2012

Risky Businesses: A Micro-Level Spatiotemporal Analysis of Crime, Place, & Business Establishment Type

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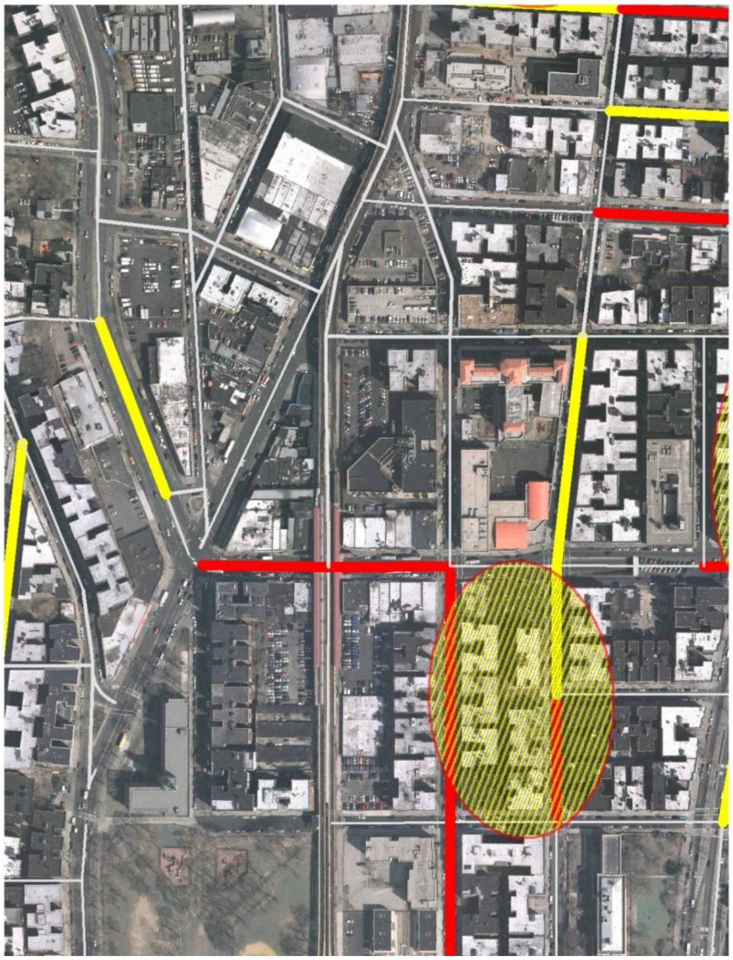

[‘Hot Streets’ & ‘High Crime Cluster’ in the 44th Precinct / Concourse section of the Bronx]

by

Christopher R. Herrmann

A dissertation submitted to the Graduate Faculty in Criminal Justice in partial fulfillment of the requirements for the degree of Doctor of Philosophy, The City University of New York.

2012

Dissertation Title: Risky Businesses: A Micro-Level Spatiotemporal Analysis of Crime, Place, & Business Establishment Type

Author: Christopher R. Herrmann

Date of defense: 03/26/2012

Time of defense: 2:00pm

This manuscript has been read and accepted by the Graduate Faculty in Criminal Justice in satisfaction of the dissertation requirement for the degree of Doctor of Philosophy.

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Abstract

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Crime, Place, & Business Establishment Type

by Christopher R. Herrmann

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Continuing advances in the fields of environmental criminology and geographical information sciences are facilitating place-based research. One of the current trends in environmental criminology is the focus on micro-level 'places' including street segments, property lots, and specific kinds of buildings and facilities in understanding crime patterns and the opportunity structure that permits crime. Despite important findings on the concentration of crime in urban areas, there continues to be substantial gaps in our knowledge about micro-level spatiotemporal patterns of crime. These gaps in micro-level environmental criminology research have primarily been a result of the lack of access to data, availability of ancillary data (land-use & business establishment data), accuracy of geocoded crime data, and availability of existing theory and methods to study crime at micro-levels.

Interestingly, many studies indicate that crimes are clustered at neighborhood level, but the entire neighborhood is rarely (if ever) criminogenic and only specific parts of neighborhoods contain high concentrations of crime. Prior studies incorrectly assume that the relationships between crime, population, land-use, and business establishment types are both homogenous and spatially stationary. Environmental criminologists using Pareto's 80/20 concept pointed out that not all parks are full of drug users/dealers, not all high schools have high rates of delinquency, not all bars contain high rates of assault, and not all parking lots have high rates of auto theft. In

fact neighborhoods contain hot spots (high density crime areas) and cold spots (low density crime areas), bad streets and good streets, and good and bad businesses.

By undertaking a micro-level spatiotemporal framework, this dissertation research is intended to promote understanding of the patterns of violent crimes and the opportunity factors that contribute to these crimes in neighborhoods, street segments, property lots and business establishment types. The integration of environmental criminological theory and novel spatial analyses at the street segment and property lot level should help criminology/criminal justice scholars and practitioners to better understand the spatial and temporal processes in the 'magma' that fuels today's hot spots.

This study integrates data compiled by the NYPD about the types, extent, and magnitude of violent crime at the micro level (n= 49,582 major violent crimes including murder, rape, robbery, shooting and assaults at the address level in Bronx, one of the five boroughs in NYC), with new micro-level census population estimates, as well as detailed spatial land-use data by the New York City Department of City Planning and Finance, and business establishment type data from InfoUSA. It therefore constitutes a study that makes unique contributions in understanding crime patterns at the micro level and in informing future research and policies for designing out crime in micro-level places.

For the purposes of this present study, violent crime was measured using a micro-level unit aggregation process that sums each individual crime location (point) to street segments, census tracts, and neighborhoods. Traditional hot spot methodologies, including nearest neighbor hierarchical clustering, kernel density estimation, and Gi* hot spot statistics were used for each violent crime and related to land-use categories and business establishment types. This assisted in evaluating the strengths and weaknesses of each of the above hot spots analytical tools/techniques.

The results of this research suggest that there are numerous (complex) spatiotemporal relationships between violent crime types, land-use categories, and business establishment types, which vary considerably over both space and time. It is important to note that a small percentage of street segments in the highest crime neighborhoods in the Bronx are responsible for a majority of the crime in those neighborhoods, while most of the street segments in high crime neighborhoods have zero crimes on them over the 5-year study period (2006-2010). Several crime specific relationships are noteworthy: robbery hot spots are strongly associated with subway stations (at certain days of the week and times of day); temporal assault hot spots are associated with clusters of licensed alcohol outlets; and murders and shootings are associated with some public housing complexes. This comprehensive micro-level ecological framework is capable of continuously *identifying* spatiotemporal patterns of crime, *monitoring* micro-level estimates of population, land-use categories, and *tracking* 'risky facilities' (e.g. businesses with crime problems) over time.

In sum, the shifting trends in criminology from offender-based theories to place-centered research have resulted in considerable reductions in crime throughout the USA and elsewhere. This research will assist law enforcement crime control strategies, advancement of environmental criminology theories at the micro-level, and expansion of existing crime prevention frameworks.

Acknowledgements

First and foremost, praise and honor to my savior Jesus Christ, for continuously providing everything I needed to complete this dissertation process and for guiding me down the very difficult road that has been criminal justice doctoral study. I want my life and this research to be ‘in Christ, by grace, through faith, by the power of his Spirit, for the praise of His glory’.

This dissertation research could not have been completed without the guidance, grace, and support of many people. I would like to thank my chair, Dr. Mangai Natarajan, for introducing me to Environmental Criminology in a graduate criminology class in 2000, publishing our class’s work in an academic journal, and helping me navigate my way through the Masters and Doctoral programs at John Jay College of Criminal Justice. Mangai has always provided me with academic guidance, knowledge of criminological theory, and good advice on many other things in life. Without her continuous support, I would not be where I am today. This research and dissertation would not have been possible without her support.

I would also like to thank my other dissertation committee members; Dr. Valerie West, Dr. Ernie Drucker, and Dr. Jim Lynch. Each was selected for their understanding of complex issues related to this work and their ability to help me embrace and appreciate these complexities. Dr. Juliana Maantay, although not a formal part of this committee, has always been the ‘basemap’ of everything I know about geography and GIS and continues to have an influence on every map I create.

The Executive Officers of the Phd Program in Criminal Justice - Todd Clear, Karen Terry, and Josh Freilich have all provided support and patience throughout my doctoral studies. Without them, I would not have started, continued, or finished this lengthy dissertation process.

I would like to acknowledge CUNY John Jay College of Criminal Justice, the National Institute of Justice, and the International Criminal Investigative Training Assistance Program, all of which have provided financial assistance at different stages of this dissertation process. Most of my doctoral study was a life of adjunct paychecks and poverty – these agencies helped sustain me when it was most needed. It has been a privilege to present various parts of this dissertation research at numerous conferences (Pittsburgh PA, 2007; New York City NY, 2007; Washington DC, 2008; Lakewood CO, 2009; New Orleans LA, 2009; Santa Barbara CA, 2010; Durban South Africa, 2011; Algiers Algeria, 2011, and Miami FL, 2011) and this would not have been possible without financial support from these respective agencies.

I continue to have the utmost respect and admiration of the New York City Police Department and the City of New York – who have provided me with the opportunity to learn about crime, crime analysis, and crime control strategies inside the best 'crime lab' in world. My sincere thanks to His honorable Police Commissioner Ray Kelly, Deputy Commissioner Mike Farrell, Assistant Commissioner Phil McGuire, Captain Joe Pascarella, and Captain Ray Martinez for approving this research and providing NYPD data throughout this process. Sergeant Jorma Huttenen has become a good friend and a most reliable crime analysis expert throughout this dissertation process – his understanding of NYPD protocols, crime data, and knowledge of Chinatown restaurants continues to impress me and I hope to have the opportunity to work with him (and the wonderful staff at OMAP) again in the future. Jorma is one of the people that made this dissertation possible; I am forever indebted to him.

Special thanks to my New York City 'ESRI family' - Dave LaShell, Paul Trevillion, Patrick Gahegan, and Tom Swanson. Dave has always been supportive of this important work and helped in countless ways to provide software, data, assistance with licenses, or anything else

I needed from ESRI (and some of its business partners). This work would not have been possible without both Dave and ESRI's support. Lauren Scott and Lauren Rosenshein introduced me to Thai food and continue to share their unending expertise in spatial statistics and geoprocessing. I am also grateful to the family of GIS users in the NYC ArcUSER group. Steve Pollackov, Timothie Biggs, Chris Goranson, and Susan Resnick have consistently provided GIS assistance, support, and encouragement along the way and I am grateful for their 'GIS friendship'.

I have had the privilege and pleasure of learning Crime Analysis and Geographical Information Science (GISc) from many of the great minds in these fields. Each person deserves some credit for influencing the shape, format, and content of this dissertation. Marcus Felson and Ron Clarke helped me to focus some of my thoughts and ideas throughout the proposal stages and assisted in the theoretical framework design. Jerry Ratcliffe and Liz Groff continue to inspire me, teach me new things, and provide numerous opportunities to learn from their intellectual pursuits. Ralph Taylor and Jim Lynch have influenced my understanding of statistics and how to properly apply them in the real world. Ned Levine, Ron Wilson, and Dick Block provided me an opportunity to learn CrimeStat at the University of Michigan, which continues to be one of my primary tools in crime analysis.

I have had the privilege and pleasure of working with David Kennedy and the Center for Crime Prevention and Control at John Jay College. David helped me to learn more about crime prevention and control through ceasefire and drug market initiatives and showed me firsthand that more police (or arrests) isn't always the best solution to our crime problems (in fact, it causes more problems sometimes!). Stephen Matthews, Don Janelle, Jared Aldstadt, Art Getis, Mike Goodchild, and the amazing people at the Center for Spatially Integrated Social Science provided me with several opportunities to learn more about spatial statistics and advanced GISc at Penn State and UC Santa Barbara. Pat Brantingham and Martin Andreesen assisted with parts of my population distribution/density issues and the temporal analysis framework. Stuart Fotheringham, Chris Brunsdon, and Martin Charlton helped me to learn, understand, and appreciate new methods that have influenced my approach to GISc research and I have had the privilege of sharing several 'pints' with these distinguished quantitative geography gurus along the way. John Ziegler provided data, encouragement, and a better understanding of the multifaceted nature of New York City's cadastral data. John is another one of those people that has made this dissertation possible.

I have also had the pleasure of learning with and from many exceptional colleagues along the way, many of which have become good friends. Andres Rengifo and Jessica Saunders cheered me thru the first few years of the doctoral program, I would not be finishing this Phd. without their early academic support, encouragement, and friendship. Travis Taniguchi and Jamie Mihoko-Doyle reminded me that learning can be fun and I will always cherish the good times shared learning GWR at Penn State and in Philadelphia eating cheesesteaks (Pat's is better than Geno's). Yolanda Ortiz-Rodriguez, Oliver Pu-Folkes, Scott White, Sue-Lin Wong, Gipsy Escobar, Odessa Simms, Julie Viollaz, and Zainab Latif, have all shared food, drink, and heartaches with me along my doctoral journey – I am forever thankful for them sharing in my good times and helping me thru the bad times.

I met Andrew Maroko early on in my GISc studies at Lehman College and he has been nothing but a supportive friend since. He has spent more time combing thru my data, wrestling with ArcGIS, discussing different methods & analyses, and teaching me more about pretty much everything in life over the past 10 years. I'd like to also thank his family, Rosemary Farrell, Peter, and Sofia for sharing many of Andrew's late nights with me these past few years. There

always seems to be an unending supply of diet Dr. Pepper, Dunkin Doughnuts, love, and laughter at the Maroko-Farrell house and they have always made me feel a welcome part of their family, whether it is working on dissertation research until the early AM hours or deep-frying turkeys. This dissertation would not be what it is without Andrew's GIS genius, his time, and his willingness to share both with me. I am forever indebted.

My church families, both First Baptist Church in Tarrytown and Ridgeway Alliance Church in White Plains have been encouraging and prayerful for Maria and I throughout this doctoral study process. Our success as a couple, through all the stresses, strains, and poverty that doctoral study provided was only possible because of the considerable support of our beloved church families. I'd like to thank the Kang and Diaz families especially, who continue to provide 'fellowship, food, and fun' for Maria and I on a weekly basis and for reminding me consistently that there is actually life outside of doctoral study and dissertation work. Thank you for listening to my headaches and heartaches along the way and for taking care of Maria when I was 'away'.

Finally, the dissertation would not have been possible without the spiritual, emotional, and financial support of my parents, Russell and Leslie Herrmann, and my beloved wife of 11 years (and 'sugar-momma'), Maria Herrmann. My wife and my parents have all shared encouraging words & notes, rearranged schedules & vacations, and sacrificed much to make this entire 8-year dissertation journey possible. It has been a long and bumpy road to finishing this dissertation and it is only possible because of their love and unending support along the way. Their names, just as much as mine, should be included on the title page.

Dedication

This dissertation is dedicated to my parents, Russell and Leslie Herrmann, who have always been and continue to be my favorite teachers in life. Mom and Dad always said I could achieve anything I put my mind and heart into and this dissertation work is a testament to their continued encouragement, support, and believing in me.

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1. INTRODUCTION

This dissertation examines five years (2006-2010) of violent crime locations in Bronx County (NY) utilizing a Geographical Information Sciences (GISc) framework. This research is unique in that it examines the various spatial relationships between violent crime, population variables, land-use categories, and business establishment types at different geographic levels. Many of the previous crime analysis studies look at cross-sectional datasets and do not take into account spatially autocorrelated crime & population data, spatial heterogeneity of land use & business establishment types, and spatial non-stationarity of theoretical processes.

Longitudinal crime (trajectory) studies have rarely taken 'space' into consideration. Similarly, cross-sectional crime analysis studies are unable to identify important relationships between temporal patterns/trends and theory as a result of the data and analytical limitations. Allowing theoretical processes to vary over micro-level spatial units will provide an interesting new look into the modifiable areal unit problem (MAUP) and current theoretical composition.

This research incorporates a very innovative dasymetrically derived census population estimates dataset that allows the construction of a traditional 'crime rate' [crime frequency / population] at both the street segment and property lot levels. The use of this new property-level census estimates and "micro-level crime rate" is a first in our field. Population density is often overlooked in criminology, but it is important to understand, because (most) high density crime relationships and patterns are simply a result of high population density (Andresen & Jenion, 2008). A micro-level population estimate allows for examination of the various micro-level crime & population relationships and provides a much more comprehensive understanding of 'crime and place' over time.

The geographical 'bottoms-up' approach looks at the various relationships between crime, crime trends, & business types from the micro-level (i.e., property lots, street segments) up to larger geographies (i.e., census tracts & neighborhoods). The micro-level unit aggregation approach clearly illustrates the variance within and between the different geographical levels/units of analysis. While traditional criminological theory has been based upon coarse aggregate datasets, such as communities and neighborhoods, we can no longer deny and overlook the significant variance at more micro-level geographies.

Moreover, the development of a new micro-level crime analysis method will allow police to identify, monitor, track, and intercede on high crime problem properties and street segments *before* they become too problematic (i.e., 'hot spot prevention'). Current police technologies, including CompStat and hot spot analyses, are unable to identify, track, and monitor micro-level units consistently over time. CompStat is performed at a very 'coarse' spatiotemporal level (NYPD Precincts are much larger than neighborhoods and average four neighborhoods per Precinct). CompStat was designed using weekly precinct-level crime trends for crime analysis, resource allocation (i.e., overtime allowances and additional manpower), and crime control.

Violent crime hot spots vary in shape, size, and temporal units by the specific hot-spot method selected (hot spot methods are explained in detail in section 2.2) to construct them and are therefore unable to track and monitor micro-level units over time. Furthermore, hot spots identify small amounts of high crime concentrations, while the micro-level unit aggregation process is comprehensive and provides a crime rate for each micro-level unit over time.

Violent crime (i.e., murder, rape, robbery, assault, and shootings) has declined 73% in the Bronx since 1990. In his new book, Zimring (2011) suggests that the historic crime drop in New York City is a result of better policing (i.e. CompStat, crime analysis, hot spots, zero tolerance, stop & frisk) and community crime interventions, including 'gun buyback' programs. This dissertation research hopes to advance these trends of increasing success for law enforcement crime control strategies, advancement of current environmental criminology theories, and expansion upon existing crime prevention frameworks. Integration of theory and new analyses at the street segment and property lot level will help criminologists, police departments, and policy makers better understand the spatial and temporal processes in the 'magma' that fuels today's crime hot spots.

In 2008, Weisburd and Piquero asked the question, "How Well Do Criminologists Explain Crime?". Their research indicated the following: (1) understanding the phenomenon of crime lies at the heart of criminology; (2) over the past 150 years, there has not been an evaluation of the explanatory power of criminological research; (3) the overall level of explanation of crime is often very low, with 80% - 90% percent of variance unexplained; and (4) criminologists should pay much more attention to what is 'not explained' if they are to make significant advances in understanding crime. Unfortunately, the link between how well criminologists explain crime is directly related to the amount of influence research has on public policy. However, if theory guides research and research results influence public policy, then the low levels of explanatory results/power (as indicated by Weisburd and Piquero) suggests that criminology today has very little influence on current public policy.

Crime and Place

Braga and Weisburd (2010), in their Editors' Introduction for the Journal of Quantitative Criminology (Volume 26:1-6) assert that for 'most of the last century criminologists have focused their understanding of crime on individuals and communities'. They suggest (and I wholeheartedly agree) that historically, the field of criminology has largely focused on individual–level and community-level factors related to crime. With regards to individuals, criminology has focused on why some individuals offend while other individuals choose not to (Akers, 1973; Cornish and Clarke, 1986; Gottfredson and Hirschi, 1990) or why some offenders start offending in their early years and desist, while other offenders continue to offend, and while even few continue to offend much later into their 'life-course' (Moffitt, 1990; Sampson and Laub, 1993; Nagin, et al., 1991; Nagin and Paternoster, 2000; Loeber and Farrington, 2001).

When focusing on the community's contribution to crime, the field of criminology has focused on why certain communities maintain high levels of crime while other communities contain little or no reported crime (Shaw and McKay, 1942; Sutherland, 1934; Kornhauser, 1978; Bursik, 1988; Skogan, 1990; Sampson, 1993; Sampson and Wilson, 1995). In addition to the differences within and between community levels of crime, several noted criminologists have also posited the impact(s) of community-level socioeconomic variables and 'social networks' on neighborhood levels of crime (Agnew, 1992; Sampson and Groves, 1989; Wilson, 1996; Sampson et al., 1997; Morenoff et al., 2001). Almost all of the above mentioned research takes place in geographic areas at the community or neighborhood level.

Preliminary analysis of violent crime, population density, land-use, and business types, was conducted on the highest violent crime neighborhood in the Bronx (see Appendix – Pilot Study).

This analysis was conducted to determine the feasibility of this dissertation research, as well as to illustrate the substantial spatial variance that occurs ‘below’ the neighborhood level in the aforementioned variables. Criminology, for a number of reasons, has designated the neighborhood as a ‘holy grail’ spatial unit of analysis. However, by relying on ‘coarse’ neighborhood level data as the unit of analysis, criminologists have overlooked much of the interesting spatial variance that occurs at more micro-levels (i.e., streets, properties, buildings). It is these micro-level units that construct the larger geographic units (i.e., census block groups, census tracts) that eventually build what we call ‘the neighborhood’.

Likewise, neighborhood boundaries vary widely according to who (i.e., what agency and what level of government [local, county, state, federal]) determines the actual neighborhood boundaries. In New York City, the NYC Department of City Planning (DCP) has defined 195 different neighborhoods across New York City. However, the DCP website also lists 17 other geographical boundary datasets (e.g. State Assembly Districts, City Council Districts, Congressional Districts, State Senate Districts, Election Districts, Municipal Court Districts, Community Districts, School Districts, FDNY Fire Company boundaries, FDNY Fire Battalion boundaries, FDNY Fire Division boundaries, NYPD Police Precincts, Department of Health - Health Center Districts, and Department of Health - Health Areas, and neighborhood projection areas) that could also be used as ‘neighborhood’ boundary files. Another commonly used ‘neighborhood boundary’ is the United States Postal Service zip codes. According to the postal service, New York City is divided up into 180 ‘zip codes’, however, zip codes are not constructed solely based on geographical boundaries (e.g., rivers, lakes, bridges) or population distribution and population density. Zip code boundaries are simply designed to facilitate efficient mail delivery.

Environmental Criminology

All of this research is firmly grounded in the foundations of environmental criminology, which unites crime pattern theory (Brantingham and Brantingham, 1984) with various aspects of routine activities theory (Cohen & Felson, 1979) and rational choice theory (Cornish & Clarke, 1986). Environmental criminology states that criminal events "must be understood as confluences of offenders, victims or criminal targets, and laws in specific settings at particular times and places" (Brantingham & Brantingham, 1991, pg. 2). Environmental Criminology focuses on spatiotemporal analysis and the detailed place and locational aspects of the criminal event.

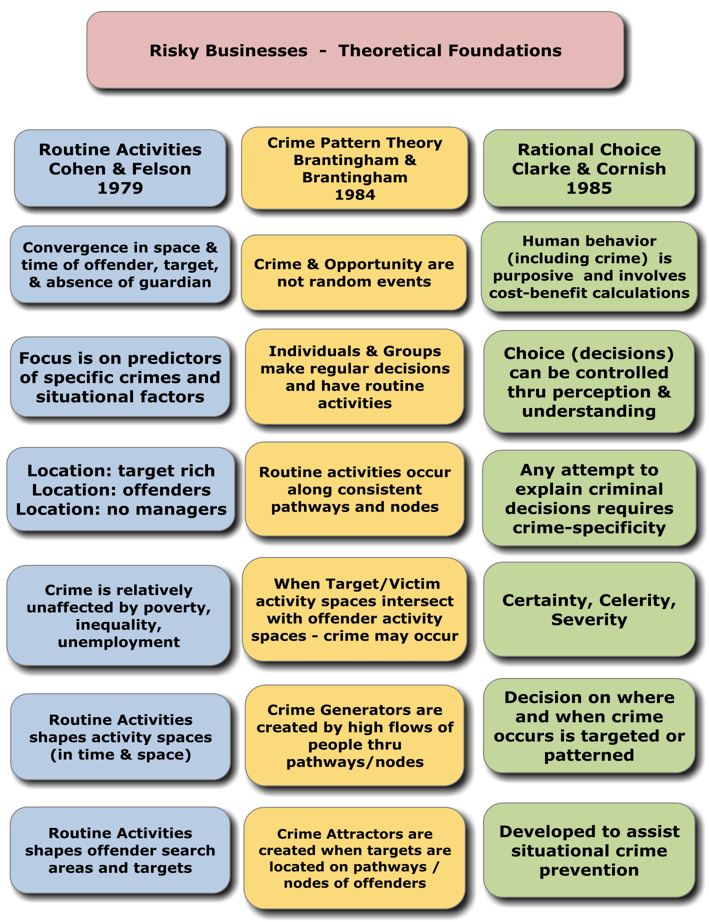


Figure 1.1 Theoretical Foundations of Environmental Criminology
Routine Activities vs. Crime Pattern vs. Rational Choice Theories

Routine activities theory states that crime is dependent on the opportunities available to potential offenders. If there is a suitable target and a motivated offender, in the absence of a capable place manager, there is an increased likelihood that a crime will occur. The routine activities approach suggests that crime remains relatively unaffected by poverty, unemployment, and social inequality (i.e. social disorganization factors) (Cohen and Felson, 1979).

Many prior studies of crime locations do not take both space and time into consideration (Felson, 2003; Ratcliffe, 2006; Agnew, 2011). Crime is patterned based upon opportunity structures (routine activity), an intentional decision making process to commit the crime (rational choice), and the availability of victims/targets & offenders (demography, rational choice, routine activities) in space and time (Felson, 2002).

Together these crime theories explain the how, when, and where of high crime opportunity, low crime opportunity, and zero crime opportunity. Opportunity structure is defined as the settings or physical requirements needed to commit a crime (Felson & Clarke, 1998). Opportunity variables consist of specified land use categories, business types, and population data (census, subway, public housing) which are theorized as criminogenic by traditional opportunity theories. The location and movement of offenders, targets, handlers, guardians, and managers across spatial and temporal patterns all relate to where and when crime opportunities are located. As such, this research examines both the spatiotemporal analysis of violent crime, as well as provides a detailed look at the specific ‘places’ where violent crime occurs.

Crime Concentrations and the 80/20 rule

One of the current trends in contemporary criminology is the study of crime at more ‘micro’ level places (i.e., buildings, properties, block faces, street segments), a geographic scale / level well below the neighborhood level. Much of the micro-level research has been done by David Weisburd and colleagues. Weisburd was recently awarded the Stockholm Prize in Criminology (2010) as a result of his well-established body of crime prevention research which indicates that a small percentage of crime locations (i.e. ‘hot spots’) contain a significant percentage of crime. This process, typically referred to as the 80/20 rule, reigns true not only in crime prevention and control, but other areas of the criminal justice field as well. This ‘theory’ suggests that by focusing or targeting the highest 20% of high crime places can have a dramatic influence on 80% of total crime. According to the 80/20 rule, the net impact of crime prevention and control strategies targeting the 20% would be much higher than attempting to target an entire neighborhood.

The infamous Wolfgang cohort (Wolfgang, 1972) indicated that 6% of male juvenile offenders were responsible for 52% of the reported delinquency in the study. Moreover, when looking at crime specific statistics, the same 6% of male juveniles were responsible for 69% of aggravated assaults, 82% of robberies, and 71% of murders. Similarly, Schumacher and Kurz (2000) in their book, *The 8% Solution: Preventing Serious, Repeat Juvenile Crime*, discovered that 8% of their juvenile probation cohort went on to become serious chronic (4 or more incidents per year) juvenile offenders.

The 80/20 rule also applies to the concept of victimization. In the UK, 4.3% of victims who responded to the British Crime Survey were ‘repeat victims’ who accounted for 43.5% of all reported victimizations (Farrell and Pease, 1993). Likewise, researchers have conducted in-depth interviews with offenders and the 80/20 rule applies to both offenders and their targets. Some examples of repeat offender crime types include convenience store burglaries (Lakewood, CO), thefts from vehicles (Newport News, VA), auto theft (Chula Vista, CA), and bank robbery (United Kingdom) (Clarke and Eck, 2005). According to Pease (1998), the best predictor of future victimization is prior victimization (not low socioeconomic status as many traditional criminologists would suggest). Therefore, understanding victimization patterns (time, place, what / whom is being targeted) can have a much more dynamic impact on overall crime reduction than programs targeting entire 'high crime neighborhoods'. Small scale crime control strategies can have large scale crime reduction effects.

As this last example suggests, the 80/20 rule also applies to specific victims, targets, or 'hot products' (Clarke, 1999). Understanding what the current hot products are is vital to crime analysis. Hot products are specific items that comprise a large percentage of personal thefts and robberies. Currently, handheld electronics including portable GPS units, cell phones, tablet computers, and e-readers are the hot products of 2012. In New York City, the latest release of Apple's iPhone 4 made personal theft in the subway system 'skyrocket', according to NYPD Transit Chief Joe Fox (NY Post, February 28th, 2012). Chief Fox added that the subway cellphone thieves were just as restless for the new version of the iPhone to be introduced as the large group of Apple iPhone buyers that always welcomes the latest iPhone model. Currently, half of thefts (from person) in the New York City transit system are 'small electronics' (primarily, cell phones and tablets/e-readers). If police consistently analyze what specific hot products are being targeted/stolen, they can then better target those areas with high concentrations of those hot targets. As will be discussed in section 3.2, hot products are tied directly to afternoon robbery locations in the Bronx, specifically robberies occurring at subway stations near high schools.

Risky Facilities

The last of the 'repeat crime concepts' where the 80/20 rule applies is 'risky facilities' (Clarke and Eck, 2007; Eck et al., 2007). Risky facilities are defined as the small percentage or small group of specific establishments (e.g., schools, bars, parking lots, convenience stores, ATMs, transit stations, etc.) that produce a significant percentage of the disorder, crime, and/or calls for police service when compared to the larger percentage of the overall group of facilities. Spellman (1995) suggests that this body of hot spots and 80/20 rule research simply confirms what we already know, that "a few, particularly frequent, offenders are responsible for a disproportionate amount of crime" (page 115).

The concept of risky facilities is central to this research because it provides a common opportunity structure for analysis that is based upon the repeat victim, repeat offender, and repeat address phenomenon. Likewise, since it is focuses on actual facilities (i.e. 'places'), it also provides a centralized spatial / locational component based upon hot spots and hot products.

Eck et al. (2007) suggests that risky facilities are a great starting point for crime analysis and problem-oriented policing projects. Since the process is facilities based, it provides an excellent vantage point into crime concentrations at the micro-level and provides a two-pronged approach towards crime reduction. First, the risky facilities analysis process can focus on specific types of crime occurring at specific types of facilities (e.g. bars and assaults, subway stations and robberies, public housing and shootings, auto thefts and parking garages, etc.). This initial scanning and analysis process may illuminate the what, where, and when part of the crime problem and provide some common causal factors which can immediately be addressed (or studied more in-depth). Second, risky facilities can assist crime prevention programs in targeting the facilities with the highest amount of crime/disorder and providing the information necessary for the response and assessment stages of crime prevention.

Clarke and Eck (2007) suggests that the concentration of crime risk and crime opportunity within and between facilities can be calculated using a six-step procedure.

1. List the facilities alongside a count of the number of relevant events
2. Rank the facilities according to the number of events associated with each (high to low).
3. Calculate the percentage of events that each facility contributes.
4. Cumulate the percentages, starting with the riskiest facility.
5. Calculate the proportion of the facilities that each single facility represents.
6. Compare the cumulative percentage of facilities to the cumulative percentage of events.
   Source: Clarke and Eck, 2007. Understanding Risky Facilities, Tool Guide #6

Clarke and Eck also suggest that there is no one universal reason for this variance in crime risk and crime opportunity for facilities. Facilities vary in crime risk and crime opportunity as a result of the size of the facility, the number of employees & customers, the type of products (especially hot products) within the facility, the location of the facility, the rate of repeat victimization per facility, the number of crime attractors (which tend to invite offenders), the overall design/layout of the facility, and the management (i.e. security) at the facility. Each of these facility factors plays an integral role in the amount of crime risk and crime opportunity for each facility. Moreover, these facility factors also create an easy ‘how-to reduce crime’ checklist for crime prevention specialists since the process identifies those facility factors that are troubling the facility and require modification.

One of the primary benefits in the risky facilities analysis process is the ability to apply well-known crime reduction strategies and proven methods to decrease crime opportunities. Recently, the Federal Department of Justice Office of Justice Programs (OJP) launched the *www.crimesolutions.gov* website that provides 'reliable research' and 'real results' regarding crime reduction program effectiveness. OJP outlines numerous community crime prevention programs, as well as programs that target violent crime and property crime reduction strategies. Many of these strategies are place-based strategies that can easily be adapted into facility-based programs.

Clarke and Eck (2007) also promote several other crime risk and crime opportunity reduction methods. These methods can include (1) increasing the publicity of the problem (i.e. shaming the business / owner), (2) applying different civil sanctions (i.e. monetary fines, liquor license revocation), (3) developing certification programs for businesses (i.e. police 'approved' parking garages), (4) encouraging local business owners to adopt a 'standard code of practice' (i.e. reduce alcohol related violence, report all crime to police), (5) performance standards for local businesses (i.e. businesses are sanctioned for long periods of time with higher than average calls for service).

Risky Facilities in Criminology

The criminology literature suggests that several 'non-residential' land uses have been associated with high crime. Roncek and colleagues (1981, 1989, and 1991) and the Blocks

(2007) have both identified relationships between crime and liquor-related outlets. The Brantinghams (1982) noted that certain fast-food restaurants were positively related to local area crime rates. Other non-residential types that have been associated with crime include parks and playgrounds (Lockwood, 2007), motels (Smith et al., 2000), public high schools (LaGrange, 1999) and abandoned buildings (Spelman, 1993).

Most of these studies focused on the contribution of the one risky facility type on a specific crime type in the context of the larger surrounding area, however, it should be noted that there could have been several other contributing factors to crime in the local area besides the risky facility type in question. Again, not all bars contain high rates of assaults, not all public housing projects contain high rates of shootings, and not all parking garages contain high rates of auto theft. This suggests that the facility itself might not be the primary culprit to a local area crime problem, but rather it is the busy-ness of the business (number of patrons, type of patrons, type and number of surrounding businesses, vehicular traffic, etc.) that provide the increased opportunities for crime. Felson (2006) calls this abnormally high density of facilities, especially well-known risky facilities that cluster together, a ‘thick crime habitat’ (page 61).

Wilcox and Eck (2011) define the occurrence of uneven crime distribution across land-uses and facility types as the “Iron Law of Troublesome Places” (page 476). They assert that their law is not bound by geographic levels, therefore it can be ‘place-based’ since the law of troublesome places apparently applies at various spatial scales (properties, streets, etc.).

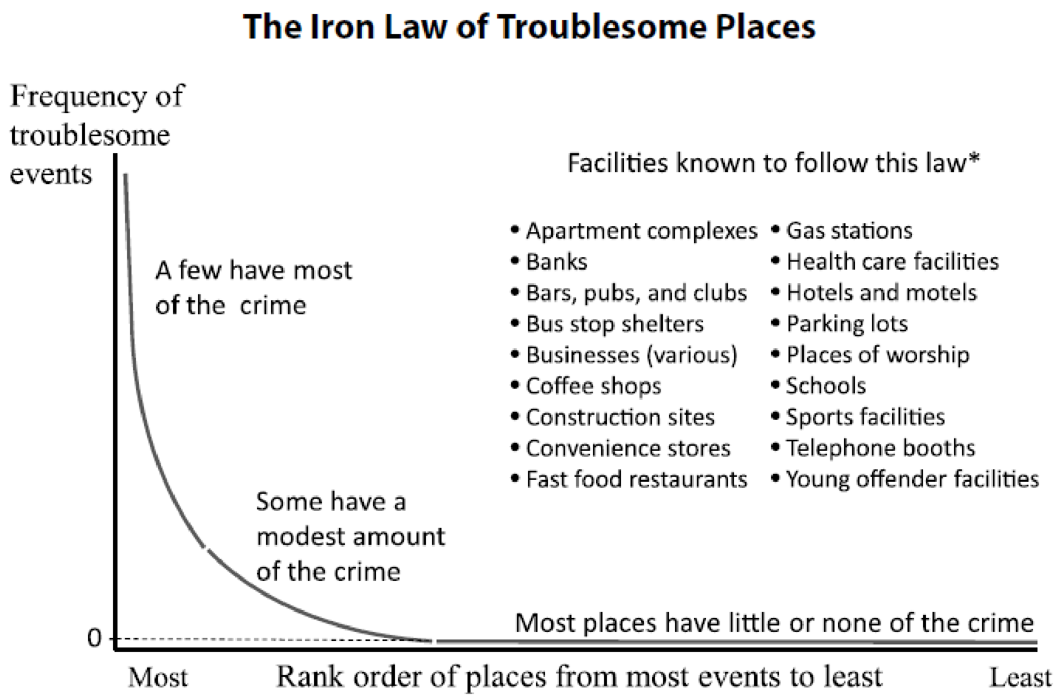


Figure 1.2: The Law of Troublesome Places
Source: Wilcox and Eck, 2011

The authors suggest their law of troublesome places has three 'articles': (Article I) a few places have most of the trouble; (Article II) most places are no trouble; and (Article III) extreme skewness is the norm. Figure 1.2, which we commonly refer to as a 'J-curve' in the crime analysis field, shows how most of the places have little or no crime and small portion of the places contain most of the crime. The law of troublesome places directly applies to this dissertation research on violent crime in the Bronx.

In this dissertation research, the violent crime locations in the Bronx were analyzed and spatially related to several 'facilities' geodatabases (i.e. InfoUSA, Plimus, and the New York State Liquor Authority). First, I determined the actual violent crime location types for each of the five violent crime types (see Appendix). Additionally, I was able to determine what specific facility types (and specific facilities) were located inside the various violent crime hot spots and high crime density zones. This will be explained further in the following data and methods section.

The appendix section also shows how Article I (few places have the most trouble) relates to the premises types for each of the five violent crime types. The appendix also shows that the majority of streets in Bronx neighborhoods contain zero violent crimes over the 5-year study period, this relates to Article II of the law of troublesome places (most places are no trouble). Article III states that skewness is the norm. The appendix shows how the frequency distributions for each violent crime becomes increasingly 'skewed' (and resembles a J-curve) as we move from the neighborhood level down to the street level.

Opportunity and the Temporal Aspects of Crime

Felson and Clarke (1998) suggest that 'opportunities to commit crime contribute to criminal motivation, and provides a perspective for developing workable solutions to prevent specific crime problems' (Opportunity Makes the Thief: Practical Theory for Crime Prevention, foreword, page iii). Just as theory should guide research and research results should guide public policy - theory should guide the development, application, and measurement of crime prevention programs. Felson and Clarke suggest that there are ten foundational principles of crime opportunity that collectively are a 'root cause' for crime. These root opportunity causes can be directly applied to both hot products and risky facilities concepts. Hot products and risky facilities are not 24 hour a day x 7 days a week x 365 days a year phenomenon, their opportunities as targets / locations for crime are strictly limited to their temporal availability (i.e. you can't steal something if it is not there and you won't have assault problems in bars when they are closed). It is important to note that time or temporal aspects play a role in more than half of the ten principles that Felson and Clarke designed.

