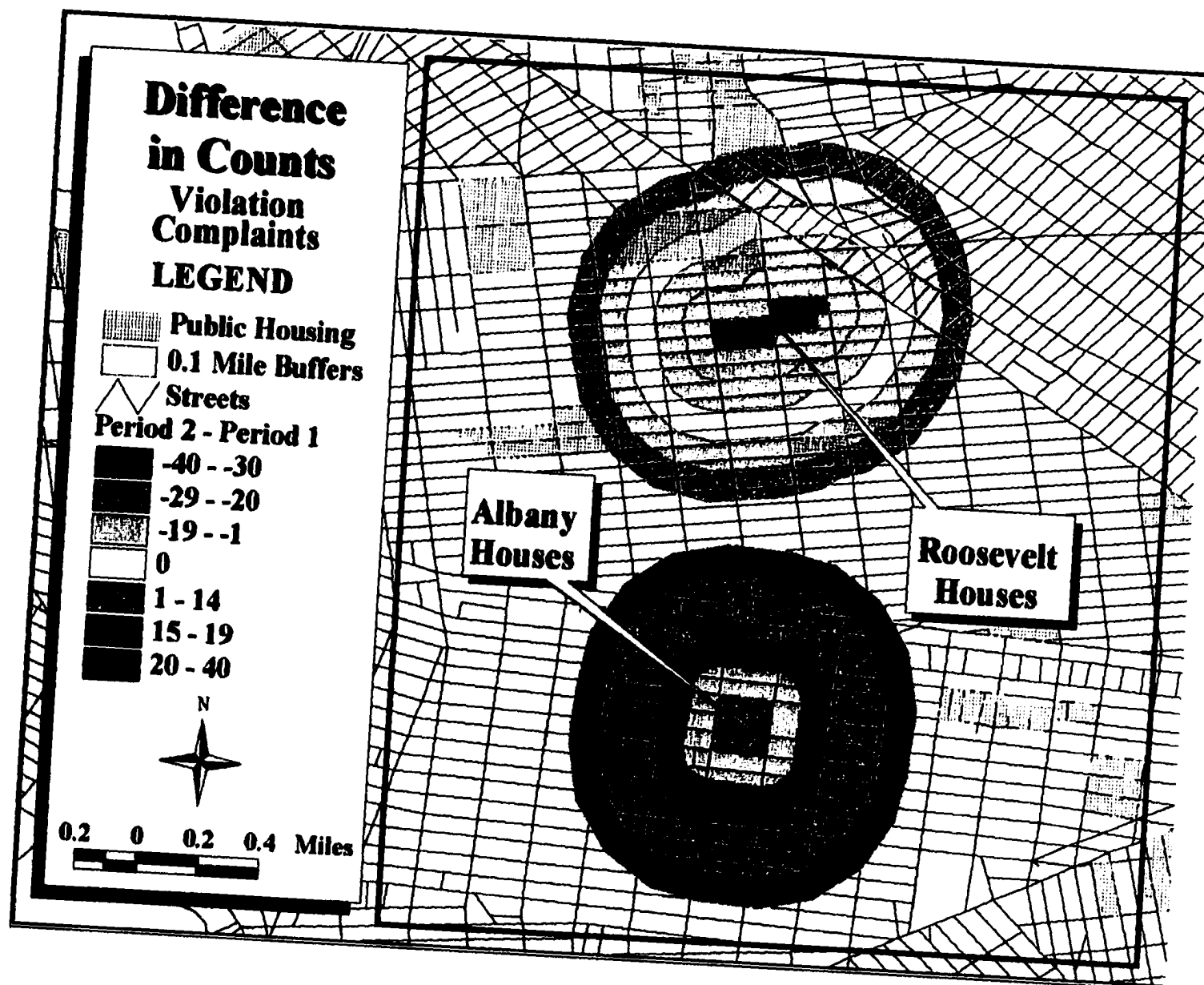


FIGURE A:5 Difference in Counts by Buffer, Violation Complaints (Period 2 - Period 1)

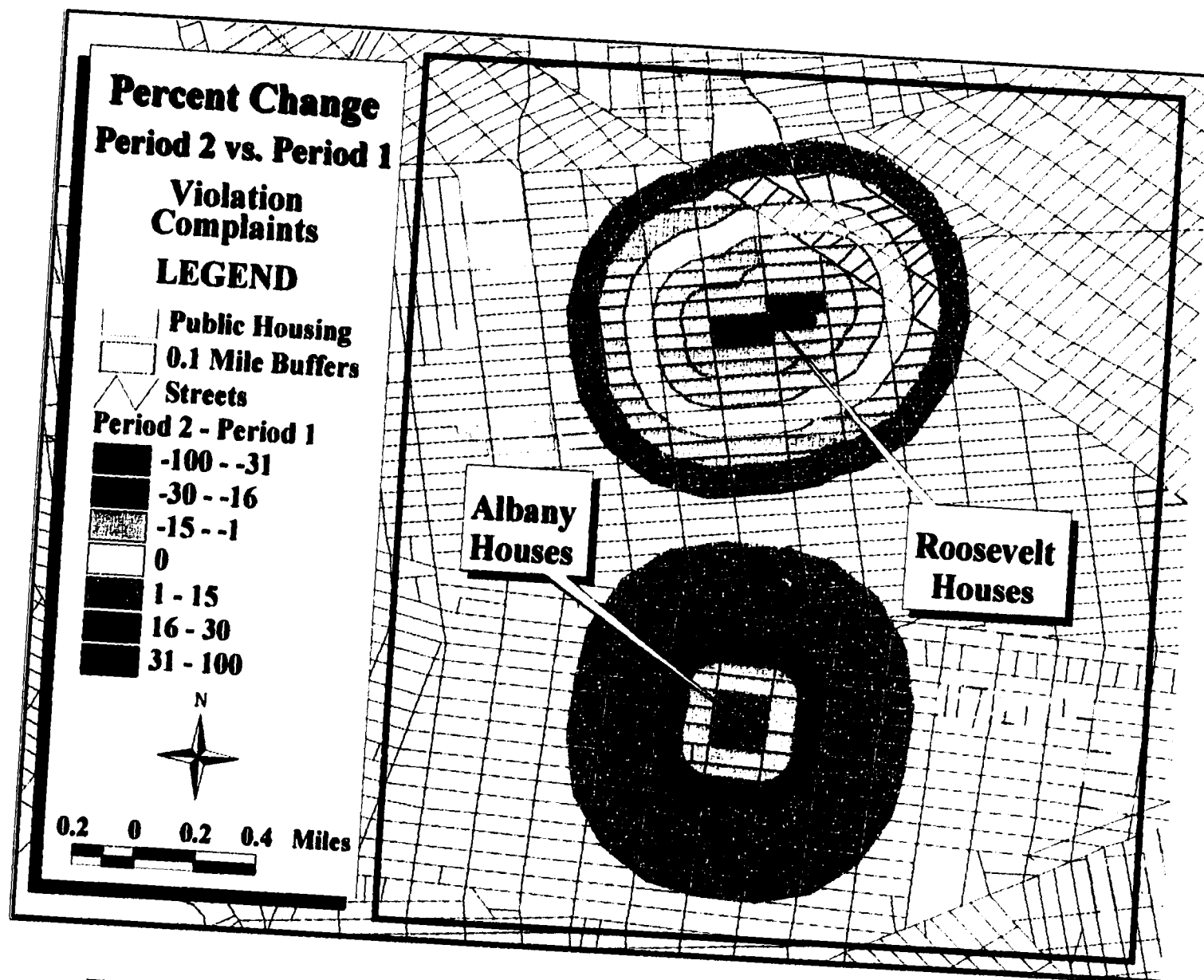


FIGURE A:6 Percent Change in Counts by Buffer, Violation Complaints (Period 2 – Period 1)

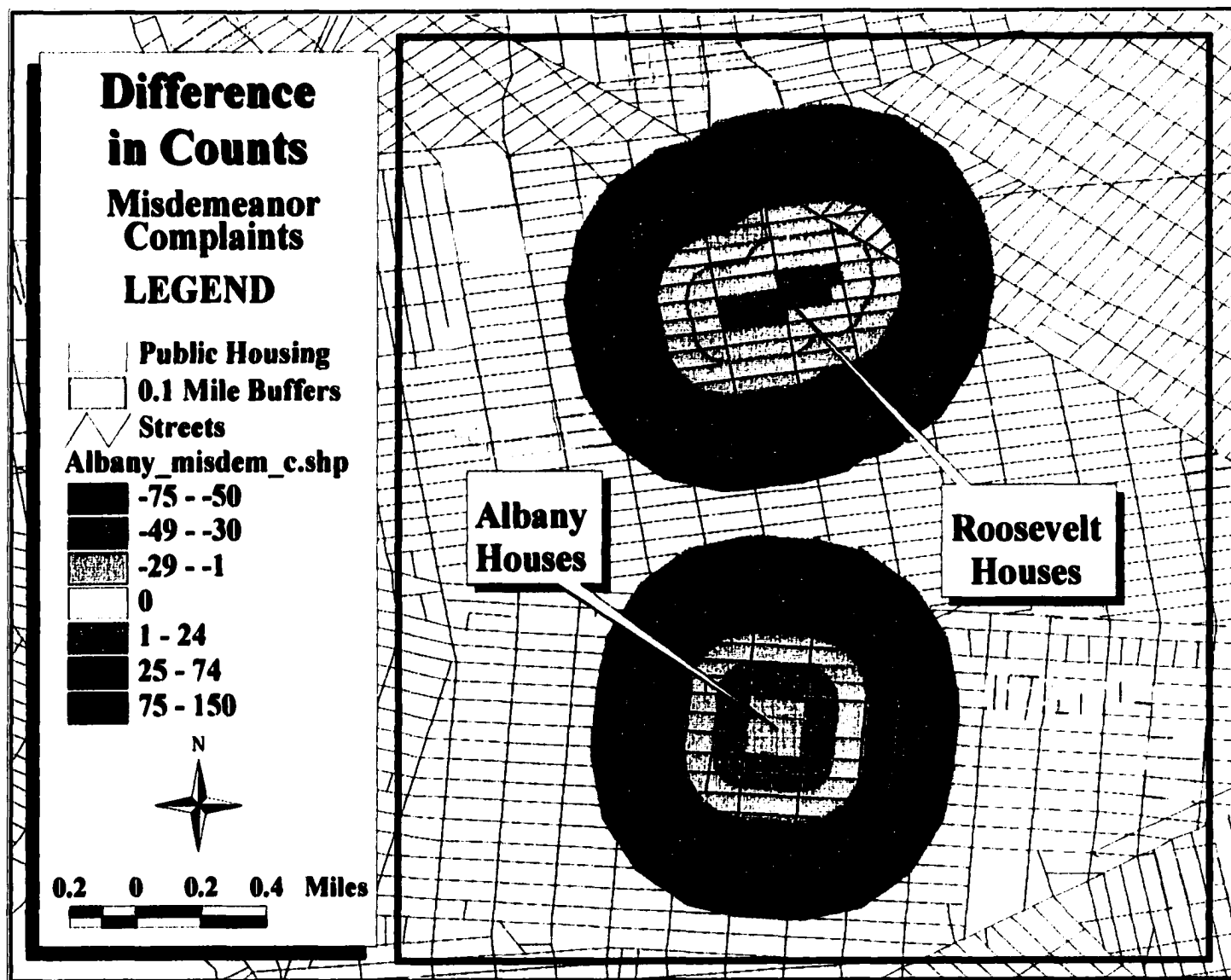


FIGURE A:7 Difference in Counts by Buffer, Misdemeanor Complaints (Period 2 – Period 1)

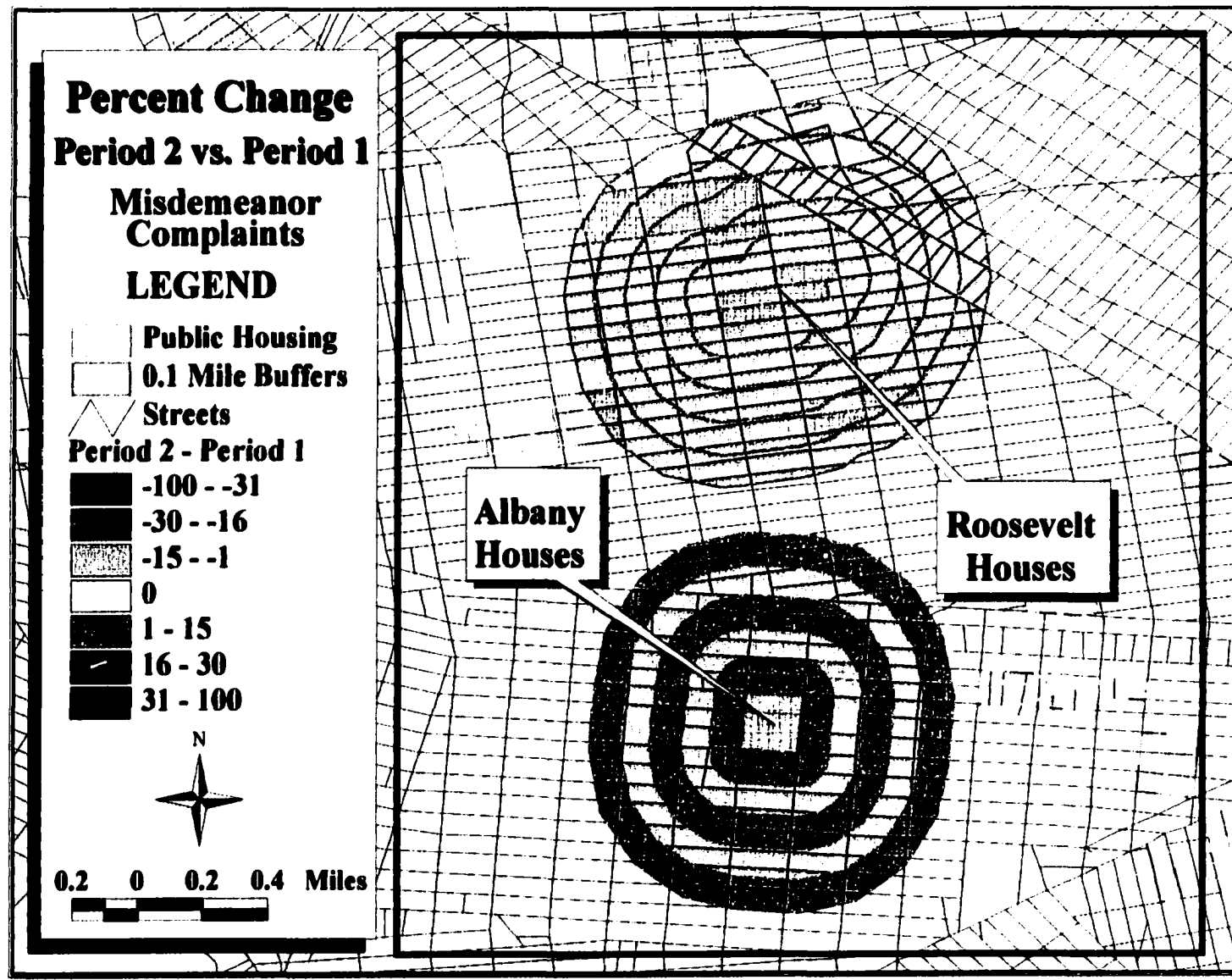


FIGURE A:8 Percent Change in Counts by Buffer, Misdemeanor Complaints (Period 2 – Period 1)

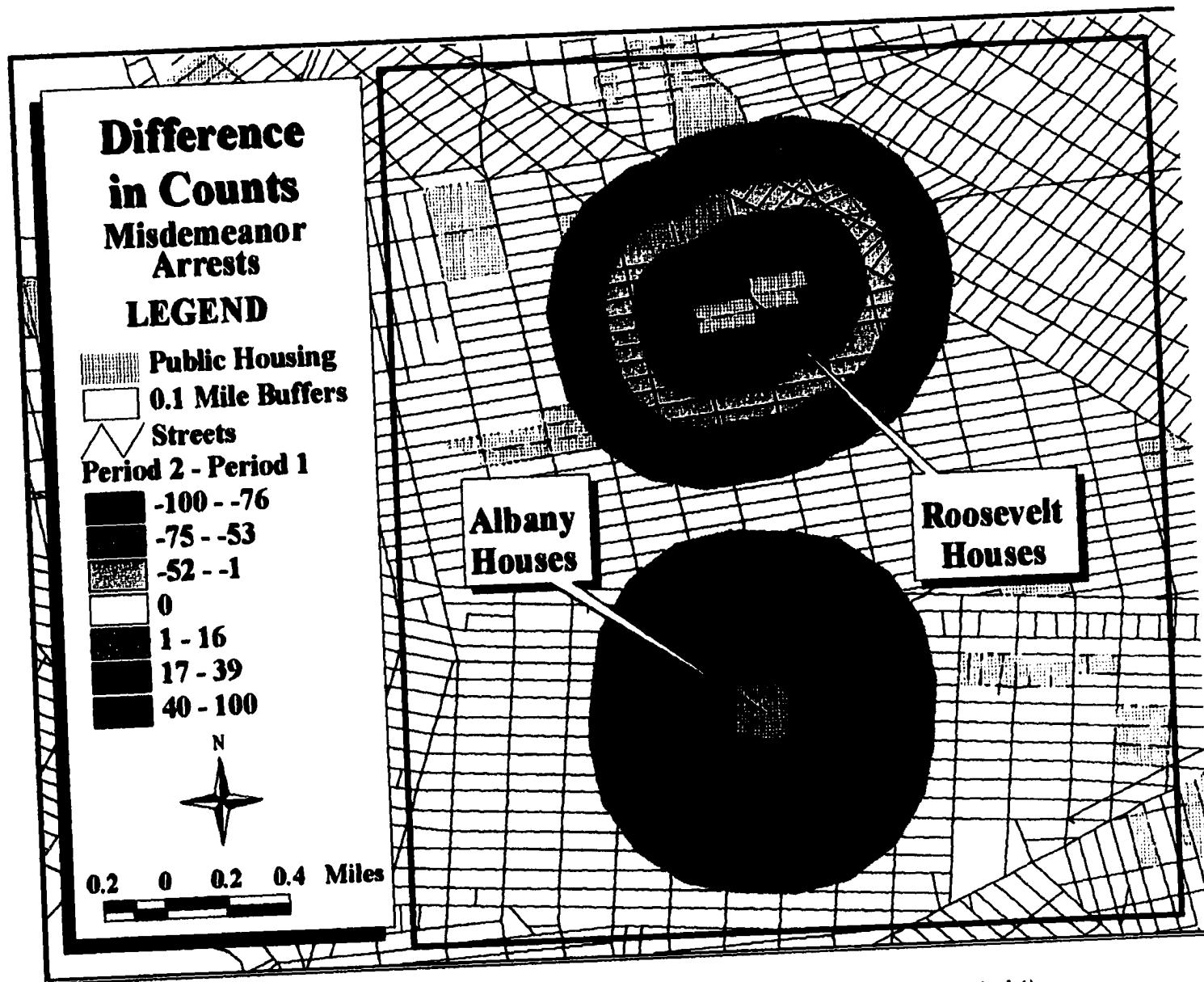


FIGURE A:9 Difference in Counts by Buffer, Misdemeanor Arrests (Period 2 – Period 1)

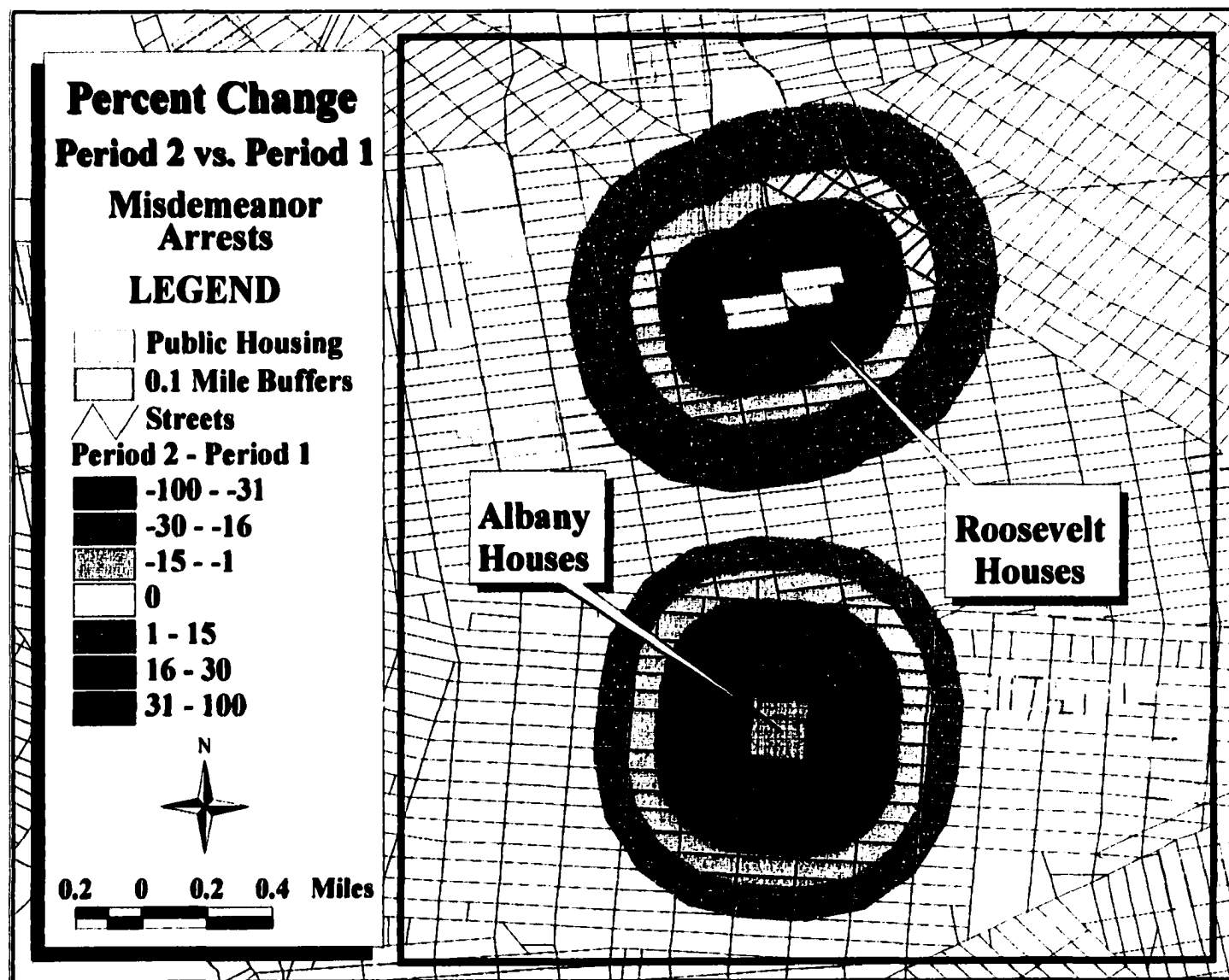


FIGURE A:10 Percent Change in Counts by Buffer, Misdemeanor Arrests (Period 2 – Period 1)

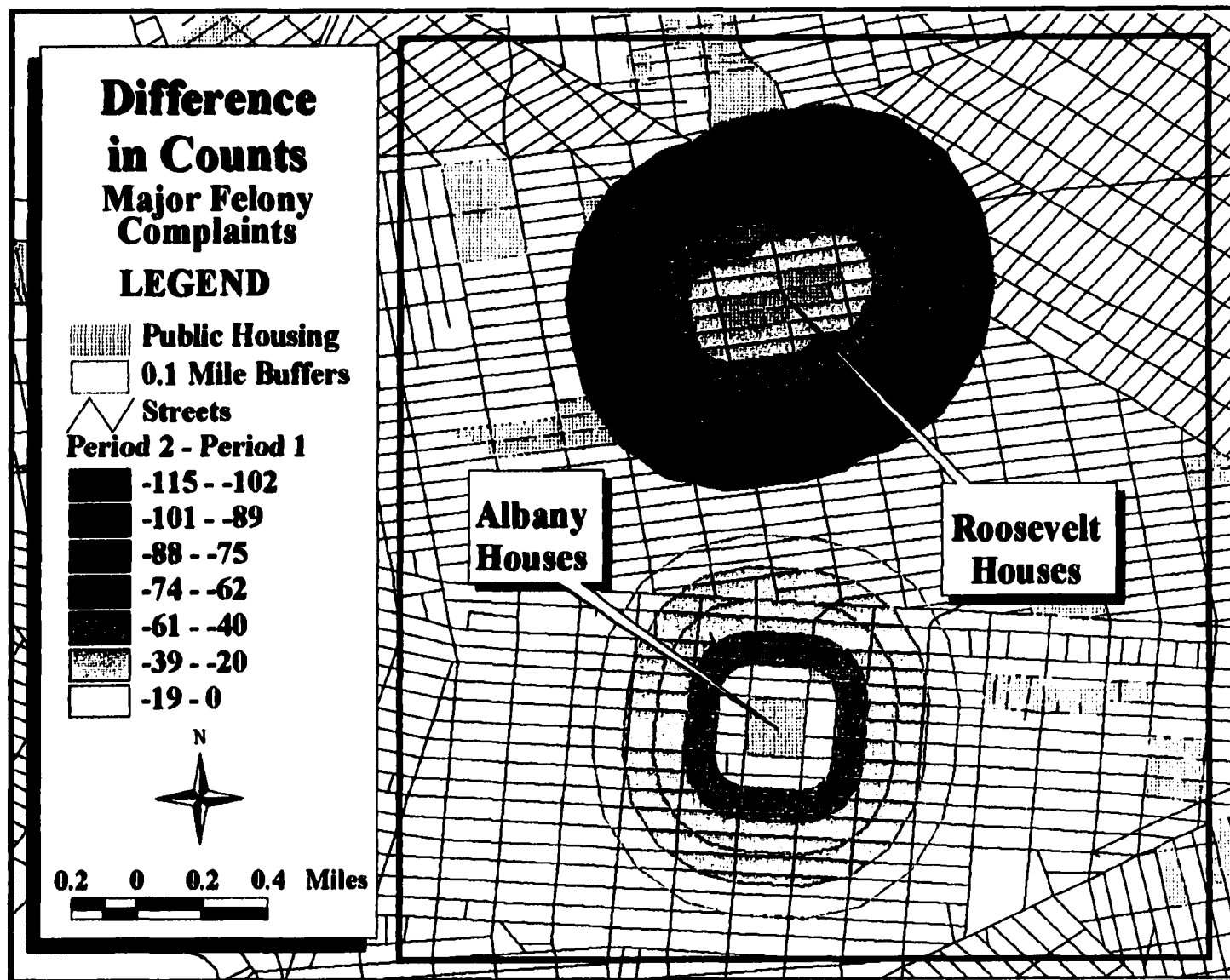


FIGURE A:11 Difference in Counts by Buffer, Major Felony Complaints (Period 2 – Period 1)

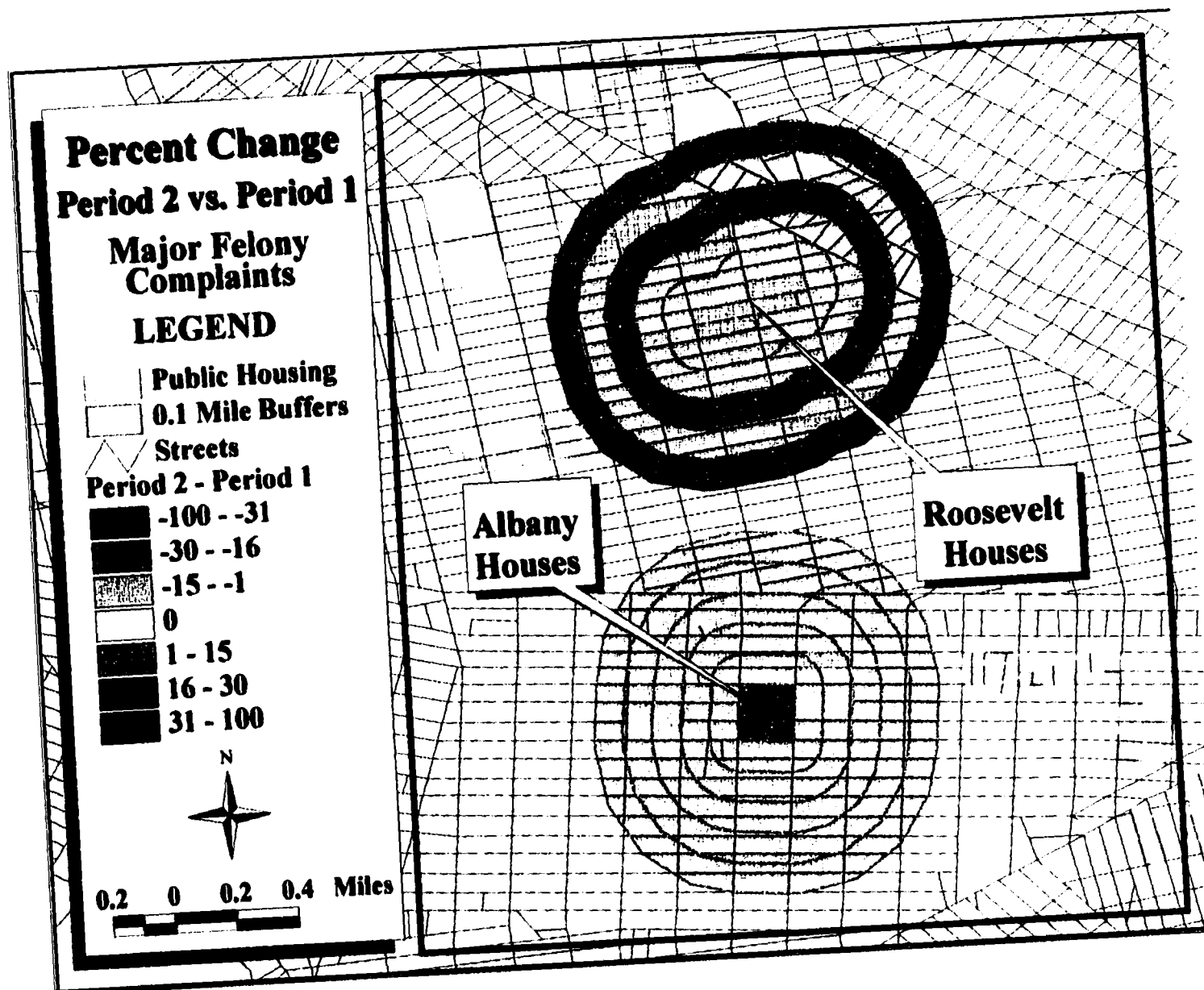


FIGURE A:12 Percent Change in Counts by Buffer, Major Felony Complaints (Period 2 – Period 1)