Crime Opportunity Principle	**Example**
Opportunities play a role in causing all crime	Studies of bars/pubs indicate their design and management play an important role in generating violence or preventing it
Crime opportunities are highly specific	Theft of cars for joyriding has an entirely different pattern of opportunity (and target) than theft of cars for parts or sale abroad
Crime opportunities are concentrated in time and space	Crime shifts considerably by hour of day and day of week, reflecting the opportunities to carry out the specific crime type
Crime opportunities depend on everyday movements of activity	Both offenders and victims modify their opportunities for crime based on trips to work, school, and leisure settings
One crime produces opportunity for another crime	Burglary precedes the sale of stolen goods, prostitution can lead to assault/robbery, a stolen bicycle can lead the victim to steal another
Some products offer more tempting crime opportunities	These opportunities reflect the value, inertia, visibility of, and access to potential targets. Small, expensive, popular electronics (e.g. iPhones as stated earlier) are typically 'hot products'
Social and technological change produces new crime opportunities	New products go thru innovation, growth, mass marketing, and saturation stages. The growth and mass marketing stages tend to produce the most theft, until 'everyone has one' or most people can afford them
Crime can be prevented by reducing opportunities	Situation crime prevention attempts to increase the perceived effort and risk to commit the crime, reduce the rewards, and remove the excuses for crime.
Reducing opportunity does not usually displace crime	Evaluations have found little displacement and all studies accomplish some real gain
Focused opportunity reduction can produce wider declines in crime	Prevention measures in one location can lead to a 'diffusion of benefits' to nearby times and places because offenders overestimate the reach of the measures

Table 1.1. Foundational Principles of Crime Opportunity Theory
Source: Adapted from Felson and Clarke, 2008 (Foreword, page iii).

There has been a significant integration of crime mapping and crime analysis by police departments since 1995 (Taylor et al., 2007). However, much of the focus of crime mapping and crime analysis has been on mapping and spatial crime patterns. Townsley (2008) suggests that there has been a 'disproportionate focus' on spatial pattern analysis at the neglect of temporal analysis (page 61). However, much of the noted temporal variance within the crime hot spots literature is a result of the spatial and temporal resolutions that are selected by the user.

Spelman (1995) notes that hot spot and 80/20 research findings provide considerable policy implications in the form of community policing, problem-oriented policing, and repeat victimization programs. He identified four distinct temporal issues related to hot spots and ‘what makes them hot’ (page 118). First, Spellman suggests that hot spots may be hot solely because of random error. If some crime incidents are truly random (in both space and time), than we sometimes might detect hot spots as a result of random ‘noise’ being added to areas that would not be hot spots otherwise. Second, there are well-known seasonal variations (i.e., peaks in the summer months) in violent crime. Third, there are considerable differences between crime locations and the way that crime is reported and handled by the police. We would expect the police to respond differently to a residential burglar alarm at a residence who consistently have ‘false alarm problems’ than a silent bank robbery alarm at a large bank that has never had a silent alarm activated. Fourth, there can be several temporal variations in locations over time. Ratcliffe (2004) defines these temporal variations as diffused (i.e. occurring randomly throughout the day), focused (i.e. notable peaks in crime throughout the course of the day), and acute (i.e. most crime is confined to a small period of time).

The temporal aspects of crime concentrations are often overlooked in criminology, hot spots research, and the field of policing. However, there are significant benefits for micro-level crime control strategies that incorporate time into the identification process of crime concentrations. The Brantinghams suggest that as we zoom in on more micro-level *spatial* concentrations of crime, it also becomes more important to zoom in on the *temporal* scale of resolution (Brantingham et al., 1976). Both Bennett (1995) and Townsley (2008) warn about the temporal stability of hot spots over short periods of time. Their research indicates that (most) crime hot spots have unstable temporal patterns. That is, the hot spots can occur at various times of the day, days of the week, week of the year. An example might be a school playground that might experience some delinquency at lunchtime (12pm – 1pm), then again after school (3pm-4pm), but this would most like occur only on school days since it a result of high teen traffic/school population. On the weekends, the same school playground might also serve as a local hangout for drug users, homeless people, and/or prostitutes. This nighttime / weekend playground population is much different than the weekday/daytime population. The nighttime/weekend population utilizes the playground, but only when the typical ‘school crowd’ (i.e. students and teachers acting as place managers on school days) is not around.

One of the benefits of this dissertation’s micro-level unit aggregation (MLUA) crime analysis process is that the ‘wheredunit’ part of the micro-level crime analysis process remains constant (i.e. buildings, properties, and streets very rarely move). This allows police and crime prevention specialists to focus on the equally important, but often overlooked, ‘whendunit’ part of micro-level crime analysis. Identifying hot streets of crime, as well as monitoring any changes in population, land-use, and business types, and the ability to track risky facilities will create new opportunities for police departments to prevent and control crime and for criminologists to study micro-level crime patterns.

The Good News about the 80/20 Rule

While many (especially those outside of the criminal justice field) might observe all of these examples of the 80/20 rule as ‘bad news’, many in the crime control and prevention world view the 80/20 rule as ‘good news’. The 80/20 rule should be welcomed news to police departments, crime analysts, and crime prevention specialists since it provides police and crime prevention programs (e.g., Problem Oriented Policing, Operation Ceasefire, Drug Market Initiative, Crime Prevention thru Environmental Design, Situational Crime Prevention, Closed-Circuit Television programs, etc.) with the opportunity to directly address their scarce crime crime control or crime prevention resources on the most concentrated targets (i.e., the 20%) with the hopes of achieving the greatest preventive benefits (i.e., significantly lowering the 80%) (Clarke and Eck, 2007). The ‘best bang for the buck’ is a principle that every police department and crime prevention specialist know all too well in today’s world of police officer layoffs, program funding cutbacks, and overall diminishing agency resources. ‘Doing more, with less’ is a mantra all too familiar in public service, however, the concept of risky facilities and micro-level crime analysis makes doing more with less a much more attainable goal, especially when guided by environmental criminology theory and innovative analytical methods.

Whereas traditional criminology has focused on individual (biological, social, psychological, economical) factors to explain crime, environmental criminologists focus on the interaction between people (both potential offenders and victims) and the environmental setting(s) where crime takes place. Figure 1.3 shows the differences in theoretical approaches to crime between traditional criminology and environmental criminology, as defined by the Brantinghams (1990).

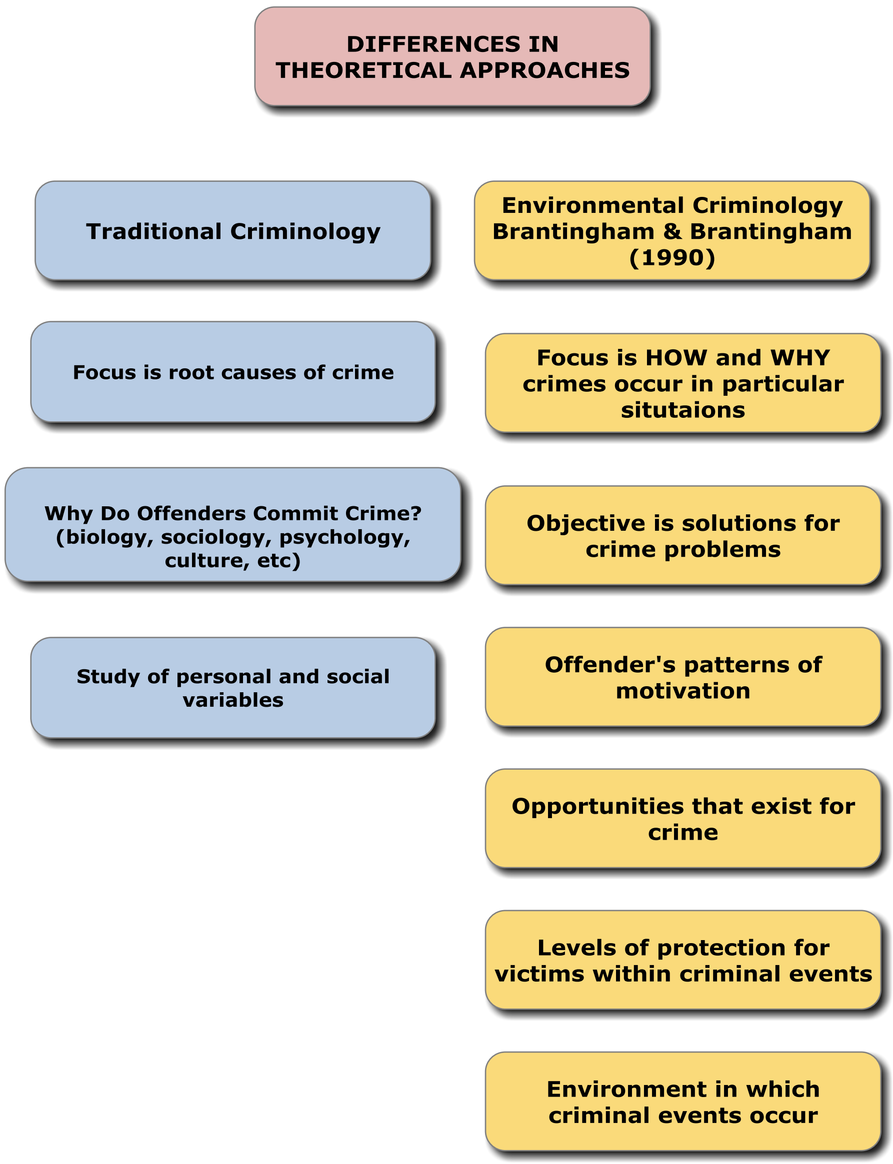


Figure 1.3. Differences in Theoretical Approaches - Traditional and Environment Criminology

Crime Opportunities, Crime Patterns, & Crime Maps

Ratcliffe (2011) states that 'crime opportunities are neither uniformly nor randomly organized in space and time' (page 5). This concept that crime is not evenly distributed across society is not new, early studies of crime in France noted spatial relationships between violent and property crime in lower-class, middle-class, and upper-class 'departments' (e.g. departments in France are somewhat equivalent in size & population to U.S. Counties) (Guerry, 1833; Quetelet, 1842). The early Chicago School mapped the residences of juvenile delinquents and explained the spatial distribution of delinquency rates in Chicago and its 'distance-decay' from the central business district (Park et al., 1925; Shaw and McKay, 1942). According to these early Chicago School social disorganization theorists, crime and delinquency was highest near the central business district (CBD) and decreased as you moved further away from the CBD (Shoemaker, 1996).

Environmental Criminologists today focus on the spatial opportunities for crime, hot spot analysis, situational crime prevention, problem-oriented policing, and geographical profiling (Wortley and Mazzerole, 2008). The role of geography and the use of crime mapping has always been a central component in environmental criminology and its examination of criminal activity. In the past 20 years, crime mapping has been widely adopted by many of the medium and large size police departments in the U.S. (Weisburd and Lum, 2005). There has also been an increase in the use of crime mapping in the development of crime prevention programs and their subsequent measure of crime and crime displacement (Weisburd et al., 2010).

Ratcliffe (2011) eloquently outlines the essential crime prevention role of crime mapping within the larger framework of criminology and crime analysis.

> "Prevention requires criminal justice agencies to be proactive rather than reactive, and proactivity requires the ability to predict crime hotspots and concentrations. Prediction is rarely possible from individual events, thus there is a direct link between prevention and patterns of criminality, in the form "prevention requires proactivity requires predictability

> requires patterns" (Ratcliffe, 2009). The importance of identifying patterns as a precursor to effective crime prevention has been identified by practitioners who recognize the inherent ability of crime mapping to identify patterns and hotspots, taking advantage of Tobler's first rule of geography, that "Everything is related to everything else, but near things are more related than distant things" (Tobler 1970: 236). (pages 6 – 7).

One of the objectives of this dissertation is to be able to identify, track, and monitor crime at the micro-level (i.e. streets and properties). In my opinion, until we know the specific spatiotemporal patterns of crime at the micro-level, we will not be able to truly comprehend the 'wheredunnit' and 'whendunnit' at the much more popular geographical levels of census tracts and neighborhoods.

This dissertation is divided into six chapters - Introduction, Methods & Data, Analysis & Results, Discussion & Conclusions, Appendix, and References. Each chapter has a number of sections and subsections. Figures, tables, and equations are numbered by the chapter to which they belong. This Introduction chapter serves as an overview of the goals and hypotheses of the dissertation itself, as well as to provide information and background regarding the content of the dissertation research. It is divided into six sections; Research Objectives (**1.1**), Hypotheses (**1.2**), Violent Crime Hot Spots (**1.3**), Land-Use Categories (**1.4**), and Business Establishment and Premises Types (**1.5**), and Introduction Summary (**1.6**).

1.1 RESEARCH OBJECTIVES

Aim #1: To analyze the spatiotemporal variations in violent crime within and between neighborhoods, census tracts, and street segments in the Bronx from 2006-2010.

Aim #2: To analyze the spatiotemporal variations within the highest violent crime (murder, rape, robbery, assault, & shootings) hot spots in the Bronx from 2006-2010.

Aim #3: To analyze the relationships between violent crime (murder, rape, robbery, assault, & shootings) and land-use categories in the Bronx from 2006-2010.

Aim #4: To analyze the relationships between violent crime (murder, rape, robbery, assault, & shootings) and business establishments / premises type in the Bronx from 2006-2010.

1.2 HYPOTHESES

The hypotheses developed for this dissertation were based on the previous research aims, as well as the introduction section. Table 1.2 explains how each of the hypotheses will be performed.

H1. Crime at the micro-level unit (property, street segment) will be generated by people (residential population density) or attracted by places (non-residential land-uses, business establishment types).

H2. Land-Use is related in scope, size, and nature of relationship to violent crime types.

- Violent crime types will vary in relationship to land-use.
- A small number of land-use categories will be responsible for a majority of violent crime.
- A small number of streets will be responsible for a significant percentage of the total crime within the larger geographical units of analysis.

H3. Business Establishment types are related in scope, size, and nature of relationship to violent crime types.

- Violent crime types will vary in relationship to business establishment types.
- When violent crime is not ‘generated’ by residential population, it will be ‘attracted’ by commercial areas and business types.

Hypotheses	Test
H1. Crime at the micro-level is generated by residential populations or attracted by land-use/business types.	**T1.** Identify micro-level crime patterns for each of the five violent crimes, while controlling for micro-level residential population and / or number and type of business establishment types. Determine if violent crime hot spot is land-use, population, or risky business related
H2. Land-Use is related in scope, size, and nature of relationship to violent crime types.	**T2.** Determine how land-use categories are related to each of the five violent crimes using cadastral (tax lot) data
H3. Business Establishment types are related in scope, size, and nature of relationship to violent crime types.	**T3.** Determine how business establishment type and premises type is related to each of the five violent crimes using cadastral (tax lot) data

Table 1.2. Hypotheses and Hypotheses Testing

1.3 VIOLENT CRIME HOT SPOTS

In this dissertation research, *violent crime* is defined as murder & non-negligent manslaughter, robbery, rape, assault, and shootings; as reported by the New York City Police Department (NYPD) for Bronx County between 2006 and 2010, inclusive. Violent crime data is collected, stored, and maintained by the New York City Police Department (NYPD/IBM Crime Data Warehouse). This data is routinely used throughout the NYPD, most notably in the Crime Analysis and CompStat units.

Few studies, examine crime, population levels, and land-use & business establishment types across street segments and property lots (Taylor, 1998; Weisburd et al., 2009; Stucky and Ottensmann, 2009). This scarceness in micro-level environmental criminology research has primarily been a result of the lack of access to data, availability of ancillary data (population, land-use, & business establishment data), accuracy of geocoded crime data, and availability of existing theory and methods to study crime at the micro-level (Weisburd et al., 2004; Ratcliffe, 2006; Groff et al., 2010).

This dissertation utilizes an ecological framework, where each individual crime location (point) is mapped and then aggregated to a higher level geography (i.e. streets, census tracts, and neighborhoods). It is these larger geographical units that are then analyzed and reported on. NYPD crime data is geocoded to a property lot, address, or intersection. Geocoding is completed using a very accurate, but rather complex, composite address geolocator (LotInfo, 2008; New York City Department of City Planning, 2008). The City of New York has been using GIS since the early 1980's. In addition, the leading GIS software company (ESRI) has had a local office established in New York City since the early 90's. This combination of New York City government investment in GIS and local expertise (ESRI) has put New York City at the forefront of GIS technology and research.

There are many prior studies that indicate that neighborhood level crime patterns are clustered (Sherman et al., 1989; Rengert and Lockwood, 2009; Kurtz et al., 1998). However, researchers know that the entire neighborhood is not criminogenic. Many studies incorrectly assume that the relationships between crime, population, land-use, and business establishment types are both homogenous and spatially stationary (Weisburd and Green, 1995; Taylor, 2001). However, not all parks are full of drug users/dealers, not all high schools have high rates of delinquency, not all bars contain high rates of assault, and not all parking lots have high rates of auto theft. Neighborhoods contain hot spots & cold spots, high density crime areas & low density crime areas, "good" streets & "bad" streets, and good businesses & bad businesses. In fact, within the highest crime neighborhoods in the Bronx, the majority of properties and street segments appear to have little or no reported violent crime at all over the 5-year study period.

Recent studies suggest that a small proportion of streets segments (Weisburd et al., 2009; Groff et al., 2009) and properties/businesses (Eck et al., 2005; Clarke & Eck, 2007; Brantingham & Brantingham, 1993) are responsible for a majority of the meso-level and macro-level (neighborhoods, communities, counties, cities) crime. The application of Pareto's principle (Juran, 1937; Reed, 2001) to micro-level crime analysis is a relatively new phenomenon. This new trend of identifying and examining micro-level crime locations is a result of timely data collection by police departments, increased statistical & spatial data available at the micro-level, and comprehensive Geographical Information Sciences (GISc) methodologies and analysis tools.

The use of GIS / GISc has transformed the way that crime hot spots are constructed and identified. The crime analysis and law enforcement communities have become very proficient in locating, tracking, and managing crime hot spots. This reiterative crime analysis & control process has resulted in a steady ebb and flow of statistical and spatial crime patterns throughout many police jurisdictions (Eck, 2002; Cahill, 2005).

However, as researchers and practitioners, rarely (if ever) do we analyze the specific units that are generating these statistical and spatial crime hot spots at the micro-level (street segment and property lot levels) (Sampson and Groves, 1989; Morenoff et al, 2001). If we embrace the theoretical foundations of environmental criminology and routine activities; we recognize that crime, criminality, & victimization are distinctively interconnected with both 'place' (i.e. land uses / business establishment types at specific locations) (Sherman et al., 1989; Roncek and Maier, 1991) and 'spatial factors' (i.e. routine activities) (Felson, 1987; Kennedy and Forde, 1990). This dissertation will examine what types of land use and what types of business establishments are responsible for statistical and spatial crime trends in high crime 'areas' in the Bronx between 2006 – 2010, inclusive.

The term 'hot spot' is usually defined as areas of concentrated crime (Eck et al, 2005). Crime analysts and researchers routinely study hot spots to try and determine the complex relationships between crime, disorder, and place. Another popular use of hot spot analyses is the various links between crime & disorder levels and the underlying social conditions within a pre-defined geographical boundary (e.g. street segment, census tract, neighborhood).

Hot spots vary significantly in size and shape, as well as the geographic level in which they are constructed. Hot spots have been identified as individual geographical points or addresses (Eck and Weisburd, 1995; Sherman et al., 1989); street segments or blocks (Taylor et al.,1984; Weisburd and Green, 1995); clusters of streets/blocks (Block and Block, 1995); neighborhoods (Bursik & Grasmick, 1993; Braithwaite & Li, 2007; Braga & Weisburd, 2010) high kernel density estimations (Levine, 2004; Chainey, 2009; Ratcliffe, 2011); or positive z-scores using the Getis-Ord Gi* statistic (Ord & Getis, 1995; Scott & Warmerdam, 2005; Chainey & Ratcliffe, 2005; Chainey, 2010).

Just as there are numerous ways to construct hot spots, crime hot spot theories also vary significantly at the different geographical units of analysis (e.g. points/addresses, lines/streets, polygons/census tracts). Place-based theories (point level) examine individual incidents to try to explain why crime (repeatedly) occurs at specific points, addresses, or locations (Townsley et al, 2003; Bowers and Johnson, 2004; Ratcliffe and Rengert, 2008). Popular place-based theories include Repeat Victimization (Laycock, 2001), Problem Oriented Policing (Weisel, 2005), and Situational Crime Prevention (Clarke, 1995). Street-level hot spot theories (line level) assert that crime patterns occur when groups of points/places cluster and create street/block based trends (Brantingham and Brantingham, 1981). Street-level theories include Routine Activities (Cohen and Felson, 1979), Crime Pattern (Brantingham and Brantingham, 1981), and Defensible Space (Newman, 1972) theories. Neighborhood (and larger geographical units) level hot spot theories (polygon level) suggest that high crime levels are related to unstable family, social, economic, educational, and political ties. Neighborhood level hot spot theories include Social Disorganization (Shaw and McKay, 1942), Broken Windows (Wilson and Kelling, 1982), and Collective Efficacy (Sampson et al., 1997). Since there are numerous levels of spatial analysis, different ways to construct hot spots, and theories to explain hot spots, there are also numerous limitations in hot spot mapping.

First, there is no one singular form of violent crime victimization. Robbery hot spots can occur at Banks (specific address points), ATMs along a street segment (street/line), or also in many different locations / areas of a large park or neighborhood (polygon). If victims are mobile (which they often are in violent crimes), point level maps will not be able to accurately display victimization trends and patterns over time. This limitation can impact the type and amount of information used in crime prevention and crime control efforts.

Second, all crimes are reported, recorded, and geocoded using geographical boundaries (i.e. street address, street intersections). This means that crime will always be analyzed at the places where it is recorded, which is not necessarily the actual crime location. An example of this is crime in the New York City parks. Since NYPD, does not analyze crime inside parks, any crime that is committed is recorded at a street intersection or address outside of the park. This creates an inaccurate description of where crime actually occurs.

Third, population is not evenly distributed across streets, tracts, and neighborhoods. This creates several difficulties in analyzing crime, most notably the denominator used to determine crime rates. Most crime hot spots can be explained by simply measuring the population within the crime hot spot (Harries, 1999; Weisburd, 2004; Eck et al, 2005). Areas containing higher population densities are much more likely to have higher amounts of crime, simply because there are more people (e.g. more potential targets/victims, as well as motivated offenders).

Fourth, just as population and crime are not evenly distributed across geographical areas, police are not evenly distributed over time and space. Varying levels of police (officer) enforcement can have significant impacts on crime reporting, apprehension of criminals, and overall police productivity (Skogan, 1976; Corman and Joyce, 1990; Moore and Braga, 2004).

Fifth, hot spot maps are typically temporally static illustrations of crime, not dynamic forms of crime analysis. Temporal patterns of crime vary significantly, especially at the micro-levels (Ratcliffe, 2006). Hot spot maps rarely take temporal factors into consideration. However, when we move down the spatial cone of resolution (Brantingham et al, 1976), we must also move down the temporal cone of resolution or the crime pattern can be 'lost'.

Sixth, hot spot methodologies like nearest neighbor hierarchical clustering and kernel density estimations include locations/streets with no reported crime. Even in the highest crime concentrated areas, there are substantial numbers of properties and streets that have zero reported crime. These findings also suggest that there is considerable 'spatial distortion' or 'crime blurring' that takes place within crime hot spots. This can create a skewed understanding of what is actually generating the hot spot (Peake, 2004; Rogerson, 2001; Tomlinson, 2007).

1.4 LAND-USE CATEGORIES

Land-use categories refer to the primary land-use for each property lot in the Bronx. In New York City, land-use is broken down into 11 different categories according to the New York City Department of City Planning guidelines (PLUTO, 2008): (1) One and Two Family Buildings, (2) Multi-Family Walk-up Buildings, (3) Multi-Family Elevator Buildings, (4) Mixed Residential and Commercial Buildings, (5) Commercial and Office Buildings, (6) Industrial and Manufacturing, (7) Transportation and Utility, (8) Public Facilities and Institutions, (9) Open Space and Outdoor Recreation, (10) Parking Facilities, and (11) Vacant Land. Unfortunately, there have been varying relationships between many of these land-use categories and violent crime.

In her seminal work on community development, Jacobs (1961) suggested that "mixed land use" (areas with both residential and commercial properties) had a positive effect on streets and that more "eyes on the street" were beneficial. Much of our land use and crime literature (Duffala, 1976; Fowler, 1987; Greenberg and Rohe, 1984; Greenberg et al., 1982; Ley and Cybriwsky, 1974; Lockwood, 2007; Smith et al., 2000; Wilcox et al., 2004) actually examines business types, as opposed to specific land uses. Most studies focusing on the relationship between crime and land use have been intermittent, incomplete, and inconsistent. These studies assume that the relationship between crime and land-use is both spatially dependent and spatially heterogeneous.

Sampson and Raudenbush (1999) included a measure of "mixed land use" in their study of violent crime in Chicago neighborhoods and determine that mixed land use was significantly associated with social disorder (or lack of collective efficacy) and robbery. Cahill (2005) and Lockwood (2007) both find that "mixed land use" is significant in their studies of "violent crime"; however, its significance is not homogenous throughout the entire study area. More recent land use and crime studies (Stucky and Ottensmann, 2009) have examined the impact of "high-density" land use and its relationship to crime frequency (e.g. high density land use = increased crime), however, other studies are now indicating that density is not the primary explanatory factor, it is the socioeconomic status of the residents that was most important (Bowers and Hirschfield, 1999; Wilcox et al, 2004).

A recent review on the relationship between land-use and crime (Stucky and Ottensmann, 2009) suggests that land use, population density, and crime are related; but these factors vary considerably according to both land-use type and violent crime type. The authors also warn that current theory only tells part of the story, “theories such as social disorganization and institutional anomie theories also need to focus on…the complex interplay of social institutions that generate particular land use configurations” (pg. 1251). This research reiterates the problems of prior land-use studies that consider the relationship between land-use and crime homogenous, regardless of social factors, including social context and neighborhood disadvantage. Many current land-use studies focus on a small number of land use types, while others aggregate land uses into indices which assume that each land-use is homogenous and uniformly contributes to the crime problem over the entire study space. What Weisburd (1993) and others have found is that crime categories are not strongly related across hot spots, something that challenges those who link all crime at places into these broad explanatory categories.

This dissertation allows the land-use category and violent crime relationships to vary over space and time. For example, not *all* of the 90 New York City Housing Authority (NYCHA) public housing projects in the Bronx have high frequency violent crime problems. There are several NYCHA projects that have some violent crime problems, but even the ‘highest-crime’ NYCHA housing projects do not contain crime problems for *all* of the five different violent crime types in this study, nor do they have crime problems all day, every day.

Land-use is the foundation for who, when, where, and how people use and travel across space and time. As such, if distinguishable patterns can be determined for people movements across space and time, violent crime place and time interactions can be predicted, prevented, and / or better controlled.

1.5 BUSINESS ESTABLISHMENTS / PREMISE TYPES

An important part of this research examines the relationships between business establishment types, premises types, and violent crime types throughout the Bronx. “A bar is not a bar is not a bar…” (Drucker, 2010). Relationships between violent crime and business types vary extensively over space and time. A bar that hosts Monday night football games with $2 draft beer specials may attract a younger male crowd and generate some assaults at closing time, however, this same bar might have a nice brunch served on Sunday afternoons that attracts a much different clientele, such as young families or older couples. Same place, different time and opportunities, attracting different clientele.

Even fewer studies of crime and place examine the specific relationship between crime, and actual business establishment types. Roncek’s studies focused on bars (Roncek and Maier, 1991; Roncek and Pravatiner, 1989) and schools (Roncek and Faggiani, 1985; Roncek and Lobosco, 1983). LaGrange (1999) indicated that schools and malls (and similar places that attract large groups of ‘strangers’) contained increased rates of “criminal mischief”. Studies that do not focus on one specific business type typically aggregate all businesses into a ‘commercial index’ (Frank and Pivo, 1995; Browning et al., 2010), which inappropriately assume that all businesses have uniform influence on crime and are homogenous in distribution (I strongly disagree with this aggregation into index methodology). Again, most of these prior studies assume that crime is homogenous throughout the entire study area – however, this is rarely, if ever, true.

Clarke & Eck (2005; 2007) have pioneered much of the research focus on crime and business types (i.e. risky facilities). Their seminal work on 'Risky Facilities' (2005), while not intended to identify each type of facility where crime occurs, indicates that a small proportion of facilities is responsible for a disproportionate amount of crime. Unfortunately, data was not always available in the format needed to define the relationships within and between facility types. Clarke & Eck (2005) suggest that the factors that contribute to explaining risky facilities includes location, crime attractors, hot products, poor place management, poor design, and large size. Prior research indicates that these relationships within facility types (e.g. parking lots) and between facilities will vary considerably over time and space (Herrmann and Maroko, 2006).

The current study seeks to fill a significant void in the literature and inform several methodologies to further our understanding of 'crime and place'. One of the importance aspects of this dissertation research is its focus on the varying relationships between crime and land-use / business establishment types and the twin spatial effects of *spatial dependence* and *spatial heterogeneity* (Anselin, 1988). The challenge is then to provide added value (i.e. data to further our understanding of crime at the micro-level) from this examination of crime, population variables, and environmental criminology data.

1.6 INTRODUCTION CHAPTER - SUMMARY STATEMENT

This introduction chapter has provided an overview of the research aims and hypotheses for this dissertation. The association between crime, land-use, and business establishment types has been described and established in general terms. The next chapter, data and methods, introduces the geospatial datasets that are used for this research and provides an overview of the more popular hot spot methodologies used in criminology and crime analysis.

2. DATA & METHODS

The objective of this dissertation is to explore and measure the various spatiotemporal relationships between violent crime, land-use categories, and business establishment / premises types at several geographic levels. There are three sections in this chapter: Data **(2.1)**, Hot Spots **(2.2)**, and the Micro-Level Unit Aggregation process **(2.3)**.

The data section is subdivided by data type; which includes Violent Crime Data **(2.1.1)**, Population Data **(2.1.2)**, Census Data **(2.1.3)**, Land-Use Category Data **(2.1.4)**, and Business Establishment / Premises Type Data **(2.1.5)**.

The violent crime hot spots section **(2.2)** is subdivided into three sections: Nearest Neighbor Hierarchical Clustering **(2.2.1)**, Kernel Density Estimation **(2.2.2)**, and Getis-Ord Gi* statistic methods **(2.2.3)**. Each of these sub-sections explains how each respective hot spot methodology identifies, constructs, and illustrates violent crime hot spots. While each hot spot method will examine the same violent crime datasets, it is important to note that each hot spot methodology identifies different spatial characteristics for each of the violent crime datasets. The Micro-Level Unit Aggregation process (MLUA, **2.3**) explains in detail the process of aggregating point or address level data up to higher level geographies, like street segments.

In addition to the demographic population (estimates) approach, the proposed GISc framework will also take into account the pathways (street & subway networks) and nodes (street intersections, subway stations) throughout the Bronx (Brantingham and Brantingham, 1985). Street-segment analysis will also help identify those features that provide an 'element of safety for every dwelling unit' (Newman, 1972, pg. 103), as well as those streets that contain zero crime over the 5-year study period.

2.1 DATA

The data section explains the various datasets and their respective sources. It also contains descriptive information, exploratory data analysis (EDA), and exploratory spatial data analysis (ESDA) on each of the datasets. The objective of the data section is to explain each dataset, show how the data are used to run spatial models, as well as explain the hypotheses. Without an intricate understanding of each dataset, especially their respective spatial and temporal factors, it would be challenging to determine how to best construct hypotheses, develop statistical & spatial models, or conclude how the outputs and study results should be interpreted.

The research area and data for this study are comprised of various Geographic Information Systems (GIS) datasets for Bronx County, including several violent crime datasets from the New York City Police Department. New York City is an ideal place to conduct geospatial research because New York City has been using GIS and collecting GIS data since the late 1970's (New York City Department of City Planning, 2010).

Geographic Levels	Bronx	Dissertation Study Area
Neighborhoods	38	36
Census Tracts	355	343
Census Block Groups	987	951
Streets	10,781	10,544
Tax / Property Lots	89,211	88,993

Table 2.1. Geographic Levels, Bronx Geographic Units, and Dissertation Study Area Units.
Source: New York City Department of City Planning and New York City Department of Finance, 2011

The GIS datasets include Bronx County (Borough), Bronx Neighborhoods (n=38), Bronx Census Tracts (n=355), Census Block Group (n=987), Street segments (n=10,781), and Property Lot data (n=89,211) from the New York City Department of City Planning (NYC-DCP) , the New York City Department of Information Technology & Telecommunications (NYC-DoITT), and the New York City Department of Finance (NYC-DOF).

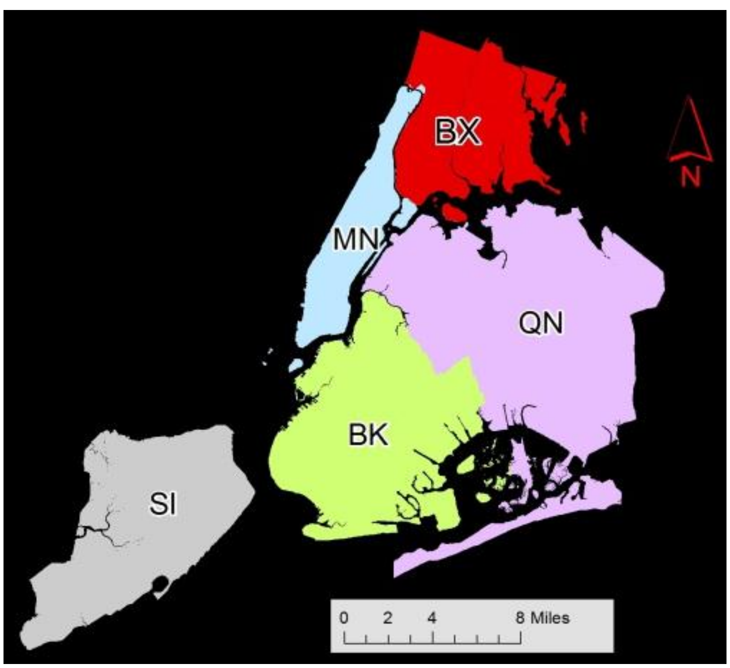


Figure 2.1: Map of the 5 Boroughs of New York City
Bronx (red), Manhattan (blue), Queens (purple), Brooklyn (green), and Staten Island (gray)

This research takes place in Bronx county (shown in red, figure 2.1), the northernmost county of the five counties that comprise New York City (i.e. Bronx, Brooklyn, Manhattan, Queens, and Staten Island). The Bronx is 42 square miles in area, which makes it 14% of New York City's total geographical area. One of the reasons the Bronx is the third most densely populated county in the United States (behind Manhattan & Brooklyn) is because about a quarter of its land area (shown in figure 2.2 in green) is uninhabited open space or industrial areas.

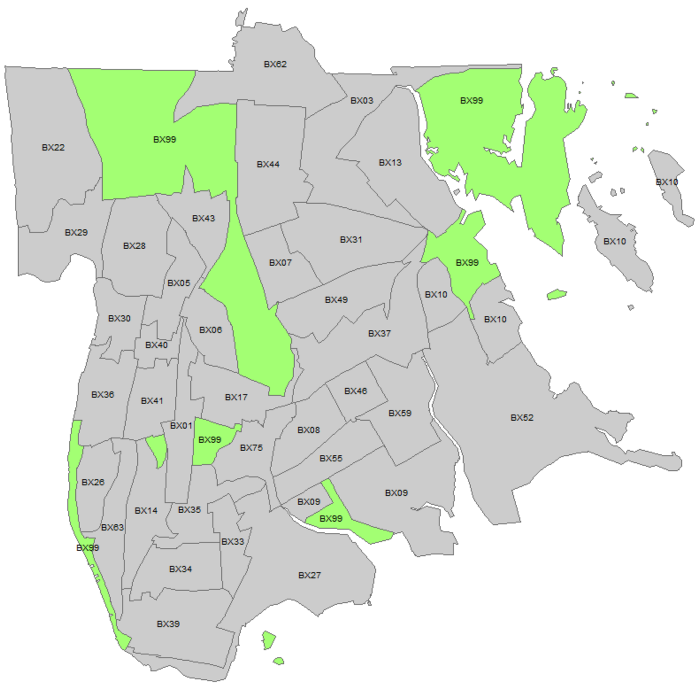


Figure 2.2: Bronx Neighborhoods and Open Space

The uninhabited open spaces include the largest park in New York City (Pelham Bay Park), the Bronx Zoo & Botanical Gardens, several large cemeteries, waterfront areas, and several industrial complexes. The Bronx is an ideal place to study violent crime because it is one of the smallest (in geographical area), one of the highest in population density, it is the most diverse in ethnic/racial composition (according to the U.S. Census), and it has a substantial amount of violent crime (from 2006 – 2010). Table 2.1 shows the violent crime totals for the five boroughs of New York City (2006 – 2010) and the percentage of Bronx crime in relation to the other boroughs.

Violent Crime (2006 – 2010)	Bronx	Brooklyn	Manhattan	Queens	Staten Island	Citywide
Murder	**657 (25%)**	1074 (41%)	371 (14%)	434 (17%)	86 (3%)	2,622
Rape	**1,512 (23%)**	1,873 (28%)	1,388 (21%)	1,624 (24%)	278 (4%)	6,675
Robbery	**23,018 (22%)**	36,616 (35%)	21,745 (21%)	22,029 (20%)	2,181 (2%)	105,589
Assault	**21,564 (26%)**	28,958 (34%)	16,015 (19%)	15,486 (18%)	2,240 (3%)	84,263
Shooting	**2,791 (31%)**	3,613 (40%)	1,094 (12%)	1,311 (15%)	222 (2%)	9,031

Table 2.2: Violent Crime Totals for the 5 Boroughs of New York City for 2006 – 2010 including the percentage for each borough/crime as part of the Citywide total.
Source: NYPD, 2011

As table 2.2 (violent crime and land area and population) indicates, the Bronx contains a disproportionate amount of violent crime when considering its size (14% of NYC's total land area) and population (17% of NYC's total population). If crime were proportionate in each borough in New York City, based on population (or even land area), then we would expect to see violent crime percentages closer to the Bronx population (17%). With the exception of Brooklyn murder and shootings, the Bronx has a much higher disproportionate rate of violent crime per capita than all of the other boroughs of New York City.

Borough	Land Area (in Sq.Miles)	Percentage of NYC Land Area	Population	Percentage of NYC Population
Bronx	**42.41**	**14%**	**1,332,650**	**17%**
Brooklyn	71.46	23%	2,465,326	31%
Manhattan	22.78	8%	1,537,195	19%
Queens	109.67	36%	2,229,379	28%
Staten Island	58.50	19%	443,728	5%
Total	**304.82**	**100%**	**8,008,278**	**100%**

Table 2.3: Land Area, Population, and the Percentage for each of the 5 Boroughs of New York City
Source: Census, 2000

The neighborhood boundaries for New York City are defined by the New York City Department of City Planning (NYC-DCP) to contain small area population projections of at least 15,000 people (NYC-DCP, 2010). Neighborhood boundaries are designated according to historical geographic and sociocultural data. The Bronx contains 38 distinct neighborhoods which incorporate entire census geographies (census block groups and tracts). These census geographies were subdivisions of New York City Public Use Microdata Area (PUMA) datasets. Within the 38 unique neighborhoods, the Bronx is further disaggregated into 355 census tracts; 987 census block groups; 10,544 street segments; 89,211 property lots; and 101,307 buildings.

This data section is arranged into four parts: Violent Crime Data **(2.1.1)**, Census Data **(2.1.2)**, Land-Use Category Data **(2.1.3)**, and Business Establishment / Premise Type Data **(2.1.4)**. The violent crime data includes traditional ‘crime report’ data for violent crime in the Bronx, which includes murder & non-negligent manslaughter, rape, robbery, assault, and shooting (incidents) locations in the Bronx from 2006–2010. Population data includes traditional sociodemographic data from the (2000) U.S. Census; including total population, race/ethnicity, poverty, and education.

The population data also includes a unique dasymetric disaggregation population estimation technique known as the Cadastral-based Expert Dasymetric System (CEDS) in section 2.1.2. In criminology and crime analysis, population counts are frequently used to determine the potential number of victim / offender interactions (Felson, 2002) or the relative risk of victimization (Sampson and Lauritsen, 1994; Gottfredson., 1981). The Land-Use Category data includes property-lot level data for each property in the Bronx, including its respective land use (e.g. one & two family buildings, mixed residential & commercial, open space & recreation, etc.). The Business Establishment / Premise Type data comes from several different geospatial datasets. The Business Establishment data was compiled using InfoUSA data exported from ESRI's Business Analyst, as well as a commercial geodatabase named Plimus. Premises Type data is also incorporated into the New York City Police Department (NYPD) Crime Data Warehouse data and includes a detailed description for each violent crime location as recorded by the reporting NYPD officer.