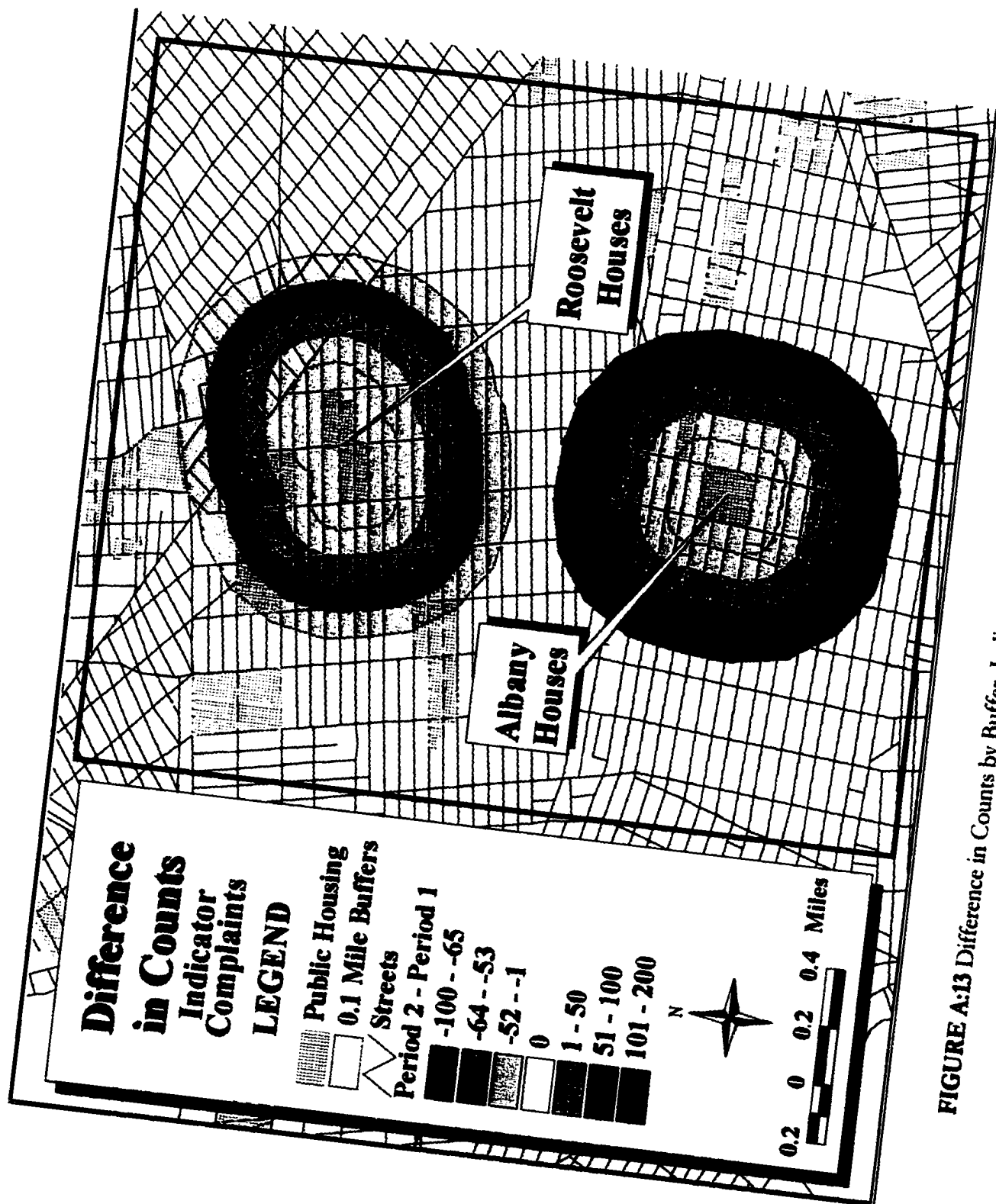


FIGURE A:13 Difference in Counts by Buffer, Indicator Complaints (Period 2 - Period 1)

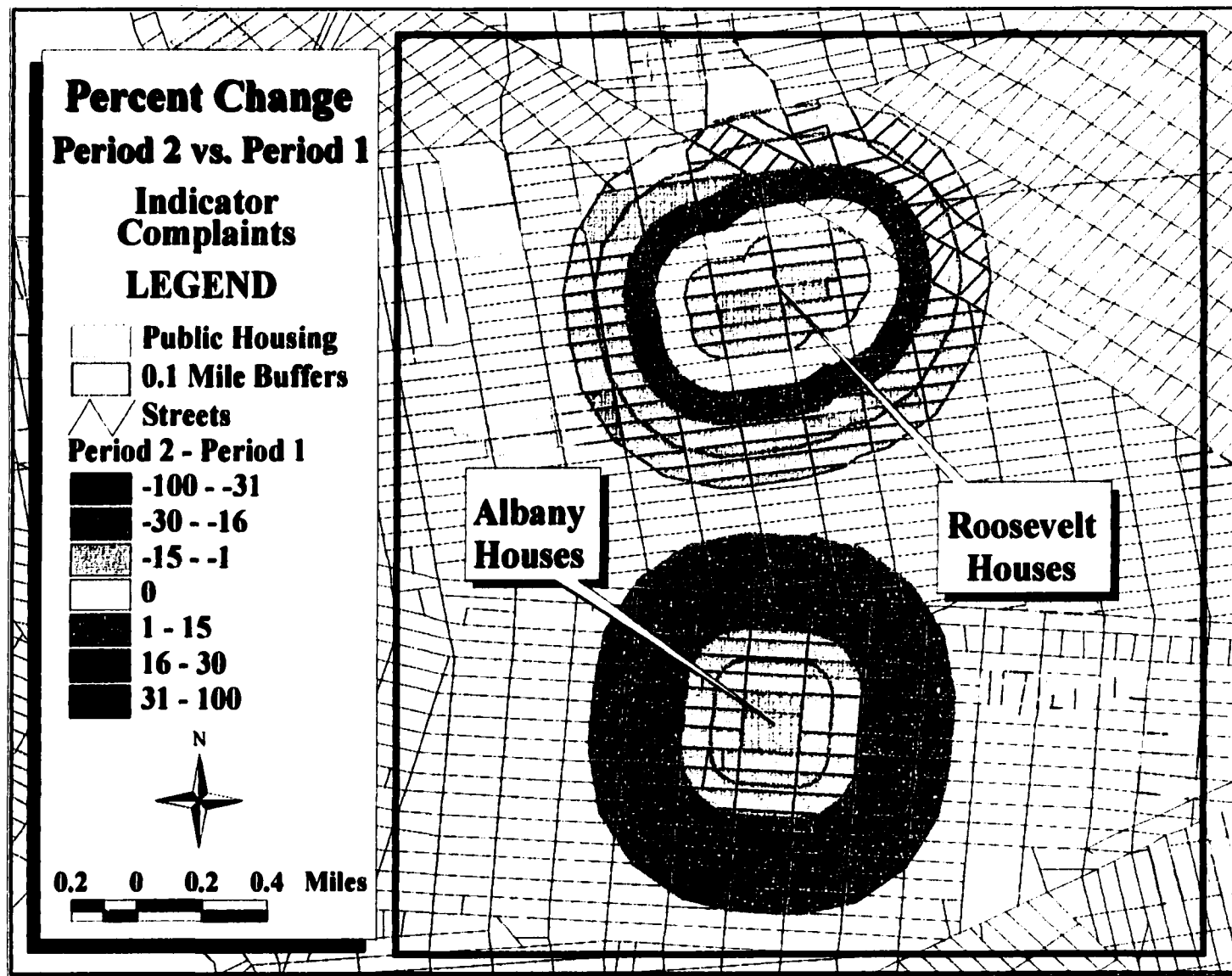


FIGURE A:14 Percent Change in Counts by Buffer, Indicator Complaints (Period 2 – Period 1)

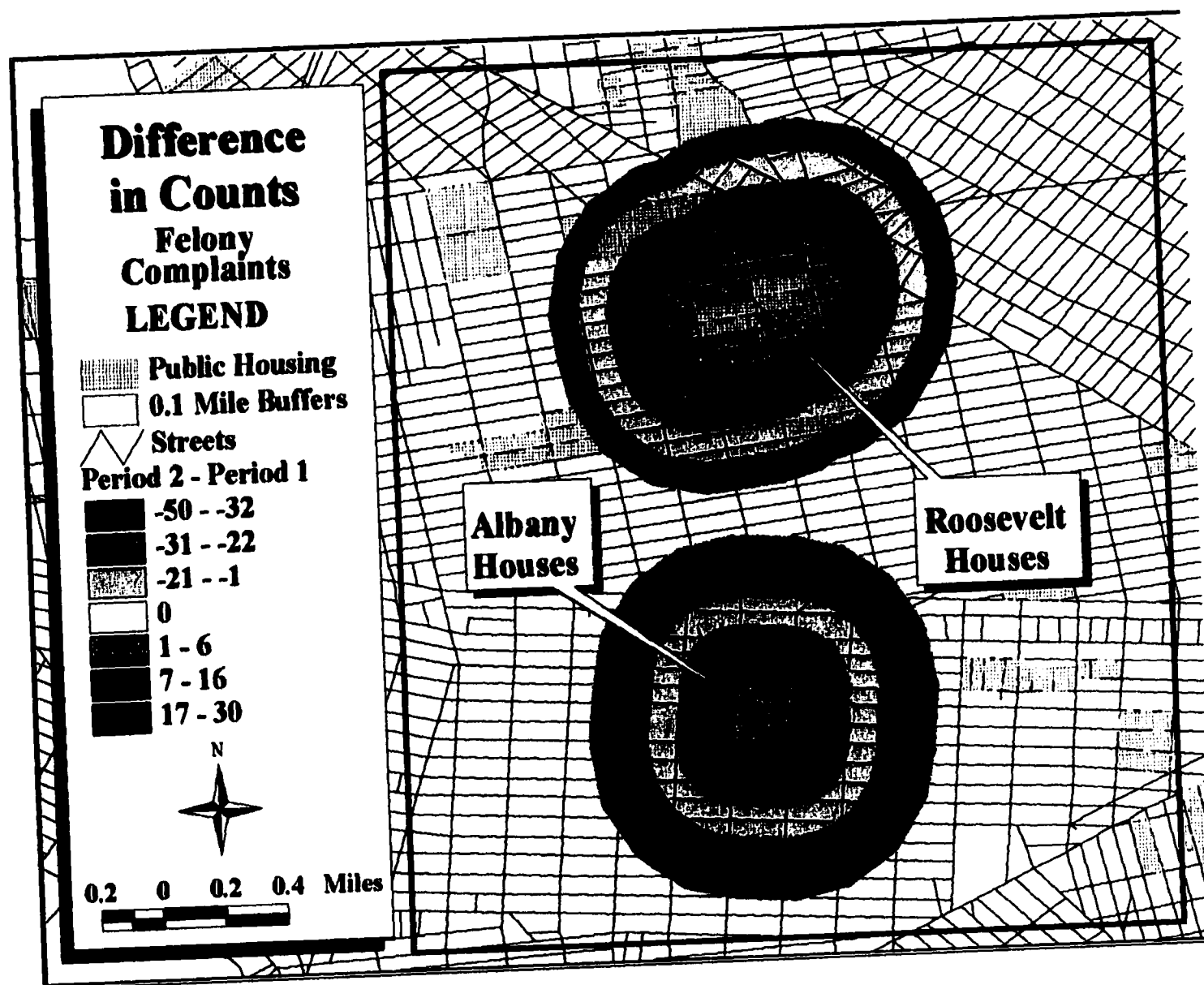


FIGURE A:15 Difference in Counts by Buffer, Felony Complaints (Period 2 - Period 1)

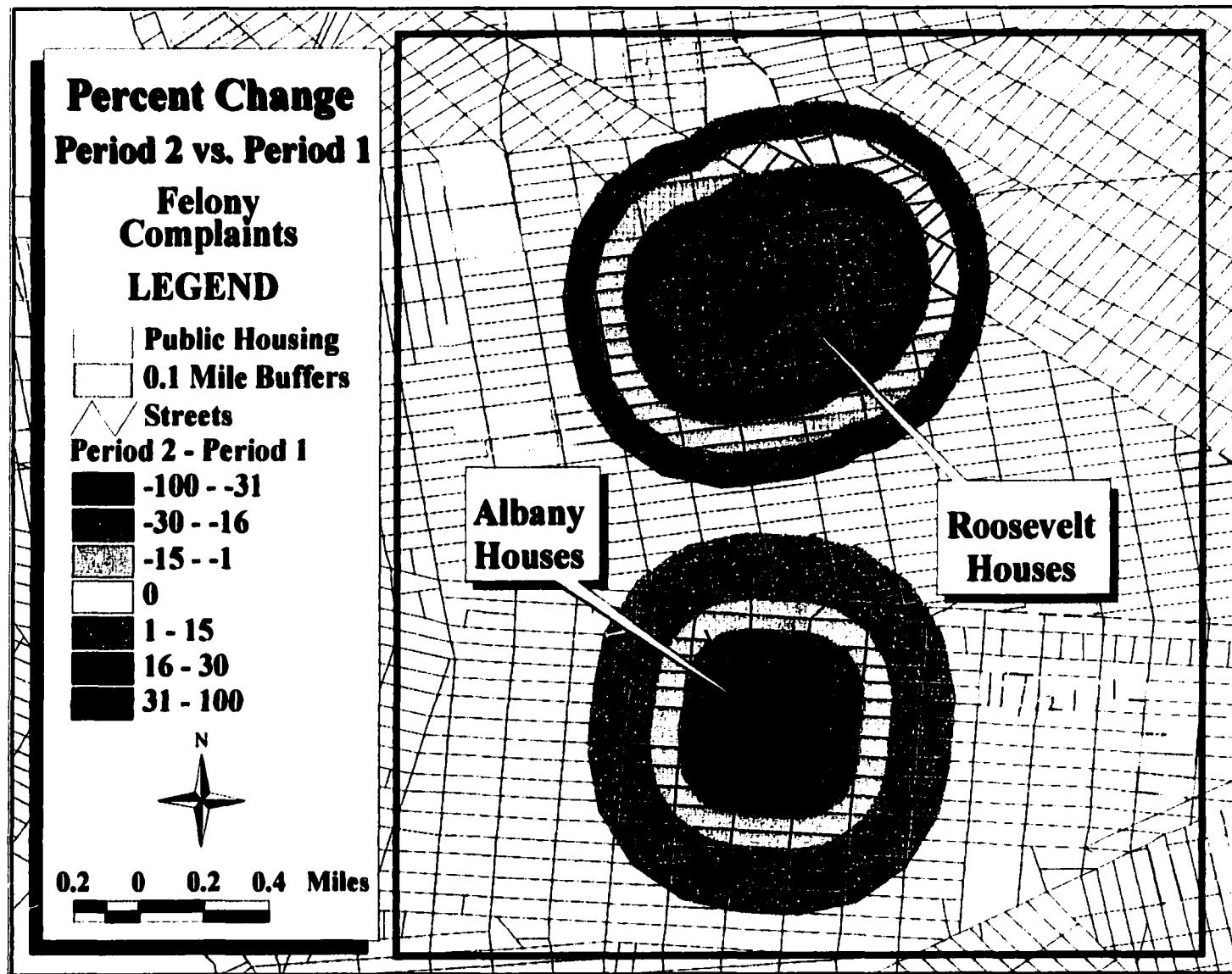


FIGURE A:16 Percent Change in Counts by Buffer, Felony Complaints (Period 2 – Period 1)

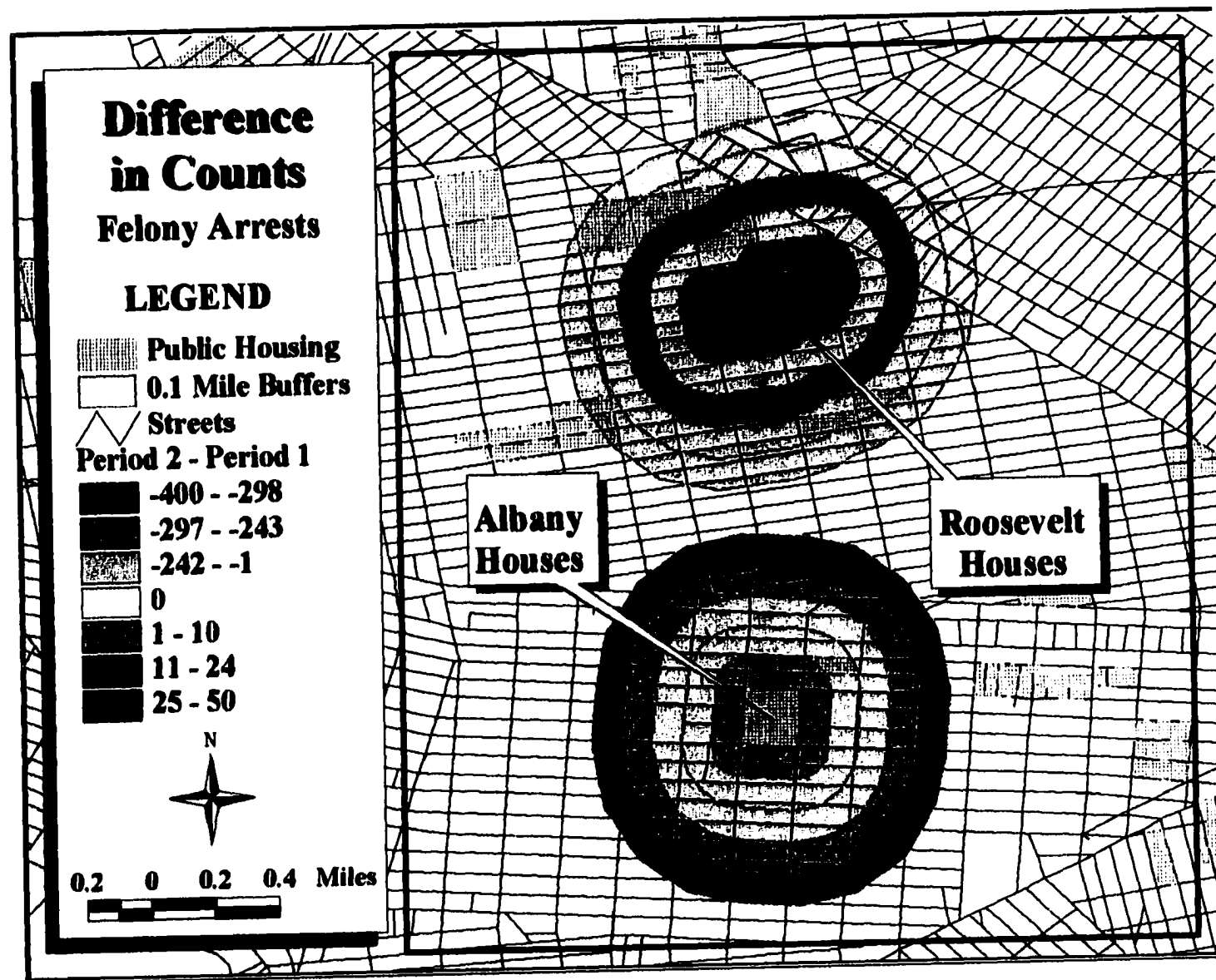


FIGURE A:17 Difference in Counts by Buffer, Felony Arrests (Period 2 – Period 1)

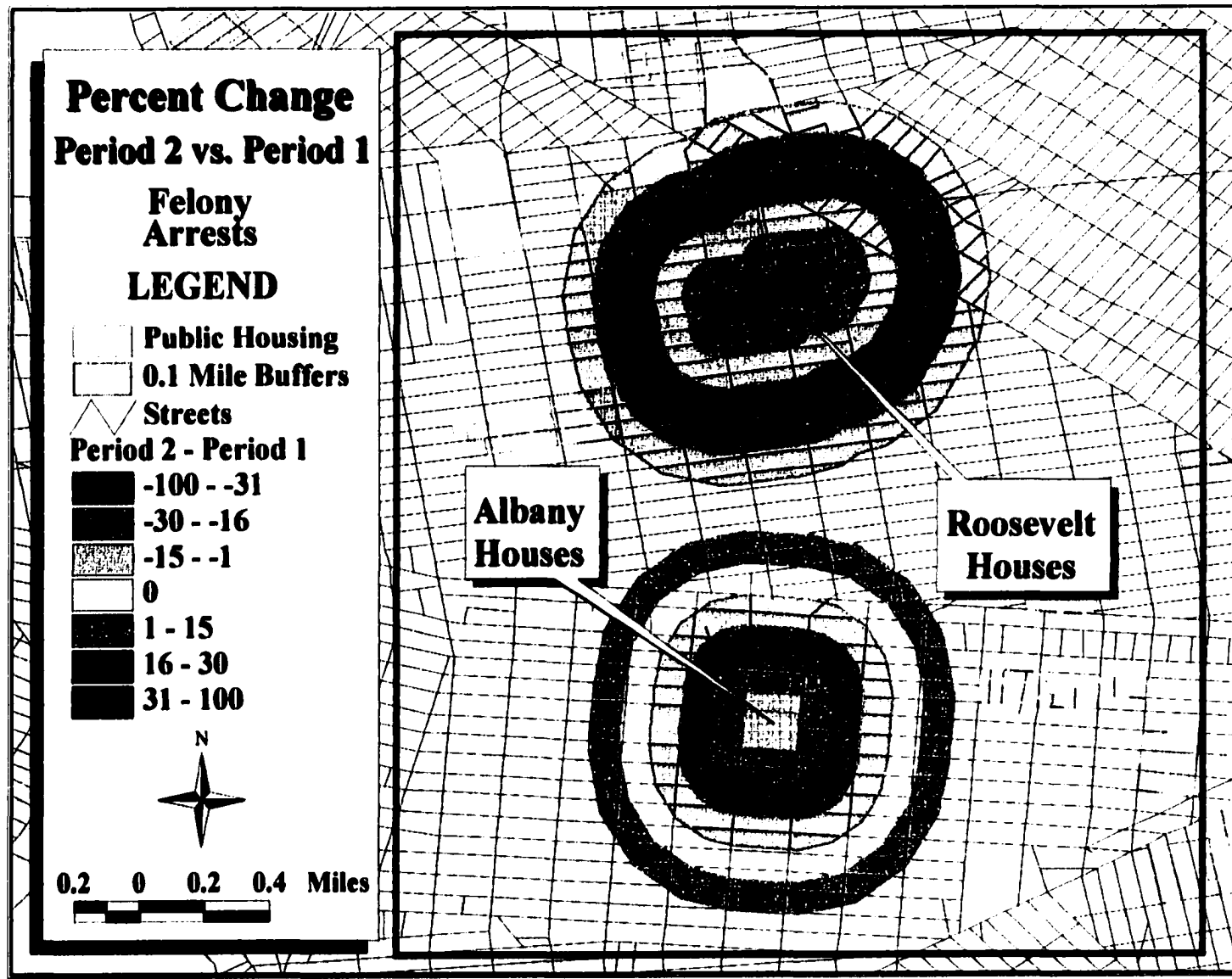


FIGURE A:18 Percent Change in Counts by Buffer, Felony Arrests (Period 2 – Period 1)

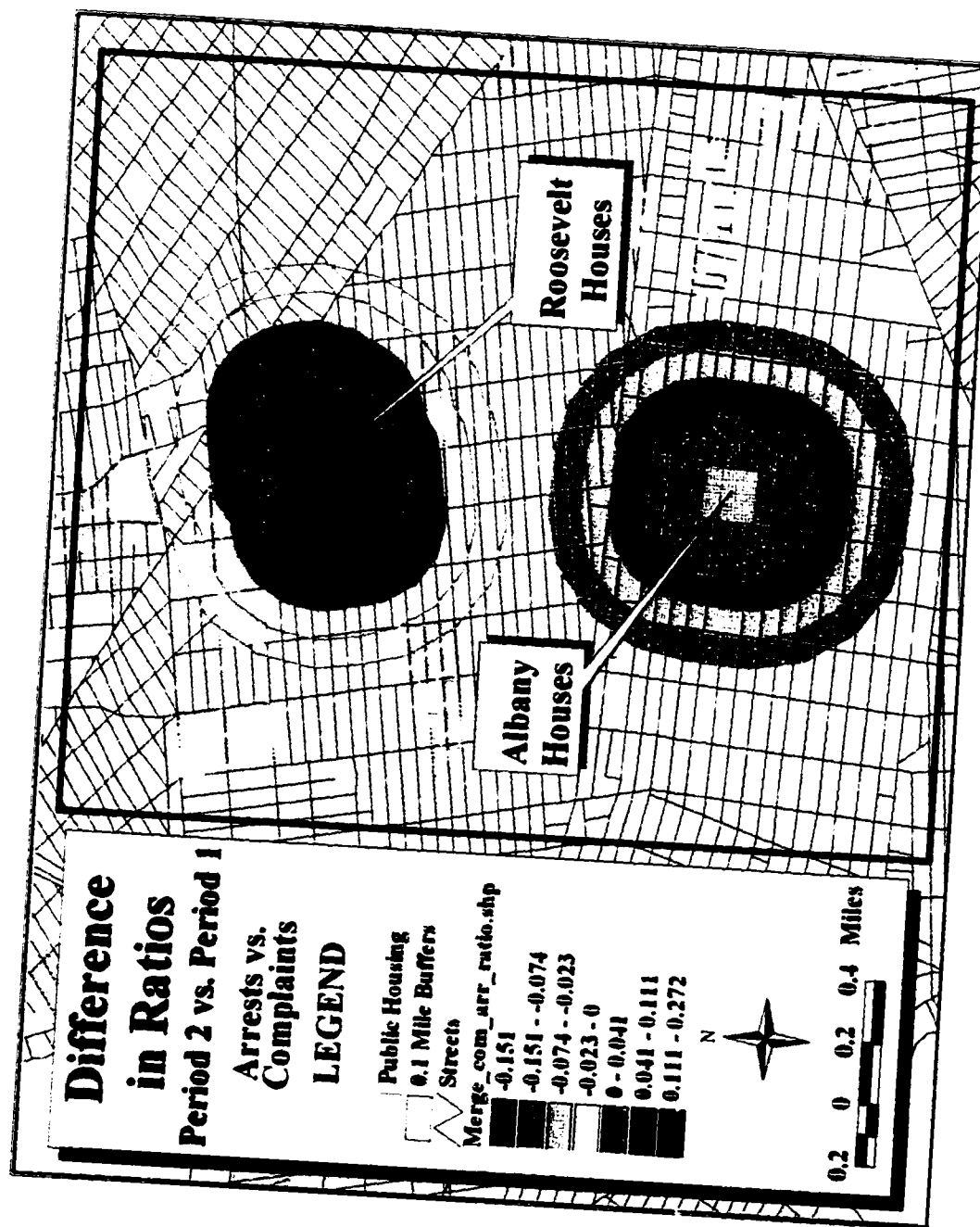


FIGURE A:19 Difference in Counts by Buffer, Ratio of Arrests to Complaints (Period 2 – Period 1)

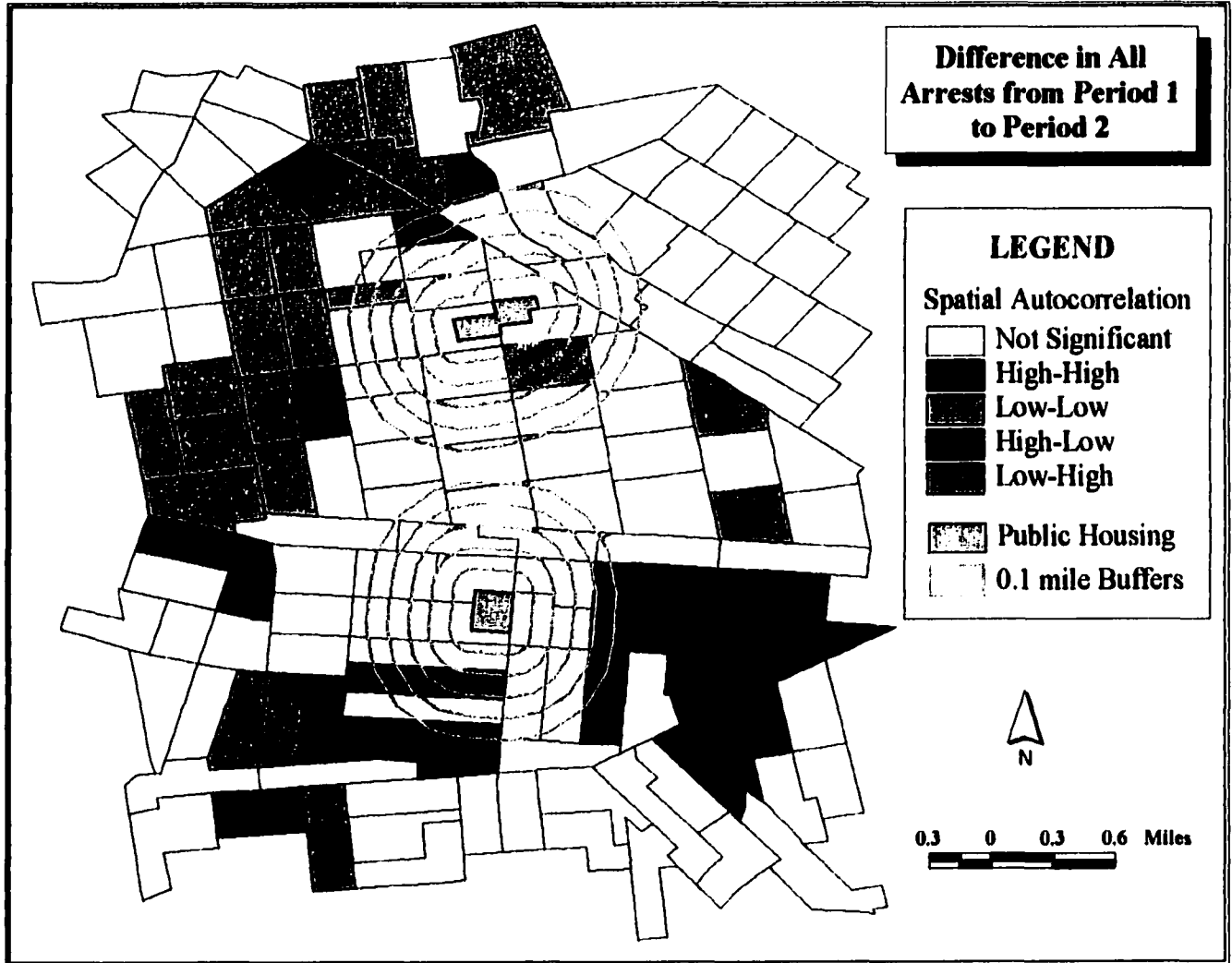


FIGURE B:1 Significant LISA Values and Relationships for Difference by Tract (All Arrests)