2.1.1 VIOLENT CRIME DATA

The NYPD has been using GIS since 1990, primarily for use in its innovative COMPSTAT process (Bratton, 1996). The violent crime datasets for this research include the traditional Uniform Crime Report (UCR) violent crime categories murder, rape, robbery, and assault. The data was queried based on location (i.e. Bronx) and time period (2006 – 2010) and exported out of the NYPD Crime Data Warehouse (NYPD Computer File, 2011) in .dbf VI format. In addition to the UCR violent crime data, shooting incidents, where shooting locations are confirmed by evidence of a shooting (shell casings, victim(s), or other physical evidence) were also included in the violent crime dataset. All of the violent crime data was geocoded to the property lot level and then aggregated up to street segments, census block groups, census tracts, and neighborhoods for analysis.

The quantity, quality, and type of crime data are central to all crime analysis studies. Most crime data consists of data entered into a '911' computer aided dispatch system and/or traditional 'calls-for-service' data. The 911 data for NYPD consists of all calls received into New York City's Emergency 911 system (approximately 4.5 million calls per year). Calls for Service data typically includes all emergency and non-emergency calls that the NYPD responds to, including unfounded calls or calls where a report is not taken by the responding officer. Crime Report data, which is the data used in this research, includes crime incidents only. Crime reports are calculated when a police officer has responded to an incident *and* recorded an official (written) report. As such, crime reports are considered the most reliable crime dataset used in crime analysis studies, because crime reports do not include unfounded calls or miscellaneous 911 calls.

The violent crime data being used in this research includes NYPD crime reports for Bronx county from 2006 – 2010. The crime data used and analyzed within the NYPD Office of Management Analysis and Planning (OMAP) Crime Analysis Unit (table 2.5) differs slightly from NYPD's CompStat Unit data (table 2.4), which sometimes takes the number of victims into consideration. All crime data at NYPD is collected, stored, and maintained by the NYPD-IBM Crime Data Warehouse. This data is routinely used throughout the NYPD and I was provided permission to access and use citywide crime data from 2000 – 2010, under an ongoing NYPD data sharing agreement (OMAP contract #2006-48). Violent crime data 'points' include murder and non-negligent manslaughter, rape [felony], shootings [incidents], robbery, and assault [felony] and are geocoded using several ArcGIS geolocators.

CRIME by Years COMPSTAT	2006	2007	2008	2009	2010	TOTAL
Murder	155	130	132	113	127	657
Rape	328	318	312	266	288	1,512
Robbery	4,891	4,608	4,792	4,117	4,610	23,018
Assault	4,363	4,408	4,050	4,308	4,435	21,564
Shootings	Counted differently (victims vs. incidents), data unavailable					

Table 2.4: Bronx Violent Crime by Year
Source: NYPD Compstat

CRIME by Years Study Area (OMAP)	2006	2007	2008	2009	2010	TOTAL
Murder	143	122	125	109	124	623
Rape	335	281	249	250	234	1349
Robbery	4,842	4,525	4,747	4,041	4,519	22,674
Assault	4,205	4,205	3,895	4,147	4,277	20,729
Shootings	591	562	538	556	543	2,791

Table 2.5: Bronx Violent Crime by Year for the Dissertation Study Area
Source: NYPD Office of Management Analysis and Planning (OMAP)

The study area for this research consists of the 36 neighborhoods in the Bronx that contain residential population. Rikers Island (neighborhood #BX98), which contains the New York City Jails and the neighborhood containing many of the largest open-spaces ("park_cemetery_etc.", neighborhood #BX99) in the Bronx, were both excluded from this analysis. In the Bronx, approximately 25% of the land area is uninhabitable space (shaded in green, figure 2.4). These open spaces include parks, beaches, recreational areas, cemeteries, and wetlands. Violent crimes that were geocoded to these open space areas were not included in this analysis. This equated to approximately 2% of the violent crimes that were recorded and geocoded by NYPD between 2006–2010 to be excluded from this research.

NYPD crime data is geocoded to property lots, intersection, and/or street centerlines based on a very accurate, but rather complex, composite address geolocators developed and maintained by NYC-DCP and NYC-DoITT. New York City has been using GIS since the 1970's. In addition, ESRI, the leading GIS software company, has had a local office in New York City since the 1980's (LaShell & Dangermond, 2010). This combination of NYC government investment in GIS and local expertise (ESRI) has put New York City at the forefront of GIS technology and research. As a result of this local GIS experience, the New York City basemap is extremely accurate, which results in very high geocoding hit rates.

The most time consuming data preparation process for the crime dataset was geocoding, spatiotemporal processing, and spatial joins (attaching geographic identifiers). Spatiotemporal processing included constructing several computer (PERL) scripts which rearranged the date (dd/mm/yyyy format) column and created numerous new variables; including hour of day, day of week, day of year, week number of year, year, and then several variations of day/week/month/year. These new temporal variables allow for unique spatiotemporal analysis, including spatio-trajectory analysis.

The final violent crime (points) dataset was then processed with dozens of tabular and spatial joins with street segment IDs, census identifiers (tract, block group, and neighborhood identifiers), CEDS populations (if applicable) and then aggregated into several new violent ‘crime layers’. The complex temporal processing routines provide crime counts (for 2006 - 2010) and population levels. The resulting dataset can be used to develop micro-level crime rates (e.g. crime / population) for each of the 88,993 properties and 10,544 street segments in the study area.

2.1.2 POPULATION DATA

Population data, including demographic and socioeconomic data are routinely used in GIS research. However, population data are rarely used in crime analysis research, especially micro-level crime analysis studies (Weisburd et al., 2009; Groff et al, 2009). The primary reason that population data is not used in micro-level crime analysis research is because of the lack of available population data at the micro-level (street segments and lower geographies). As such, population distribution and population density, which both have a significant impact on both crime distribution and spatiotemporal crime trend(s), has been unable to be used in micro-level crime analyses, until now.

The decennial census has been conducted by the U.S. Government every 10 years since 1790 and is the primary source of population data for GIS research. While the U.S. Census collects data at the household level, the census reports and shares census data at aggregated geographic levels called census units. The most commonly used census units include census blocks, census block groups, and census tracts. In the Bronx, census blocks typically resemble a city block. In New York City, a city block is defined as the areas between street segments that contain buildings (i.e. not the street centerline area).

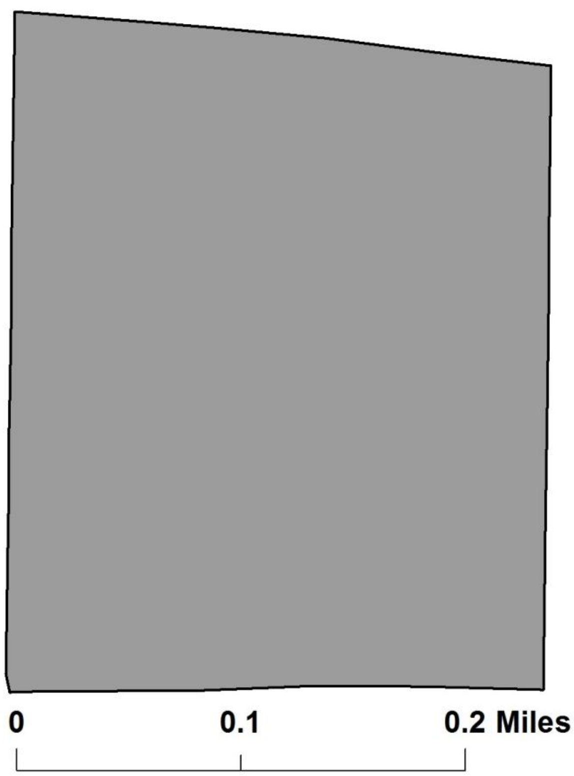


Figure 2.3: Census Tract Example

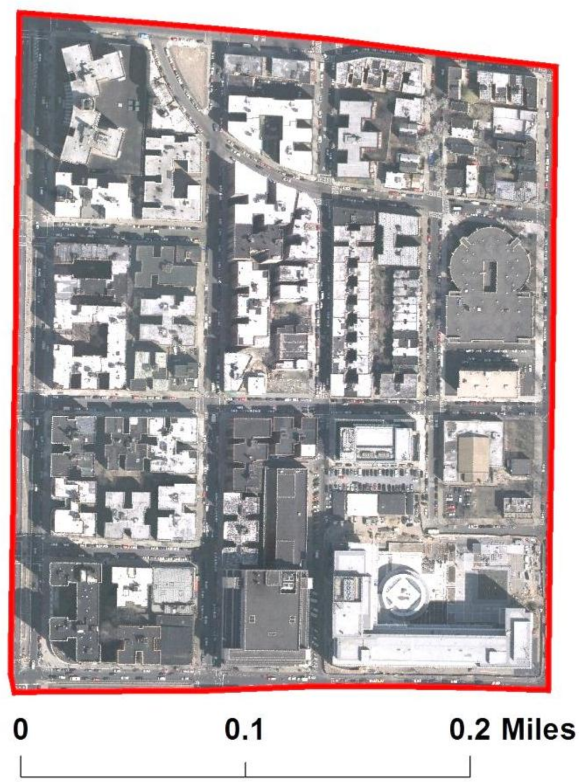


Figure 2.4: Census Tract Example Orthophotograph

Census block groups contain several census blocks. Census tracts contain several census block groups. In crime analysis, we define the street segment as an individual street centerline between two intersection or end points. In the Bronx, street centerline segments contain both sides of the block or 'block faces' for each street block.

Anatomy of a Bronx Census Tract

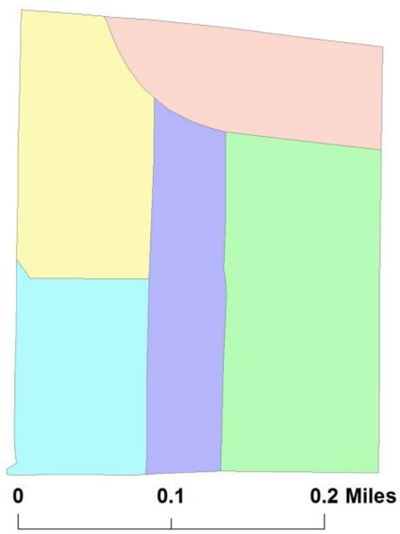


Figure 2.5
Census Block Groups within Tract

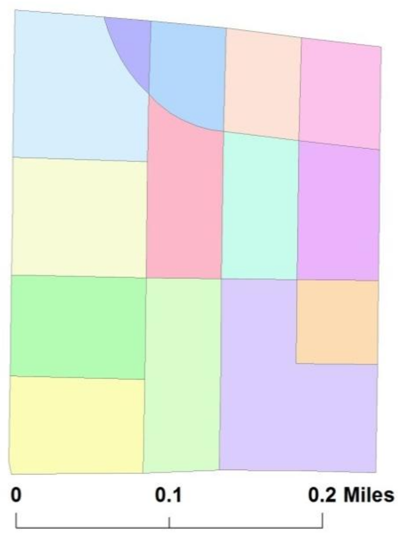


Figure 2.6
Census Blocks within Tract

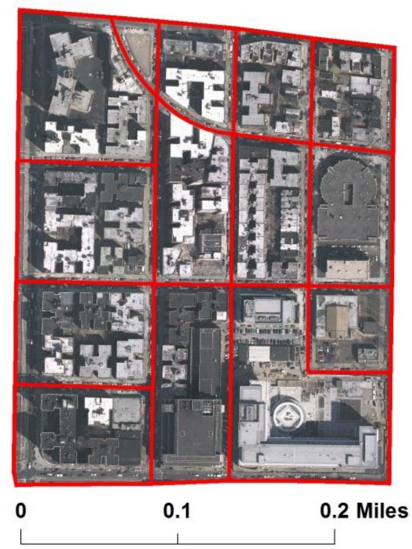


Figure 2.7 Orthophoto
Census Blocks within Tract Orthophoto

Bronx Population

The population of the Bronx is 1.33 million (U.S. Census, 2000), which makes it 17% of the total New York City population. Figure 2.8 & 2.9 shows the population density and figure 2.11 shows the population distribution by race throughout the Bronx. The Bronx River runs thru the middle of the Bronx and creates a natural east / west separation.

	Total Population	Percent non-Hispanic White	Percent non-Hispanic Black	Percent Hispanic / Latino	Percent without High School Degree	Median Household Income	Percent Below Poverty
Bronx	1,332,650	14.6	31.2	48.4	37.7	27,611	30.7

Table 2.6: Sociodemographics for Bronx County
Data source: US Census, 2000.

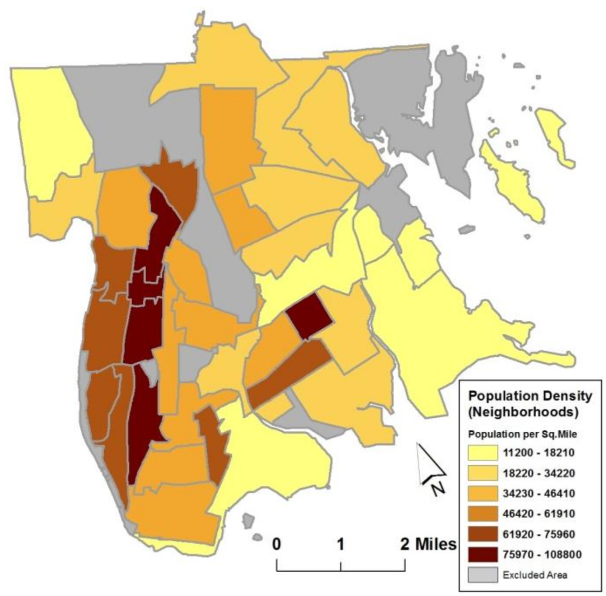


Figure 2.8 Population by Neighborhood

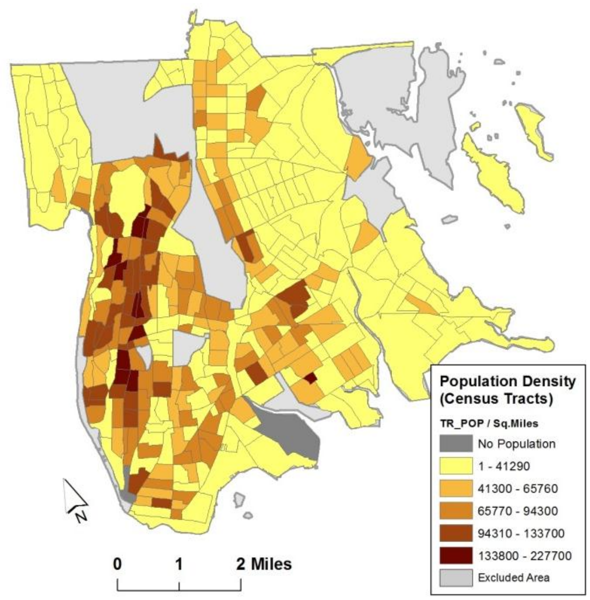


Figure 2.9 Population by Census Tract

Figure 2.8 and 2.9 illustrate population density (not population distribution, per se) by neighborhood and census tract. As you can see, the areas in the central and southern parts of the Bronx contain higher population densities than the eastern and northern sections. Bronx residents are not randomly distributed throughout the 38 Bronx neighborhoods and 355 census tracts.

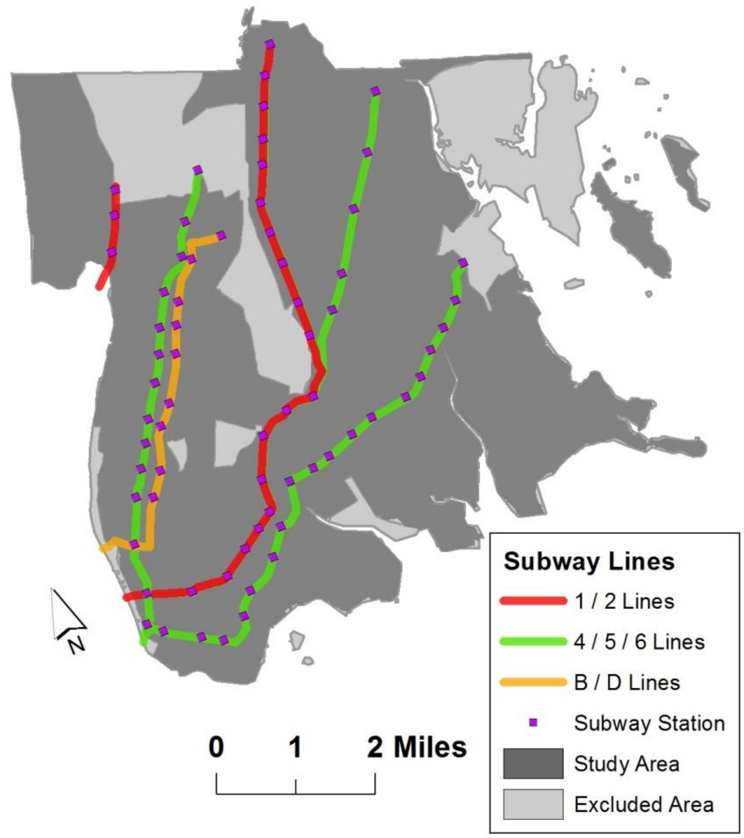


Figure 2.10. Bronx Subway Lines and Stations

If you compare the neighborhood and tract population density maps (figures 2.8 and 2.9) with the subway lines and station map (figure 2.10), you will notice that the highest population density areas contain subway lines (thru them) and many of the highest density tracts contain subway stations. On average 367,000 people utilize one or more subway stations every day. Many of them commute to work in the morning, between 6:30am – 9:00am and evening between 3pm – 7pm. This high number of people using public transportation every day creates a very easy target for motivated offenders, since it creates a substantial bottleneck (in space and time) of potential targets (i.e. hot products) and victims.

The U.S. Census (2000) indicates that the Bronx is the most diverse county in the US: 15% Non-Hispanic White, 31% Non-Hispanic Black, 49% Hispanic, and 5% other. According to the U.S. Census, if you randomly selected two Bronx residents, 90% of the time they would be of a different race or ethnicity (Newsweek, 2009). Not only is the Bronx racially diverse, but it also contains substantial segregation by race. Figure 2.11 illustrates the dominant population distributions by race at the census tract level.

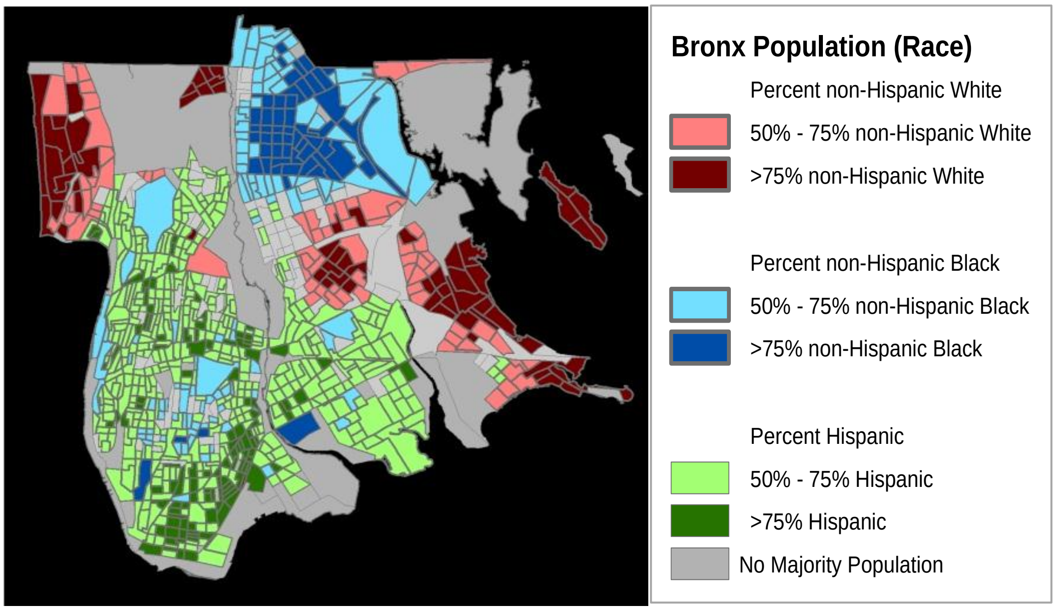


Figure 2.11 Bronx Population Distribution by Race (Tract)

Population distribution (where people live/work/play) and population density (the number of people per geographical unit) play a very important role in crime opportunity and crime risk analysis. Population factors, especially traffic flow and people movements, can play a significant role in the number of available victims and/or offenders. Population distribution and population density play an even more significant role in micro-level crime analyses because people (i.e. potential victims and/or offenders) can either be present or absent from the actual location. Obviously if the potential victims are not present, a crime will not occur.

In criminology, we consider population distribution and population density as an approximation on the number of potential offenders, potential victims, or potential targets (Watts, 1931; Harries, 1999; Harries, 2006). Police departments on the other hand, rarely take population density into consideration and understandably so, they are primarily interested in the highest crime locations (e.g. 'just the facts'), regardless of the number of people who live or work in the area. This difference in approach remains a fundamental difference between crime analysis in police departments and criminology in academia.

Crime analysts are typically concerned about where the highest amounts (i.e. frequency) of crimes occur, whereas criminologists may be more interested in the specific rate of victimization (number of crimes / underlying population at risk). An example of this would be subway station robberies, something this dissertation covers later. Crime analysts working for the police department typically want to find out which subway stations have the highest number(s) of robberies so they can allocate more personnel to these stations (hopefully at the appropriate times). Criminologists may also be interested in the highest crime subway stations, but they are also interested in the stations that contained the highest rate of robbery victimization (i.e. the number of robberies / subway ridership for each station). The first method provides you with the stations with the highest number of robberies, the second method provides you with the stations that contain the highest rate of robbery victimization (i.e. similar to comparing UCR crime counts per county vs. UCR crime rates per 100,000 people). These are two separate, but equally important concepts that are frequently overlooked, but need to be determined prior to the beginning of the analysis.

Thankfully, the micro-level unit aggregation process that I developed for this dissertation research calculates both the highest crime frequency properties and street segments, as well as the properties/street segments with the highest rate(s) of violent crime (when controlling for residential or 'commercial' population). The micro-level population estimates are calculated by using micro-level population estimates, including a dasymetrically derived residential population estimate and employee estimates contained in the commercial/business geodatabases (this is discussed in depth in the next section).

2.1.3 CENSUS DATA

The sociodemographic data used in this study includes total population, percent Non-Hispanic White (NHWH), percent Non-Hispanic Black (NHBL), percent Non-Hispanic Asian (NHAS), Percent Hispanic/Latino (HISP), percent below poverty (POV), and the percent of adults over 25-years-old without a high school diploma (NOHS). Census derived rates; specifically crime, race, poverty, and education rates were calculated by dividing the primary group by the appropriate secondary denominator (e.g. the count of Hispanics divided by the total population multiplied by 100 equals the percentage of Hispanics). Similarly in crime analysis, census population data is commonly used to determine population distribution which is necessary for calculating an accurate denominator to calculate crime rates by geographical areas/units.

However, some researchers (Andresen and Jenion, 2008) have noted that using census data as a denominator can be very misleading, since census data identifies residential population (i.e. where people sleep at night). One thing that is often overlooked regarding (residential) census population is that you can use the inverse of the residential population to estimate a daytime population (i.e. the majority of residential population is *not* at home during the daytime). There are also several ways to estimate daytime population - by taking the total population for an area, then adding the total number of workers living in the area, then subtracting the number of workers *working* in the area. This daytime population could also be dasymetrically derived using the CEDS process (explained later in this section) and the requisite commercial / residential information contained in the cadastral (tax lot) dataset. Daytime population was not calculated for this dissertation, however, I do plan on completing this same process with the updated 2010 census data for future research.

It should be noted that Hispanics comprise almost half of the population (49%) in the Bronx, however, while the census (typically) treats all Hispanic (nationalities) as one homogeneous group, there are over 20 different Hispanic nationalities represented in the Bronx (U.S. Census, 2000). While these nationalities share a common bond of language, many of them are not homogeneous in their cultural traditions. In the 2000 Census, the Census Bureau identified Hispanic as an ethnicity, not a race. Therefore, in order to obtain accurate estimates of race groups, Hispanics that identified themselves as White or Black, were not included in their respective racial group.

The Cadastral-Based Estimated Dasymetric System (CEDS)

One of the significant shortcomings of criminology and crime analysis has been the relationship between population distribution (e.g. where people actually live/work/play), population density (e.g. how many people actually), and crime (type and frequency) at the micro-level. This is because when we analyze crime (or anything else related to population distribution and density) below the census block level, we no longer have an accurate count or estimate of population. The block level is the lowest geographic level that the U.S. Census (SF-1) reports population counts, however, this data does not include other important variables, including race or economic (e.g. poverty, education, language) variables. As such, the lowest geographic level that most crime researchers use is census block groups. However, using census blocks (or higher level geographies including census block groups/tracts, zip codes, or neighborhoods) as the unit of analysis can mask, blur, or improperly approximate the complex relationships between population distribution, population density, and crime. Since crime, land-use categories, and business establishment / premise types are all recorded at the point/address level geography, it becomes critical to also have a population estimate at the same spatial resolution as the other geodatabases.

As the preliminary analysis maps and tables indicate (see Appendix pages 3-8), there is considerable spatial heterogeneity and clustering of violent crime, population, land-use categories, and business establishments in the Bronx. However, in order to better understand the complex micro-level relationships between crime and population, land-use, and business establishments/premise types, we must first calculate a micro-level population estimate that mirrors the spatial accuracy/resolution of the other micro-level datasets. The necessity for a micro-level population estimate was the primary reason that the Cadastral-based Expert Dasymetric System (CEDS) was devised and developed in 2006 (Maantay, Maroko, & Herrmann, 2007).

In its simplest form, the CEDS process provides a statistically accurate population estimate for each of the 89,211 property tax lots in the Bronx. These new micro-level population estimates allow for the calculation of micro-level crime trends and patterns, while controlling for residential population at the micro-level.

Currently, the CEDS process (Maantay, Maroko, Herrmann, 2007) is the leading way to accurately measure the relationships between population and other micro-level datasets. CEDS has been effective in estimating population in crime analysis (Herrmann and Maroko, 2006), flood risk (Maantay and Maroko, 2008), proximity analysis (Maantay et al., 2010), pollution analysis (Maantay et al., 2009), and health-risk exposure (Maroko, 2010).

The CEDS methodology estimates total population (including sub-populations) for the Bronx (and the other boroughs of New York City) based upon cadastral (tax lot) level data provided by the New York City Department of City Planning and the New York City Department of Finance. The end result of the CEDS process is a micro-level population estimate, which can act as an improved 'denominator' when calculating rates (i.e. crime rates at the property or street segment or population levels inside hot spot geographies). This new denominator can also be used to improve on micro-level measures / models between population distribution, population density, and related factors (i.e. crime, land-use, business establishment / premise types).

One of the significant limitations of hot spot and density maps is that it was never possible to accurately estimate the population within the hot spot/kernel density boundaries. The CEDS data can be *clipped* by hot spot boundaries or kernel density outlines, which would then provide a population estimate (i.e. crime/population = risk exposure) for each hot spot / high density crime zone. For the first time in criminology and crime analysis, the CEDS process can provide an accurate (and comprehensive) look at the relationship between population distribution, population density, and crime at the micro-level.

Poulsen and Kennedy (2004) used a similar dasymetric methodology to disaggregate municipal level UCR/NIBRS burglary data using land and housing data in Massachusetts. According to the authors, there are several well-known shortcomings of areal choropleth (map) analyses; larger areal units cartographically misrepresent the actual distribution, areal/polygon mapping typically guises any lower-level clustering, and (most) choropleth boundaries are arbitrarily selected administrative boundaries (which do not actually take population distribution or population density into account).

There are several ways that dasymetric mapping techniques have been utilized in other fields, including demography, quantitative geography, urban planning, and environmental management (Bielecka, 2005; Eicher et al., 2001; Forster, 1985; Holt et al., 2004; Holloway et al., 1997). However, many of these dasymetric techniques use low resolution orthophotographs, remote sensing data, or land cover datasets as the subordinate dataset (Langford et al., 1991; Mennis, 2003; Sleeter, 2004; Wu and Murray, 2007; Wu et al., 2005).

The CEDS process takes advantage of the New York City cadastral data (tax lot level information) and redistributes population(s) based upon several complex residential / non-residential variables. This method provides a significant improvement over its remote-sensing counterparts, especially in very heterogeneous urban environments, like the Bronx. The concept of spatial heterogeneity can be particularly problematic when trying to quantify a micro-level crime rate (e.g. number of victims / number of potential victims) (Townsley, 2009; McCord et al., 2007). The problem is that population counts are extremely biased within census units (i.e.

people are not evenly distributed throughout the respective census unit). Additionally, CEDS uses an expert system and validation against other various census enumeration units in order to further refine the population estimate for each tax lot.

Figure 2.12: Land-Use Heterogeneity of a Bronx census tract. The orthophoto (above) illustrates the uneven distribution of land use categories and residential units at the tax-lot level. (There are, on average, more than 13 census blocks per census tract and 10 census tracts per neighborhood in the Bronx). If you compare this map with the map on the following page, you can note the property lots/buildings that contain population and how the population distribution and population density is unevenly distributed throughout this census tract.
Data source: NYCMap, 2008; NYC-DCP, 2008; LotInfo, 2008.

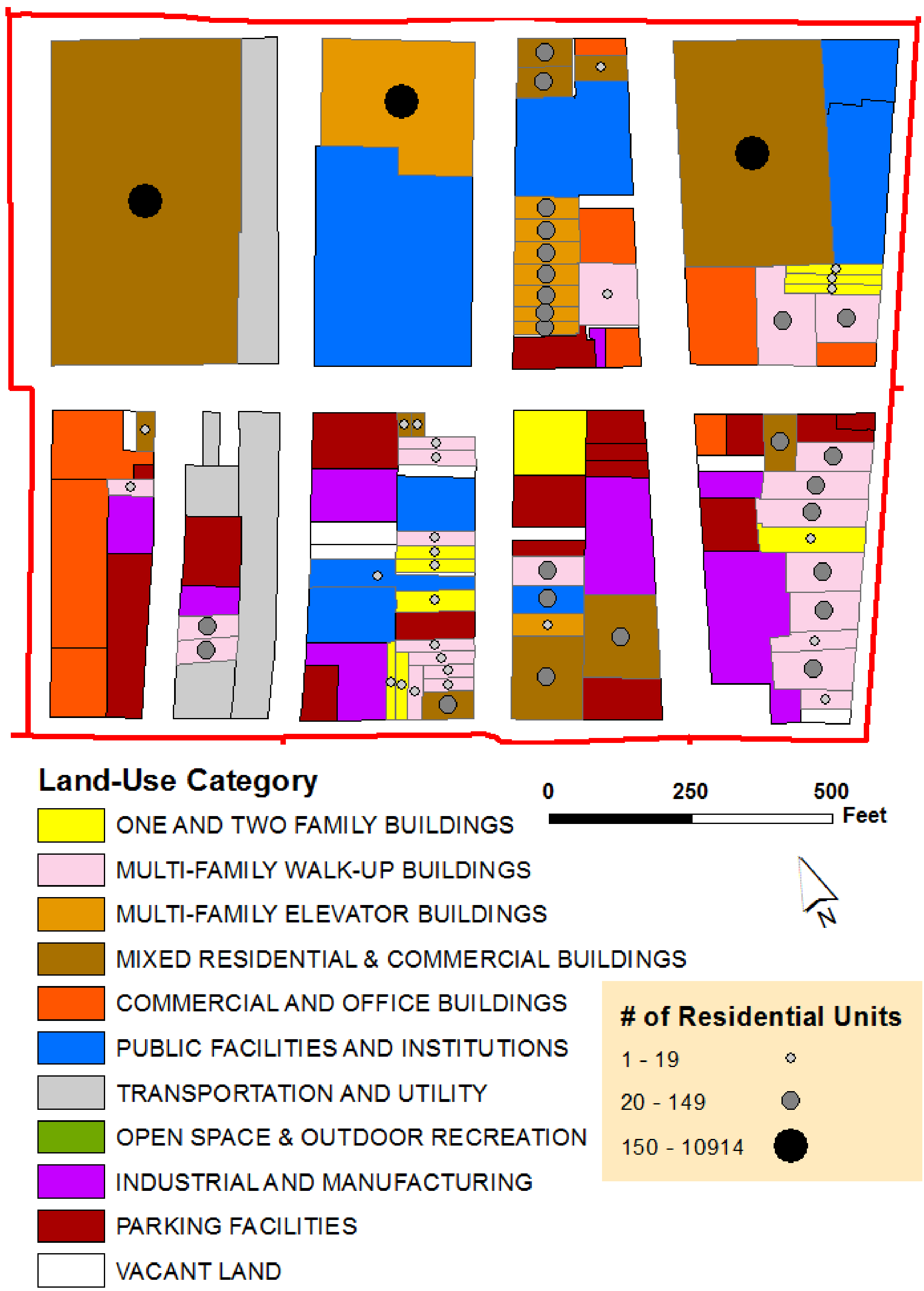


Figure 2.13 The cadastral map (above) illustrates the uneven distribution of land use categories and residential units at the tax-lot level. Note how the population distribution, specifically, how the mixed residential and commercial tax lots (and buildings) vary is size, distribution, and population throughout the census tract.
Data source: NYCMap, 2008; NYC-DCP, 2008; LotInfo, 2008.

There are several standard methods to disaggregate spatial data. The most common disaggregation methods used in GIS are Areal Weighted (AW) interpolation and Filtered Areal Weighting (FAW). These two dasymetric methods are popular because the secondary dataset that is used to disaggregate the primary dataset is readily available in most cities throughout the USA. For example, if the secondary dataset (e.g. census tract population) has 40% of its area within a crime hot spot boundary, areal weighting would estimate that 40% of the population in that census tract falls inside the crime hot spot.

The preceding maps and following formulas explain in detail, how the CEDS population estimate is calculated. The first equation (equation 2.1) shows how the estimated population is calculated by using the source zone population and the area of the target zone and source zone.

$$\mathbf{POP_{AW} = POP_S * AREA_t / AREA_S} \qquad \textbf{Eq. 2.1}$$

where:

POP_{AW} = estimated population in target zone from areal weighting;

POP_S = source zone population (known quantity from census tract, block group, etc.);

$AREA_t$ = area of target zone (e.g. area exposed to pollution)

$AREA_S$ = area of source zone (e.g. census tract, block group, etc.).

Filtered Areal Weighting FAW) improves on Areal Weighting (AW) by removing all non-residential areas (e.g., parks, open spaces, and water bodies) (equation 2.2).

$$\mathbf{POP_{FAW} = POP_S * M\_AREA_t / M\_AREA_S} \qquad \textbf{Eq. 2.2}$$

where:

POP_{FAW} = estimated population in target zone from filtered areal weighting;

POP_S = source zone population (known quantity from neighborhood, census tract, block group, etc.);

M_AREA_t = modified area of target zone (open spaces excluded); and

M_AREA_S = modified area of source zone (e.g. census tract area with open spaces excluded).

The CEDS method utilizes the tax-lot level data from NYC-DCP and NYC-DOF which contains the amount of residential area (RA) and the number of residential units (RU) for each of the 89,211 tax lots in the Bronx. While it is easy to explain and understand the CEDS methodology, it should be noted that CEDS is an extremely complex procedure that requires very precise and reliable tax lot level data in order to work accurately.

The CEDS population estimates are calculated by taking the total number of residential units (RU) and the total residential area (RA) in the source zones (e.g. census block groups). After this step, the RU and RA are then calculated for the target zones (e.g. tax lots). After the source zones and target zones have been established, a ratio is calculated for both source and target zones and that ratio is multiplied by the population in the source zone. The results from this last step equate to estimated population(s) for the target zone (one estimate for RA and another estimate for RU).

The CEDS methodology then employs an expert system which disaggregates the data from a larger source zone (e.g. census tract) to a smaller, but known, target zone (e.g. census block group). Since the target zone's 'true' data are known, the expert system compares RU-based and RA-based estimates to these known quantities and selects the better performing dataset (equation 2.5).

$$\mathbf{POP_{CEDS} = POP_S * U_t / U_S} \qquad \textbf{Eq. 2.3}$$

where:

POP_{CEDS} = CEDS-derived lot-level population;

POP_S = source zone population (block group or tract);

U_t = the number of proxy units (RU or RA) in the target zone (e.g. tax lot); and

U_S = the number of proxy units (RU or RA) in the source zone (e.g. census tract or block group).

$$\mathbf{POP_{diff} = | POP_{BG} - POP_{est} |} \qquad \textbf{Eq. 2.4}$$

where:

POP_{diff} = the difference between census and estimated populations per block group;

POP_{BG} = census block group population; and

POP_{est} = estimated population (*RU* or *RA*) derived from the census tract (not block group).

Since the CEDS process is comparing its population estimate against the known census population for both RU-based and RA-based values, we assume that the superior source zone would be the one that is more similar to the actual census block group values (i.e. smallest POPdiff values). After re-joining the POPdiff data with the tax lot data, the expert system then selects the superior proxy unit for each source zone (e.g. block group). This can be illustrated in equation 2.5.

$$\textbf{IF } \mathbf{RU\_POP_{diff} <= RA\_POP_{diff}}\textbf{, THEN } \mathbf{POP_{l} = POP_{RU\_BG}}\textbf{, ELSE } \mathbf{POP_{l} = POP_{RA\_BG}} \qquad \textbf{Eq. 2.5}$$

where:

RU_POP_{diff} = the absolute difference between the census block group population and the estimated block group population derived from the census tract population based upon number of residential units;

RA_POP_{diff} = the absolute difference between the census block group population and the estimated block group population derived from the census tract population based upon residential area;

POP_{l} = the final estimated tax lot population dasymetrically derived from the census block group population (not the census tract);

POP_{RU_BG} = the estimated tax lot population dasymetrically derived from the census block group population (not the census tract) based on number of residential units; and

POP_{RA_BG} = the estimated tax lot population dasymetrically derived from the census block group population (not the census tract) based on the adjusted residential area.

In the Bronx, CEDS was completed by first determining the tract-level disaggregation proxy units, which then determined the proxy units for census block groups. The end result is a dasymetrically derived population estimate for each of the 89,211 tax lots that is customized for each Bronx census block group. It should be noted that the CEDS process is pycnophylactic in nature, which means that the sum of the estimated populations will be the same as the census block groups from which the estimates were derived from.

The differences in these three disaggregation techniques – areal weighting, filtered areal weighting, and the cadastral-based expert dasymetric system – are usually best understood diagrammatically (Figure 2.14).