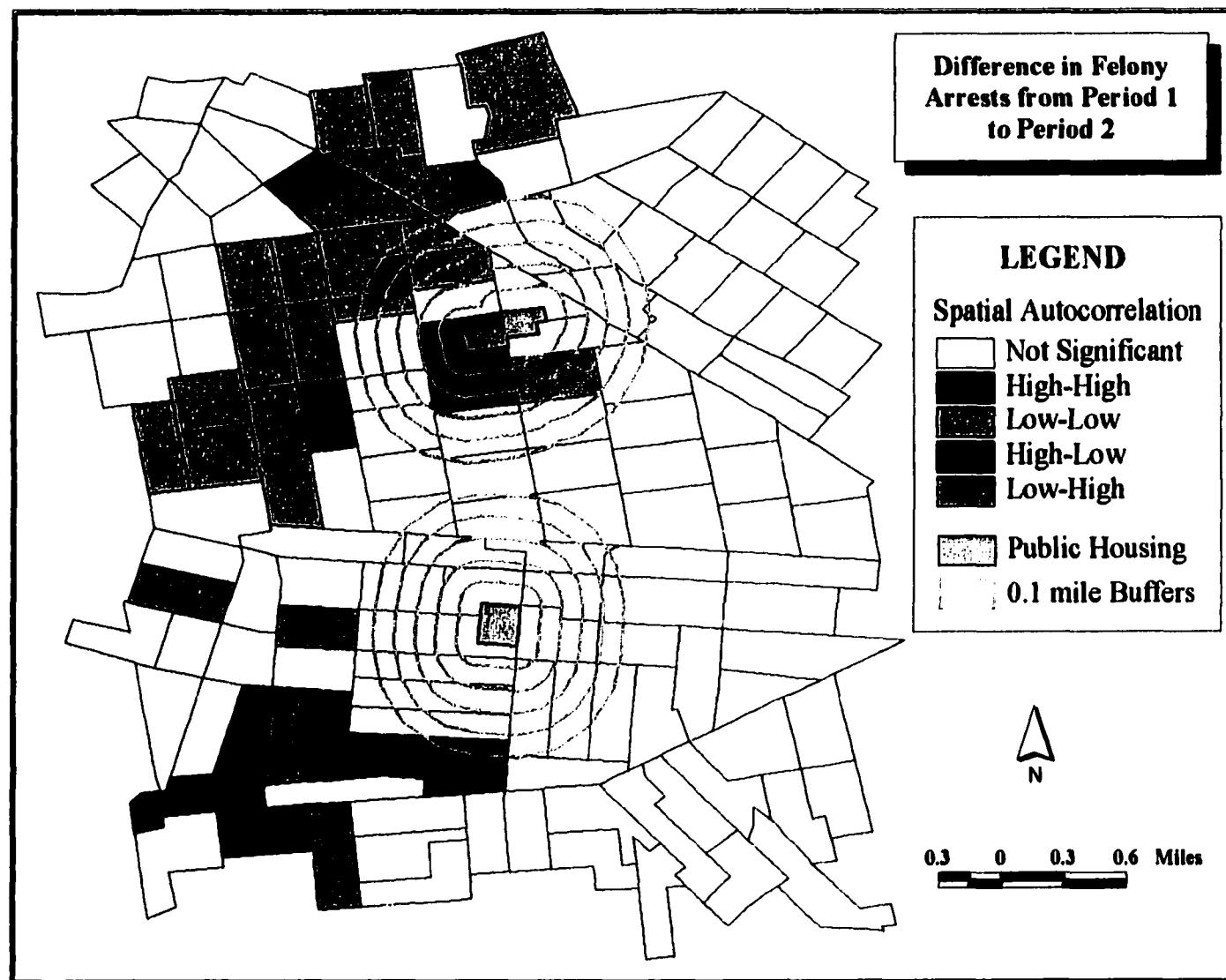


FIGURE B:2 Significant LISA Values and Relationships for Difference by Tract (Felony Arrests)

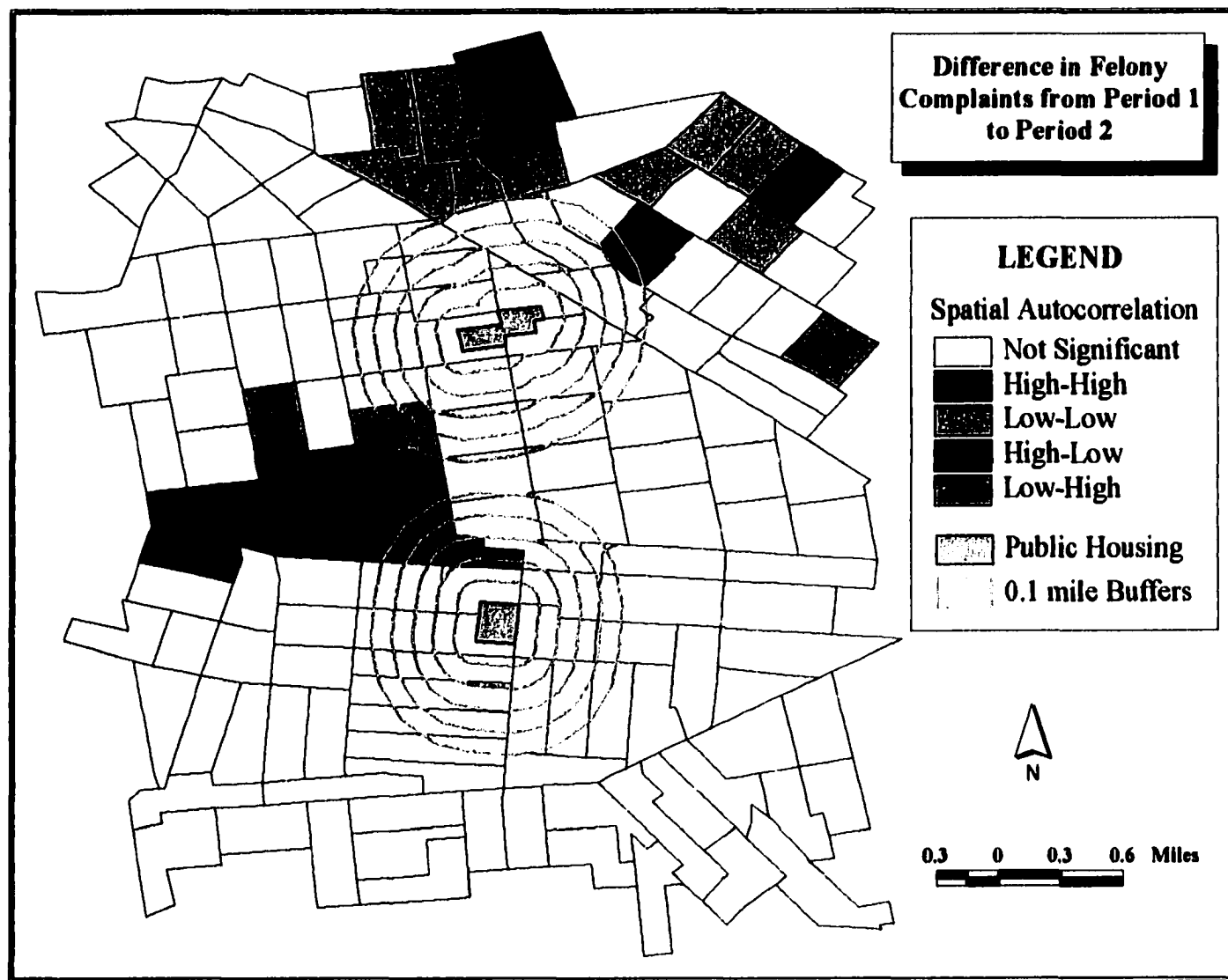


FIGURE B:3 Significant LISA Values and Relationships for Difference by Tract (Felony Complaints)

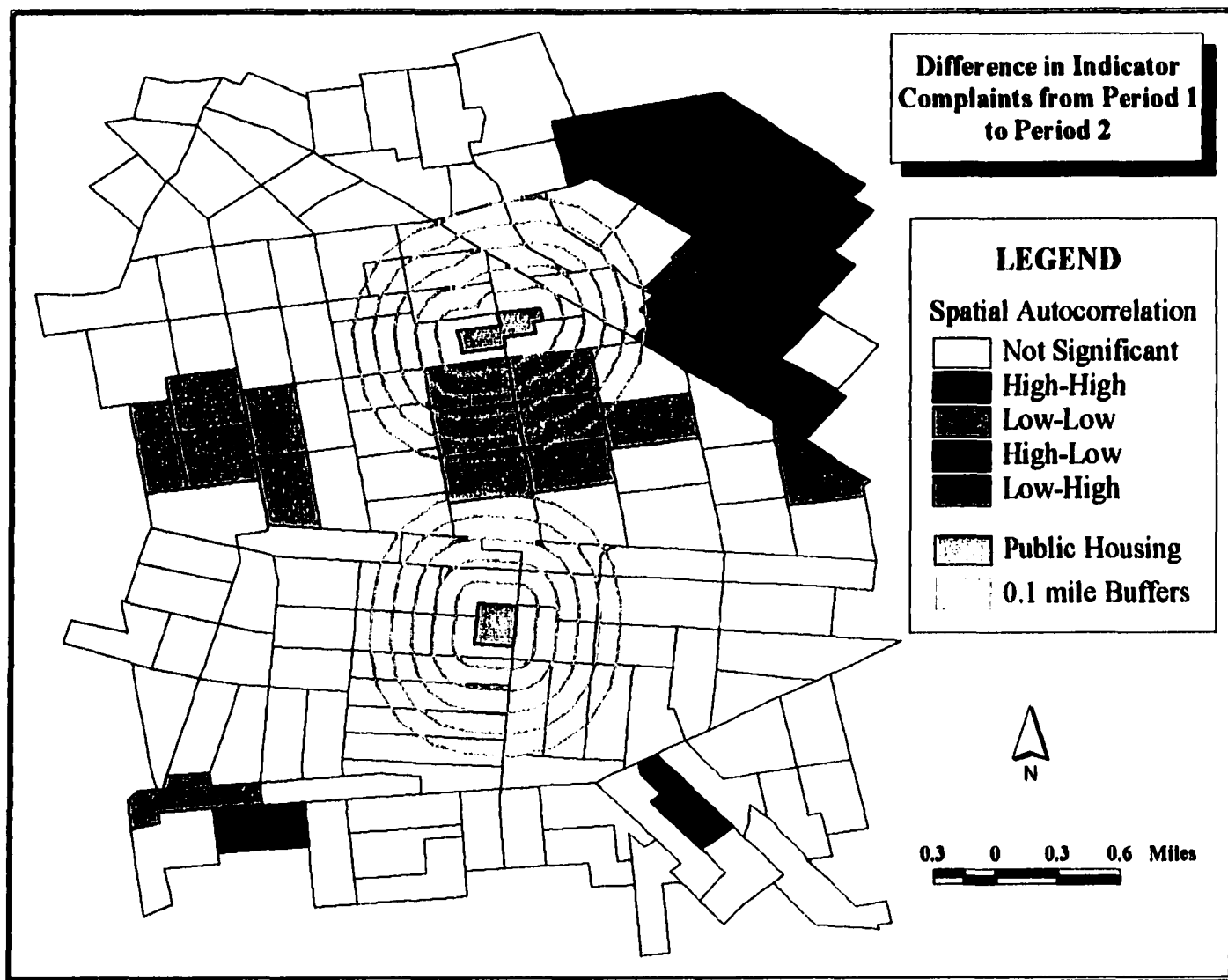


FIGURE B:4 Significant LISA Values and Relationships for Difference by Tract (Indicator Complaints)

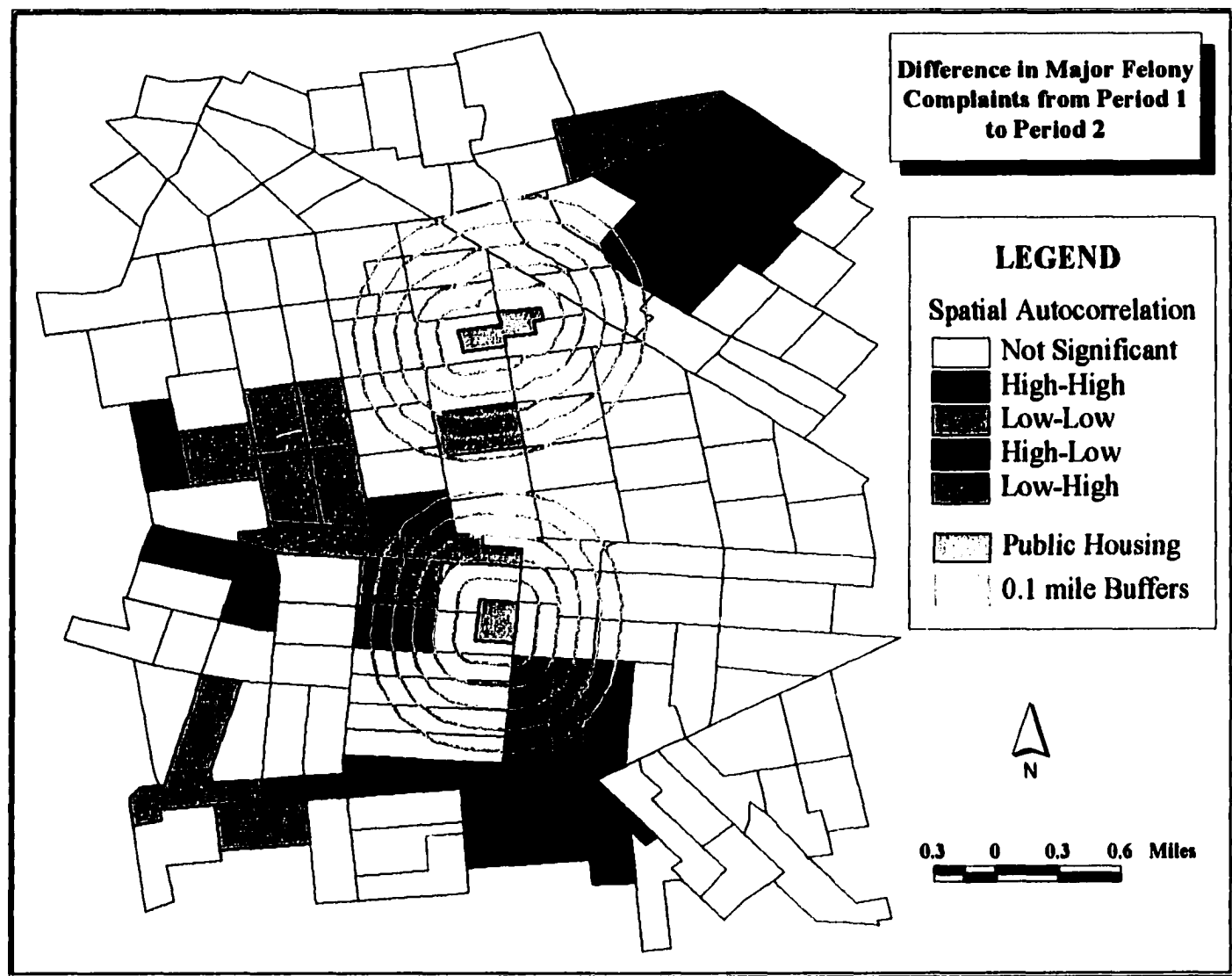


FIGURE B:5 Significant LISA Values and Relationships for Difference by Tract (Major Felony Complaints)