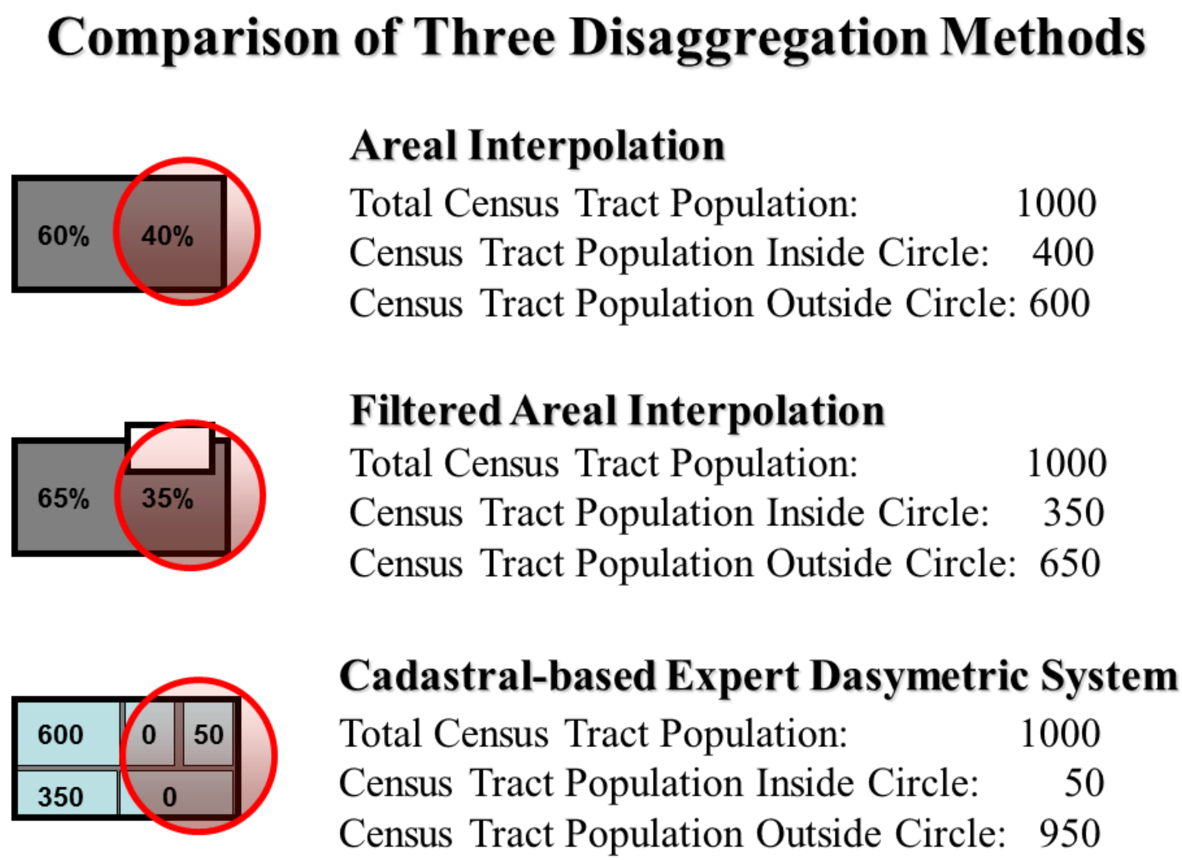


Figure 2.14: Diagrammatic comparison of spatial disaggregation methods. (a) Areal Weighting (AW): Census Tract intersected by a hot spot. (b) Filtered Areal Weighting (FAW): Census Tract intersected by a hot spot, and showing an uninhabited area (dark rectangle). (c) CEDS: Census Tract showing tax lot boundaries intersection the hot spot.

The CEDS methodology was validated similarly to how the expert system was employed in the CEDS process. First, census Tract (CT) data were disaggregated to census block groups (BG) using the CEDS technique, the ratio of residential area, ratio of residential units, and filtered areal weighting (please note that the residential area and residential unit ratios are intermediate steps only used when utilizing the expert system). The Bronx tax lot population estimates for each method are compared to the 'observed' or actual Bronx block group populations recorded by the U.S. Census (2000). The CEDS method in the Bronx clearly outperforms the FAW-based, RA-based, and RU-based tax lot level populations when estimating Bronx block group population based on Bronx tract level populations.

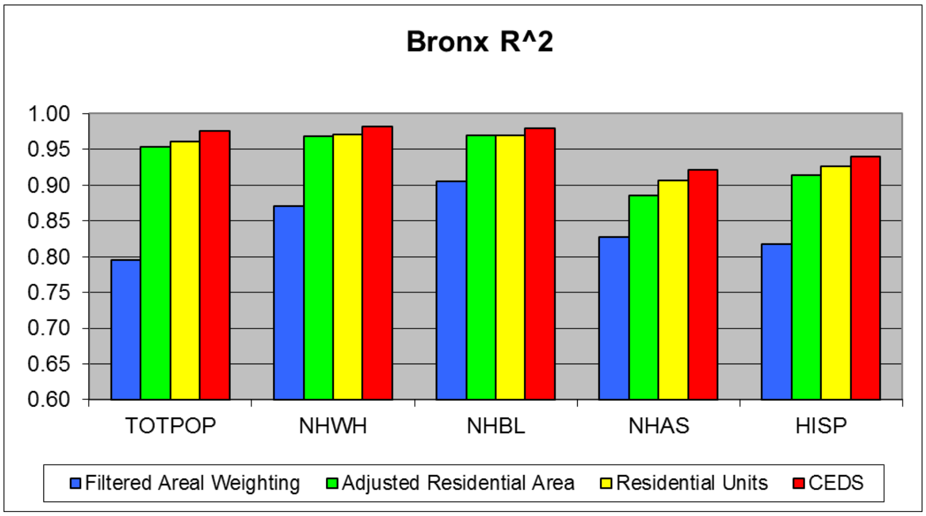


Figure 2.15: R-squared values from linear regressions of selected populations for filtered areal weighting, residential area, residential units, and CEDS estimated block group populations vs. Census-reported block group population.

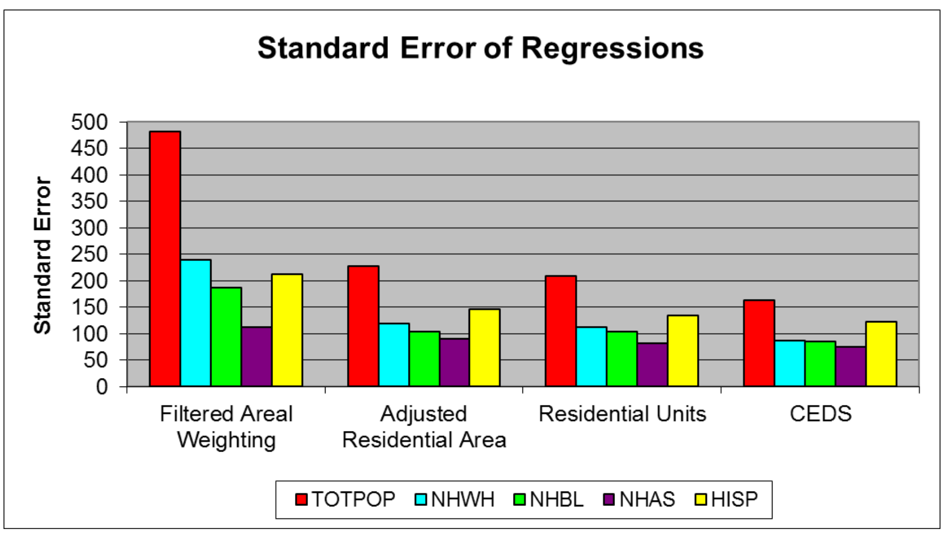


Figure 2.16: Standard Errors from linear regressions of selected populations for filtered areal weighting, residential area, residential units, and CEDS estimated block group populations vs. Census-reported block group population.

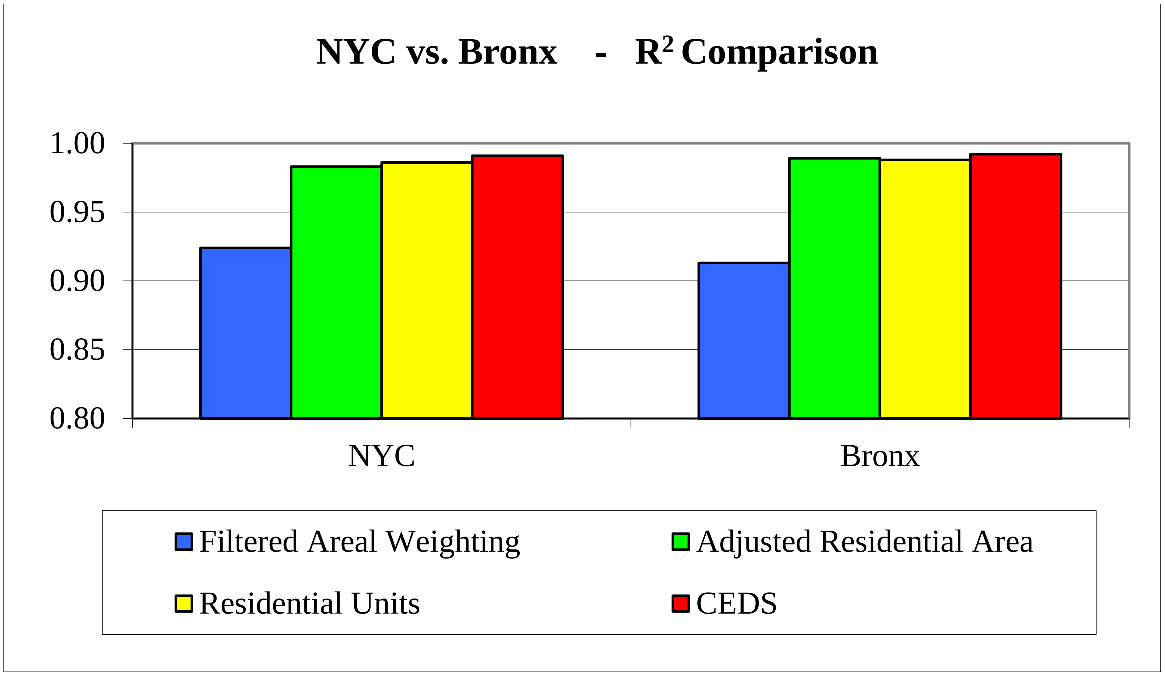


Figure 2.17: Comparison of R-square for each of the disaggregation methods

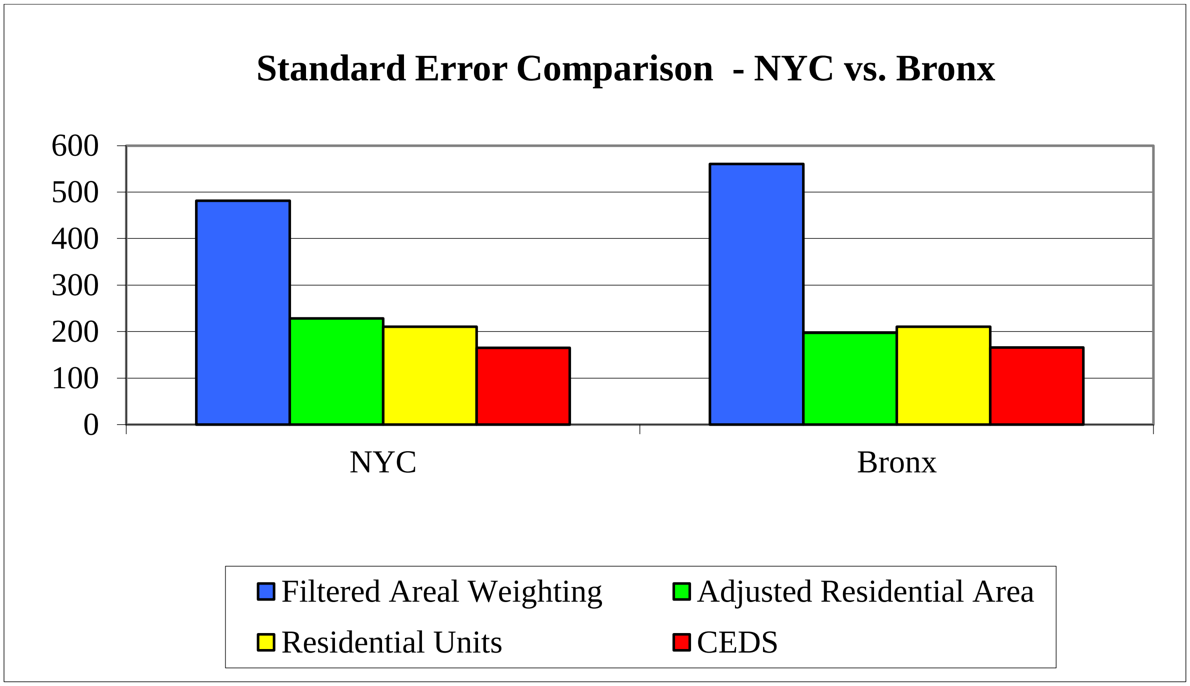


Figure 2.18: Standard Error Comparison of simple linear regression

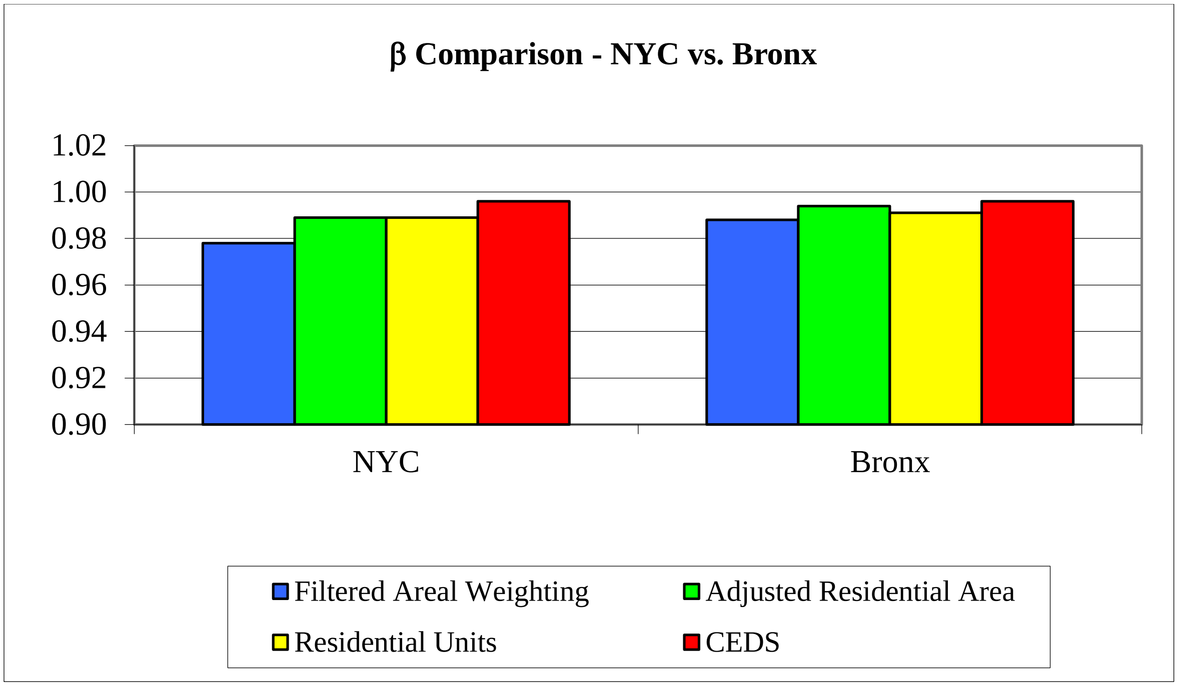


Figure 2.19: Beta Comparison - regression slopes for NYC vs. the Bronx.

The relationship between estimated and observed population values can be observed graphically using scatter plots. The scatterplots clearly suggest that the CEDS estimates are more like the observed census values more than the filtered areal weighting estimates at the block group level (Figure 2.20, 2:21).

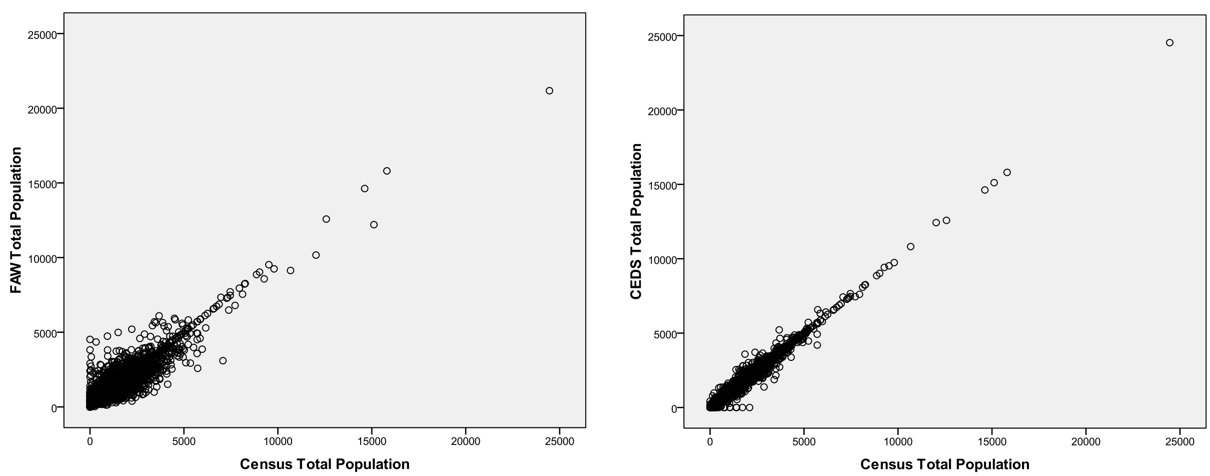


Figure 2.20 and 2.21: Scatterplots of FAW-derived (left) and CEDS-derived (right) block group estimates of total population vs. census-reported block group total population.

There were three additional validation measures employed on the total population and racial/ethnic demographic categories. These were bias, distance, and correlation validation measures. Bias was measured by simply comparing the mean average of the estimated block group data (filtered areal weighting, residential area, residential units, and CEDS) and the "observed" data (Census-reported block group populations) (Equation 2.6).

Mean Error = $(\Sigma\varepsilon)/N$ **Eq. 2.7**

where:

ε = error

N = number of observations

Distance was measured using the root-mean squared error (RMSE). The RMSE quantifies how close the estimated data are to the observed data by calculating the "distance" from each estimate to the observed value, squaring this value (to prevent negative numbers from cancelling out positive ones), then calculating the mean, and taking the square root. As such, the smaller the RMSE, the closer the 'fit' is to the original census values. Put simply, the RMSE is the average distance of estimated data from the observed data (Equation 2.8).

RMSE = $[(1/N)\ \Sigma\varepsilon^2]^{0.5}$ **Eq. 2.8**

where:

RMSE = root mean square error

ε = error

N = number of observations

Correlation is calculated using both Pearson and Spearman correlation tests, which results in "goodness-of-fit" measures either parametrically (Pearson) or non-parametrically (Spearman). The results of the three diagnostic measures indicate that there is slightly more bias with the

CEDS process when compared to FAW. Moreover, FAW tends to overestimate, whereas the cadastral data and CEDS process tend to underestimate. In terms of distance and correlation, CEDS outperforms the other methods with consistently lower RMSE values and higher Pearson's and Spearman's correlations (Table 2.7).

Population Group	Disaggregation Method	BIAS	CORRELATION		DISTANCE
		Mean of Estimate - Mean of Census	Pearson Correlation	Spearman's Rho	RMSE
Total Population	Filtered Areal Weighting	1.334	.891	.789	482.72
	Residential Area	-2.336	.977	.954	229.39
	Residential Units	-2.297	.980	.960	211.08
	CEDS	-5.540	.988	.975	164.96
non-Hispanic White	Filtered Areal Weighting	1.180	.934	.947	239.58
	Residential Area	-0.907	.984	.975	118.75
	Residential Units	-0.859	.986	.974	112.72
	CEDS	-0.792	.991	.979	87.85
non-Hispanic Black	Filtered Areal Weighting	-0.003	.950	.937	186.39
	Residential Area	-0.718	.985	.959	103.95
	Residential Units	-0.771	.985	.959	104.08
	CEDS	-1.727	.990	.964	84.51
non-Hispanic Asian	Filtered Areal Weighting	0.036	.910	.924	112.03
	Residential Area	-0.144	.941	.942	91.82
	Residential Units	-0.129	.952	.942	82.89
	CEDS	-0.459	.960	.948	75.52
Hispanic / Latino	Filtered Areal Weighting	0.099	.904	.899	214.60
	Residential Area	-0.512	.956	.944	145.96
	Residential Units	-0.487	.962	.949	135.21
	CEDS	-0.713	.969	.956	122.22

Table 2.7: Validation diagnostics for filtered areal weighting, residential area-based disaggregation, residential unit-based disaggregation, and CEDS.

The validation diagnostics suggest that the CEDS technique provides an improved estimator of population distribution when compared to filtered-areal weighting. However, there are several limitations to the CEDS technique. It appears that the underestimation bias may be a result of an incomplete cadastral dataset (or possibly errors within the tax lot data). If there are block groups wherein none of the tax lots have information regarding residential area or residential units, then the CEDS method will fail (assuming that there is actual population within the block group). This type of failure may lead to an underestimation bias and loss of the pycnophylactic nature of the CEDS technique. This phenomenon can be seen in the scatter plots (Figure 2.20, 2.21) with the "line" of points that have zero CEDS-estimated population and existing Census-reported population.

It should be noted that this only appears to be an issue with less than 2% of the CEDS data (citywide, it is even less for the Bronx). However, there are a number of ways that the CEDS shortcomings can adequately be addressed. The easiest way is the use of an additional ancillary data set to be used when the residential proxies (residential area or residential units) do not work dependably or fail. This alternative could also use the total lot area (independent of building class), the total land area (independent of lot size), or some combination of other variables (eg. total property lot area minus commercial/industrial lot area).

Another limitation of CEDS is its use in regression analysis. While the absolute numbers of the estimated CEDS populations and sub-populations are reliable, the rates within each tax lot (e.g., percent non-Hispanic Black) are not truly independent from the higher level census geographies. In other words, if the block group contained a population that is 50% non-Hispanic Black, then all the populated tax lots within that block group would have very similar rates – this results in data that are not truly independent or uncorrelated. As such, the CEDS process is ideal when working with absolute numbers, or for the purpose of re-aggregating the data into non-census boundaries (e.g., zip codes, police precincts, crime hot spots).

For this micro-level crime analysis research, CEDS has been used to estimate population (counts) at the tax lot level, population counts along each street segment (network), and detailed population distribution and densities (below the census block level) for different crime hot spot geographies. The Bronx is comprised of complex racial, socioeconomic, physical and social heterogeneity structures. Since the CEDS process estimates population at a much higher spatial resolution (i.e. the 89,211 tax lots) than traditional census units (i.e. 355 census tracts or 36 neighborhoods), it is currently the best available method for estimating populations (and selected sub-populations) at the micro-level.

2.1.4 LAND-USE CATEGORY DATA

The land-use data that was used for this research consists of property tax lot (polygon) level data collected by the NYC-DCP and NYC-DOF, and maintained by LotInfo (2008). The 2008 LotInfo cadastral dataset is extremely comprehensive and contains 89,211 individual property lot records for Bronx County. Each property lot is assigned a unique identifier based on the borough, block, and lot (BBL) number where it resides. The land-use category variable is based on the property's primary land-use function according to the NYC-DOF.

In New York City, land use is divided into 11 different categories. Table 2.8 illustrates the distribution of land-use categories within the Bronx.

Land Use Category Description	Property Lots in the Bronx |(2008)	Total Bronx Lot Area (Square Miles)	Percentage of Total Lot Area
01 = One and Two Family Buildings	51,190	5.62	19%
02 = Multi-Family Walk-up Buildings	16,762	2.27	7%
03 = Multi-Family Elevator Buildings	2,000	2.62	9%
04 = Mixed Residential & Commercial Buildings	3,624	.90	3%
05 = Commercial and Office Buildings	3,096	1.38	5%
06 = Industrial and Manufacturing	1,373	1.18	4%
07 = Transportation and Utility	982	1.79	6%
08 = Public Facilities and Institutions	1,811	3.45	11%
09 = Open Space and Outdoor Recreation	562	8.91	29%
10 = Parking Facilities	2,528	.60	2%
11 = Vacant Land	4,657	1.05	3%
99= Missing Data	626	.72	2%
TOTAL	**89,211**	**30.49**	**100%**

Table 2.8: Land-Use Categories by Property Lot and Area for the Entire Bronx County

The total Bronx property dataset (89,211 lots) was *clipped* to include only those property lots that are contained within the dissertation study area (i.e. excluding the open space areas, see figure 2.8). After the cadastral dataset was clipped, there were 88,993 lots remaining in the study area tax lot dataset. The study area equates to 99.8% of the total Bronx property lots dataset and 74.1% of the total Bronx land geography. Comparison of the total Bronx land (table 2.8) and the dissertation study area (table 2.9) indicates that the research area contains 20% less open space and outdoor recreation (land use #9) area than the total Bronx area. As such, the majority of the tax lots/land that was clipped for this dissertation research was uninhabitable, non-residential open space areas.

Land Use Category Description	Property Lots in the Study Area |(2008)	Total Lot Area in the Study Area (Sq.Miles)	Percentage of Total Lot Area in Study Area
01 = One and Two Family Buildings	51,156	5.59	25%
02 = Multi-Family Walk-up Buildings	16,762	2.27	10%
03 = Multi-Family Elevator Buildings	2,000	2.61	12%
04 = Mixed Residential & Commercial Buildings	3,624	.90	4%
05 = Commercial and Office Buildings	3,092	1.37	7%
06 = Industrial and Manufacturing	1,357	1.12	5%
07 = Transportation and Utility	958	1.57	7%
08 = Public Facilities and Institutions	1,809	2.88	12%
09 = Open Space and Outdoor Recreation	524	2.06	9%
10 = Parking Facilities	2,522	.59	2%
11 = Vacant Land	4,591	.97	4%
99= Missing Data	598	.67	3%
TOTAL	**88,993**	**22.60**	**100%**

Table 2.9: Land-Use Categories by Property Lot and Area for the Dissertation Study Area

The LotInfo property lot data is categorized by county boundaries, so the data processing that was necessary included numerous tabular joins between property lots and crime points, as well as numerous spatial joins between property lots and street segment IDs, census identifiers, and population estimates. The end result of the tabular and spatial join processes is a property data layer where each property lot polygon contains a violent crime count, census population estimate, unique street identifier, census geography identifiers (both block group & tract), and neighborhood identifiers.

2.1.4 BUSINESS ESTABLISHMENT / PREMISES TYPE DATA

The business establishment and premises type data that was used for this research consists of four geospatial datasets. The business establishment data consists of three datasets;

InfoUSA data exported from ESRI's Business Analyst (2008), Plimus commercial data (2009), and data exported from the New York State Liquor Authority database (NYS-SLA, 2009). The fourth dataset is the Premises Type data, which also includes location identification categories for each of the violent crimes as recorded in the NYPD Crime Data Warehouse database.

GeoSpatial Dataset	Number of Records	Descriptive Data	Categorical Data
1. InfoUSA (2008)	29,153	Company Name	6-digit SIC, 8-digit NAICS, Sales Volume, Number of Employees
2. Plimus (2009)	36,037	Company Name, Address,	6-Digit SIC,
3. NYS-Liquor Authority (2009)	689	Company Name, Company Address	Alcohol Beverage Control Type & Class
4. NYPD Premises Type	48,166	Crime Type, Address, Premises Type	Premise Type Identifier, one for each crime location

Table 2.10: Number of Records, Descriptive Type, and Descriptive Data for each of the GeoSpatial Datasets

The InfoUSA database was exported from ESRI's Business Analyst (2008) suite. ESRI's Business Analyst (BA) suite consists of customized online, desktop, and server applications that calculate micro-level location-based intelligence, based on proprietary advanced spatial analytics of several demographic and business datasets (i.e. InfoUSA). The BA desktop software allows for geospatial analysis, as well as geovisualization of extensive micro-level datasets.

While each business listing contains a business name, the significant shortcoming of the InfoUSA dataset (when exported from ESRI's Business Analyst) is that it does not contain a physical street address. This means that InfoUSA is unable to be geocoded using local geolocators. However, InfoUSA data does contain geospatial identifiers (X & Y Coordinates) which allows it to be mapped (e.g. the points fall on the centerlines). The InfoUSA database classifies businesses by business name and 6-digit Standard Industrial Classification (SIC) system. The 29,153 businesses in the study were categorized into 1,711 different SIC code classes. The top ten most popular business types in the Bronx are listed in table 2.11. Each business listing was spatially and/or tabular joined to street and census identifiers, which allows it to be spatially related (e.g. proximity analysis) to each of the violent crime locations.

The other business dataset that was used for this research was the PlimUS dataset. This geodatabase is similar to the InfoUSA database in that it contains geospatial data on business listings throughout the Bronx. PlimUS is a commercial business listings database which contains similar, but slightly more detailed information than InfoUSA. PlimUS contains the company name, street address (which allow you to geocode with local geolocators), number of employees, estimated sales volume, and 6-digit standard industrial code (SIC). SIC codes provide identification of the specific business type (first four-digits of the SIC), as well as detailed information within each SIC code (last two-digits in the SIC). For example, restaurants are classified with the 4-digit SIC code '5812'. In the Bronx, the 1,298 restaurants are further classified into 81 different restaurant types (e.g. Caterer, Chinese, Coffee Shop, Deli, Diner, Ice Cream, etc.).

Standard Industrial Code (SIC)	**Number of Businesses**
Restaurants	1,298
Locksmiths	1,259
Non-Classified Establishments	1,171
Grocers	1,035
Beauty Salons	908
Physicians	845
Real Estate	739
Church	620
Schools	436
Attorneys	435

Table 2.11: Standardized Industrialization Codes (SIC) for the Top 10 Businesses

Since the PlimUS dataset contains detailed street address information, this made it possible to geocode (and/or tabular join) the business listings to the Bronx property lots (which already contained the other geographic identifiers). Moreover, this dataset provides the ability to aggregate SIC codes (e.g. business types) to street, tract, and neighborhood level geographies which allows me to calculate the number of businesses (and business types) for each geographic level of analysis (i.e. streets, tracts, and neighborhoods).

The New York State Liquor Authority (SLA) Division of Alcoholic Beverage Control is the State agency that reviews, licenses, and provides permits for the distribution and retail sale of alcoholic beverages in New York State. In the Bronx, the SLA licenses 689 different businesses to distribute and/or sell alcoholic beverages. The SLA dataset contains a detailed address, business name, SLA license number, and the SLA class & SLA business type. The SLA classifies Bronx businesses that sell/distribute alcohol into 14 different classes and 13 different types. The top 5 classes and types are listed below in table 2.12.

SLA Class	SLA Type	Business Classification	Number of Licenses
252	OP	Off-Premises Food & Beverage	369
341	RW	Restaurant (Wine)	161
141	EB	Eating Place (Beer)	69
243	CL	Club (Liquor)	24
241	RL	Restaurant (Liquor)	10

Table 2.12: NY State Liquor Authority Class, Type, Classification, and Number of Businesses

The SLA dataset, since it contains detailed address information, allows it to be geocoded (or tabular joined) to the existing property lot level basemap. As such, establishments that distribute / sell alcohol can be disaggregated into their respective SLA Types/Classes, while also being aggregated up to the different geographic levels of analysis (e.g. streets, tracts, neighborhoods). SLA business listings were also spatially/tabular joined to the existing geographic identifiers such that each business is identified by its respective street, census tract, and neighborhood identifiers.

The last of the business establishment / premises type datasets is the NYPD Premises Type data that is contained within the NYPD Crime Database. According to the 48,166 violent crimes in the Bronx that are included in this research study, there are 68 different premises types that identify and explain actual locational information about the respective crime location reported. NYPD Premises Types are simple explanations or identifiers of each crime location, as reported by the responding NYPD officer. Table 2.13 identifies the top 10 premise types for all of the violent crime included in this research. In the analysis and results section, I will explain some of the variation in these premises types when analyzed by the five different violent crime types. The complete list of premises types for each of the five violent crimes is located in the appendix.

Bronx Violent Crime – Top 10 Premises Types	Count
Street	21,693
Residence – Apartment	11,047
Residence – Public Housing	3,255
Residence – House	1,878
Other	973
Transit – Subway	912
Grocery / Bodega	696
Park / Playground	620
Public School	464
Bar / Night Club	424
Total	**41,962**

Table 2.13: Top 10 Premises Type for Bronx Violent Crimes (2006-2010). There were 66 different premises types listed for the 48,166 total violent crimes in the Bronx. Note that the top 10 most popular premises types account for 87% of the total violent crimes.

Not surprisingly, 'streets' are identified as the most popular violent crime premises type, with 45% of the violent crime actually occurring 'on the street'. Interestingly, the percentage of crime that occurred on the street varied considerably by violent crime type (see Appendix for the complete list). Since almost half of the Bronx violent crimes between 2006-2010 occured on the street level, this reinforces the need and importance of examining street-level spatiotemporal crime patterns and trends.

2.2 HOT SPOT METHODS

This section will explain the different hot spot methodologies that are commonly used in crime analysis research today. It will also outline some of the complex measurement, spatial distribution, and temporal analysis issues in crime analysis and how they can benefit from micro-level exploration and geovisualization within a geographical information system framework. Understanding both spatial and temporal variations of violent crime hot spots at the street level (e.g. hot streets) can have direct implications on apprehending criminals, police resource allocation & planning, crime modeling & forecasting, and evaluation of crime prevention & crime control programs (Ratcliffe, 2004; Boba, 2001).

In our current state of shrinking agency operating budgets, law enforcement (and other government agencies) needs to take the temporal dimensions of spatial patterns into consideration when identifying, exploring, and managing crime 'hot spots'. We can no longer rely on Sherman's concept of 'wheredunit' (1989) for hot spots, when we can calculate a combination of 'wheredunit' & 'whendunit' at a more micro-level.

The idea of hot spots (Sherman et al., 1989; Block and Block, 1995; Levine, 1999; Weisburd & Green, 1995; Peuquet, 1994; Ratcliffe, 2002, 2004) has been the fuel for much of our current interest in 'crime and place' research. Ever since the Sherman et al. article (1989), there has been a substantial body of literature that supports the concept of crime hot spots and crime concentrations. Hot spots can be calculated many different ways, including Nearest Neighbor Hierarchical clusters, Getis-Ord Gi* statistics, Kernel Density Estimation, Standard Deviation Ellipses, K-Means Clustering, and Local Moran's I statistics. But none of these methods take the temporal aspect of crime into consideration during calculation [1]. Any geographic cluster of crime can typically be referred to as 'hot spots', however, not all hot spots are the same. There are numerous ways to detect, construct, and illustrate hot spots.

The crime analysis and crime mapping communities have become very proficient in locating, tracking, and managing 'hot spots'. This iterative process of crime analysis and crime control has resulted in a steady ebb and flow of statistical and spatial crime patterns throughout many geographic levels (e.g. streets, census tracts, police precincts, neighborhoods). Traditional hot spots, such as Nnh clusters and KDE outlines, were always illustrated as odd shaped 'blobs' on the map (Chainey, 2010). Current research (Weisburd et al., 2009; Groff et al., 2010; Block and Bernasco, 2011; Herrmann, 2011) indicates that as we drill down into the micro-levels of geography (e.g. streets, tax lots, buildings), crime hot spots start to form new shapes (e.g. lines, points), sizes, and patterns.

In New York City, previous analyses conducted with NYPD indicate that not all violent crime hot spots act the same and almost all hot spots have significant internal spatiotemporal variance. Not only do hot spots 'move' over time, but if you conduct temporal analysis on large scale time periods (i.e. years), you will notice that hot spots have temporal variations within the hot spot. This intra-hotspot temporal variance is usually much more concentrated at the micro-level (Ratcliffe, 2004; Ratcliffe, 2006; Groff, 2010). Similar to the 80/20 rule, this intra-hot spot variance is good news and bad news to crime analysts. This is good news because many hot spots have specific temporal 'trends' within them, usually based on the land-uses, facility types, and routine activities of the people within the hot spots. When temporal analysis is conducted within each hot spot, a temporal trend can normally be identified and then an appropriate police

[1] For information on spatiotemporal clustering methods, see Kulldorff (1997) and Hardisty & Klippel (2010).

response can be developed. However, the bad news is that if temporal analysis is not conducted on each hot spot, police resources and patrol will be ineffective at best and 'wasted' at worst.

Crime analysts and criminologists should not simply view hot spots as geographic polygons that become objectives for crime prevention, crime control, and targeted patrol efforts. Hot spots need to be examined from within. Spatial concentrations of crime (almost) always vary over time. Rarely do we ask what (specifically) is generating each hot spot ? On what days of the week and at what times of day are the problems occurring within each hot spot? How many explicit problem properties ('hot points') and/or street segments ('hot streets') are there within the hot spot? Is the crime problem dispersing, clustering, or spatially stationary? Are the problem areas diffused, focused, or temporally acute? Are the trends increasing, decreasing, or remaining flat? (Ratcliffe, 2004). Understanding the temporal variations within and between hot spots is an important process in crime reduction strategies.

A recent Crime Prevention Research Review (Braga, 2008) that was conducted for the Community Oriented Policing Services (COPS) office indicates that a majority of medium & large size police departments are using crime analysis and crime mapping to identify crime hot spots. In his systematic review of hot spot interventions, Braga selected nine hot spot evaluations that were identified and reviewed for their effectiveness and impact on managing crime hot spots. He noted that seven of the nine selected studies contained significant crime reductions.

Table 2.14 indicates some of the diverse locations and approaches to hot spots crime prevention programs that have been conducted. However, as an increasing number of police departments conduct hot spots programs, it becomes considerably more important to determine 'what works, what doesn't work, and what looks promising'. One noted negative effect that came about from the review of the hot spot policing programs was a neighborhood's sense of fairness by the police (i.e. residents in some hot spot neighborhoods felt like they were being 'targeted' by the police). Rarely do we hear about negative effects of hot spots policing, but as hot spot policing programs become more prominent in policing, so too will the complaints about profiling and fair police practices.

Hot Spot Study	Program Elements
Minneapolis (MN) RECAP Sherman, Buerger, and Gartin (1989)	Problem-oriented policing to control crime at high-activity addresses; interventions comprised mostly traditional enforcement tactics with some situational responses.
Minneapolis (MN) Hot Spots Sherman and Weisburd (1995	Increased uniformed police patrol in crime hot spot areas; treatment group, on average, experienced twice as much patrol presence as the control group.
Jersey City (NJ) DMAP Weisburd and Green (1995)	Well-planned crackdowns on street-level drug markets followed by preventive patrol to maintain crime control gains
Jersey City (NJ) POP at Violent Places Braga et al. (1999)	Problem-oriented policing to prevent crime at violent hot spot areas; interventions comprised mostly aggressive disorder enforcement tactics with some situational responses.
St. Louis (MO) POP in Three Drug Areas Hope (1994)	Problem-oriented policing to prevent crime at three high-drug activity addresses; interventions comprised mostly traditional enforcement tactics with some situational responses.
Kansas City (MO) Crack House Raids Sherman and Rogan (1995a)	Court-authorized raids on crack houses conducted by uniformed police officers.
Kansas City (MO) Gun Project Sherman and Rogan (1995b)	Intensive enforcement of laws against illegally carrying concealed firearms in targeted beat through safety frisks during traffic stops, plain view, and searches incident to arrest on other charges.
Houston (TX) Targeted Beat Program Caeti (1999)	Patrol initiative designed to reduce Index crimes in seven beats: Three beats used "high visibility patrol" at hot spots Three beats used "zero tolerance" policing at hot spots One beat used a problem-oriented policing approach that comprised mostly traditional tactics to control hot spots.
Beenleigh (AUS) Calls for Service Project Criminal Justice Commission (1998)	Problem-oriented policing to control crime at high-activity crime addresses; interventions comprised mostly traditional enforcement tactics with some situational responses.

Table 2.14: Review of Hot Spot Policing Programs
Source: Braga, 2008

Moreover, Clarke and Weisburd (1994) indicate that there is routinely a 'diffusion of benefits' that results from police hot spot interventions. Not only does crime decrease throughout the targeted hot spot area as a result of the applied intervention(s), but the surrounding areas also typically experience a decrease in crime (even though they are not within the specified intervention boundaries). It should be noted that of the nine studies selected and reviewed by Braga, none of the studies focused specifically on spatiotemporal clusters of crime, but rather traditional (spatial) hot spots.

Hot Spots: Nnh Clusters, Gi Points/Gi* Streets, and Kernel Densities*

The remaining part of this section will explain the three most popular hot spot methods (Nearest Neighbor Hierarchical Clustering, Getis-Ord Gi*; & Kernel Density Estimation), describe how each hot spot method constructs its hot spots, illustrate how these hot spots are created on the map, and explain the differences between the three hot spot methods.

The nearest neighbor hierarchical clustering (Nnh) methodology identifies groups of violent crime incidents that are 'spatially near'. Nnh clustering is a hierarchical clustering routine that clusters points together on the basis of some type of precise criteria (ie. number of points per specified areal unit). The clustering routine is repeated until either all points are grouped into a single cluster or the clustering criterion fails. Nnh clustering is the most efficient way to identify the highest crime areas within a study region. On the other hand, Kernel Density Estimation (KDE) has become popular since it provides the researcher with an aggregated 'view' of the data distributions over various spatial unit(s). Kernel density estimation, also known as 'kernel smoothing', is typically considered a more refined statistical hot spot methodology when compared to traditional Nnh cluster analysis. Kernel smoothing involves placing a symmetrical surface over each individual point, evaluating the distance from that point to a referenced location based on a pre-defined mathematical function, and summing the value of all the surfaces for that referenced location (Levine, 1999). The Getis-Ord Gi* statistic varies significantly from NNh clustering and KDE because Gi* identifies clusters of high violent crimes and also clusters of low violent crimes (ie. hot spots & cold spots). When using Gi*, high value clusters are not necessarily statistically significant. High value clusters are only significant when surrounded by other high value features.

2.2.1 NEAREST NEIGHBOR HIERARCHICAL CLUSTERING

Nearest Neighbor Hierarchical Clustering generates a specific type of hot spot map which illustrates defined areal boundaries that contain specified concentrations of crime within a specified geographic region, over a specific period of time (Sherman and Weisburd, 1995).

The nearest neighbor hierarchical clustering (Nnh) routine (in CrimeStat 3.1) is simple to understand, runs quickly on most computers, and is the customary hot spot methodology for identifying groups or clusters of incidents that are spatially ‘near’ to one another. The Nnh routine assembles crimes (points) together based on a pre-defined search criterion (typically, the number of points over a specified area). The clustering routine is then repeated until either all points are grouped into a single cluster or the clustering criterion fails.

Hierarchical clustering methods are among the oldest of cluster routines (Everett, 1974; King, 1967) that have been used in quantitative geography, epidemiology, environmental criminology, and other ‘spatial’ research fields. Several different clustering methods have been advanced using the nearest neighbor method (Johnson, 1967; D'andrade. 1978), farthest neighbor, the centroid method (King, 1967), median clusters (Gowers, 1967), group averages (Sokal and Michener, 1958), and minimum error (Ward, 1963) routines.

As a result of the availability, popularity, price, and speed of the software program CrimeStat, the Nnh clustering method has become one of the more popular tools for calculating crime clusters (and crime densities) within the crime analysis community. However, one of the significant shortcomings of this hot spot method is that Nnh clustering does not take temporal values into its clustering calculation.

Figure 2.22: Robbery Nnh Ellipses

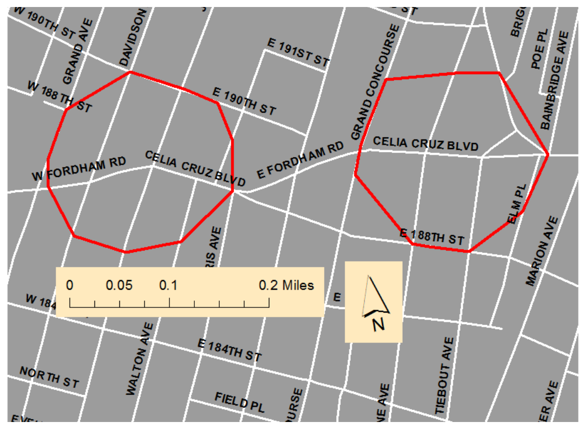


Figure 2.23: Robbery Nnh Convex Hulls

The CrimeStat Nnh routine provides the option to cluster crimes (points) based on a random or fixed threshold search distance and compares this threshold search distance to the respective distances for all other points within the study area. Only those crimes (points) that are closer to one or more other crimes (points) than the specified threshold distance are selected for clustering. In the crime analysis field, the Nnh routine is commonly used to find the highest concentrations (e.g. robberies per half mile, shootings per quarter mile) of crime events over a specified geographic area. Crime clusters can be calculated as convex hulls or ellipses.

In CrimeStat 3.1, I selected the expected random nearest neighbor distance for first-order nearest neighbors and a one-tailed confidence interval around the random expected nearest neighbor distance. The t-value selected was .01 (t<1%) and corresponds to the probability level, t, from the Student's t-distribution under the assumption that the degrees of freedom are at least 120. The mean random distance was defined as:

$$\text{Mean Random Distance} = d(ran) = 0.5\ \text{SQRT}\left[\frac{A}{N}\right]$$

Eq 2.9: where A is the area of the region and N is the number of crime incidents. The confidence interval around that distance is defined as

$$\text{Confidence Interval for Mean Random Distance} = \text{Mean Random Distance} \pm t^{*}\ SE_{d(ran)}$$

$$= 0.5\ \text{SQRT}\left[\frac{A}{N} \quad \frac{0.26136}{\text{SQRT}[N_2/A]}\right]$$

Eq 2.10: where A is the area of the region, N is the number of crime incidents, t is the t-value associated with a probability level in the Student's t-distribution.

The lower limit of this confidence interval is

$$\text{Lower Limit of Confidence Interval for Mean Random Distance} = 0.5\ \text{SQRT}\left[\frac{A}{N}\right] - t\left[\frac{0.26136}{\text{SQRT}[N2/A]}\right]$$

Eq 2.11 Nnh Lower Limit of the Clustering Confidence Interval

and the upper limit of this confidence interval is

$$\text{Upper Limit of Confidence Interval for Mean Random Distance} = 0.5\ \text{SQRT}\left[\frac{A}{N}\right] + t\left[\frac{0.26136}{\text{SQRT}[N2/A]}\right]$$

Eq 2.12: Nnh Upper Limit of the Clustering Confidence Interval
Source: Levine, 2010

Only crimes (points) that fit both criteria; closer than the specified fixed search threshold *and* belonging to a cluster group having the minimum number of points, are clustered at the first level (i.e. first-order clusters). The clustering routine then conducts subsequent clustering to produce the hierarchy of clusters (i.e. second order, third order, etc.). The first-order clusters are themselves clustered into second-order clusters. Again, only clusters that are spatially closer than the specified threshold distance (which is recalculated for each additional level) are included. The second-order clusters, in turn, are clustered into third-order clusters, and this re-clustering process is continued until either all clusters converge into a single cluster or, much more likely, the clustering criteria fails.

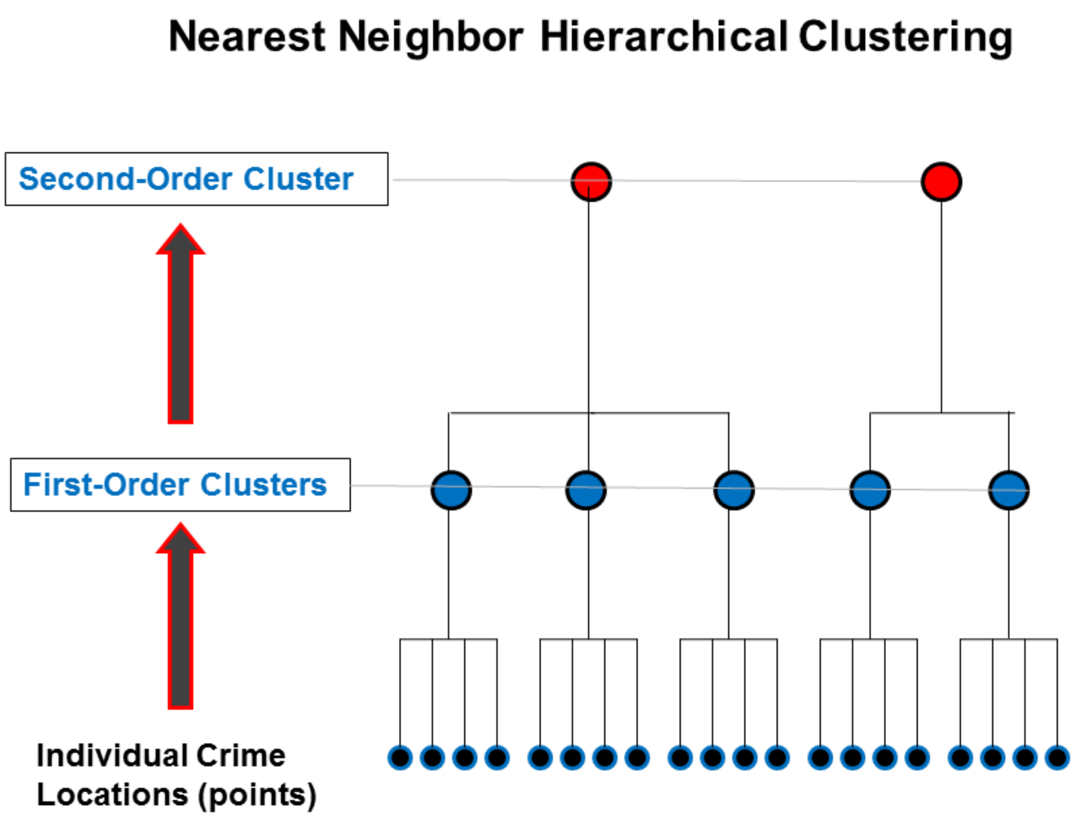


Figure 2.24: Nearest Neighbor Hierarchical Clustering – First and Second Order Clusters

There are several advantages to the Nnh clustering technique. First, it can identify small geographical environments where there are crime concentrations (e.g. ‘hot lots’, hot streets’, parts of street segments). As such, the Nnh routine can be useful for micro-level targeting, either by police deployment or community interventions (Levine et al., 1986; Maltz et al., 1991). There are clearly some individual locations/places that generate crime incidents in this research (e.g. Yankee Stadium). The Nnh technique tends to identify these areal crime concentrations because the lower limit of the mean random distance is used to group first order crime clusters. The CrimeStat Nnh routine can also control the size of the grouping area by ‘loosening or tightening’ the search threshold distance (i.e. quarter-mile radius) or the minimum number of required points required for clustering. As such, the sizes of the crime clusters can be adjusted to fit particular groupings of points or to identify specific areas for crime prevention and/or crime control interventions.

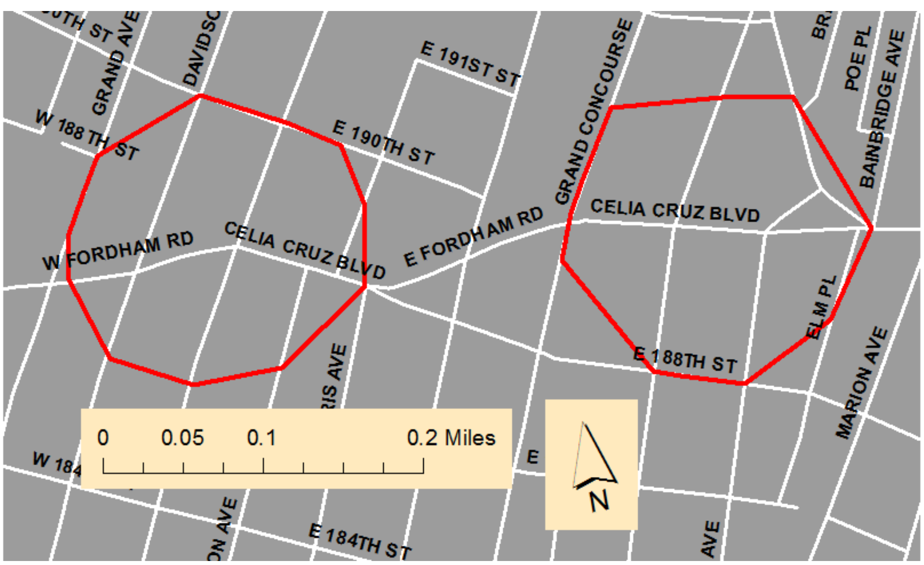


Figure 2.25: Example of two, Tenth-Mile Robbery Nnh Convex Hulls

Second, the Nnh technique can be applied to an entire data set or large-scale region, such as an entire neighborhood or Bronx County. This flexibility increases the ease of use and can also facilitate comparisons between different crime clusters without having to limit the size of the crime (points) dataset or the areal size of the study region (polygon).

Third, the linkages between several small crime clusters can be observed through the second-order crime clusters (or higher-order crime clusters). Frequently, ‘hot spots’ are located near other ‘hot spots’ (see figure 2.26), which in turn, are located near other ‘hot spots’. In other words, there are different scales or spatial resolutions for the clustering of crimes (points) - different geographical levels, per se, and the hierarchical clustering technique can identify many of these levels.

Fourth, each of the geographic levels implies different policing strategies. For the smallest level, ‘beat / foot-patrol officers’ can intervene effectively on small areas, like street segments. Second-order clusters, on the other hand, are more appropriate for ‘sector / patrol car officers’; these areas are larger than first-order clusters, but may include several first-order clusters within them. If third- or higher-order clusters are identified, these are generally areas with very high concentrations of crime incidents over a fairly large section of the Bronx (e.g. police precinct, neighborhood). These third-order areas start to approximate precinct sizes and can be thought of in terms of an integrated management strategy - police deployment, crime prevention, community involvement, and long-term crime strategies (i.e. closed-circuit television camera placement, shotspotter placement). Thus, the hierarchical clustering techniques provide a coherent way of approaching various spatial levels and identifies processes for different crime prevention and crime control strategies to be developed (Eck and Weisburd, 1995).

Fifth, since Nnh ellipses are standardized by (pre) selected units, crime clusters will show increasingly reliable patterns when the analysis is repeated over time. Since spatial patterns are best visualized in small-scale maps, Nnh ellipses or convex hulls also provide an interesting temporal inspection of micro-temporal units (minutes, hours, days of the week) or over larger periods of time (weeks, months, years). Nnh ellipses are traditionally used to determine directionality and movement of the phenomenon being studied. This is the primary reason that Nnh clusters are combined with Kernel Density Estimation (KDE) routines. Since KDE does not show direction, but does a much better job illustrating crime intensities over large areas. Nnh convex hulls create a bounding polygon that contains each crime (point) located inside the crime cluster (polygon) and corresponds directly with the shape of the cluster, and are best visualized using larger area maps.

In this research, Nnh clusters (convex hulls) were constructed for each of the five violent crimes. The parameters selected were *fixed distance* (.1 mile area); minimum number of points (varies by violent crime type), see table 2.15), and 100 Monte Carlo *simulation runs*. The minimum number of points was selected based on an iterative process whereas the top five or six highest clusters were selected for each violent crime per approximated .1 square mile area. The table below shows the type of violent crime, the number of crimes for each of the violent crimes in the violent crime dataset, the minimum number of crimes per cluster selected in CrimeStat, and the resulting number of clusters given the selected parameters.

Crime	Number of Crimes (2006 – 2010)	Minimum Number of Crimes per Cluster	Number of Resulting Clusters
Murder	623	5	6
Rape	1,349	10	5
Robbery	22,674	150	5
Assault	20,729	120	5
Shooting	2,791	23	6

Table 2.15 Number of Violent Crimes, Minimum number of Crimes per Cluster and Number of Resulting Clusters

By incorporating various temporal resolutions to hot spots of violent crime, law enforcement can have a much more robust understanding of street-level crime patterns. These micro-level street patterns can assist police departments in developing improved geospatial models for targeted police patrols and also provide criminologists with a much more comprehensive understanding of the complex relationships between violent crime and micro-level places.

Throughout the study of crime and place, criminologists have examined the various relationships between crime and social forces at various geographic levels. There have been numerous studies of crime at larger ‘macro’ levels; such as countries (Weir & Bang, 2007; Gartner, 1990), states (Rosenfeld et al., 2001; Faggiani et al., 2001), counties (Block and Perry, 1993; Baller et al., 2001), cities (Martin et al., 1998; Cork, 1999), and neighborhoods (Elffers, 2003; Tita & Cohen, 2004). Many of these studies have indicated various relationships between crime and socioeconomic factors (poverty, race, education, etc.).

In the past 30 years, there has been a renewal in interest in crime at a more micro-level. Instead of looking at crime relationships at the county, city, and neighborhood levels – we are starting to recognize the value of studies of crime at the micro-level (Groff et al., 2010; Weisburd et al., 2009; Taylor, 1998). The current trend in crime and place research is micro-level geographies, where the micro-level is defined as street segments, properties, and/or buildings. Most of this renewed interest is a result of micro-level research conducted in Minneapolis (Sherman, 1989), Baltimore (Taylor, 2001), Seattle (Weisburd, 2004), & Jersey City (Weisburd, 1994).

Figure 2.26 illustrates the size and spatial distributions of the 27 violent crime clusters that were created using the Nnh parameters.

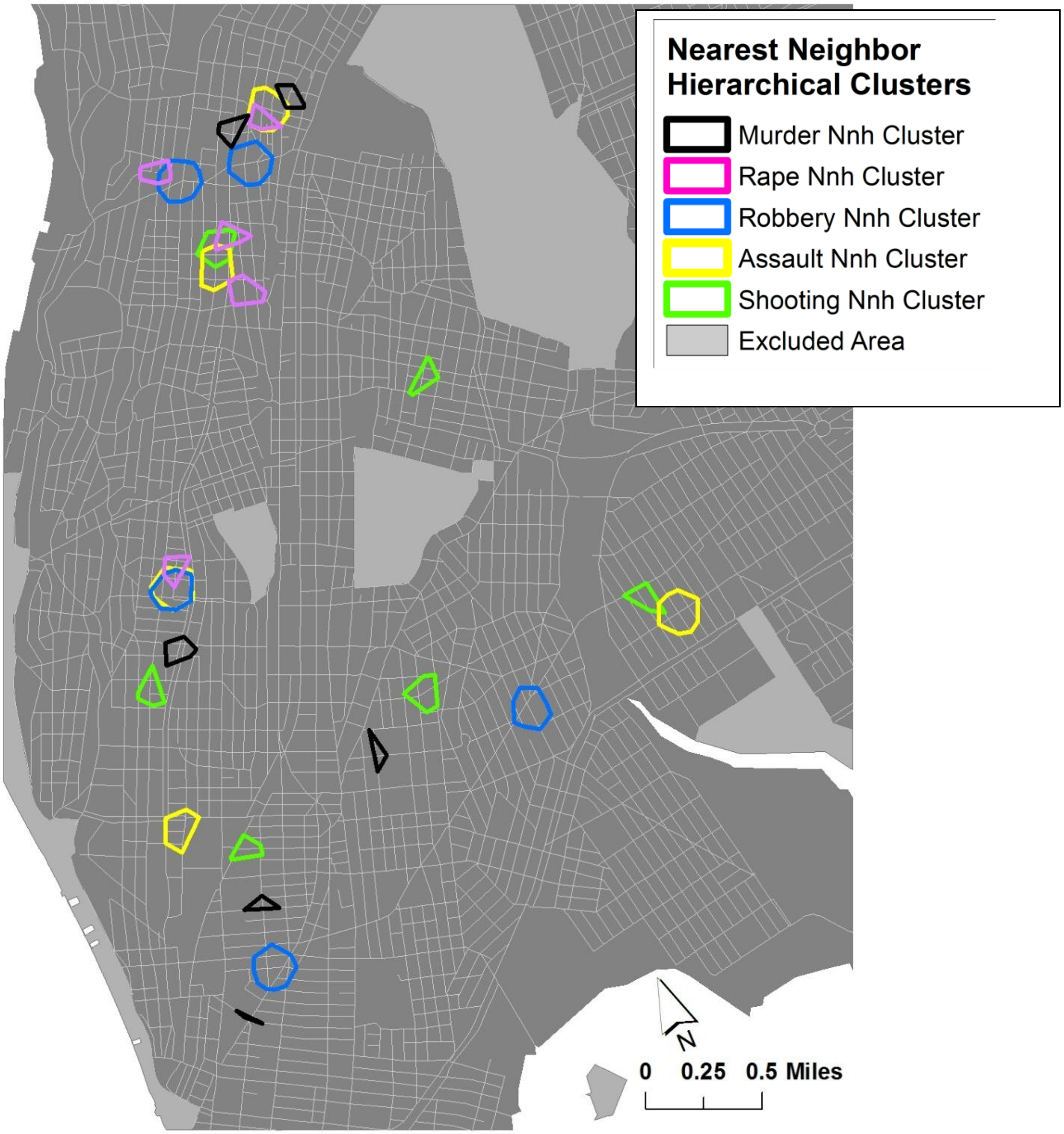


Figure 2.26: Spatial Distribution of Violent Crime Nnh Clusters

Nnh Summary: Nnh clustering continues to be the most efficient tool in identifying the highest number of crimes per user specified. The above map shows the spatial distribution of violent crime clusters. These 1/10 mile area violent crime clusters will be further analyzed for the residential population within them, as well as the percentage of different land-use categories, type and number of business establishments, and premises types for each of the 27 violent crime clusters Unlike the KDE maps in the following section, the Nnh clusters are much easier to 'manage' because of their distinct geographical shape and boundaries.

2.2.2 KERNEL DENSITY ESTIMATION

Kernel Density Estimation (KDE) (sometimes referred to as Kernel Density Interpolation or Kernel Smoothing) is a hot spot method that generalizes or 'smooths' crime incidents over the entire study area. While Nnh clustering provides a spatial distribution (crimes per specified geographical unit) and statistical summary for each respective cluster, KDE interpolates the crime incidents over the entire study area and provides an estimate (z-score) for every part of the study area (i.e. all cells within the region). The resulting density estimate or z-score is best visualized as a surface (i.e. raster) map or a contour map that indicates categories of intensity values over the entire region.

The KDE method, which is typically accomplished using CrimeStat (or ESRI Spatial Analyst), has become the de facto standard for hot spot mapping within the crime analysis community because it provides a comprehensive illustration of crime distribution over a large study area (Chainey and Ratcliffe, 2005). KDE is accomplished by placing a raster surface (i.e.

fishnet) over the entire study area, calculating the distance between the crime point and the reference point based on a mathematical (quartic) function, summing the values for each cell, then calculating all of the surfaces for all of the cells over the entire study area.

According to Bowman and Azalini (1997), the interpolation/smoothing process creates three distinct spatial statistical problems. First, micro-level kernel estimates can be discarded (depending on the size of the selected bandwidth) since each crime is 'smoothed' to the central point in the reference cell. Second, the geospatial categories connect the midpoints for each cell in order to create a continuously smooth surface, when in reality; there may be considerable discontinuity in the topographical surface as a result of edge effects, geographical barriers/gaps (e.g. rivers, bridges), or few/no cases to construct reliable estimates. Third, since the selection of the cell size and bandwidth is principally arbitrary and defined by the user, this can lead to inconsistent results in repeat studies where different cell size/bandwidths are used.

The formula for Kernel Density Estimation (KDE) is below in equation 2.13.

$$\hat{f}(x;h) = \frac{1}{nh}\sum_{i=1}^{n} K\{(x - X_i)/h\}$$

Eq 2.13: where *K* is a function satisfying $\int K(x)\,dx = 1$
The function *K* is referred to as the *kernel*
h is a positive number referred to as the *bandwidth*

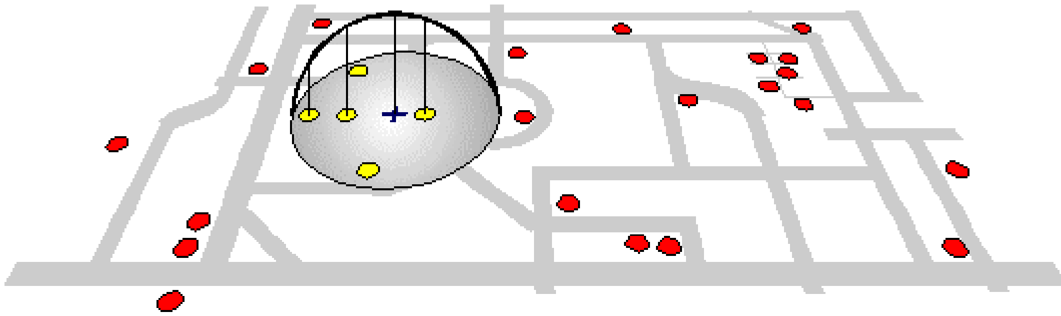


Figure 2.27 Kernel Density Bandwidth
Source: Ratcliffe, 1999

Similar to Nnh, KDE has several user-defined functions that make it flexible and applicable to crime at different geographic levels. By taking the map scale into consideration prior to beginning the KDE analysis, the user can select the appropriate grid cell size and bandwidth that coordinates with the geographic levels of interest. Larger cell sizes and bandwidth run very quickly in CrimeStat and are appropriate for large-scale maps. For micro-level mapping, the user would need to 'tighten up' both the bandwidth and the cell size to correspond to the micro-level of interest (e.g. street segments, property lots, buildings).

The following maps show the crime densities for each of the five violent crimes in this study.

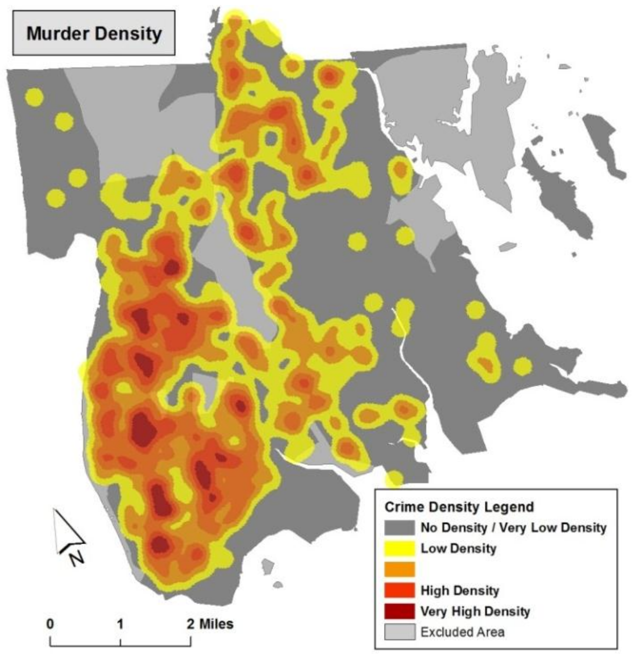


Figure 2.28: Single Kernel Density Estimation for the 623 Bronx Murders

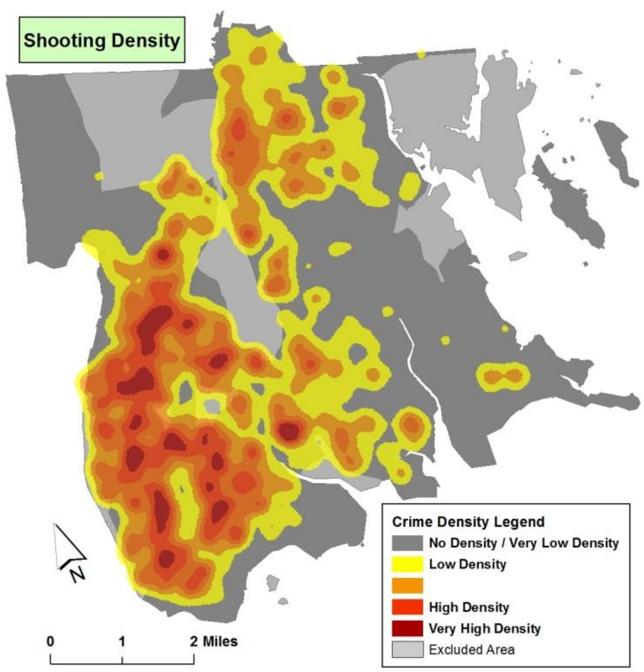


Figure 2.29: Single Kernel Density Estimation for the 2,791 Shootings

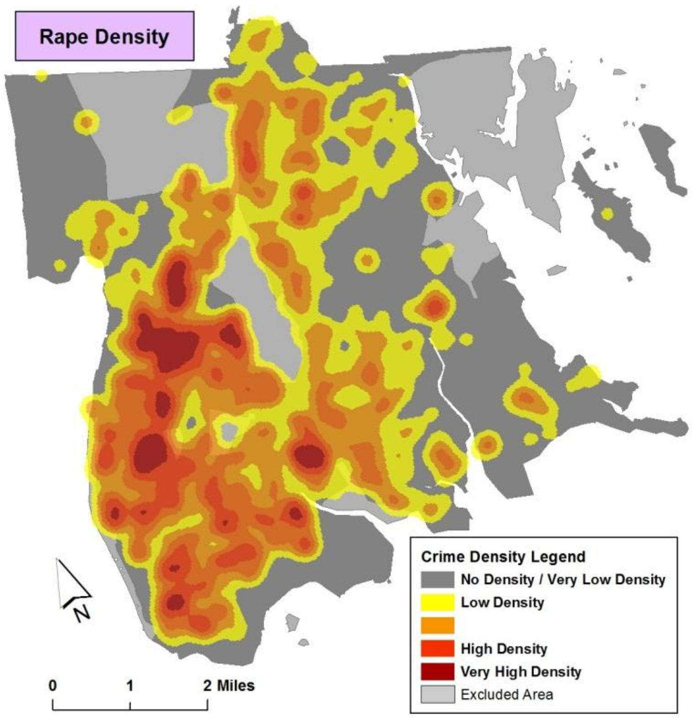


Figure 2.30: Single Kernel Density Estimation for the 1,349 Bronx Rapes

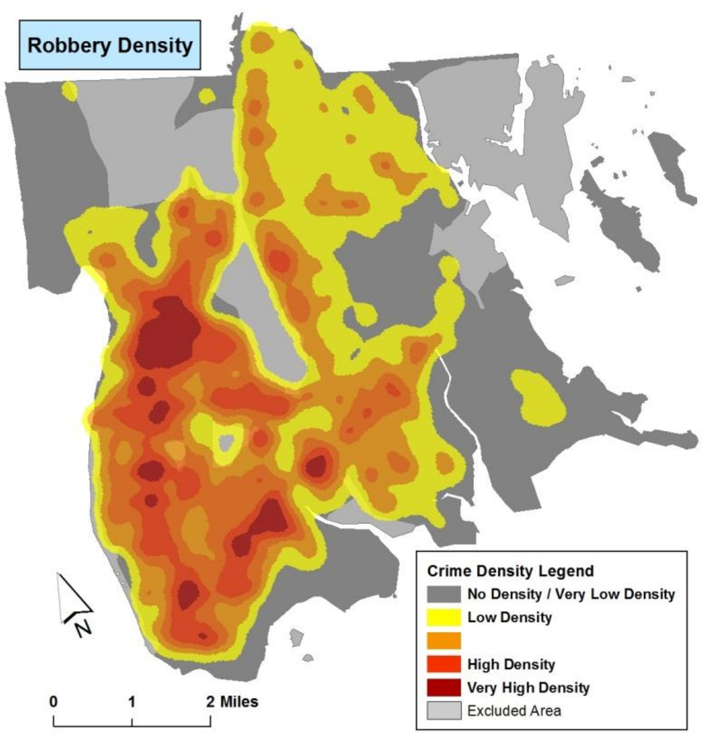


Figure 2.31: Single Kernel Density Estimation for the 22,674 Bronx Robberies

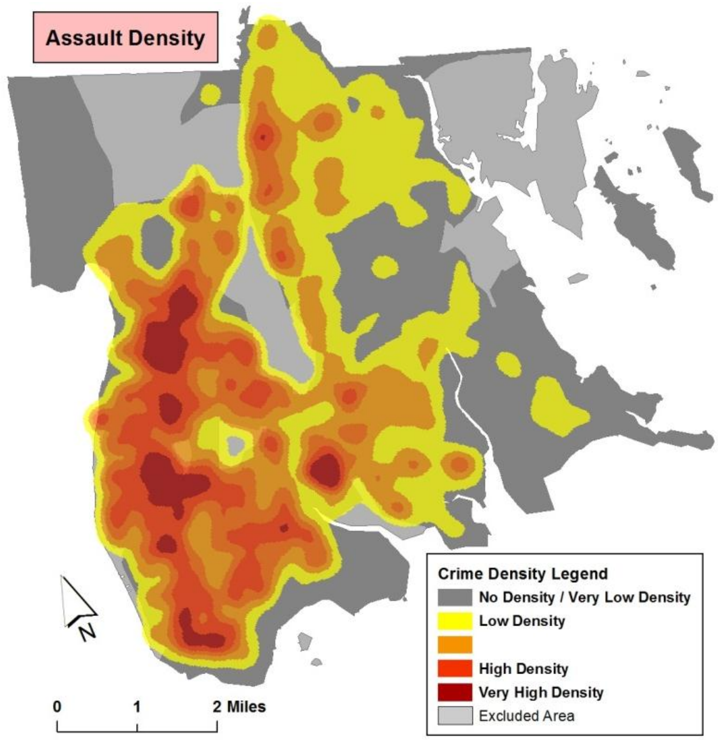


Figure 2.32: Single Kernel Density Estimation for the 20,729 Assaults

When using the quartic KDE method (which is the most popular), the resulting z-score output(s) are easy to interpret since the values are standardized based on the geographical cell size unit (e.g. robberies per square foot, murders per square mile). One of the shortcomings of the KDE method is how to best categorize and visualize the resulting output (e.g. groups of z-scores). Again, since this is another arbitrary process defined by the user, this can often lead to inconsistent results in repeat studies where different cell size/bandwidths and category ranges (and classification methods) are used.

KDE Summary: In this research, two different KDE models were run for each of the violent crimes, based on the 5-year dataset for the Bronx. The objective was to find spatial relationships between the 'high density' (i.e. hot spots) crime zones and the underlying geographical units that comprise the high density (HD) zones. Two models for each of the five violent crimes were run in CrimeStat 3.1. The parameters selected were *quartic* interpolation, *fixed* bandwidths (.2 miles and .1 miles), and *relative densities*. The resulting 10 shapefiles were then *imported* into ArcGIS, *symbolized* using several different categorization methods, *selecting* the highest category z-scores, *dissolving* into the highest density areas for each of the five crimes, and *clipping* the resulting layer into unique high crime density regions (i.e. high crime density polygons). The underlying micro-level crime, population data, land-use, and business establishment/premises type units were then *clipped* and *summed* based on these new high crime density polygons. The end result of this process is s high-density crime zone (HD Zone) for each crime containing crime information (type of crime, day of week, time of day, premises type, etc), population information, land-use, and business establishment. The results for each of the five violent crimes will be explained in the results and discussion section.

2.2.3 GETIS-ORD G_i*

The Getis-Ord Gi* statistic calculates a statistic for each unit of analysis (crime point, street, tract, neighborhood) in the dataset by examining each unit in comparison to its neighboring units. Units with high amounts of crime, do not necessarily create a statistically significant hot spot according to the Gi* statistic. In order for a Gi* hot spot to be significant, the units must contain higher values of crime than normal *and* also be surrounded by similar high count crime units. The local sum of each crime unit and its neighboring crime units is compared (proportionally) to the sum of all the neighboring crime units. When the local sum of crimes is significantly different from the expected local sum of crimes *and* the difference is larger than the result of random chance, a statistically significant z-score is assigned.

The null hypothesis for the Gi* statistic method is complete spatial randomness (CSR). The z-score and p-value results for Gi* indicate when to accept or reject the null hypothesis. When studying several years of violent crime throughout the entire Bronx, it is expected to have numerous statistically significant hot spots. As such, crime points/streets with high z-scores allow us to reject the null hypothesis of CSR because there is definitive spatial clustering.

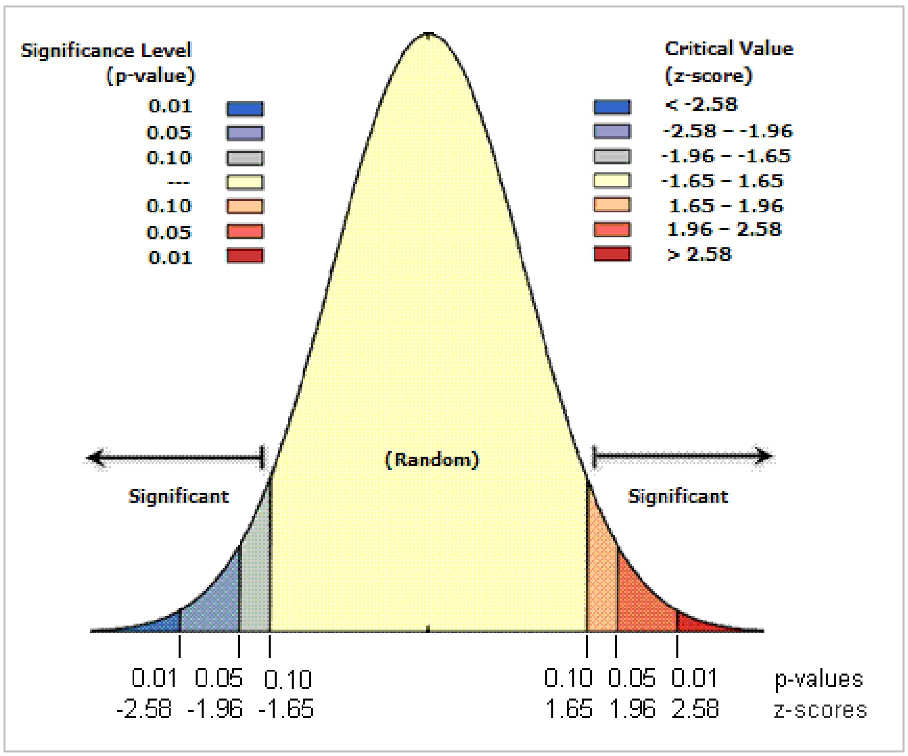


Figure 2.33 Significance Levels (p-values) and Critical Values (z-scores)
Source: ESRI, 2005

The p-value is the probability that the observed spatial pattern of crime points is randomly distributed. When the p-value is very small (-.01 - -.05 and +.05 - +.01), this indicates that there is a small probability (<5% or <1% chance) that the observed spatial crime pattern is randomly distributed (so we would reject the null hypothesis of CSR). The z-score that is returned by the Gi* process are standard deviations from the mean. Similar to the p-value, a very high positive z-score or very low negative z-score indicates that the observed spatial crime pattern is not likely to be a result of a randomly distributed pattern (i.e. CSR) (Mitchell, 2005).

The formula in equation 2.13 explains the Gi* statistic formula in detail.

The Getis-Ord local statistic is given as:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j} \right)^2 \right]}{n-1}}} \quad (1)$$

where x_j is the attribute value for feature j, $w_{i,j}$ is the spatial weight between feature i and j, n is equal to the total number of features and:

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \quad (2)$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left(\bar{X}\right)^2} \quad (3)$$

The G_i^* statistic is a z-score so no further calculations are required.

Eq 2.13: Gi* Statistic Formula
Source: ESRI, 2010

The Gi* function returns a statistic (z-score) for each crime (point) in the geodatabases, this also includes crimes that are aggregated to higher level units of analysis (e.g. streets). When the crime units (points and streets) have high positive z-scores, the crime units indicate more intense clustering (i.e. hotter spots/streets). When the Gi* statistic returns high negative z-scores, this indicates more intense clustering of low values (i.e. cold spots). The Gi* statistic is the best method for examining unusual spatial patterns of crime concentrations, since it compares local averages to global averages *and* identifies those locations where the local averages are significantly different from the global averages (Scott and Rosenshein, 2010).

While Kernel Density Estimation calculates and illustrates crime densities, the Gi* statistic applies significance testing to each of the crime points/crime streets and indicates what is statistically ‘hot’ and what is statistically ‘not’. As such, the legend for the following crime hot spot maps and crime hot street maps is as follows.

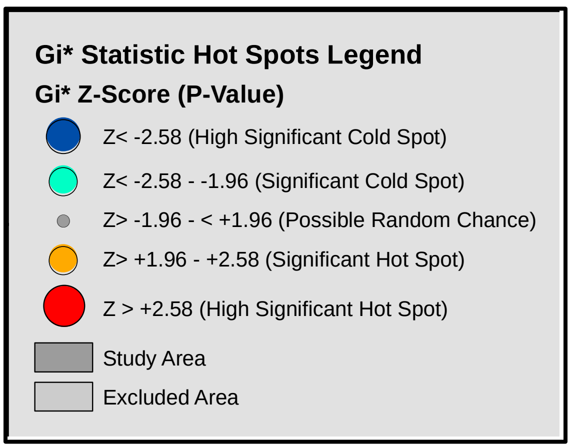


Figure 2.34: Gi* Hot Spot Legend

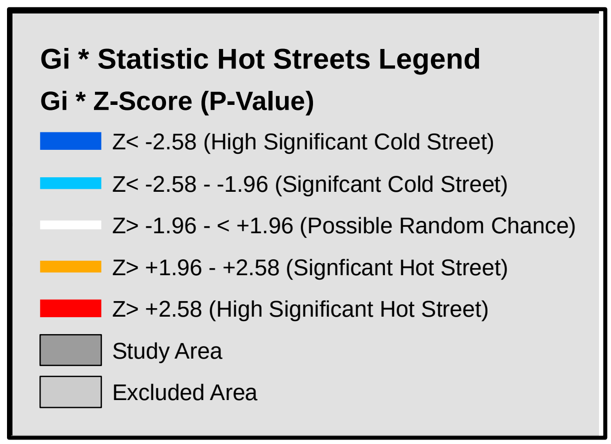


Figure 2.35: Gi* Hot Street Legend

The resulting output of the Gi* function contains a z-score and p-value for each of the crime points and crime streets within the study area. For this research, the Gi* function was run several times on each of the violent crimes (points) and each of the violent crime streets (crime points aggregated to street segments). The resulting maps are on the following pages. You will notice that the Gi* results are much different than both the Nnh and KDE maps.