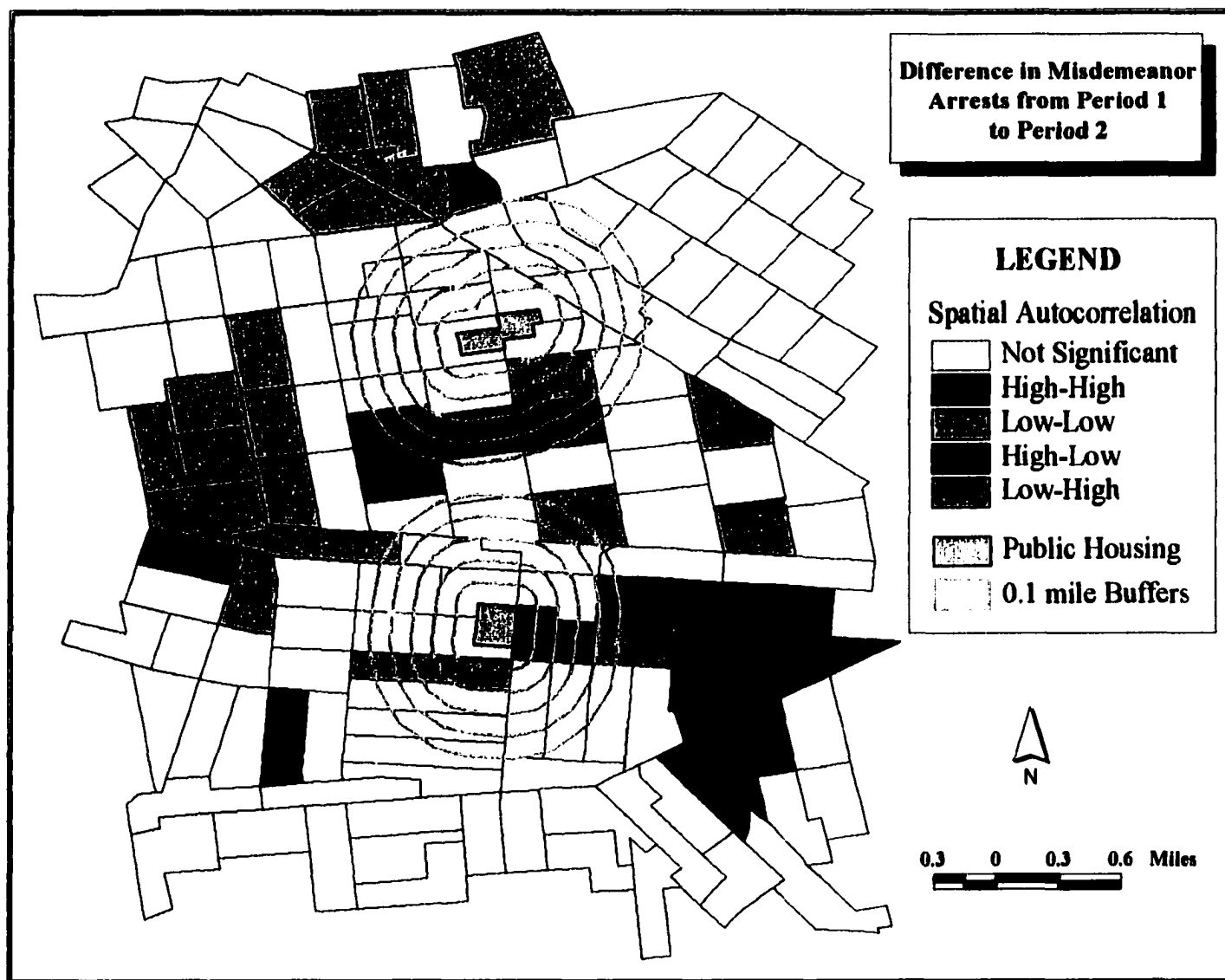


FIGURE B:6 Significant LISA Values and Relationships for Difference by Tract (Misdemeanor Arrests)

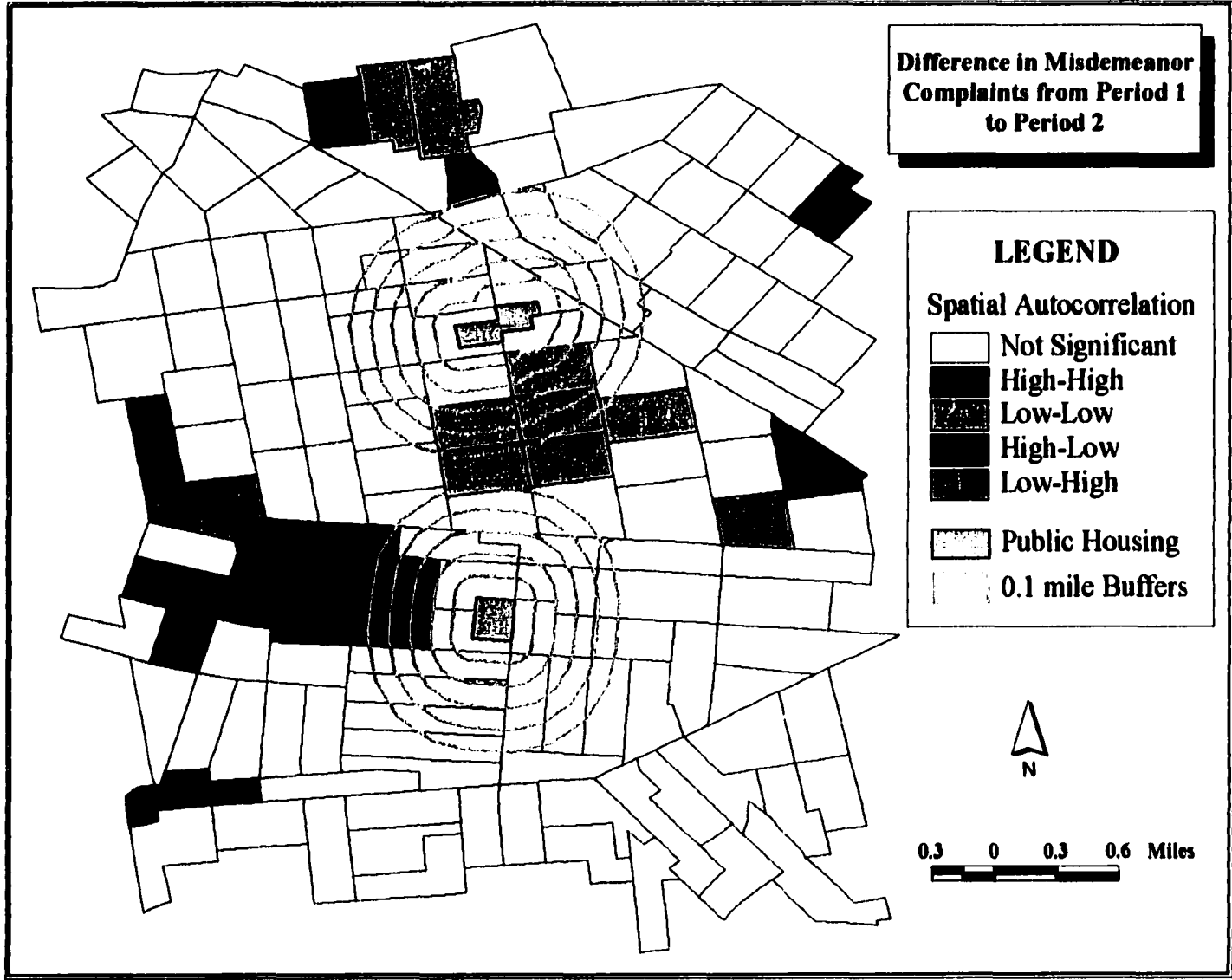


FIGURE B:7 Significant LISA Values and Relationships for Difference by Tract (Misdemeanor Complaints)

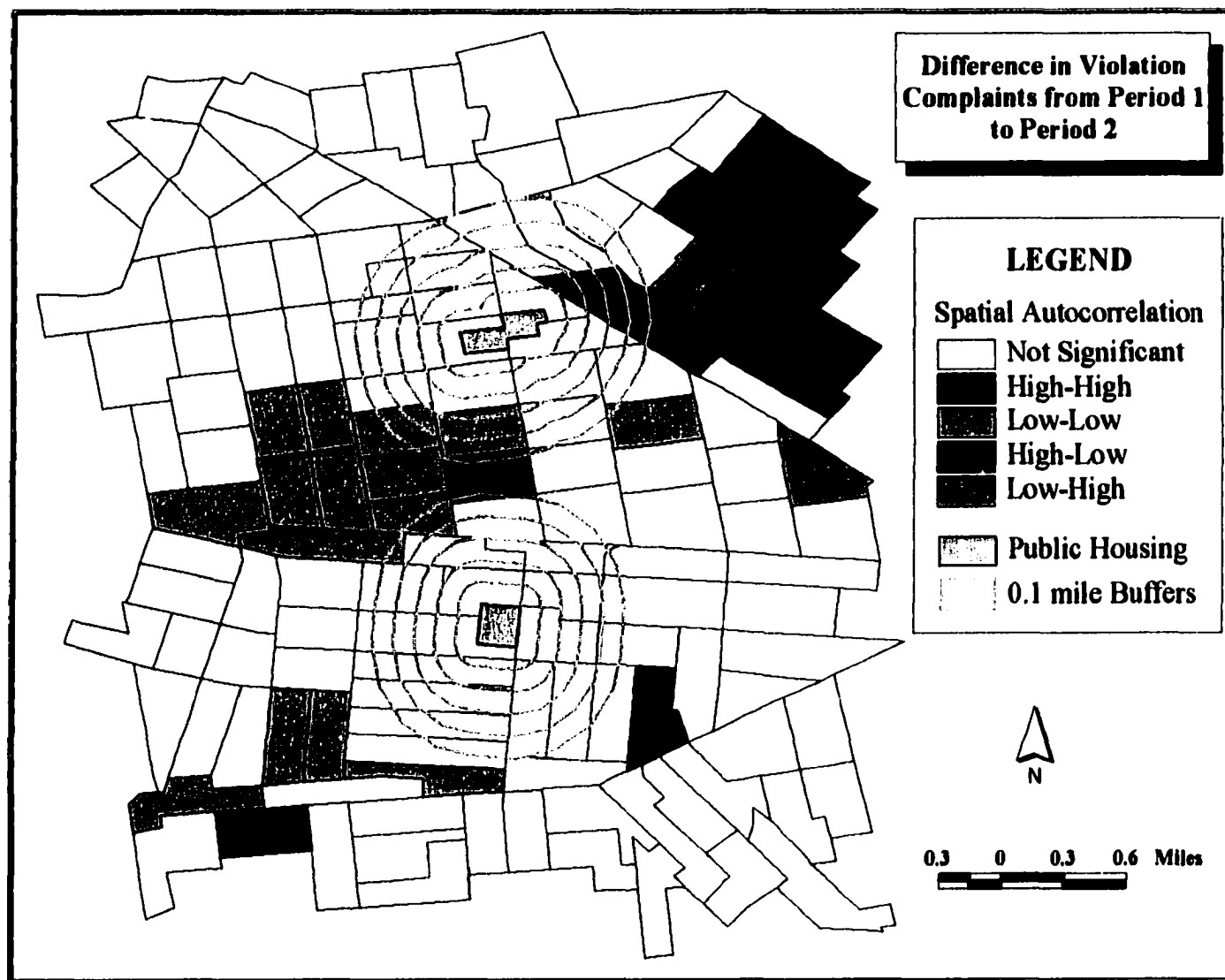


FIGURE B:8 Significant LISA Values and Relationships for Difference by Tract (Violation Complaints)