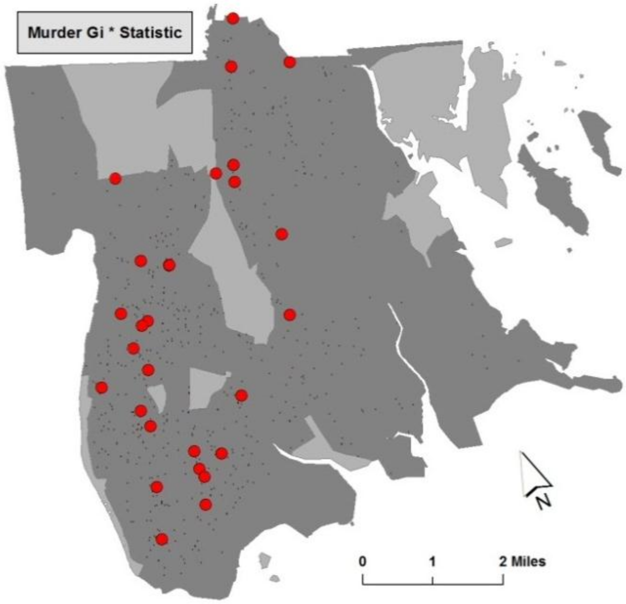


Figure 2.36: Gi* Murder Hot Spots

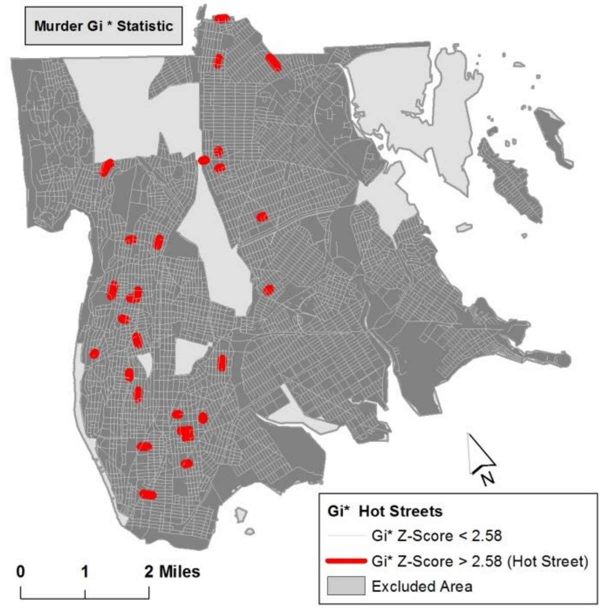


Figure 2.37: Gi* Murder Hot Streets

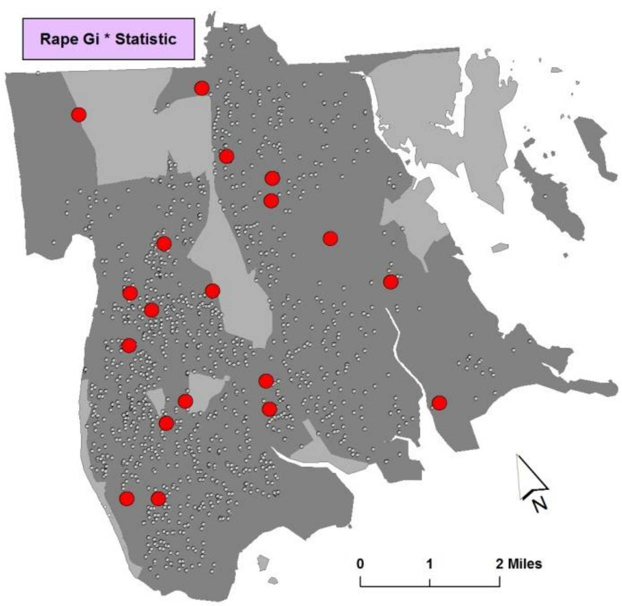


Figure 2.38: Gi* Rape Hot Spots

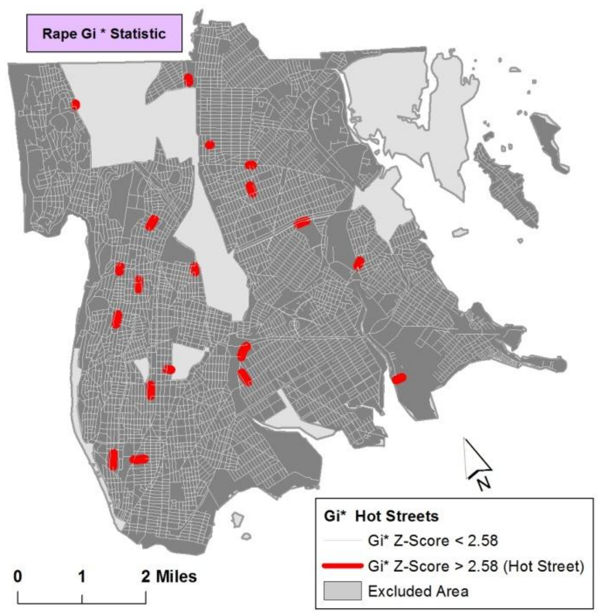


Figure 2.39: Gi* Rape Hot Streets

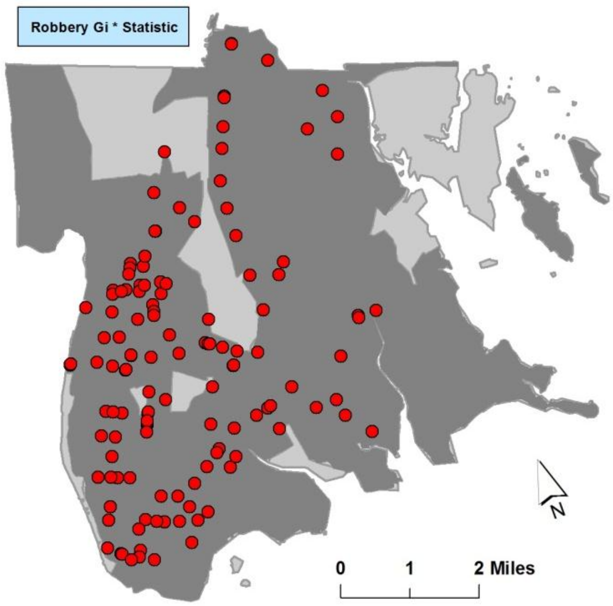


Figure 2.40: Gi* Robbery Hot Spots

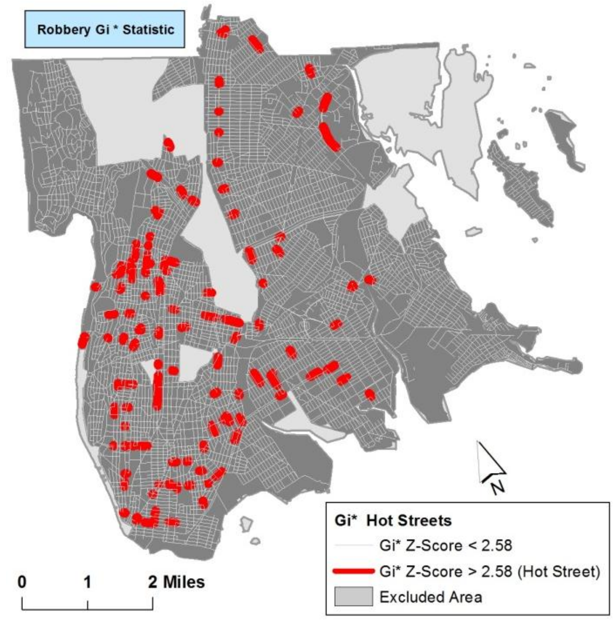


Figure 2.41: Gi* Robbery Hot Streets

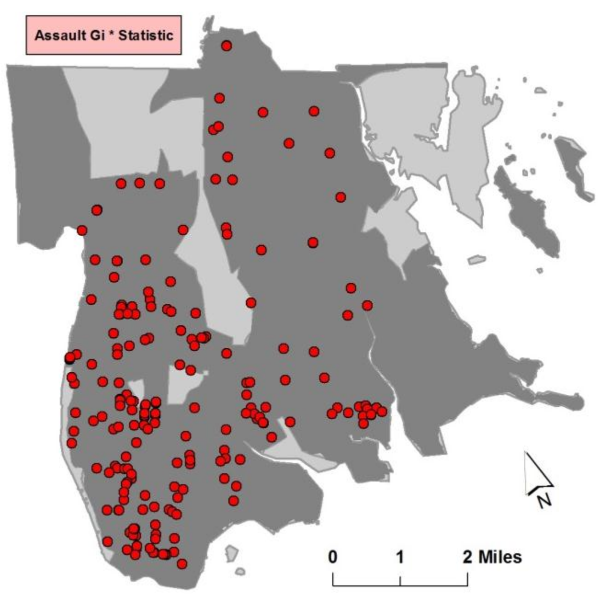


Figure 2.42: Gi* Assault Hot Spots

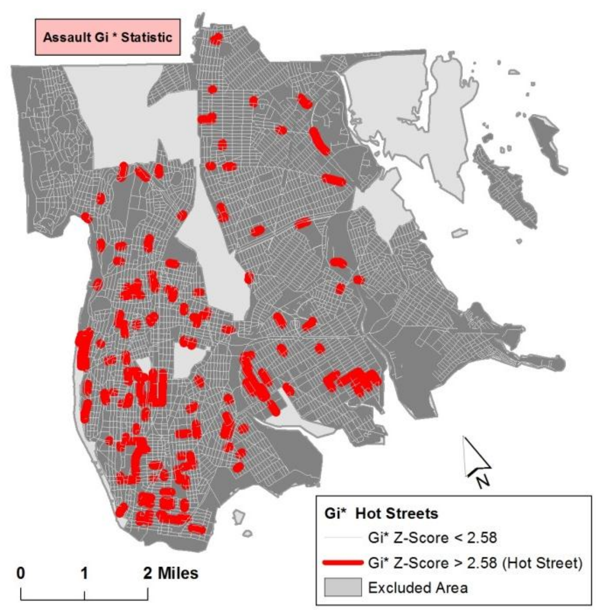


Figure 2.43: Gi* Assault Hot Streets

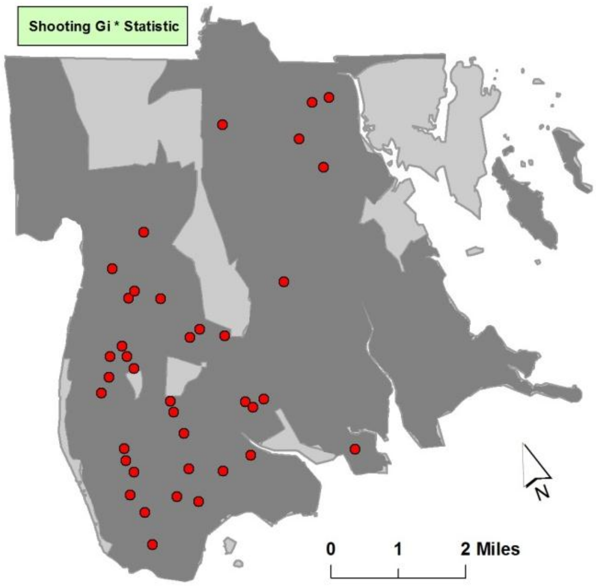


Figure 2.44: Gi* Shooting Hot Spots

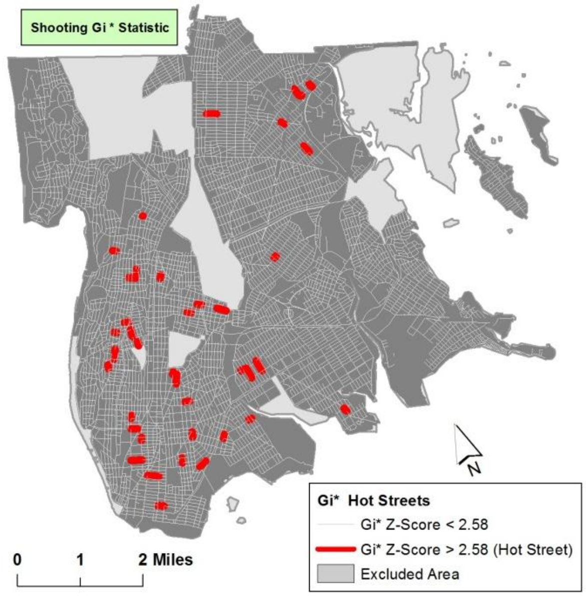


Figure 2.45: Gi* Shooting Hot Streets

The parameters selected for the Gi* Hot Spots function for the crime points included: (1) *inverse distance squared* conceptualization of spatial relationships, whereby crimes that are 'near' have a larger influence on crime locations than features that are further away (i.e. Tobler's First Law); (2) *Euclidean distance*, which measures the straight-line distance between two points (i.e. 'as the crow flies'). The parameters selected for the Gi* Hot Streets function for the crime streets included inverse distance conceptualization of spatial relationships and Manhattan distance, which measures the distance between two points along axes containing 90-degree right angles. The Manhattan distance is calculated by summing the absolute differences between all of the x-coordinates and y-coordinates (both measured in linear feet). Manhattan distance was selected over Euclidean distance for the hot streets because the units of analysis are the street segments, which obviously represent a traditional street network.

The Gi* statistic process resulted in five separate crime point layers (one point layer for each violent crime) containing z-scores and p-values for each crime location. The Gi* function was also run on the street segments units which contain the aggregated sums of crimes for each of the 10,544 street segments. The result of this process was an additional five 'hot street' layers containing z-scores and p-values for each street segment.

One of the significant shortcomings of the Gi* statistic, as with all of the other hot spot methods utilized in this research, is that it does not take temporal patterns into consideration. This makes it difficult to ascertain spatiotemporal crime patterns at any of the geographic levels of analysis. In order to calculate spatiotemporal hot spots using the Gi* statistic, the primary feature dataset would need to be clipped/calculated based upon the temporal unit of interest. If the primary dataset was queried based on temporal units (e.g. day of week, hour of day), you could then run the same analysis on the queried points (e.g. 1am robberies) and calculate a Gi* hot spots map for that time period.

Significance Level (P-Values)	Critical Value (Z-Scores)	Robbery Gi* Z-Scores
.01	< -2.58	0
.05	-2.58 - -1.96	0
.10	-1.96 - -1.65	0
----	-1.65 – 1.65	2705
.10	1.65 – 1.96	66
.05	1.96 – 2.58	350
.01	>2.58	2289

Table 2.16: P-Values, Z-Scores, and Resulting Gi* Z-Scores for the 22,674 Robbery Points

Table 2.16 shows the distribution of z-scores for the 22,674 robbery points. As you can see, there were zero robbery points designated as ‘cold spots’ (clusters of low z-scores), 350 robberies occurring in significant ‘warm spots’, and 2289 robberies occurring in highly significant robbery hot spots.

For this dissertation research, the Gi* hot streets were combined together and analyzed as one unit. A population estimate was calculated for the sum of all hot street segments, as well as the relationship between each violent crime hot street set and land-use. While some of the violent crime hot streets are clustered near one other, the spatial distribution for each of the violent crime hot streets is rather dispersed. As a result of the number and dispersed area of the violent crime hot streets, generalization and assigning resources becomes much more difficult.

2.3 MICRO-LEVEL UNIT AGGREGATION (MLUA)

The micro-level unit aggregation (MLUA) process sums each individual crime location (point) to a higher level geography (i.e. street segments, census tracts, and neighborhoods). For this research, the violent crime points were aggregated to 10,544 street segments (lines), which were then aggregated to the 343 census tracts (polygons), which were then aggregated to the 36 neighborhoods (polygons) in the Bronx. Before I explain the MLUA process and describe the methods and output, I think it is important to look at the need for this type of analysis.

The following maps and tables will identify and illustrate some of the inherent problems in neighborhood level research in the Bronx (and any other densely populated urban area). As you will see, there is such a wide range in crime at the neighborhood level, when compared to the census tract and street segment levels. Note that the range of crimes 'tightens' from neighborhood to street segment levels. The mean average and standard deviation of crime at each level also decreases significantly as we move down the geographic 'cone of resolution', from neighborhoods (green) to census tracts (pink) to street segments (blue).

Neighborhood Level - Crime	N	# of Neighborhoods	Crime Range in neighborhoods	Neighborhood Mean	Std. Dev.
Murder	623	36	1 – 39	17.30	10.40
Rape	1,349	36	4 – 68	37.47	17.12
Robbery	22,674	36	65 – 1,299	629.83	282.78
Assault	20,729	36	50 – 1,323	575.81	298.08
Shootings	2,791	36	3 – 175	77.53	50.97
Total Neighborhoods = 36					

Table 2.17: Descriptive statistics of the 36 Neighborhoods included in the study area. Note the larger range, higher average, and standard deviations when compared to the tract level and street level tables below.

Census Tract Level - Crime	N	# of Tracts with crime	Crime Range in Census Tracts	Tracts Mean	Std. Dev.
Murder	623	226	1 – 12	2.76	1.93
Rape	1,349	284	1 – 17	4.75	3.54
Robbery	22,674	339	1 - 319	66.88	52.01
Assault	20,729	341	1 – 286	60.79	48.29
Shootings	2,791	294	1 – 48	9.49	8.54
Total Tracts = 344					

Table 2.18: Descriptive statistics of census tracts included in study area. Note the lower range, lower mean, and lower standard deviation compared to the neighborhood level (above). Also note the higher range, higher mean, and higher standard deviation when compared to the street level (below).

Street Segment Level - Crime	N	# of Streets with crime	Crime Range in Streets	Streets Mean	Std. Dev.
Murder	623	538	1 - 5	1.15	.438
Rape	1,349	999	1 – 8	1.35	.754
Robbery	22,674	5,343	1 – 61	4.25	5.16
Assault	20,729	4,855	1 – 85	4.27	5.10
Shootings	2,791	1,276	1 – 24	2.19	1.98
Total Streets = 10,544					

Table 2.19: Descriptive Statistics of Street Segments (n=10,544). Note that the street level contains the highest number of crime units, the lowest crime range, the lowest mean average, and the lowest standard deviation for each of the five violent crimes compared to the other two geographical levels.

The end result of the MLUA process are micro-level (i.e. properties and street segments) GIS layers which contain the specific numbers of violent crimes for each of the respective micro-level geographical units for the Bronx. While the goal of the hot spot methodologies is to identify high crime areas, the goal of MLUA process is to explain and illustrate how *all violent crime* is distributed throughout the Bronx *at the micro-level*, examine how these crime distributions *vary between and within each geographical level*, and explore the micro-level *spatiotemporal patterns* for each of the violent crimes. The MLUA process, since it begins at the address level (most GIS datasets are also address-level), allows for the calculation of crime, population, land-use categories, and business types (or any other GIS datasets that have address-level data) from the 'bottom-up'. The bottoms-up approach is much better equipped to deal with common 'aggregation issues', especially 'zonal effects' like the modifiable areal unit problem (Openshaw, 1981), edge effects (Ratcliffe, 2005), and boundary effects (Harries, 1999).

One of the secondary objectives of the MLUA crime analysis process was to design it so it can act as a 'hot spot prevention' tool. The MLUA process accomplishes 'hot spot prevention' by:

1. Identifying micro-level spatiotemporal crime patterns (before they become hot spots)
2. Providing immediate notification to police of properties or streets that are exhibiting higher than normal rates of crime (i.e. syndromic surveillance)
3. Continuously monitoring spatiotemporal patterns in crime, population, land-use, and business types (and any other address level data of interest)
4. Recording and tracking of changes in population, land-use, or business type (and any other address level data of interest)

CompStat was originally designed (at NYPD) as an information-driven management process that provides police managers with timely information to better allocate personnel. The goal of CompStat was two-fold, (1) the reduction of crime and (2) the enhancement to the community's quality of life. CompStat accomplishes these goals by (1) the timely, accurate collection and analysis of crime data, (2) effective crime prevention and control strategies, (3) rapid and effective deployment of personnel, and (4) relentless follow-up and assessment.

The MLUA process preserves the overall spirit of NYPD CompStat, but applies it at a much higher spatial and temporal resolution (e.g. properties and streets, hours and days). While CompStat in the Bronx monitors crime on a weekly basis in the 12 NYPD Precincts, the MLUA process can continuously monitor crime over each of the 89,211 tax lots and 10,544 street segments in the Bronx, 24-hours a day, 7-days a week.

The following tables show each of the top five neighborhoods for each of the five violent crimes in this study and their respective neighborhood population characteristics.

Top Five Murder Neighborhoods (ID#)	# of Murders	# of Tracts	Murder Range within Tracts	Street Range within Tracts	Murder Range within Streets	% of Zero Murder Streets
East Concourse (15) Concourse Village	39	10	0 - 10	14 - 39	0 – 2	88%
Mott Haven (4) Port Morris	38	16	0 - 9	9 - 73	0 - 3	93%
Mount Hope (21)	37	13	0 - 8	13 - 37	0 – 3	90%
Williamsbridge (29) Olinville	34	20	0 – 7	7 - 49	0 – 3	94%
Melrose South (27) Mott Haven North	32	8	1 - 11	22 - 53	0 - 3	91%
Total Neighborhoods = 36 (**29% of murder occurs in the top 5 murder neighborhoods**) Total Tracts = 344 **(91% of streets in the top 5 murder neighborhoods contain zero murders)** Total Streets = 10,544						
Total Murders (2006 – 2010) = 623						

Table 2.20: Top 5 Murder Neighborhoods – population, murders per neighborhood, tracts per neighborhood, murder range in tracts, street range in tracts, and murder range in streets.

Top Five Murder Neighborhoods (ID#)	Total Population	Percent NHWH	Percent NHBL	Percent HISP	Percent POV	Percent NOHS
East Concourse (15) Concourse Village	62,681	2	45	50	40	47
Mott Haven (4) Port Morris	49,311	1	24	73	45	54
Mount Hope (21)	53,357	2	27	66	38	50
Williamsbridge (29) Olinville	52,850	5	71	19	23	33
Melrose South (27) Mott Haven North	28,752	2	23	71	41	57
Total Neighborhood Population = 1,294,855 The Top 5 Murder neighborhoods contain 19% of the total Bronx population						

Table 2.21: Top 5 Murder Neighborhoods – total population, percent non-Hispanic White, percent non-Hispanic Black, percent Hispanic, percent of population in poverty, percent of population > 25 years old without a high-school diploma

Top Five Rape Neighborhoods (ID#)	# of Rapes	# of Tracts	Rape Range in Tracts	Street Range in Tracts	Rape Range in Streets	% of Zero Rape Streets
Mott Haven (4) Port Morris	68	15	0-11	9 - 73	0 – 4	89%
Williamsbridge (29) Olinville	68	20	1 – 9	7 – 49	0 - 3	87%
East Concourse (15) Concourse Village	66	10	0 – 17	14 – 39	0 - 5	83%
Mount Hope (21)	66	13	1 – 9	13 – 37	0 – 3	83%
Melrose South (27) Mott Haven North	59	8	2 - 14	22 - 53	0 - 3	83%
Total Neighborhoods = 36 Total Tracts = 343 Total Streets = 10,544	**(24% of rape occurs in the top 5 rape neighborhoods)** (85% of streets in the top 5 rape neighborhoods contain zero rapes)					
Total Rape (2006 – 2010) = 1,349						

Table 2.22: Top 5 Rape Neighborhoods – population, rapes per neighborhood, tracts per neighborhood, rape range in tracts, street range in tracts, and rape range in streets.

Top Five Rape Neighborhoods	Total Population	Percent NHWH	Percent NHBL	Percent HISP	Percent POV	Percent NOHS
Mott Haven (4) Port Morris	49,311	1	24	73	45	54
Williamsbridge (29) Olinville	52,850	5	71	19	23	33
East Concourse (15) Concourse Village	62,681	2	45	50	40	47
Mount Hope (21)	53,357	2	27	66	38	50
Melrose South (27) Mott Haven North	28,752	2	23	71	41	57
Total Neighborhood Population = 1,294,855 The Top 5 Rape neighborhoods contain 19% of the total Bronx population						

Table 2.23: Top 5 Rape Neighborhoods – total population, percent non-Hispanic White, percent non-Hispanic Black, percent Hispanic, percent of population in poverty, percent of population > 25 years old without a high-school diploma

Top Five Robbery Neighborhoods	Robbery	# of Tracts	Robbery Range in Tracts	Street Range in Tracts	Robbery Range in Streets	% of Streets with Zero Robbery
Mott Haven (4) Port Morris	1,299	15	5 - 223	9 - 73	0 – 46	45%
East Concourse (15) Concourse Village	1,112	10	45 - 266	14 – 39	0 - 52	30%
East Tremont (11)	1,064	13	34 – 141	13 – 53	0 - 54	28%
Bedford Park (19) Fordham North	1,037	10	38 – 184	8 - 35	0 - 40	22%
Melrose South (27) Mott Haven North	1,014	8	85 - 171	22 - 53	0 - 45	28%
Total Neighborhoods = 36 **(24% of robbery occurs in the top 5 robbery neighborhoods)** Total Tracts = 343 **(31% of the streets in the top 5 robbery neighborhoods contain zero robberies)** Total Streets = 10,544						
Total Robbery (2006 – 2010) = 22,674						

Table 2.24: Top 5 Robbery Neighborhoods – population, robberies per neighborhood, tracts per neighborhood, robbery range in tracts, street range in tracts, and robbery range in streets.

Top Five Robbery Neighborhoods	Total Population	Percent NHWH	Percent NHBL	Percent HISP	Percent POV	Percent NOHS
Mott Haven (4) Port Morris	49,311	1	24	73	45	54
East Concourse (15) Concourse Village	62,681	2	45	50	40	47
East Tremont (11)	39,312	2	31	65	46	49
Bedford Park (19) Fordham North	54,360	12	18	59	35	41
Melrose South (27) Mott Haven North	28,752	2	23	71	41	57
Total Neighborhood Population = 1,294,855 The Top 5 Robbery neighborhoods contain 18% of the total Bronx population						

Table 2.25: Top 5 Robbery Neighborhoods – total population, percent non-Hispanic White, percent non-Hispanic Black, percent Hispanic, percent of population in poverty, percent of population > 25 years old without a high-school diploma

Top Five Assault Neighborhoods	Assault	# of Tracts	Assault Range in Tracts	Street Range in Tracts	Assault Range in Streets	% of Zero Assault Streets
Mott Haven (4) Port Morris	1,323	15	4 - 163	9 - 73	0 – 48	47%
East Concourse (15) Concourse Village	1,231	10	28 - 286	14 – 39	0 – 58	35%
Williamsbridge (29) Olinville	1,065	13	13 - 138	13 – 53	0 – 26	33%
Mount Hope (21)	928	10	30 – 111	8 - 35	0 – 21	35%
University Heights (13)	898	8	7 - 145	22 - 53	0 - 85	35%
Total Neighborhoods = 36 Total Tracts = 343 Total Streets = 10,544	**(26% of the assaults occur in the top 5 assault neighborhoods)** **(37% of streets in the top 5 assault neighborhoods contain zero assaults**)					
Total Assault (2006 – 2010) = 20,729						

Table 2.26: Top 5 Assault Neighborhoods – assaults per neighborhood, tracts per neighborhood, assault range in tracts, street range in tracts, and assault range in streets.

Top Five Assault Neighborhoods	Total Population	Percent NHWH	Percent NHBL	Percent HISP	Percent POV	Percent NOHS
Mott Haven (4) Port Morris	49,311	1	24	73	45	54
East Concourse (15) Concourse Village	62,681	2	45	50	40	47
Williamsbridge (29) Olinville	52,850	5	71	19	23	33
Mount Hope (21)	53,357	2	27	66	38	50
University Heights (13)	54,162	1	40	55	40	46
Total Neighborhood Population = 1,294,855 The Top 5 Assault neighborhoods contain 20% of the total Bronx population						

Table 2.27: Top 5 Robbery Neighborhoods – total population, percent non-Hispanic White, percent non-Hispanic Black, percent Hispanic, percent of population in poverty, percent of population > 25 years old without a high-school diploma

Top Five Shooting Neighborhoods	# of Shootings	# of Tracts	Shooting Range Tract Level	Street Range Tract Level	Shooting Range Street Level	% of ZERO Shooting Streets
Mott Haven (4) Port Morris	175	15	0 - 44	9 - 73	0 - 10	83%
Williamsbridge (29) Olinville	175	13	0 - 21	13 - 53	0 - 7	80%
West Concourse (30)	164	8	1 - 32	10 - 65	0 - 11	82%
Mount Hope (21)	158	10	1 - 26	8 – 35	0 - 11	81%
East Concourse (15) Concourse Village	154	10	2 - 42	14 - 39	0 - 14	78%
Total Neighborhoods = 36 **(30% of shootings occur in the top 5 shooting neighborhoods)** Total Tracts = 343 **(81% of streets in the top 5 shooting neighborhoods contain zero shootings)** Total Streets = 10,544						
Total Shootings (2006 – 2010) = 2,791						

Table 2.28: Top 5 Shooting Neighborhoods – population, shootings per neighborhood, tracts per neighborhood, shooting range in tracts, street range in tracts, and shooting range in streets.

Top Five Shooting Neighborhoods	Total Population	Percent NHWH	Percent NHBL	Percent HISP	Percent POV	Percent NOHS
Mott Haven (4) Port Morris	49,311	1	24	73	45	54
Williamsbridge (29) Olinville	52,850	5	71	19	23	33
West Concourse (30)	41,109	2	26	67	40	50
Mount Hope (21)	53,357	2	27	66	38	50
East Concourse (15) Concourse Village	62,681	2	45	50	40	47
Total Neighborhood Population = 1,294,855 The Top 5 Shooting neighborhoods contain 20% of the Bronx total population						

Table 2.29: Top 5 Shooting Neighborhoods – population, shootings per neighborhood, tracts per neighborhood, shooting range in tracts, street range in tracts, and shooting range in streets.

MLUA Summary: the results of the MLUA process are much more comprehensive than the traditional hot spot methodologies, since MLUA analyzes and explains *all violent crimes* *within the study area*, not just the high (and low) crime clusters, crime densities, and Gi* hot spots/hot streets. MLUA does not reduce the data to hot spots, but leaves the micro-level data in a more ‘raw’ format so that otherwise undetectable phenomena can be discovered. For example, MLUA would be able to detect streets with small amounts of crime that would normally fall ‘under the radar’ of traditional hot spot methods. Moreover, the MLUA process can efficiently monitor change of crime rates over time because the micro-level geography (i.e. property, street segment) is not moving or changing over time.

Combining temporal analysis at the street level also provides police with a much better understanding of crime patterns for each street segment. It is this ability to study spatiotemporal violent crime patterns at the street-level that can provide law enforcement, as well as criminologists, with a new understanding of the fluctuating relationships between violent crime, land use, and business establishment types. Again, since the street segments do not move over time, this allows for temporal patterns to be calculated, monitored, and addressed by police when patterns/trends ‘deviate from the norm’.

3. ANALYSIS & RESULTS

Crime	Results Summary
Murder	• 41% of murders occurred on the street • 91% of streets in the top 5 highest murder neighborhoods contained zero murders • Half of the Murder Hot Spots were spatially related to Public Housing • Murder hot spots were all located in residential areas
Rape	• 87% of rapes occurred in residential properties • 85% of streets in the top 5 highest rape neighborhoods contained zero rapes • All of the Rape Nnh clusters indicate smaller 'Apartment' buildings as the primary crime location (not large elevator apartment buildings or public housing) • Rape HD Zones indicate spatial relationships to NYCHA public housing, but only in the South Bronx
Robbery	• 58% of robbery occurred on the street • 31% of streets in the top 5 highest robbery neighborhoods contained zero robberies • Robbery Nnh clusters indicate strong relationships to streets, subway stations, and mixed residential-commercial areas. • Robbery has two distinct spatiotemporal 'peaks', 3pm and 1am, related to public high schools and high population density residential areas
Assault	• 39% of assaults occurred on the street • 37% of streets in the top 5 highest assault neighborhoods contained zero assaults • Assault Nnh clusters indicate streets, apartment houses, and the Bronx Criminal Court are the primary assault locations • Similar to robbery, assault has two spatiotemporal peaks, 3pm and 1am, related to public high schools and alcohol outlets
Shooting	• 40% of shootings occurred on the street (69% of the premises data was missing for shootings) • 81% of streets in the top 5 highest shooting neighborhoods contained zero shootings • Shooting Nnh clusters indicate streets, public housing, and apartment houses are the primary shooting locations • In the highest shooting neighborhood (Mott Haven), 60% of the shootings occur during a two-hour time period

Table 3.1: Analysis & Results Summary

This analysis and results chapter of this dissertation utilizes the output/results from the previous methods section to examine the research objectives and hypotheses stated in Section 1 as well as compare the results from the various hot spot methods (section 2.2).

Hypotheses	Test
H1. Crime at the micro-level is generated by residential populations or attracted by land-use/business types.	**T1.** Identify micro-level crime patterns for each of the five violent crimes, while controlling for micro-level residential population and / or number and type of business establishment types. Determine if violent crime hot spot is land-use, population, or risky business related
H2. Land-Use is related in scope, size, and nature of relationship to violent crime types.	**T2.** Determine how land-use categories are related to each of the five violent crimes using cadastral (tax lot) data
H3. Business Establishment types are related in scope, size, and nature of relationship to violent crime types.	**T3.** Determine how business establishment type and premises type is related to each of the five violent crimes using cadastral (tax lot) data

Table 3.2: Hypotheses and Hypotheses Testing

Few of the previous macro-level studies indicate that there is significant variation beneath the unit of analysis that is central to the research. When studying country level crime rates, we need to recognize that the entire country is not high crime or low crime, there is significant variation in crime at the state level within the country. When studying state-level crime rates, it is important to recognize that the entire state is not high crime or low crime, there is significant variation at the county level within each state. When studying county level crime rates, there is significant variation between cities/towns within each county. Lastly, within the cities and towns, there is significant variation at the neighborhood level. It is also important to note that crime is not the only thing that varies 'beneath' neighborhoods and census tracts. All of the crime, population (including socioeconomic factors), land-use, and business type factors that are of interest to criminologists also vary 'beneath the surface' of neighborhoods and census tracts. Moreover, the unique relationships between crime, land-use, and business establishments also vary beneath the surface.

3.1 HOT SPOT ANALYSIS

There were three different hot spot methods introduced in the Methods section (2.2).

(1) Nearest Neighbor Hierarchical (Nnh) clustering using Crimestat 3.1 (section 2.2.1)

(2) Kernel Density Estimation (KDE) using Crimestat 3.1 (section 2.2.2)

(3) the Gi* Statistical Hot Spot (section 2.2.3) using ArcGIS 10.

Hot Spot Method	Pros	Cons	Illustration
Nearest Neighbor Hierarchical Clustering (Nnh) CrimeStat 3.1	Easy to use, fast, efficient, identifies highest crimes per (user specified) area, definitive boundaries	Only provides clusters of high crime areas, does not provide 'big picture' analysis, user defined inputs are arbitrary	Convex Hulls Ellipses
Kernel Density Estimation (KDE) CrimeStat 3.1 ESRI Spatial Analyst	Provides a crime density estimate for the entire study area. Excellent for 'big picture' analysis	Slow, output can be large, takes time to illustrate, user defined inputs make it difficult to replicate maps over time, repeat analysis	Raster, 'fishnet'
Gi* Hot Spot Statistic ESRI Spatial Statistics toolbox	Provides a statistically significant way to identify hot spots (and cold spots)	Does not necessarily find the hottest spots, output can be confusing to explain	Points

Table 3.3: Hot Spot Method Comparison

In the case of Nnh clustering, crime points/locations were grouped into clusters based on micro-proximity (.1 square mile clusters) and a minimum number of points. KDE provides a z-score for each cell within the study region which quantifies the amount of crime risk over a region or study area. The Gi* hot spot method identifies those high crime area points that fall 'near' other high crime area points and thus becomes statistically significant 'Gi* hot spots'.

Hot spots were constructed for each violent crime and the underlying population, land-use, and business establishment data were then *clipped* to the respective hot spot geography. The analysis section illustrates how the hot spot construction and clip processes were completed and the resulting findings.

Nearest Neighbor Hierarchical Cluster Analysis

The Nnh data was prepared by constructing the clusters based upon an iterative data reduction technique, where numerous cluster processes were run until the top 4 – 6 hot spots (per tenth-mile area) were defined for each of the five violent crime categories. After each respective group of violent crime clusters was constructed, the underlying data (crime, population, land-use, business establishment) was clipped and analyzed. One of the benefits of Nnh clustering in this research is that it provides definitive boundaries, unlike KDE which provides a raster output and Gi* which provides points. With definitive polygon boundaries, you can definitively ascertain whether secondary datasets (population, land-use, businesses, etc.) fall inside or outside the crime hot spot.

Crime	Number of Crimes (2006 – 2010)	Minimum Number of Crimes per Cluster	Number of Resulting Clusters
Murder	623	5	6
Rape	1,349	10	5
Robbery	22,674	150	5
Assault	20,729	120	5
Shooting	2,791	23	6
Total	**48,166**		**27**

Table 3.4: Number of Violent Crimes, Minimum number of Crimes per Cluster and Number of Resulting Clusters

Table 3.4 shows the number of crimes, minimum number of crimes per cluster, and number of resulting clusters created using the Nnh clustering method. Figure 3.1 shows the spatial distribution of the violent crime clusters.

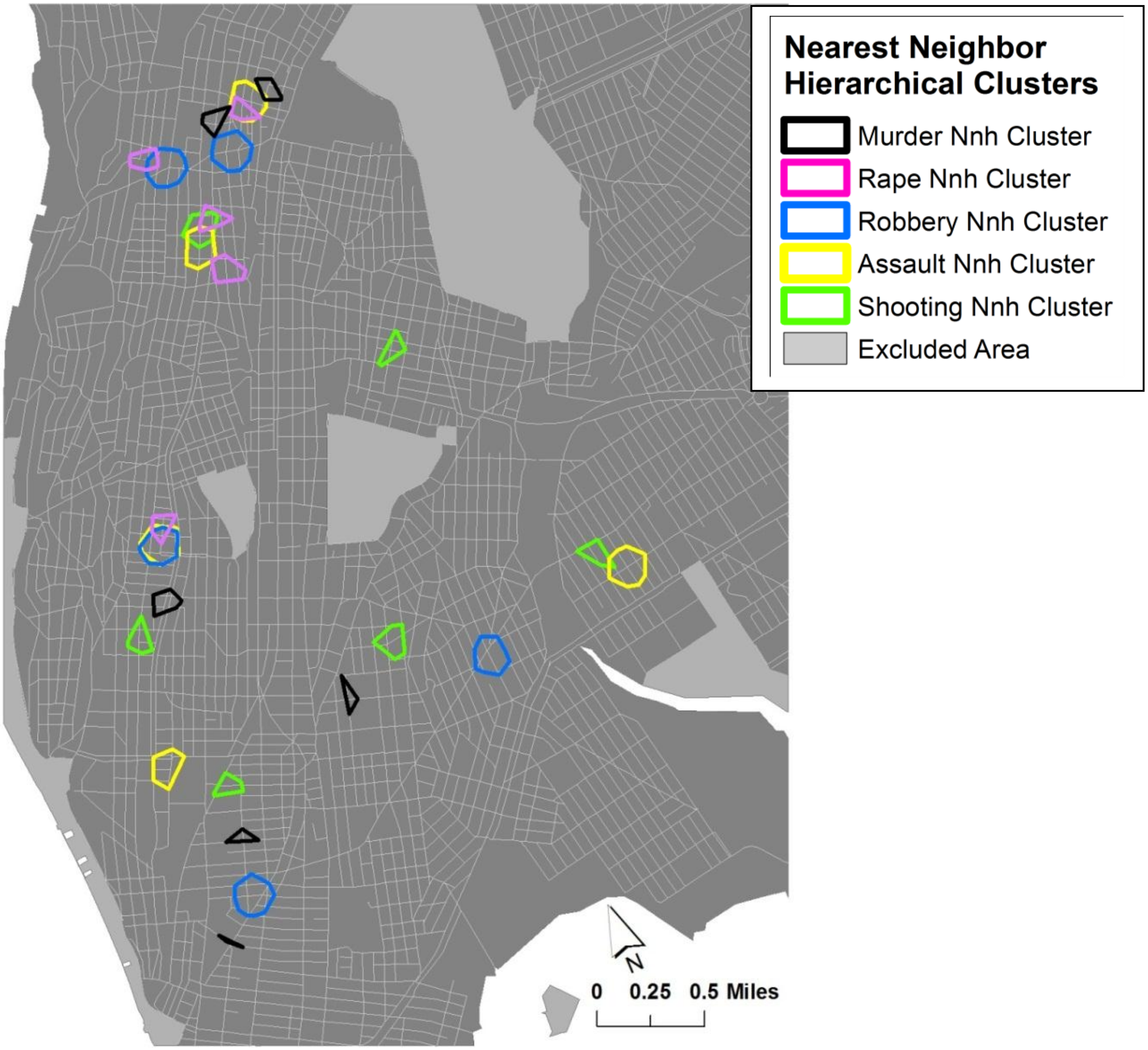


Figure 3.1: Tenth-Mile Area Nearest Neighbor Hierarchical Clusters for all 5 Violent Crimes

As suggested in section 3.1, violent crime tends to attract other violent crime. Of the 27 violent crime clusters identified using the iterative Nnh process, 41% (11 clusters) fall within a half-mile area convex hull (see figure 3.2).

The tendency when this phenomenon occurs is to consider the half-mile area (outlined by a red polygon in figure 3.2) as a second-order crime cluster that contains analogous first-order clusters, however, this half-mile area contains 2 murder clusters, 4 rape clusters, 2 robbery clusters, 2 assault clusters, and 1 shooting clusters. Not only are the enclosed clusters not all within the same crime category, but there is also notable temporal variance between the crime clusters within the same category (see appendix). The 27 violent crime clusters are described further in the following sections.

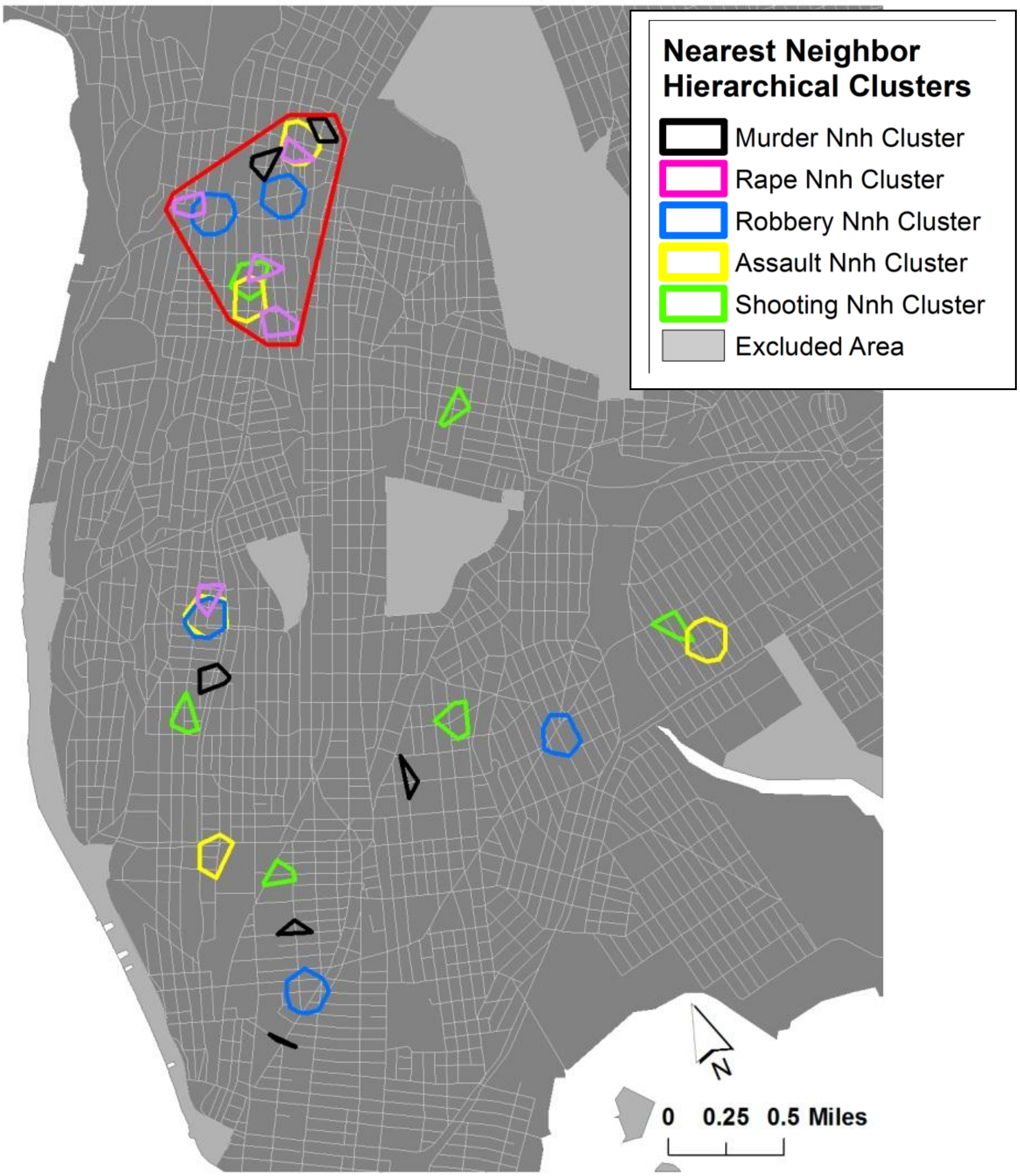


Figure 3.2: Tenth-Mile Area Nearest Neighbor Hierarchical Clusters for all 5 Violent Crimes with Second-Order Nnh Cluster noted (red outline)

3.2 LAND-USE ANALYSIS

This land-use crime analysis section examines the relationships between the five different violent crime types and the eleven different land-use categories. The tax lot level land-use data was clipped by the hot spot boundaries (for Nnh and KDE) or identified using spatial and/or tabular joins with regards to the Gi* Hot Spot points / Hot Streets.

Murder Hot Spots

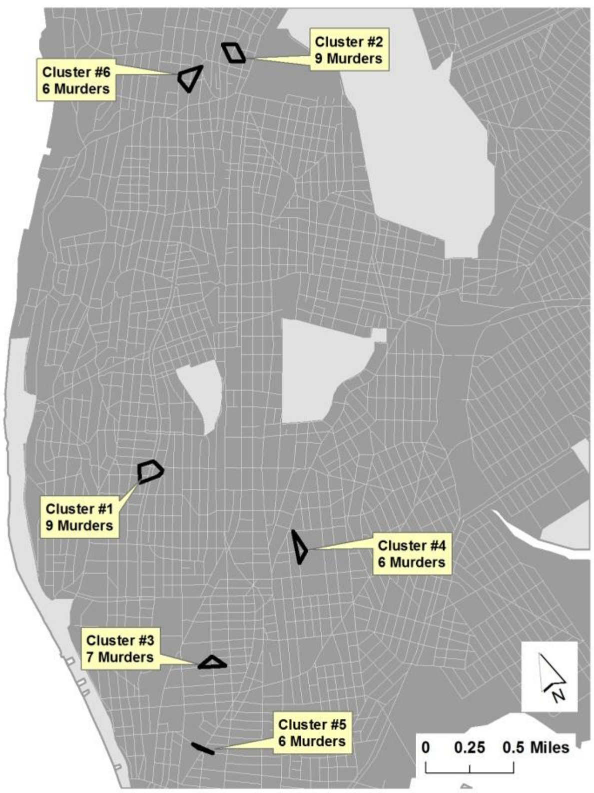


Figure 3.3: Nnh Murder Clusters

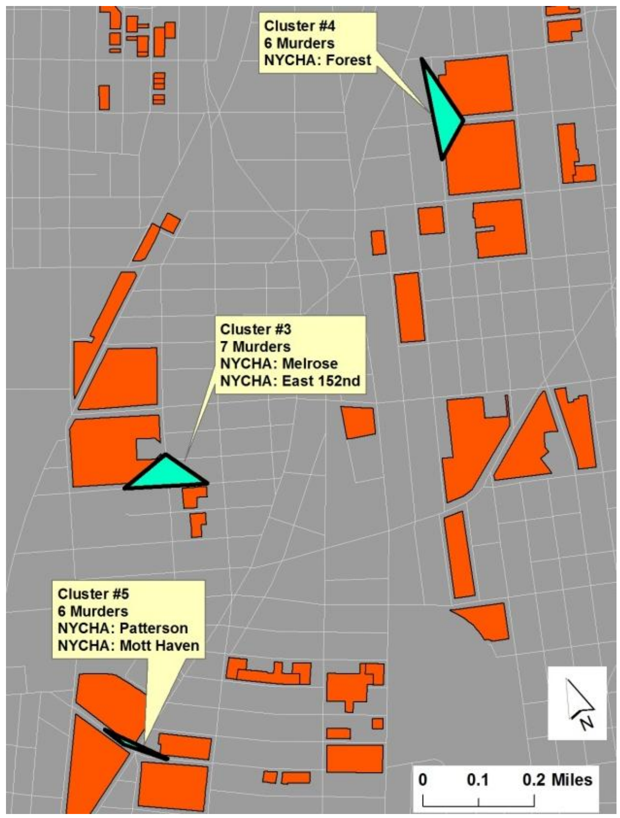


Figure 3.4: Nnh Murder Clusters (Black/Blue polygons) and NYCHA Housing building outlines (orange polygons)

There are two murder clusters (cluster #2 and #6) located in the central part of the Bronx, near the eastern border of Van Cortlandt Park. Table 3.5 indicates that there is a strong relationship between murder and residential land-use, primarily with multi-family elevator buildings. Further analysis (figure 3.4) of the multi-family elevator buildings indicates that these are (mostly) NYCHA public housing developments in the South Bronx. However, it is not all 90 NYCHA developments in the Bronx that are associated with murder clusters, it only 5 specific NYCHA developments (Forest, Melrose, East 152nd, Patterson, & Mott Haven) that are related to half of the Nnh murder clusters.

Murder Cluster ID	Cluster Area (Sq. Miles)	Percent Land-Use Area Inside Murder Clusters	Primary Land Use in Murder Cluster
1	.01 Square Miles	LU2 Multi-Family Walk-up Buildings: 37% LU3 Multi-Family Elevator Buildings: 30% LU4 Mixed Residential and Commercial Buildings: 15% LU8 Public Facilities and Institutions: 15% LU1 One and Two Family Buildings: 3%	Multi-Family Walk-up
2	.007 Square Miles	LU3 Multi-Family Elevator Buildings: 36% LU2 Multi-Family Walk-up Buildings: 31% LU1 One and Two Family Buildings: 16% LU4 Mixed Residential and Commercial Buildings: 11% LU7 Transportation and Utility: 4% LU9 Open Space and Outdoor Recreation: 1% LU10 Parking Facilities: 1%	Multi-Family Elevator
3	.004 Square Miles	LU3 Multi-Family Elevator Buildings: 66% LU9 Open Space and Outdoor Recreation: 13% LU2 Multi-Family Walk-up Buildings: 7% LU4 Mixed Residential and Commercial Buildings: 6% LU1 One and Two Family Buildings: 4% LU5 Commercial and Office Buildings: 3% LU10 Parking Facilities: 1% LU11 Vacant Land: 1%	Multi-Family Elevator
4	.004 Sq. Miles	LU2 Multi-Family Walk-up Buildings: 57% LU1 One and Two Family Buildings: 43%	Multi-Family Walk-up
5	.001 Square Miles	LU3 Multi-Family Elevator Buildings: 42% LU4 Mixed Residential and Commercial Buildings: 42% LU5 Commercial and Office Buildings: 8% LU8 Public Facilities and Institutions: 8%	Multi-Family Elevator
6	.008 Square Miles	LU9 Open Space and Outdoor Recreation: 38% LU4 Mixed Residential and Commercial Buildings: 23% LU5 Commercial and Office Buildings: 15% LU3 Multi-Family Elevator Buildings: 10% LU2 Multi-Family Walk-up Buildings: 8% LU11 Vacant Land: 3% LU8 Public Facilities and Institutions: 2%	Open Space & Recreation

Table 3.5: Nnh Murder Cluster ID #, Cluster Area in Square Miles, and Percent Land-Use Categories

Crimestat identified 6 Nnh clusters for the murder dataset, it also calculated 11 different high density (HD) murder zones using KDE. These murder HD zones are illustrated overlapping all of the 6 Nnh murder clusters in figure 3.5. This illustration shows one of the significant differences between Nnh clustering and KDE, which is that KDE is more inclusive, since it smooths all of the murder points in relation to the entire study area. However, since the HD zones are not of equal size or shape, it is not possible to compare them to one another, as is possible with Nnh clustering.

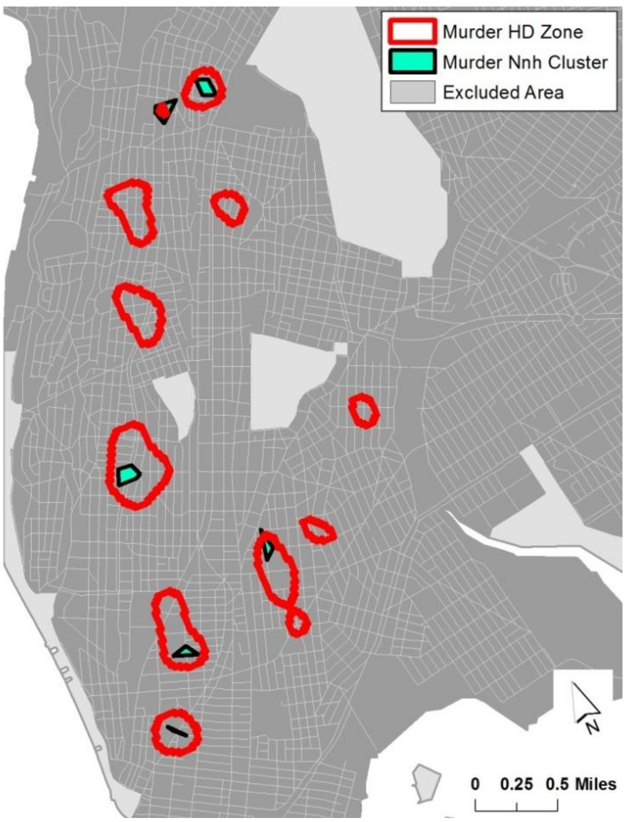


Figure 3.5: Murder HD Zones (KDE)

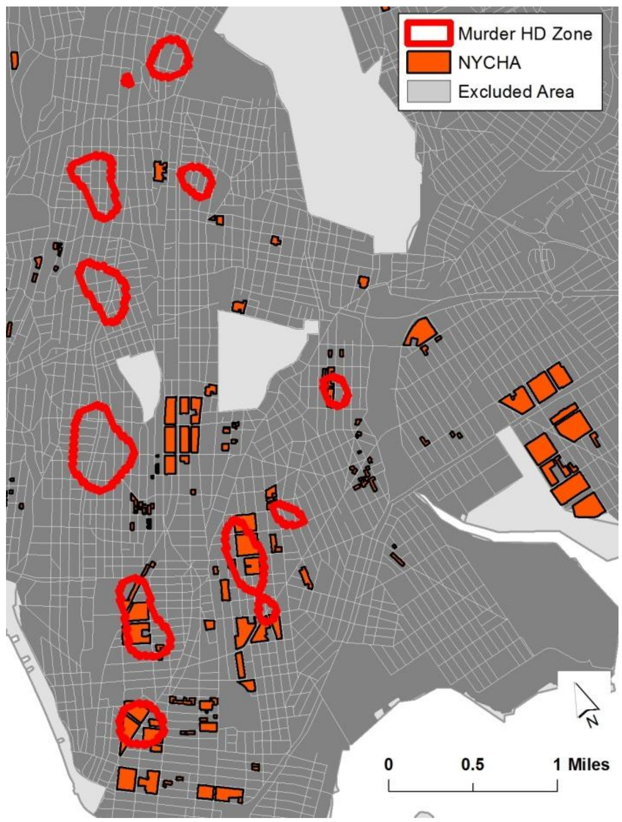


Figure 3.6: Murder HD Zones and NYCHA Building Outlines (Orange)

Murder HD Zones	Murder HD Zones (Sq. Miles)	Percent Land-Use Area Inside Murder Clusters	Primary Land Use in Murder HD Zones	Population Estimate in HD Zone
10	.56 Square Miles	LU2 Multi-Family Walk-up Buildings: 31% LU1 One and Two Family Buildings: 23% LU4 Mixed Residential and Commercial Buildings: 11% LU3 Multi-Family Elevator Buildings: 9% LU10 Parking Facilities 6% LU11 Vacant Land: 6% LU5 Commercial and Office Buildings: 4% LU6 Industrial and Manufacturing 1% LU7 Transportation and Utility 1% LU8 Public Facilities and Institutions: 5% LU9 Open Space and Outdoor Recreation: 1%	Multi-Family Walk-up Buildings	92,559

Table 3.6: Murder HD Zones, HD Zone Area, Percent Land-Use inside HD Zone and Population

Table 3.6 indicates the relationship between the murder HD zones and land-use. Similar to the clustering routine, the KDE table (3.6) indicates that the highest percent of land-use categories for the murder HD zones is Multi-Family Walk-up Buildings (LU2). Figures 3.5 (KDE/Cluster) and 3.6 (KDE/NYCHA) indicate that the KDE method overlaps the Nnh clusters completely, however, the KDE method overlaps 6 different NYCHA developments (KDE added the NYCHA Adams Houses, which are located .2 miles south of Nnh Cluster #4, see figure 3.4).

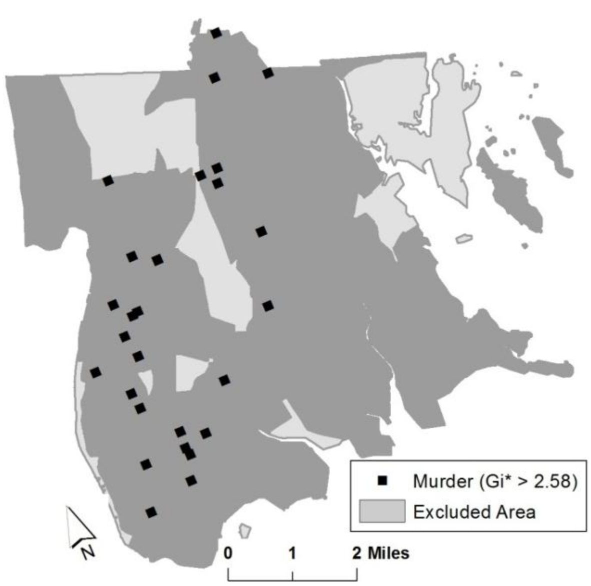


Figure 3.7: Gi* Murder Hot Spots

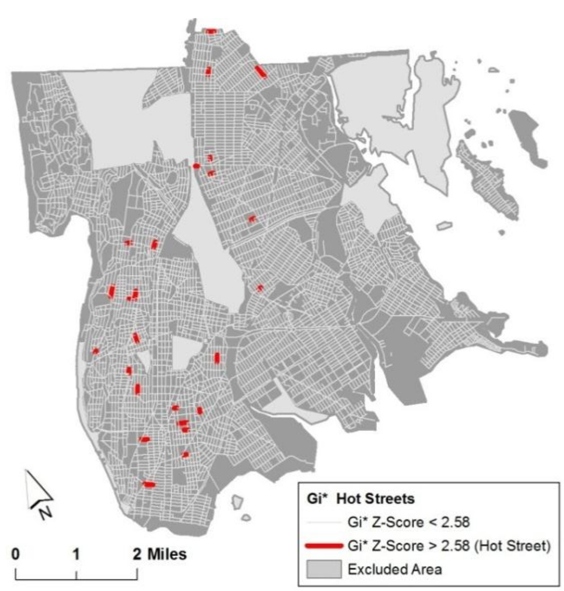


Figure 3.8: Gi* Murder Hot Streets

Figures 3.7 and 3.8 illustrate the statistically significant Gi* statistic hot spots (n=55) and hot streets (n=27). Hot streets were created by spatially joining the hot spots to the street segments. Several hot spots were located at the same location or were on the same street segment which resulted in 27 total murder hot streets. The murder hot streets were then aggregated and their land use was analyzed, the results are in table 3.7. Temporal analysis of Gi* Hot Spots and Gi* Hot Streets was not possible because of the separate GIS layer files that were created from the Gi* methods.

Murder Hot Streets	Murder Hot Streets (Linear Miles)	Percent Land-Use Area on Murder Hot Streets		Primary Land Use on Murder Hot Streets	Population Estimate on Hot Streets
31	2.95 Linear Miles	LU1 One and Two Family Buildings:	24%	Multi-Family Walk-up Buildings	9481
		LU2 Multi-Family Walk-up Buildings:	27%		
		LU3 Multi-Family Elevator Buildings:	15%		
		LU4 Mixed Residential and Commercial Buildings:	12%		
		LU5 Commercial and Office Buildings:	2%		
		LU8 Public Facilities and Institutions:	9%		
		LU9 Open Space and Outdoor Recreation:	9%		
		LU10 Parking Facilities	2%		

Table 3.7: Gi* Murder Hot Streets and Land-Use – number of hot streets, total length of hot streets, percent of land-use categories, primary land-use, and population estimates on Gi* murder hot streets.

Similar to Nnh and KDE, the Gi* Hot Streets indicate that significant murder hot spots occur on street segments with a high percentage of multi-family walk-up buildings.

Rape Hot Spots

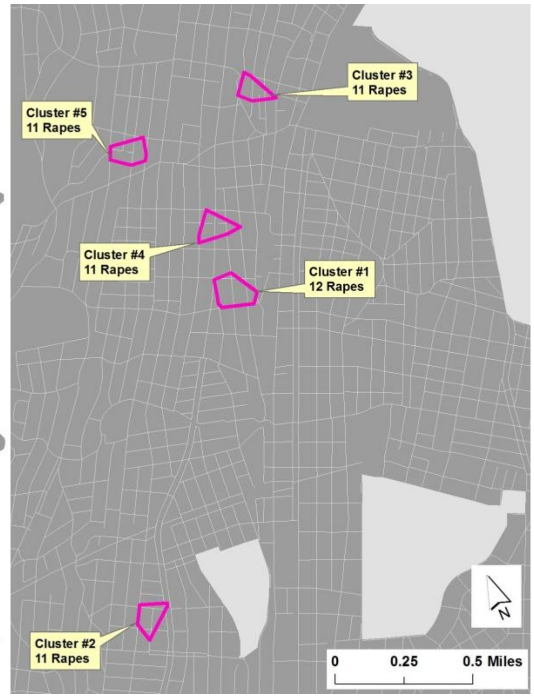


Figure 3.9: Nearest Neighbor Hierarchical Clustering Clustering Rape Hot Spots

Figure 3.10: Nearest Neighbor Hierarchical Rape Hot Spots (zoomed)

Figure 3.9 (above) indicates that most of the rape clusters occur in the central part Bronx. The Nnh rape clusters are not associated with NYCHA public housing, like the murder clusters are. Table 3.8 indicates that there is a very strong relationship between rape and residential land-use, primarily with multi-family walk-up buildings. Crimestat identified 5 Nnh clusters for the rape dataset, it also calculated 20+ different high density (HD) rape zones. These rape HD zones are illustrated overlapping the 5 Nnh rape clusters in figure 3.18. Rape appears to be much more spatially related to population density and multi-family walk-up land-use than murder.

Rape Cluster ID	Land-Use Categories inside Rape Clusters		Primary Land Use in Cluster
1	LU2 Multi-Family Walk-up Buildings: LU8 Public Facilities and Institutions: LU1 One and Two Family Buildings: LU4 Mixed Residential and Commercial Buildings: LU3 Multi-Family Elevator Buildings: LU5 Commercial and Office Buildings: LU9 Open Space and Outdoor Recreation: LU10: Parking Facilities	29% 22% 13% 13% 12% 5% 2% 2%	Multi-Family Walk-up
2	LU3 Multi-Family Elevator Buildings: LU4 Mixed Residential and Commercial Buildings: LU2 Multi-Family Walk-up Buildings: LU5 Commercial and Office Buildings: LU11 Vacant Land:	66% 17% 12% 3% 2%	Multi-Family Elevator
3	LU2 Multi-Family Walk-up Buildings: LU3 Multi-Family Elevator Buildings: LU4 Mixed Residential and Commercial Buildings: LU1 One and Two Family Buildings: LU8 Public Facilities and Institutions: LU11 Vacant Land: LU5 Commercial and Office Buildings: LU10 Parking Facilities:	38% 24% 16% 7% 7% 3% 2% 1%	Multi-Family Walk-up
4	LU2 Multi-Family Walk-up Buildings: LU1 One and Two Family Buildings:	57% 43%	Multi-Family Walk-up
5	LU2 Multi-Family Walk-up Buildings: LU3 Multi-Family Elevator Buildings: LU5 Commercial and Office Buildings: LU9 Open Space and Outdoor Recreation: LU4 Public Facilities and Institutions: LU1 One and Two Family Buildings:	48% 17% 12% 9% 8% 6%	Multi-Family Walk-up

Table 3.8: Nnh Rape Clusters, Area in Square Miles, and Percent Land-Use Categories

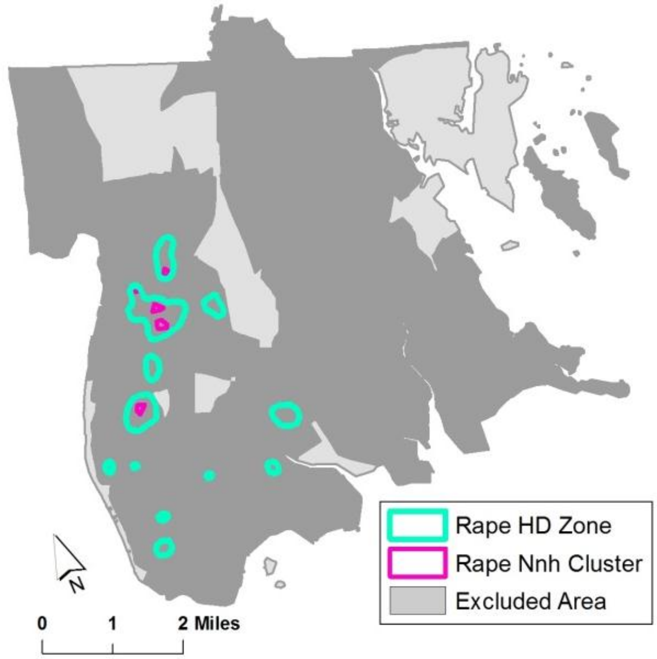


Figure 3.11: Rape HD Zones (blue) over Rape Nnh Clusters (pink)

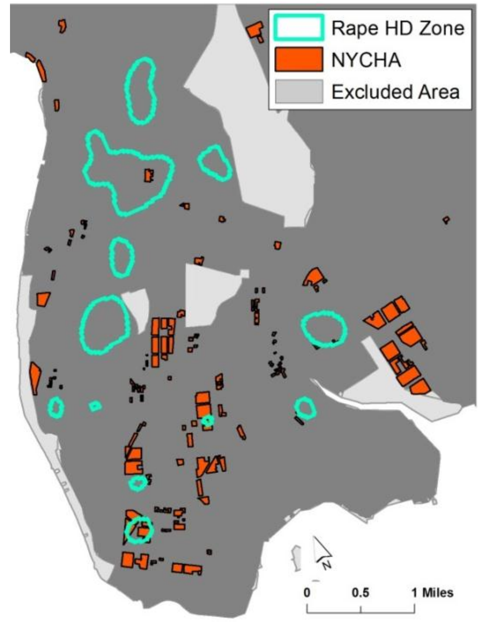


Figure 3.12: Rape HD Zones (blue) over NYCHA building outlines (orange)

According to figures 3.11 and 3.12, there is a definitive spatial relationship between the rape HD Zones and NYCHA public housing projects in the south parts of the Bronx. This also coincides with the Nnh cluster finding that rape was more likely to occur in higher population density areas, such as NYCHA housing projects.

Rape HD Zones	Rape HD Zones (Sq. Miles)	Percent Land-Use Area Inside Rape Clusters		Primary Land Use in Rape HD Zones	Population Estimate in HD Zone
12	.92 Square Miles	LU2 Multi-Family Walk-up Buildings:	35%	Multi-Family Walk-up Buildings	149,117
		LU1 One and Two Family Buildings:	28%		
		LU4 Mixed Residential and Commercial Buildings:	10%		
		LU3 Multi-Family Elevator Buildings:	7%		
		LU5 Commercial and Office Buildings:	6%		
		LU10 Parking Facilities	4%		
		LU11 Vacant Land:	4%		
		LU8 Public Facilities and Institutions:	3%		
		LU6 Industrial and Manufacturing	1%		
		LU7 Transportation and Utility	1%		
		LU9 Open Space and Outdoor Recreation:	1%		

Table 3.9. Rape HD Zones. Number of Rape HD zones, square miles of HD zones, percent land-use categories inside rape HD zones, primary land-use category, and population estimate inside rape HD zones.

Table 3.9 indicates the relationship between the rape HD zones and land-use categories. Similar to the Nnh clustering routine, the KDE table indicates that the highest percent of land-use for the rape HD zones is Multi-Family Walk-up Buildings (LU2, 35%), followed by one and two family buildings (LU1, 28%). Figure 3.11 (KDE/Cluster) indicate that the KDE method overlaps the Nnh clusters completely.

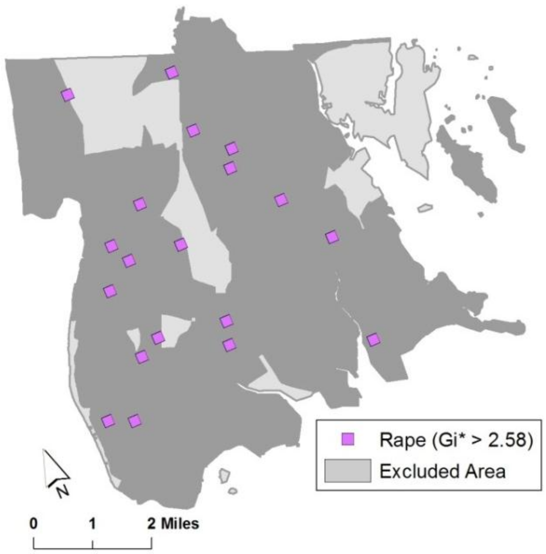


Figure 3.13: Rape Gi* Hot Spots

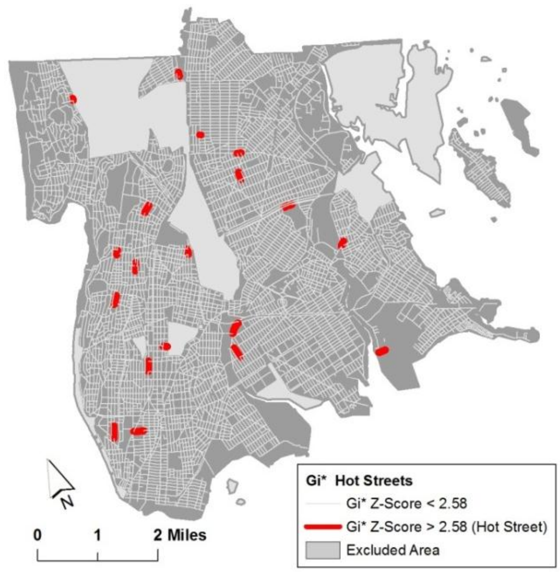


Figure 3.14: Rape Gi* Hot Streets

Figures 3.13 and 3.14 illustrate the significant rape Gi* statistic hot spots (n=74) and rape hot streets (n=19). The hot streets were created by spatially joining the rape hot spots to the street segments. Several hot spots were located at the same address or on the same street segment which resulted in 19 total rape hot streets. The rape hot streets were then aggregated and their land use was analyzed, the results are in table 3.10.

Rape Hot Streets	Rape Hot Streets (Linear Miles)	Percent Land-Use Area on Rape Hot Streets	Primary Land Use on Rape Hot Streets	Population Estimate on Rape Hot Streets
19	2.23 Linear Miles	LU3 Multi-Family Elevator Buildings: 49% LU5 Commercial and Office Buildings: 18% LU2 Multi-Family Walk-up Buildings: 16% LU1 One and Two Family Buildings: 8% LU4 Mixed Residential and Commercial Buildings: 2% LU7 Transportation and Utility 3% LU8 Public Facilities and Institutions: 2% LU11 Vacant Land 2%	Multi-Family Elevator Buildings	150,040

Table 3.10: Rape Gi* Hot Streets. Number of hot streets, linear miles, percent land-use categories, primary land-use and population estimate on Gi* rape hot streets.

Table 3.10 shows that the Gi* Hot Streets indicate that the Gi* rape hot spots occur on street segments with a high percentage of multi-family elevator buildings, this is slightly different from the Nnh cluster and KDE HD Zone results, but also endorses the overall relationship between rape hot spots and higher population density areas.

Robbery Hot Spots

Robbery is the most common of the five violent crimes in this study. Likewise, robbery hot spots continue to be the primary 'target' for many of NYPD's (street) crime control strategies.

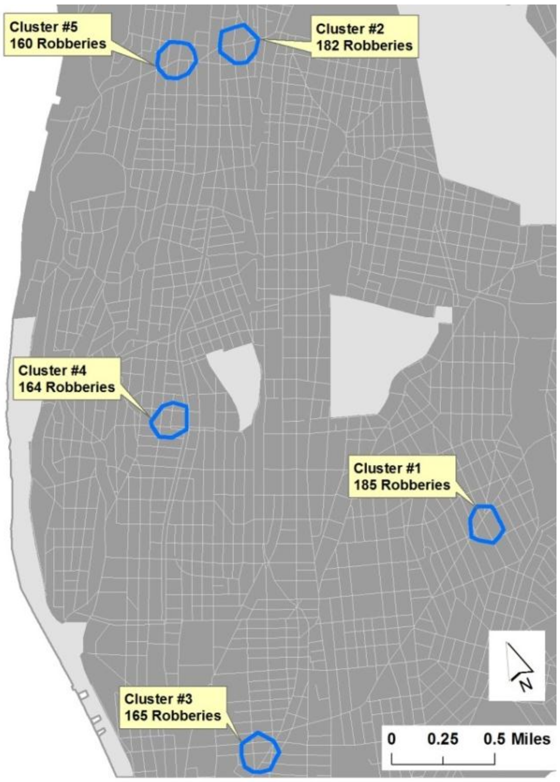


Figure 3.15: Nearest Neighbor Hierarchical Robbery Clusters

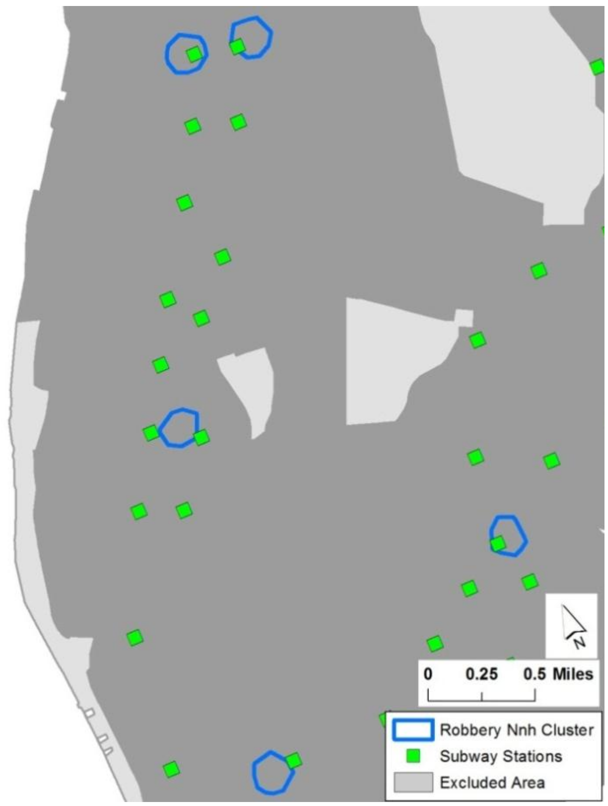


Figure 3.16: Robbery Nnh Clusters & Subway Stations

Robbery is the most common form of violent crime in the Bronx (n=22,674) and one that many researchers consider to be the best indicator of street-level and neighborhood 'safety' (Groff, 2007; Kennedy & Baron, 1993; Bernasco & Block, 2010). Robbery and assault are the most common forms of violent crimes in the Bronx and comprise 90% of the five violent crimes in this dissertation research.

Figure 3.16 indicates that all of the Nnh robbery clusters contain or are attached to subway stations (B/D/4 Fordham Rd; B/D/4 170th Street; 2/5 149th Street; and 2/5 Simpson Street). This is a distinct land-use difference from all of the other violent crimes studied. Table 3.11 indicates that there is a strong relationship between robbery and residential land-use, primarily with multi-family walk-up buildings.

Robbery Cluster ID	Land-Use			Primary Land Use in Cluster
1	LU5	Commercial and Office Buildings:	37%	Commercial & Office Buildings
	LU1	One and Two Family Buildings:	19%	
	LU4	Mixed Residential and Commercial Buildings:	18%	
	LU2	Multi-Family Walk-up Buildings:	8%	
	LU9	Open Space and Outdoor Recreation:	8%	
	LU8	Public Facilities and Institutions:	4%	
	LU10	Parking Facilities:	4%	
	LU11	Vacant Land:	2%	
2	LU3	Multi-Family Elevator Buildings:	66%	Multi-Family Elevator Buildings
	LU4	Mixed Residential and Commercial Buildings:	17%	
	LU2	Multi-Family Walk-up Buildings:	12%	
	LU5	Commercial and Office Buildings:	3%	
	LU11	Vacant Land:	2%	
3	LU2	Multi-Family Walk-up Buildings:	38%	Multi-Family Walk-Up Buildings
	LU3	Multi-Family Elevator Buildings:	24%	
	LU4	Mixed Residential and Commercial Buildings	16%	
	LU1	One and Two Family Buildings:	7%	
	LU8	Public Facilities and Institutions:	7%	
	LU11	Vacant Land:	3%	
	LU5	Commercial and Office Buildings:	2%	
	LU10	Parking Facilities :	1%	
4	LU2	Multi-Family Walk-up Buildings:	57%	Multi-Family Walk-Up Buildings
	LU1	One and Two Family Buildings:	43%	
5	LU2	Multi-Family Walk-up Buildings:	48%	Multi-Family Walk-Up Buildings
	LU3	Multi-Family Elevator Buildings:	17%	
	LU5	Commercial and Office Buildings:	12%	
	LU9	Open Space and Outdoor Recreation:	9%	
	LU4	Mixed Residential and Commercial Building	8%	
	LU1	One and Two Family Buildings:	6%	

Table 3.11: Nnh Robbery Clusters, Area in Square Miles, and Percent Land-Use Categories

The highest robbery cluster (#1) indicates more than a 1/3 of the area is commercial and office buildings (LU5). This finding is much different than every other violent crime cluster studied. Only one other violent crime clusters contain commercial and office buildings (LU5) as the primary land-use for the crime cluster.