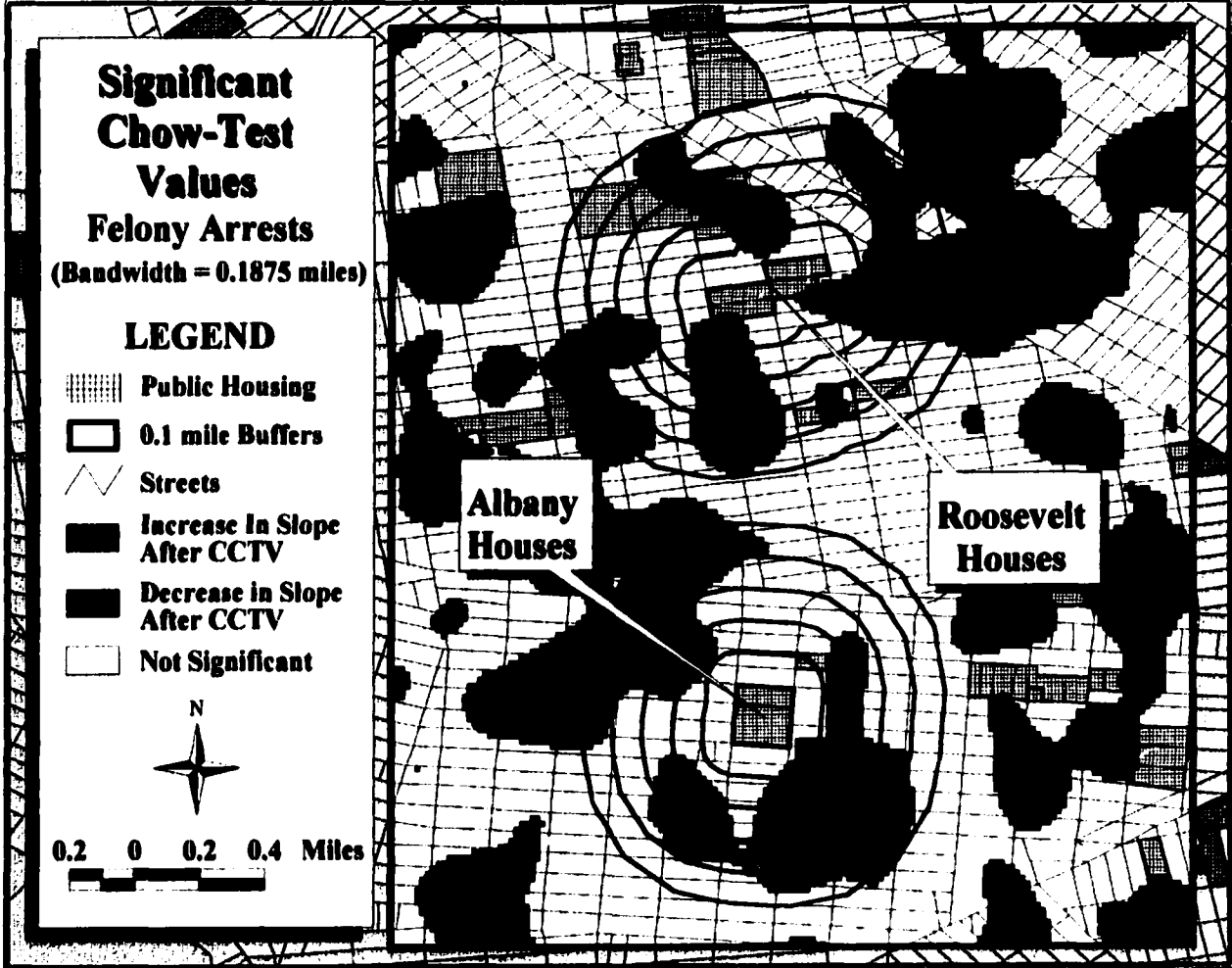


FIGURE C:1 Significant F Values and Trend of Slope Values, Felony Arrests



FIGURE C:2 Significant F Values and Trend of Slope Values, All Complaints

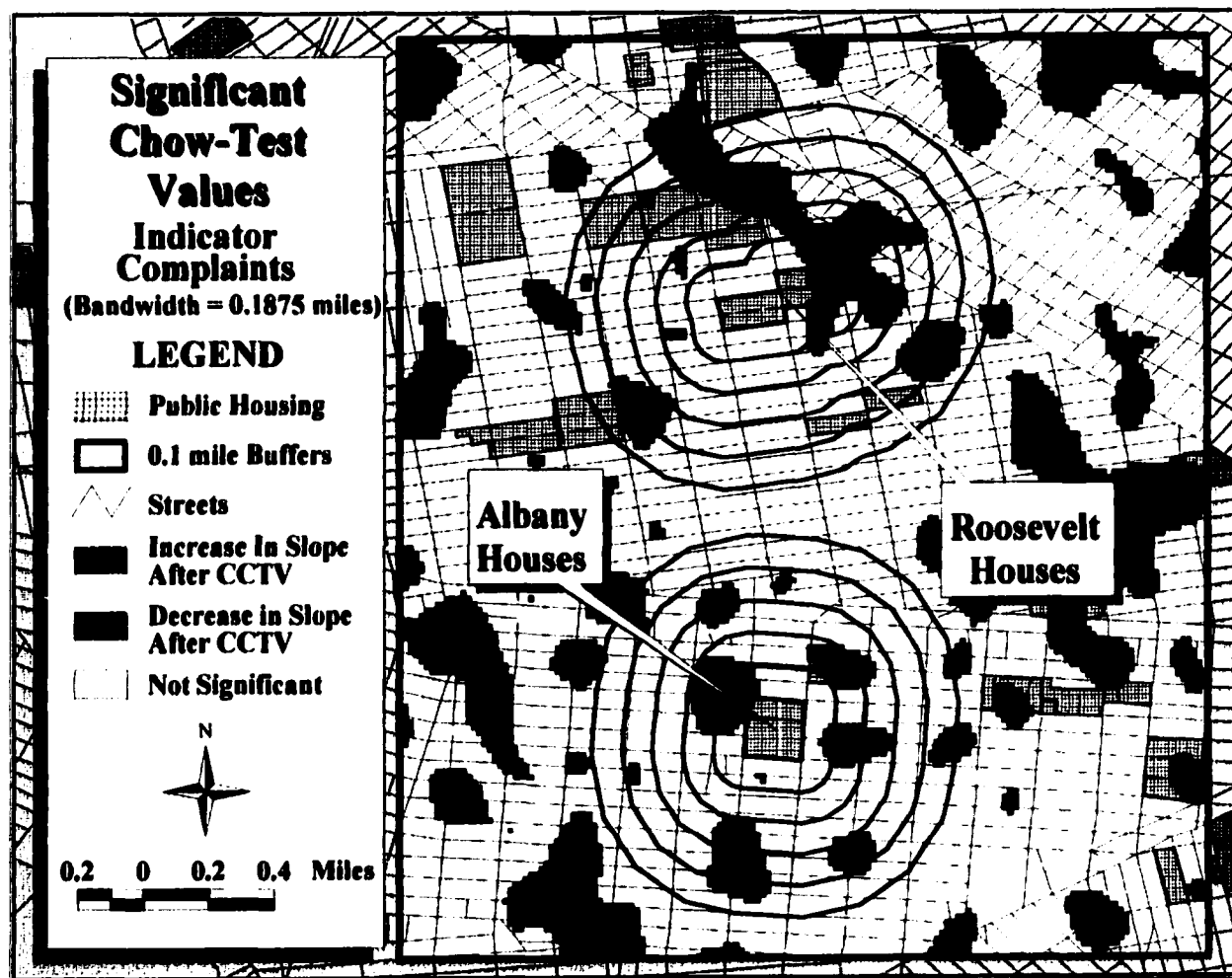


FIGURE C:3 Significant F Values and Trend of Slope Values, Indicator Complaints

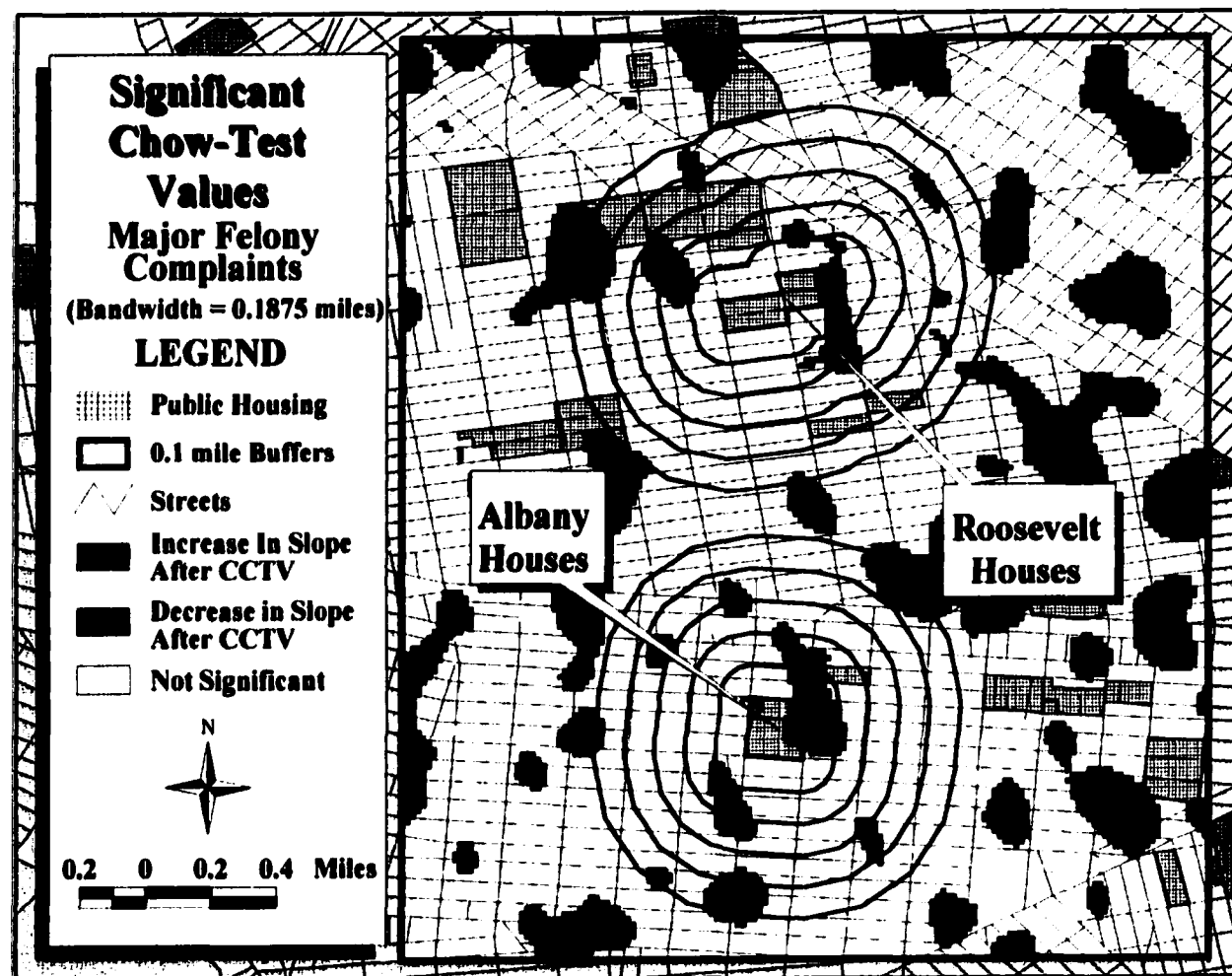


FIGURE C:4 Significant F Values and Trend of Slope Values, Major Felony Complaints

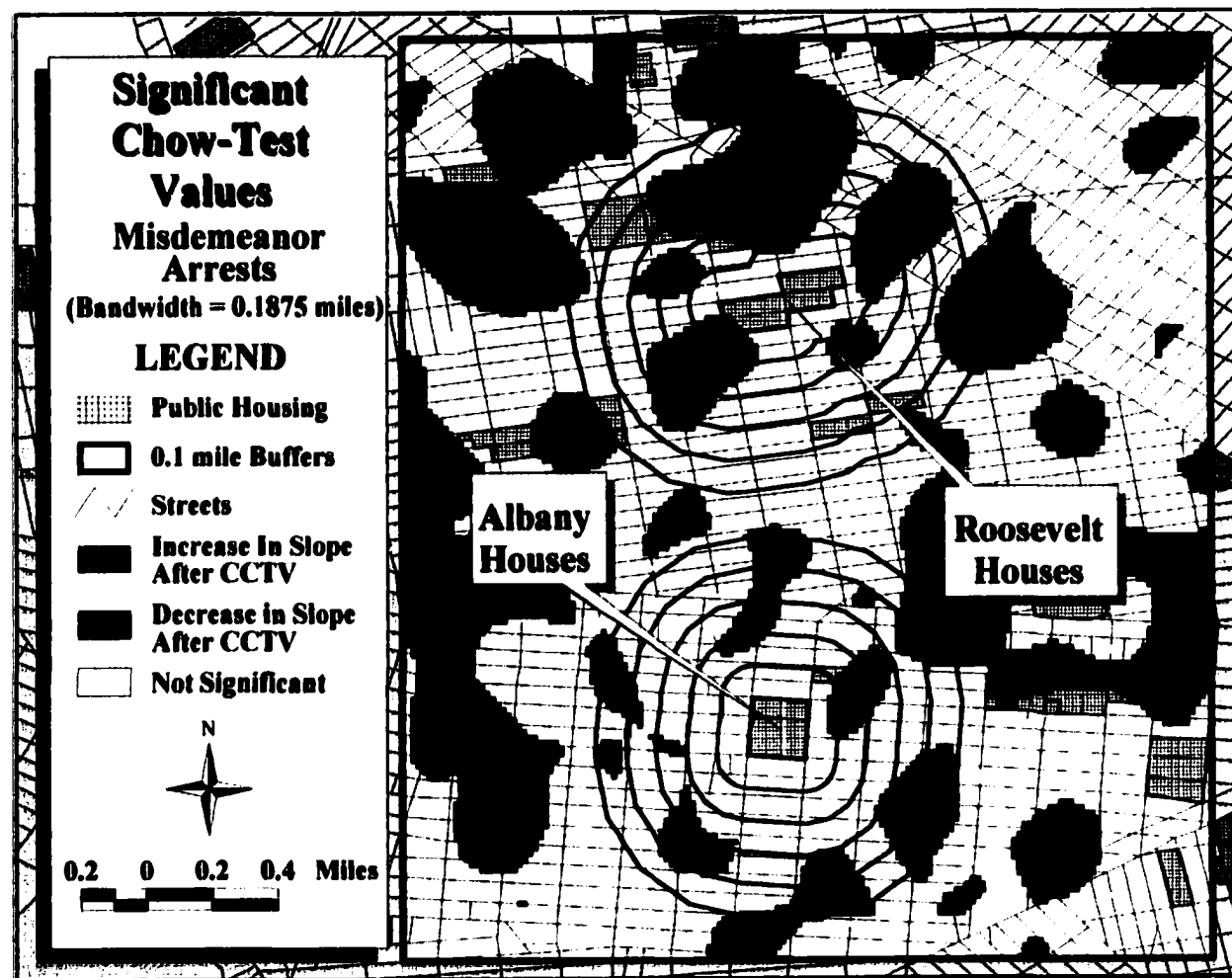


FIGURE C:5 Significant F Values and Trend of Slope Values, Misdemeanor Arrests

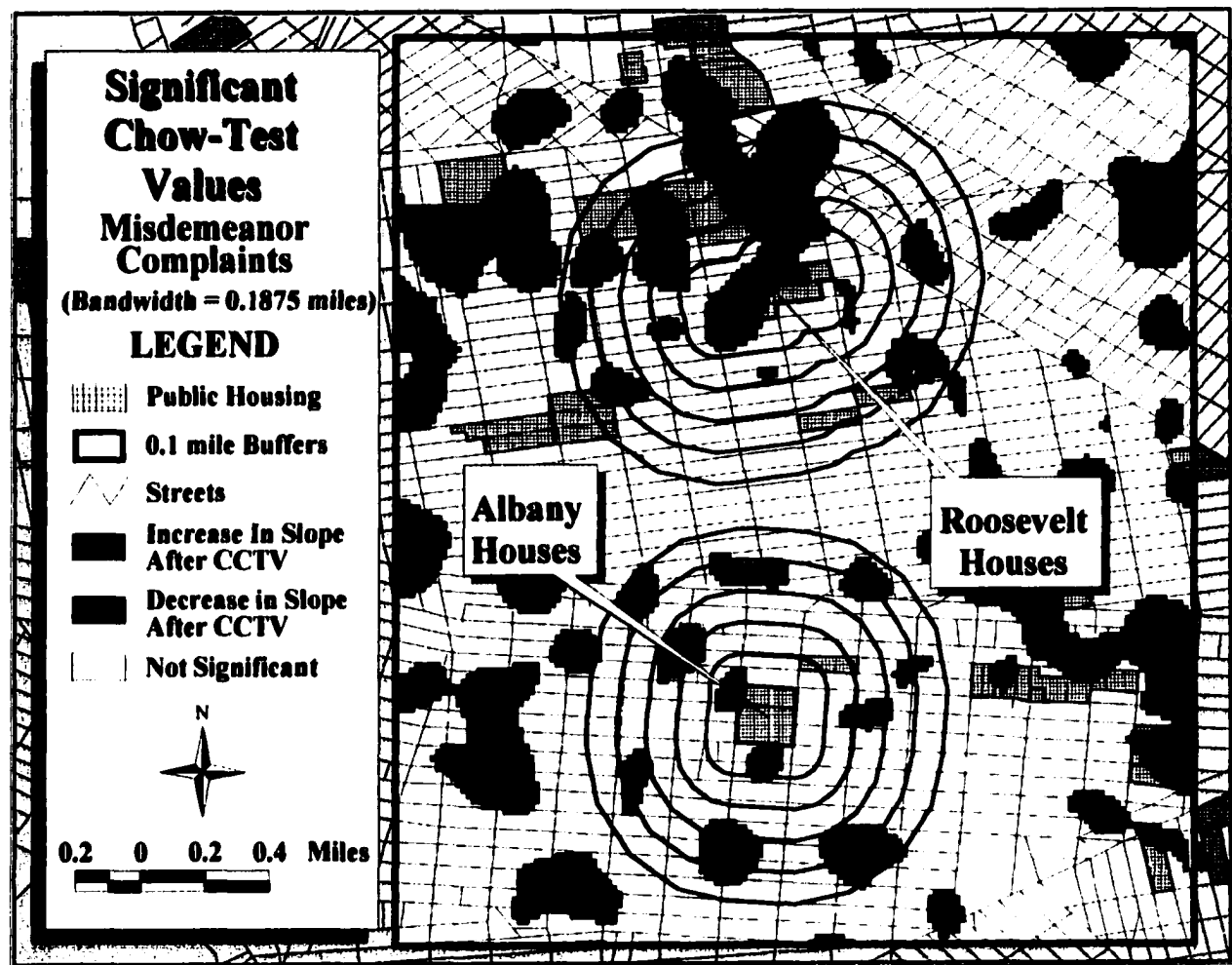


FIGURE C:6 Significant F Values and Trend of Slope Values, Misdemeanor Complaints

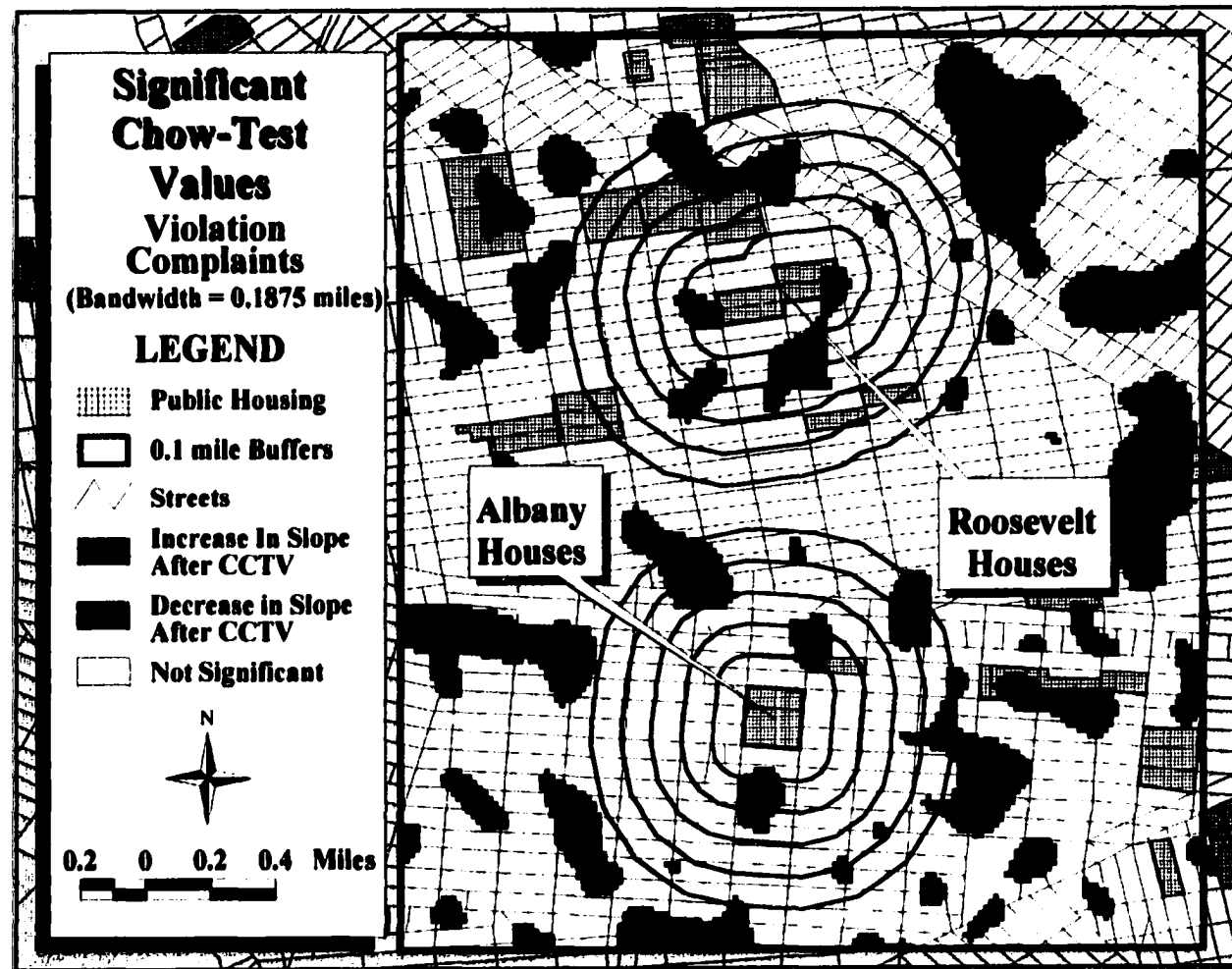


FIGURE C:7 Significant F Values and Trend of Slope Values, Violation Complaints

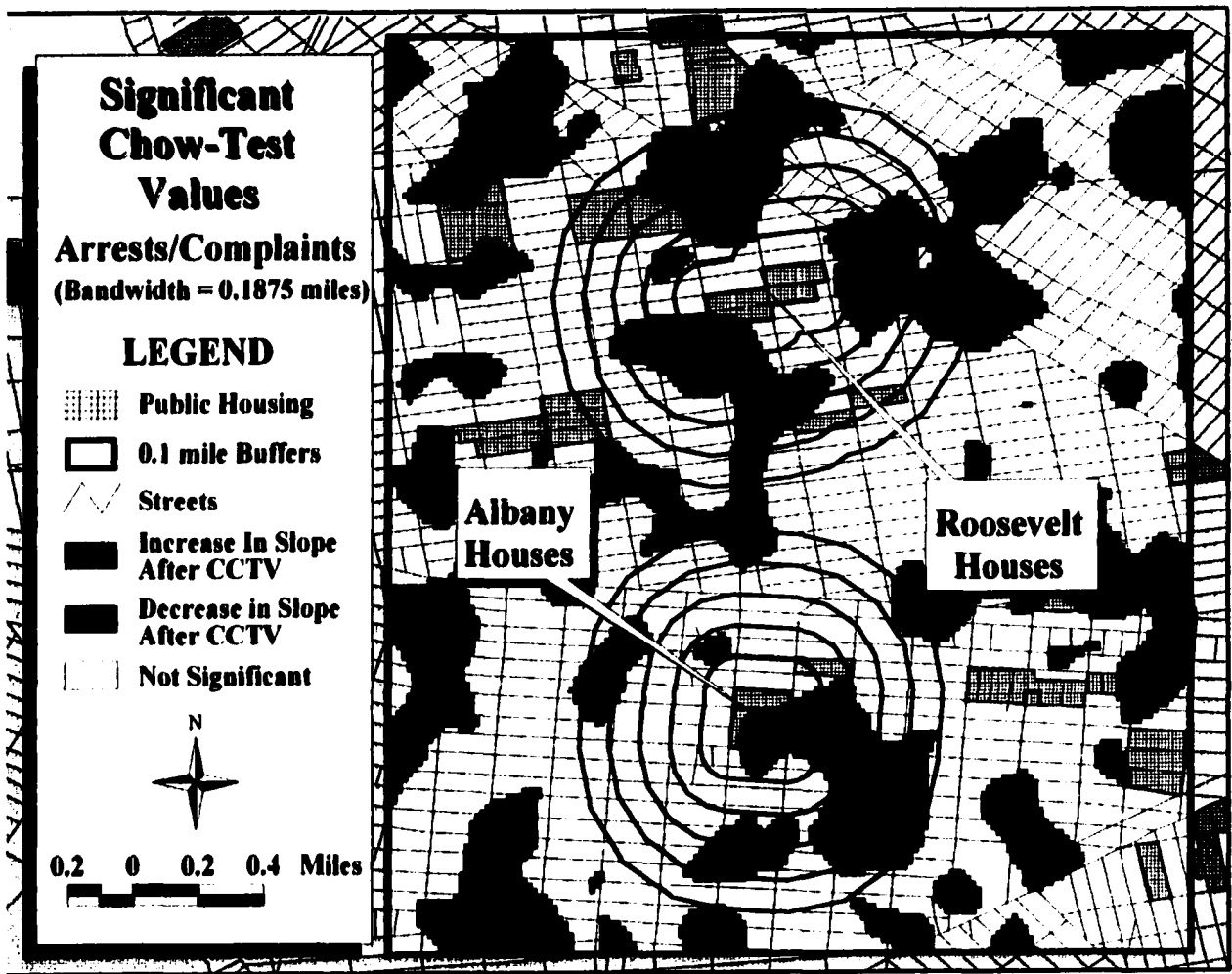


FIGURE C:8 Significant F Values and Trend of Slope Values, Ratio of Arrests versus Complaints

APPENDIX D

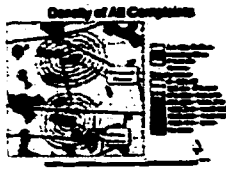


image001

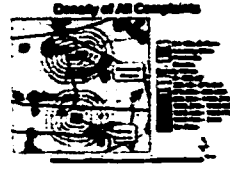


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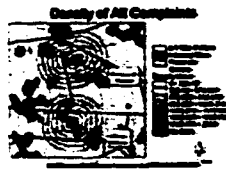


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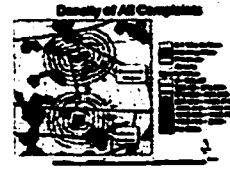


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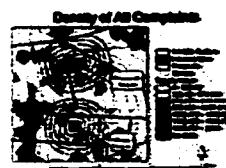


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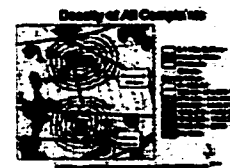


image006

FIGURE D:1 Sample Animation Images

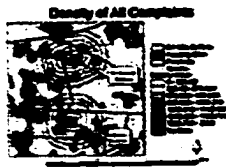


image007

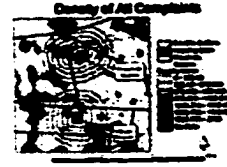


image008



image009

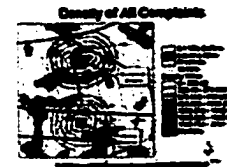


image010

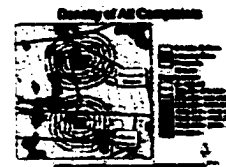


image011

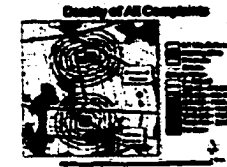


image012

FIGURE D:2 Sample Animation Images

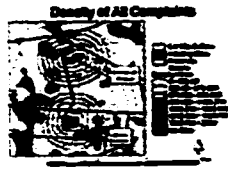


image013

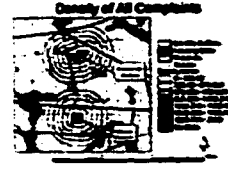


image014

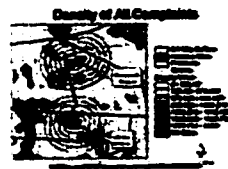


image015

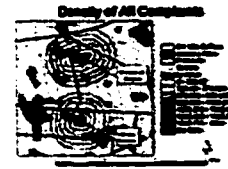


image016

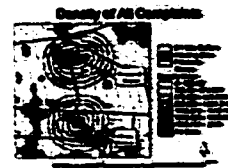


image017

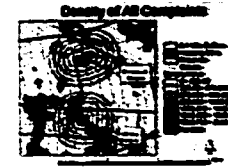


image018

FIGURE D:3 Sample Animation Images

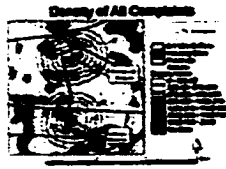


image019



image020

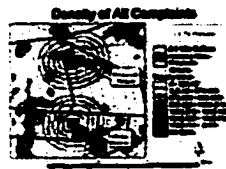


image021

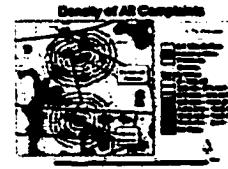


image022

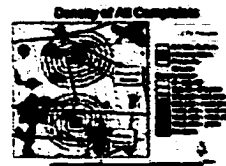


image023

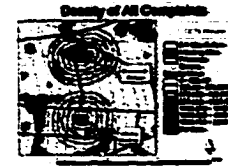


image024

FIGURE D:4 Sample Animation Images

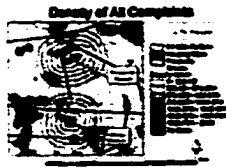


image025

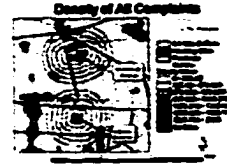


image026

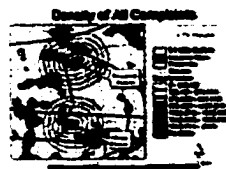


image027

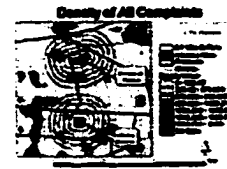


image028

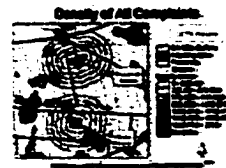


image029

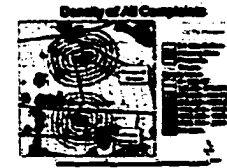


image030

FIGURE D:5 Sample Animation Images

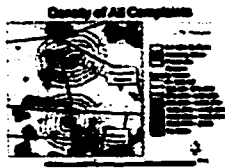


image031

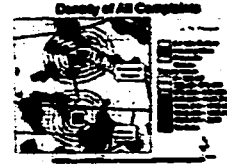


image032

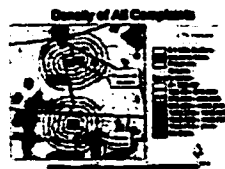


image033

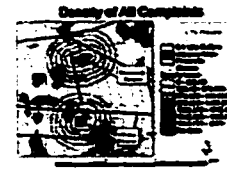


image034

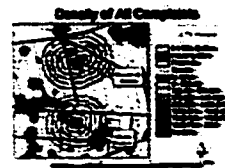


image035

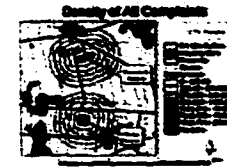


image036

FIGURE D:6 Sample Animation Images



image001

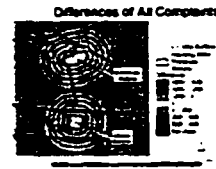


image002

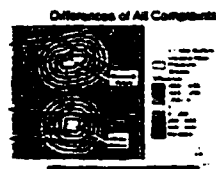


image003



image004



image005



image006

FIGURE D:7 Sample Difference Animation Images

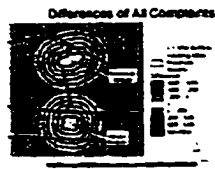


image007

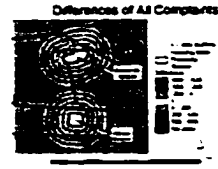


image008

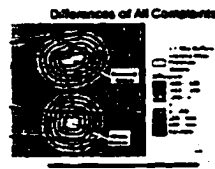


image009

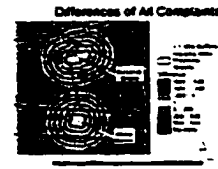


image010

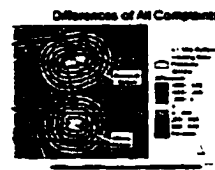


image011

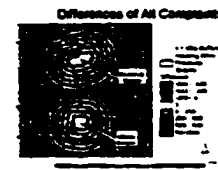


image012

FIGURE D:8 Sample Difference Animation Images

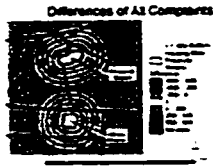


image013

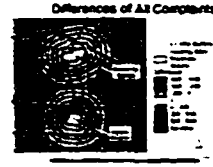


image014

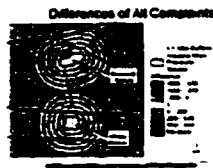


image015

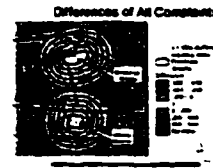


image016



image017

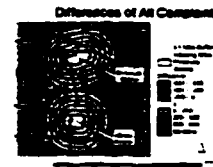


image018

FIGURE D:9 Sample Difference Animation Images

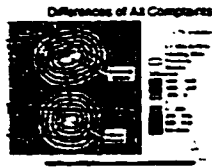


image019

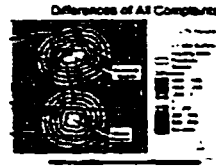


image020

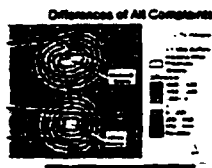


image021

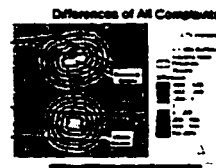


image022

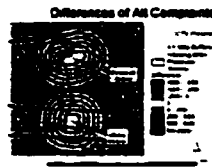


image023

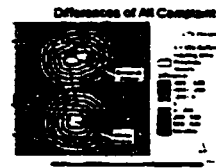


image024

FIGURE D:10 Sample Difference Animation Images

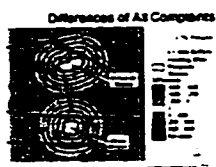


image025

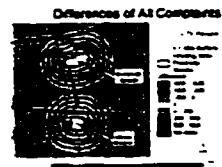


image026

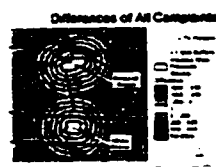


image027

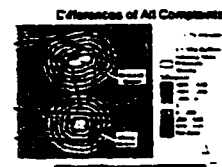


image028



image029



image030

FIGURE D:11 Sample Difference Animation Images

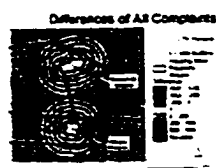


image031

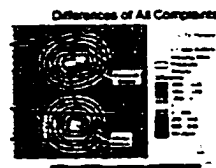


image032

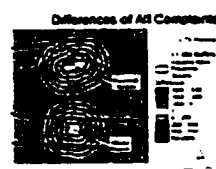


image033

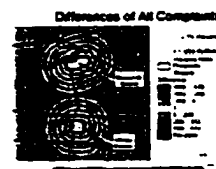


image034

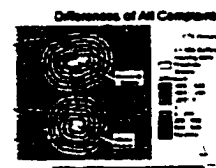


image035

FIGURE D:12 Sample Difference Animation Images

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