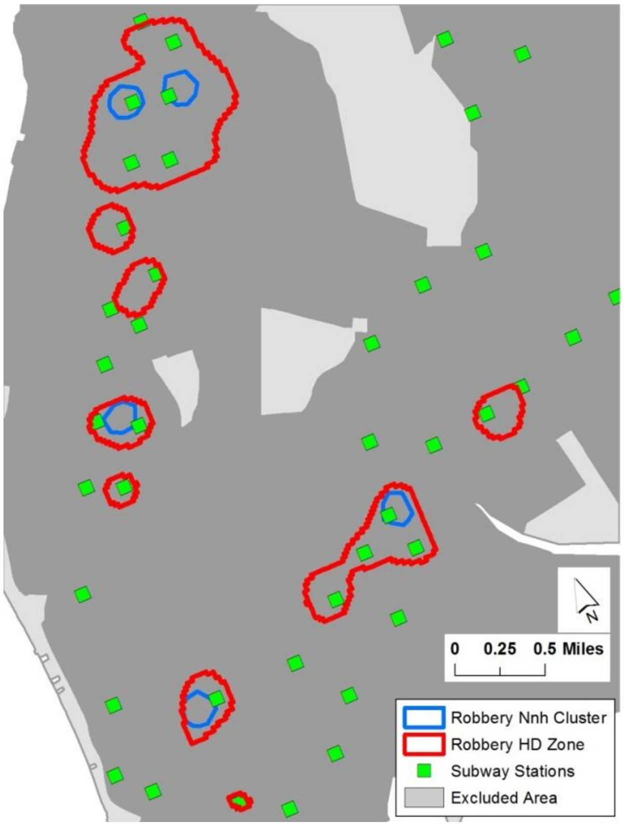


Figure 3.17: Robbery HD Zones, Nnh Clusters, and Subway Stations

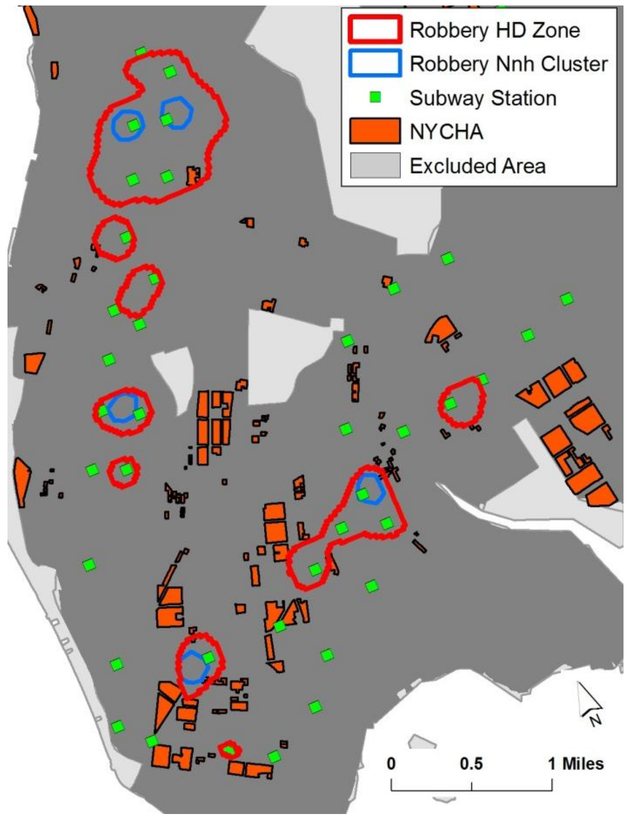


Figure 3.18: Robbery HD Zones, Nnh Clusters, Subway Stations and NYCHA

Crimestat identified 5 Nnh clusters for the robbery data. It also calculated 9 different high density (HD) robbery zones. Similar to all of the other violent crime HD zones analyzed, the robbery HD zones (KDE) contain all of the Nnh robbery clusters in figure 3.17. It is also important to note the significant spatial relationship(s) between the robbery HD zones (KDE) and the subway stations. Just like the robbery Nnh clusters, all of the robbery HD zones contain one or more subway stations. Some of the Robbery HD Zones are also associated with NYCHA public housing projects (see figure 3.18).

Robbery Hot Streets	Robbery Hot Streets (Linear Miles)	Percent Land-Use on Robbery Hot Streets	Primary Land Use in Robbery Hot Streets	Population Estimate on Hot Streets
122	8.46 Linear Miles	LU5 Commercial and Office Buildings: 24% LU4 Mixed Residential and Commercial Buildings: 19% LU3 Multi-Family Elevator Buildings: 17% LU2 Multi-Family Walk-up Buildings: 12% LU8 Public Facilities and Institutions: 8% LU1 One and Two Family Buildings: 7% LU10 Parking Facilities 4% LU11 Vacant Land: 4% LU9 Open Space and Outdoor Recreation: 3% LU7 Transportation and Utility 2%	Commercial and Office Buildings	19,648

Table 3.12: Gi* Robbery Hot Streets, Land-Use, and Population Estimates

Table 3.12 indicates the relationship between the robbery Gi* hot streets and land-use. The Hot Streets land-use table indicates that the highest percent of land-use for the robbery hot streets is Commercial and Office Buildings (LU5). This land-use pattern varies significantly from the Nnh clustering/land-use and KDE/land-use patterns, both of which had Multi-Family residential buildings as the primary land-use relationship. Figure 3.19 shows the definitive spatial relationship between Gi* hot spots and the Bronx subway lines.

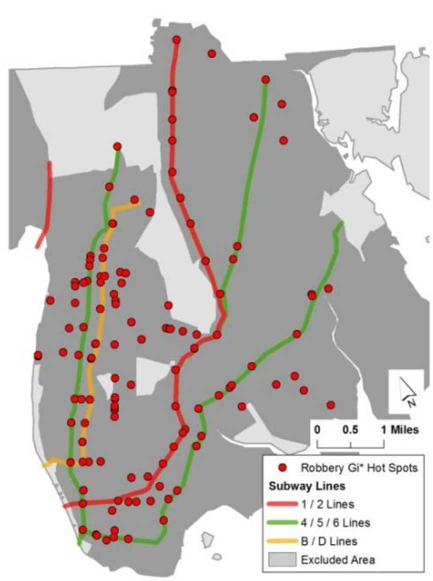


Figure 3.19: Robbery Gi* Hot Spots & Subway Lines

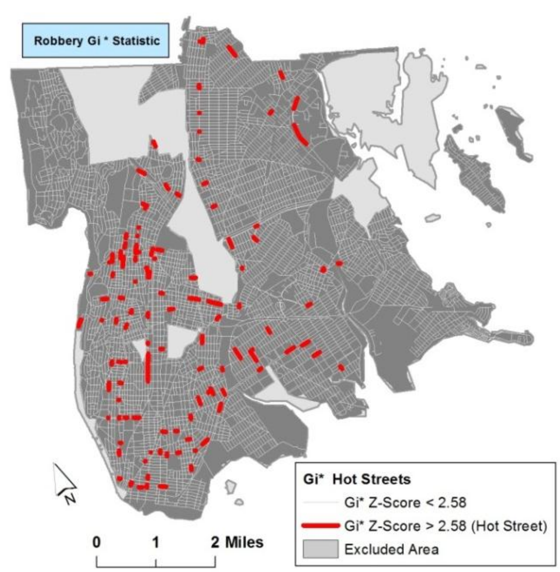


Figure 3.20: Robbery Gi* Hot Streets

Assault Hot Spots

Figure 3.21: Nearest Neighbor Hierarchical Assault Clusters

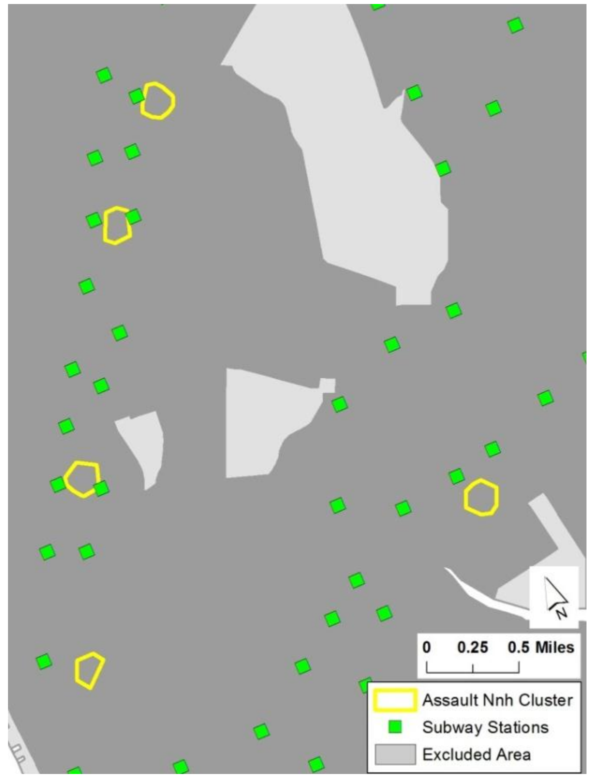


Figure 3.22: Nearest Neighbor Hierarchical Assault Clusters and Subway Stations

Figures 3.21 and 3.22 indicate that the assault clusters are relatively dispersed throughout the central and southern part of the Bronx. Almost all of the assault clusters appear to follow the subway lines and are related to areas with subway stations (assault cluster #5 is the exception). However, the premises data for robbery and assaults indicate that a very small percentage of assaults actually occur at subway stations, they are more likely occurring near subway stations, when people are coming home from work/school/play.

Table 3.13 indicates that there is a strong relationship between assault and residential land-use, primarily with multi-family elevator buildings. There is also a positive spatial relationship between assault and population density within each of the assault clusters.

Assault Cluster ID	Percent Land-Use Area Inside Assault Clusters		Primary Land Use in Cluster
1	LU2 Multi-Family Walk-up Buildings: LU4 Mixed Residential and Commercial Buildings: LU3 Multi-Family Elevator Buildings: LU5 Commercial and Office Buildings: LU1 One and Two Family Buildings: LU10 Parking Facilities: LU8 Public Facilities and Institutions: LU11 Vacant Land:	49% 17% 16% 8% 7% 2% 1% 1%	Multi-Family Walk-Up Buildings
2	LU3 Multi-Family Elevator Buildings: LU2 Multi-Family Walk-up Buildings: LU4 Mixed Residential and Commercial Buildings: LU5 Commercial and Office Buildings: LU1 One and Two Family Buildings: LU10 Parking Facilities: LU8 Public Facilities and Institutions: LU11 Vacant Land:	34% 24% 18% 10% 7% 3% 2% 2%	Multi-Family Elevator Buildings
3	LU2 Multi-Family Walk-up Buildings: LU4 Mixed Residential and Commercial Buildings: LU5 Commercial and Office Buildings: LU3 Multi-Family Elevator Buildings: LU8 Public Facilities and Institutions: LU11 Vacant Land:	27% 26% 18% 17% 11% 1%	Multi-Family Walk-up Buildings
4	LU2 Multi-Family Walk-up Buildings: LU1 One and Two Family Buildings: LU3 Multi-Family Elevator Buildings: LU4 Mixed Residential and Commercial Buildings: LU8 Public Facilities and Institutions: LU5 Commercial and Office Buildings: LU11 Vacant Land:	36% 21% 20% 11% 7% 3% 2%	Multi-Family Walk-Up Buildings
5	LU5 Commercial and Office Buildings: LU4 Mixed Residential and Commercial Buildings: LU3 Multi-Family Elevator Buildings: LU8 Public Facilities and Institutions: LU10 Parking Facilities: LU7 Transportation and Utility:	56% 17% 11% 10% 3% 2%	Commercial & Office Buildings

Table 3.13: Assault Cluster ID, Percent Land-Use Category Area inside Nnh Assault Clusters, Primary Land-Use

Crimestat identified five different tenth-mile Nnh assault clusters for the assault data. It also calculated 6 different high density (HD) assault zones. The assault HD zones contain (or overlap) all 5 Nnh assault clusters in figure 3.23. All of the assault HD zones are spatially related to subway stations, with the exception of the southernmost cluster/HD zone. As table 3.13 indicates, assault cluster #5 is much different than all of the other assault clusters. Its primary land-use is commercial and office buildings (LU5). Further analysis of this cluster indicates that this is the area that contains the Bronx County Criminal Court, Family Court, the District Attorney's office, and the New York City Department of Probation.

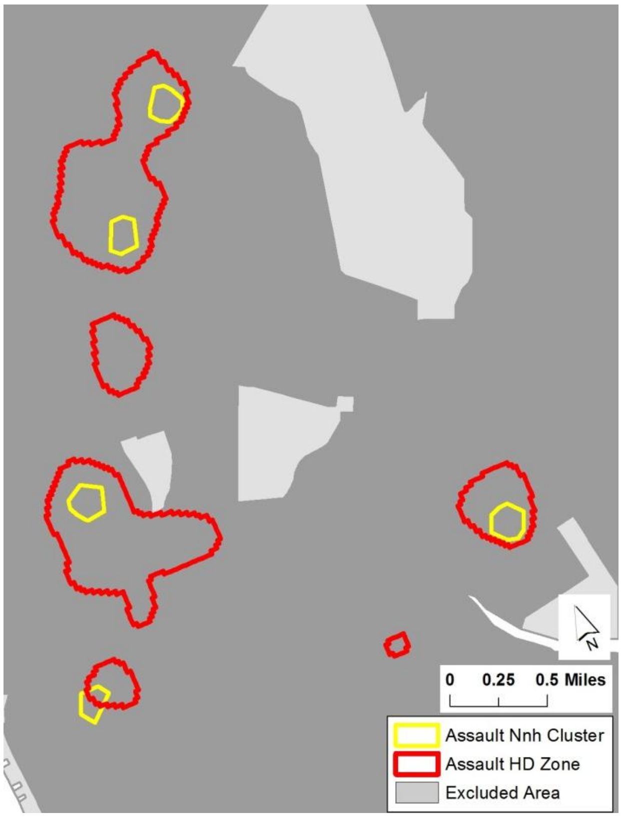


Figure 3.23: Assault HD Zones (KDE) and Nnh Clusters

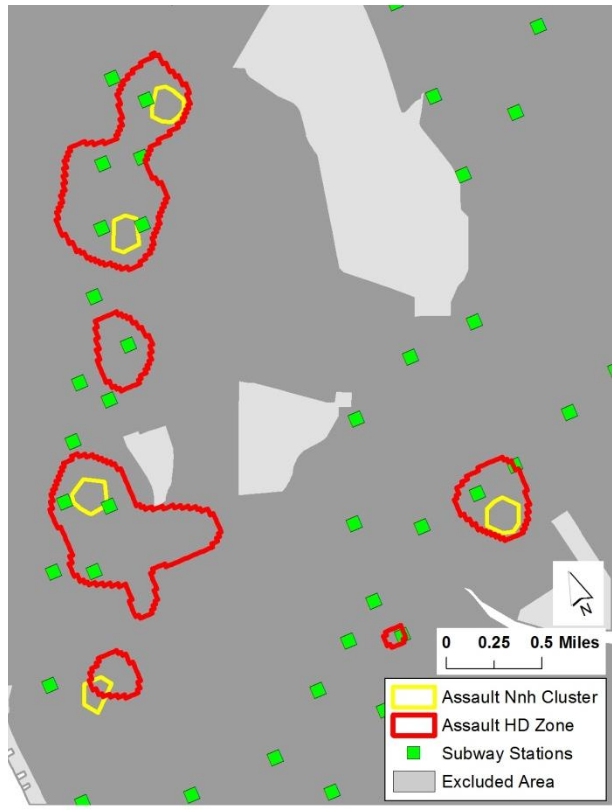


Figure 3.24: Assault HD Zones, Nnh Clusters and Subway Stations

Assault HD Zones	Assault HD Zones (Sq. Miles)	Percent Land-Use Area Inside Assault HD Zones	Primary Land Use in Assault HD Zones	Population Estimate in HD Zone
6	1.19 Square Miles	LU2 Multi-Family Walk-up Buildings: 25% LU3 Multi-Family Elevator Buildings: 21% LU4 Mixed Residential and Commercial Buildings: 15% LU5 Commercial and Office Buildings: 11% LU8 Public Facilities and Institutions: 10% LU1 One and Two Family Buildings: 9% LU9 Open Space and Outdoor Recreation: 3% LU10 Parking Facilities 3% LU11 Vacant Land: 2% LU6 Industrial and Manufacturing <1% LU7 Transportation and Utility <1%	Multi-Family Walk-up Buildings	186,499

Table 3.14. Assault HD Zones, HD Zone Area, Percent Land-Use inside HD Zone and Population

Table 3.14 indicates the relationship between the assault HD zones and land-use. Similar to the clustering routine, the KDE table indicates that the highest percent of land-use for the assault HD zones is Multi-Family Walk-up Buildings (LU2). Figures 3.23 (KDE/Cluster) and 3.24 (KDE/Subway) indicate that the KDE method overlaps the Nnh assault clusters, however, the KDE method also overlaps 12 subway stations.

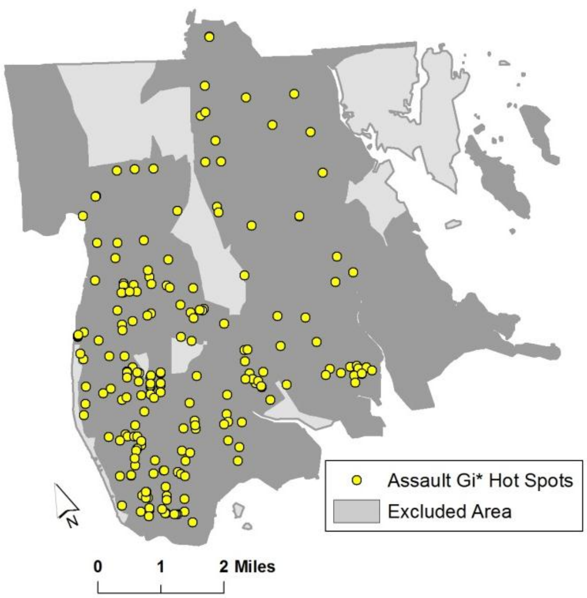


Figure 3.25: Assault Gi* Hot Spots

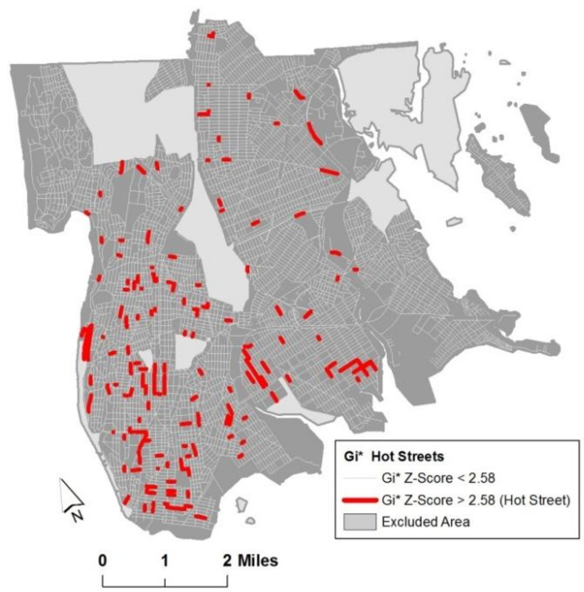


Figure 3.26: Assault Gi* Hot Streets

Figures 3.25 and 3.26 above illustrate the significant Gi* statistic hot spots (n=2,223) and hot streets (n=170). Hot streets were created by joining the assault hot spots to the street segments. The assault hot streets were then aggregated and their respective land use was analyzed, the results are in table 3.15.

As opposed to Nnh and KDE hot spots, the Gi* Hot Streets indicate that the Gi* assault hot spots occur on street segments with a high percentage of multi-family elevator buildings. This spatial relationship with high population density land areas is consistent with both the Nnh assault clustering and KDE assault HD Zones.

Assault Hot Streets	Assault Hot Streets (Linear Miles)	Percent Land-Use Area on Assault Hot Streets	Primary Land Use on Assault Hot Streets	Population Estimate on Hot Streets
170	16.75 Linear Miles	LU3 Multi-Family Elevator Buildings: 33% LU8 Public Facilities and Institutions: 16% LU2 Multi-Family Walk-up Buildings: 13% LU4 Mixed Residential and Commercial Buildings: 10% LU5 Commercial and Office Buildings: 10% LU1 One and Two Family Buildings: 7% LU6 Industrial and Manufacturing: 1% LU7 Transportation and Utility: 1% LU9 Open Space and Outdoor Recreation: 3% LU10 Parking Facilities: 3% LU11 Vacant Land: 3%	Multi-Family Elevator Buildings	58,427

Table 3.15: Gi* Assault Hot Streets, Land-Use, and Population

Shooting Hot Spots

Figure 3.27: Nearest Neighbor Hierarchical Shooting Clusters

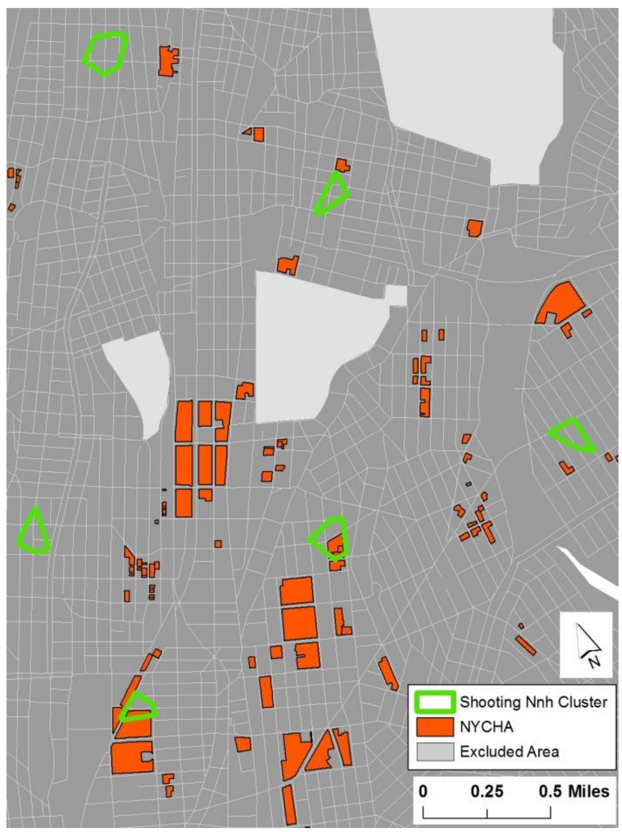


Figure 3.28: Nearest Neighbor Hierarchical Shooting Clusters and NYCHA Building Outlines

Figure 3.28 indicates that most of the shooting clusters occur in the South and Central parts of the Bronx. Table 3.16 indicates that there is a strong spatial relationship between shooting clusters and Multi-Family Walk-up Buildings, as well as Multi-Family Elevator Buildings. Further analysis of the multi-elevator buildings indicates that these are (mostly) NYCHA public housing developments in the south Bronx.

Shooting Cluster ID	Land-Use in Shooting Clusters		Primary Land Use in Cluster
1	LU2 Multi-Family Walk-up Buildings: LU3 Multi-Family Elevator Buildings: LU5 Commercial and Office Buildings: LU4 Mixed Residential and Commercial Buildings: LU10 Parking Facilities: LU1 One and Two Family Buildings:	61% 15% 11% 7% 5% 1%	Multi-Family Walk-Up Buildings
2	LU2 Multi-Family Walk-up Buildings: LU3 Multi-Family Elevator Buildings: LU4 Mixed Residential and Commercial Buildings LU5 Commercial and Office Buildings: LU1 One and Two Family Buildings: LU8 Public Facilities and Institutions: LU10 Parking Facilities: LU11 Vacant Land: LU9 Open Space and Outdoor Recreation:	29% 26% 16% 12% 7% 3% 3% 2% 1%	Multi-Family Walk-Up Buildings
3	LU8 Public Facilities and Institutions: LU3 Multi-Family Elevator Buildings: LU2 Multi-Family Walk-up Buildings: LU1 One and Two Family Buildings: LU11 Vacant Land: LU4 Mixed Residential and Commercial Buildings: LU5 Commercial and Office Buildings:	52% 18% 14% 9% 5% 1% 1%	Public Facilities & Institutions
4	LU2 Multi-Family Walk-up Buildings: LU3 Multi-Family Elevator Buildings: LU8 Public Facilities and Institutions: LU5 Commercial and Office Buildings: LU1 One and Two Family Buildings: LU11 Vacant Land: LU10 Parking Facilities:	22% 21% 20% 17% 14% 4% 2%	Multi-Family Walk-Up Buildings
5	LU3 Multi-Family Elevator Buildings: LU2 Multi-Family Walk-up Buildings: LU11 Vacant Land: LU1 One and Two Family Buildings: LU4 Mixed Residential and Commercial Buildings: LU10 Parking Facilities: LU5 Commercial and Office Buildings:	65% 14% 9% 3% 3% 3% 1%	Multi-Family Elevator Buildings
6	LU3 Multi-Family Elevator Buildings: LU2 Multi-Family Walk-up Buildings: LU11 Vacant Land:	65% 14% 9%	Multi-Family Elevator Buildings

	LU4	Mixed Residential and Commercial Buildings :	3%	
	LU10	Parking Facilities:	3%	
	LU1	One and Two Family Buildings:	3%	
	LU5	Commercial and Office Buildings:	1%	
	LU8	Public Facilities and Institutions:	1%	

Table 3.16: Nnh Shooting Clusters, Area in Square Miles, and Percent Land-Use Categories

Crimestat identified 6 Nnh clusters for the shooting data, it also calculated 15 different high density (HD) shooting zones. The shooting HD zones are illustrated overlapping all of the 6 Nnh shooting clusters in figure 3.29. More than 20% of the Bronx NYCHA developments intersect or are contained within shooting HD zones, however, most of these NYCHA developments are concentrated in the southern section of the Bronx.

Figure 3.29: Shooting HD Zones and Nnh Clusters

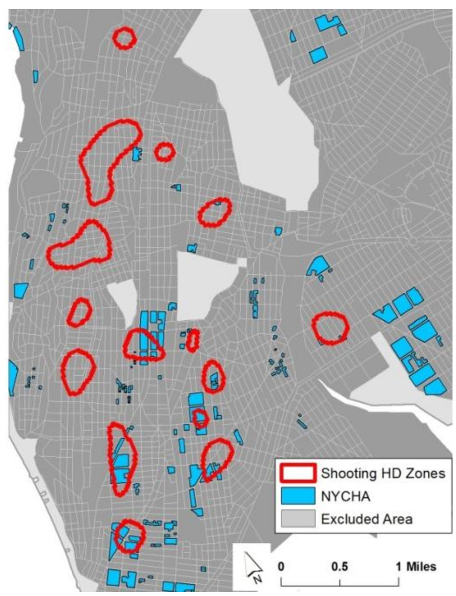


Figure 3.30: Shooting HD Zones and NYCHA

Figure 3.30 shows the relationship to shooting HD Zones and NYCHA Housing. There is a definitive spatial pattern, very similar to murder and rape, in the NYCHA Projects in the southern part of the Bronx.

Shooting HD Zones	Shooting HD Zones (Sq. Miles)	Percent Land-Use Area Inside Shooting HD Zones		Primary Land Use in Shooting HD Zones	Population Estimate in HD Zone
14	.84 Square Miles	LU3 Multi-Family Elevator Buildings:	31%	Multi-Family Elevator Buildings	141,918
		LU2 Multi-Family Walk-up Buildings:	20%		
		LU7 Transportation and Utility	16%		
		LU8 Public Facilities and Institutions:	16%		
		LU4 Mixed Residential and Commercial Buildings:	12%		
		LU5 Commercial and Office Buildings:	7%		
		LU1 One and Two Family Buildings:	5%		
		LU9 Open Space and Outdoor Recreation:	2%		
		LU10 Parking Facilities	3%		
		LU11 Vacant Land:	3%		
		LU6 Industrial and Manufacturing	<1%		

Table 3.17. Shooting HD Zones, HD Zone Area, Percent Land-Use inside HD Zone and Population

Table 3.17 indicates the relationship between the shooting HD zones and land-use. Similar to the clustering routine, the KDE table indicates that the highest percent of land-use for the shooting HD zones is Multi-Family Elevator Buildings (LU3), which is consistent with its relationship with NYCHA Housing in the south Bronx. Figures 3.29 (KDE/Cluster) and 3.30 (KDE/NYCHA) indicate that the KDE method overlaps the Nnh clusters completely; however, the KDE method also overlaps 20 different NYCHA developments.

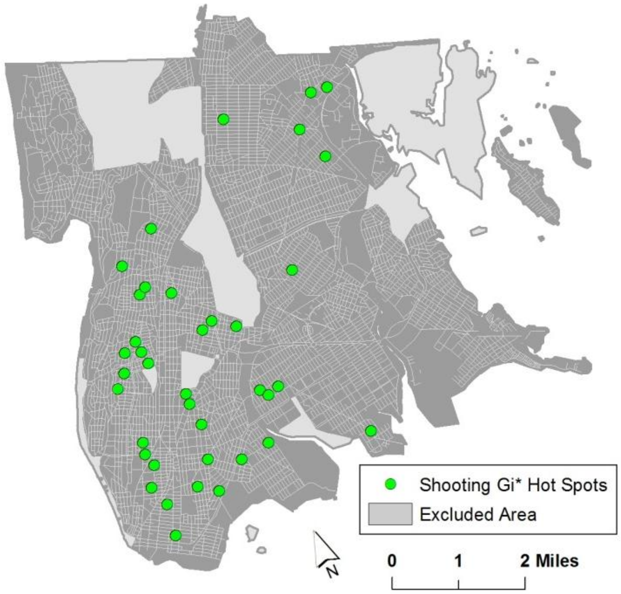


Figure 3.31: Shooting Gi* Hot Spots

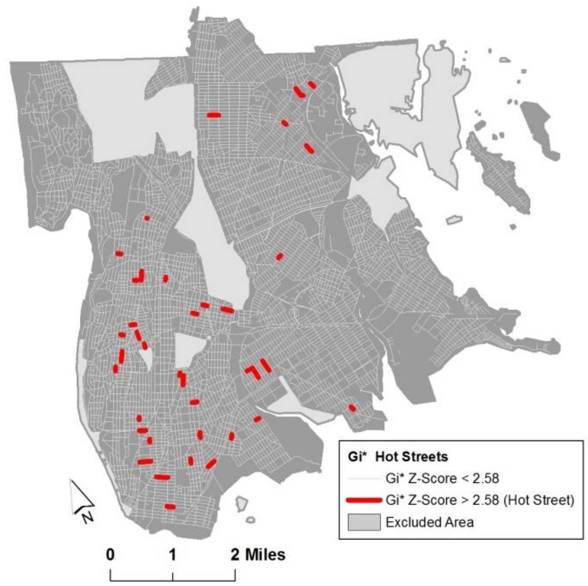


Figure 3.32: Shooting Gi* Hot Streets

Figures 3.31 and 3.32 above illustrate the statistically significant Gi* statistic shooting hot spots (n=262) and hot streets (n=38). Hot streets were created by spatially joining the shooting hot spots to the street segments. The shooting hot streets were then aggregated and their land use was analyzed, the results are in table 3.15.

Shooting Hot Streets	Shooting Hot Streets (Linear Miles)	Percent Land-Use Area on Shooting Hot Streets	Primary Land Use on Shooting Hot Streets	Population Estimate on Hot Streets
38	3.58 Linear Miles	LU2 Multi-Family Walk-up Buildings: 33% LU3 Multi-Family Elevator Buildings: 16% LU1 One and Two Family Buildings: 13% LU5 Commercial and Office Buildings: 10% LU4 Mixed Residential and Commercial Buildings: 7% LU9 Open Space and Outdoor Recreation: 5% LU10 Parking Facilities 5% LU8 Public Facilities and Institutions: 4% LU11 Vacant Land: 4% LU6 Industrial and Manufacturing 2% LU7 Transportation and Utility 1%	Multi-Family Walk-up Buildings	141,918

Table 3.18: Gi* Shooting Hot Streets, Land-Use, and Population

The Gi* Shooting Hot Streets indicate that the statistically significant shooting hot spots occur on street segments with a high percentage of multi-family elevator buildings. This finding is different from the Shooting HD zones, but is consistent with the Nnh shooting cluster results.

Temporal Analysis

If micro-level clusters or a small number of street segments are responsible for a majority of crime within an entire neighborhood, certainly a targeted strategy would have a much more significant crime prevention and/or crime control benefit than police randomly patrolling entire neighborhoods. Moreover, incorporating temporal trends into these spatial micro-level strategies will also maximize police impact and outcomes.

One of the more interesting findings in this research was the temporal differences between robbery and assault, when compared to the other violent crimes. Robbery and Assault have two distinct hour of day and day of week patterns. For both crimes, there is a daytime weekday pattern and an evening / nighttime weekend pattern. Further analysis of these two patterns revealed a very interesting space-time pattern that validates much of this land-use/business establishment type research and the routine activities theory.

Figure 3.33 shows the day of the week patterns for all 5 violent crimes, where the X-axis is the day of the week, from Monday (day #1, on the left) to Sunday (day #7, on the right), and the Y-axis is the frequency of each respective violent crime between 2006-2010. Robbery (center, green line) has a noticeably different day of week temporal pattern when compared to the other violent crimes.

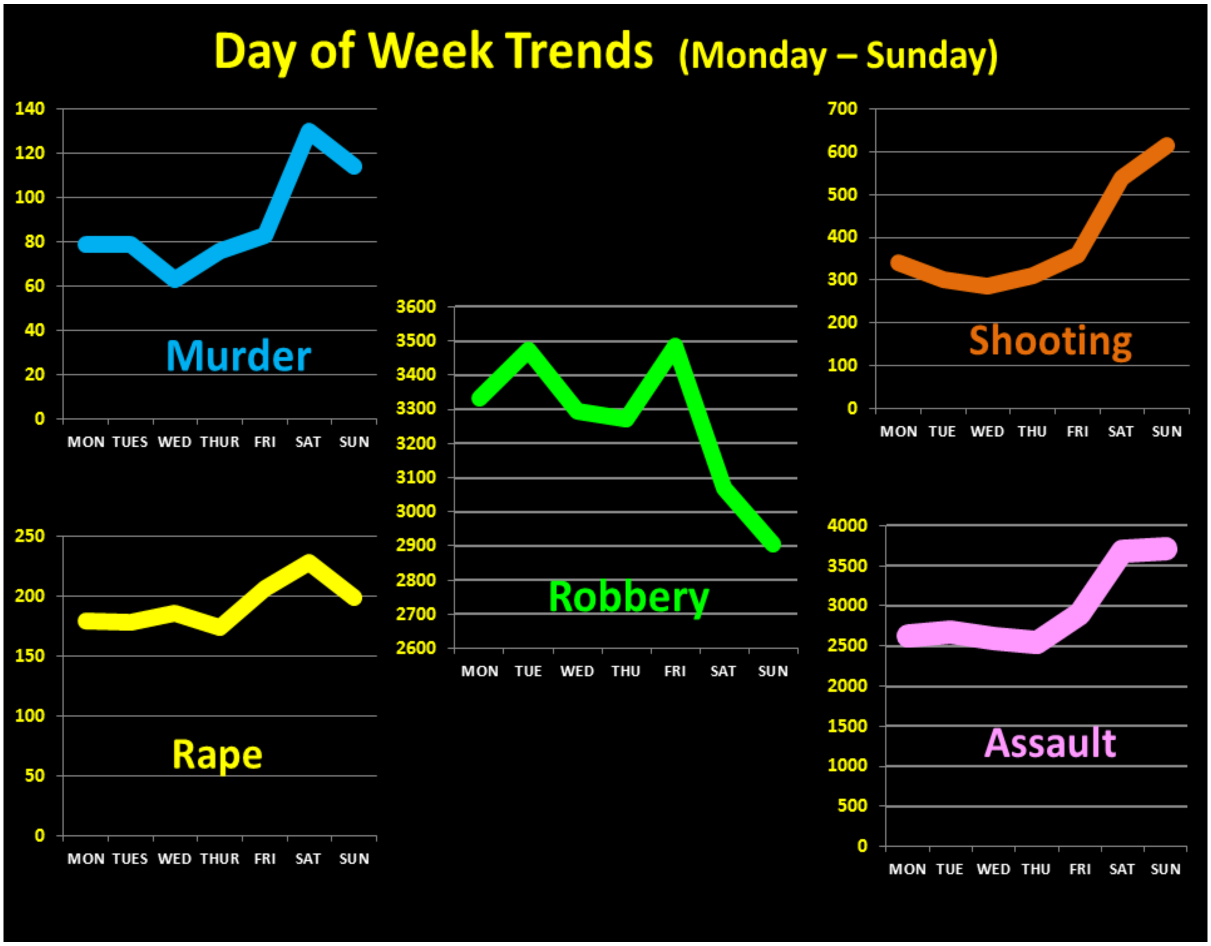


Figure 3.33:: Day of Week analysis for the 5 Violent Crime types. As you can see, robbery (middle, green line) has a distinctively different day of week pattern from the other violent crimes.

Figure 3.34 and figure 3.35 show the hour of day temporal trends for the 5 different violent crimes.

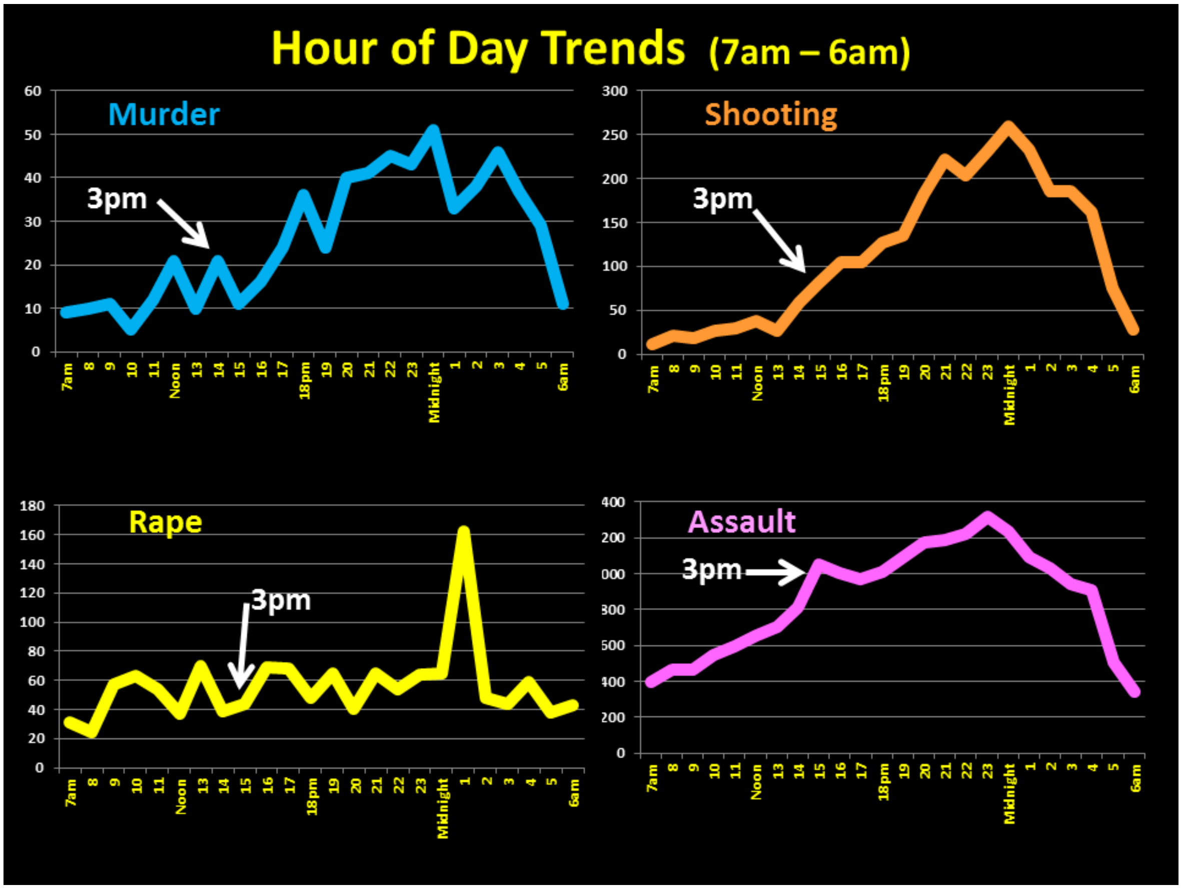


Figure 3.34: Hour of Day temporal trends for Murder, Shootings, Rape, and Assault. Note that one of these 4 violent crimes peaks at 3pm and all of these crimes peak at midnight-1am.

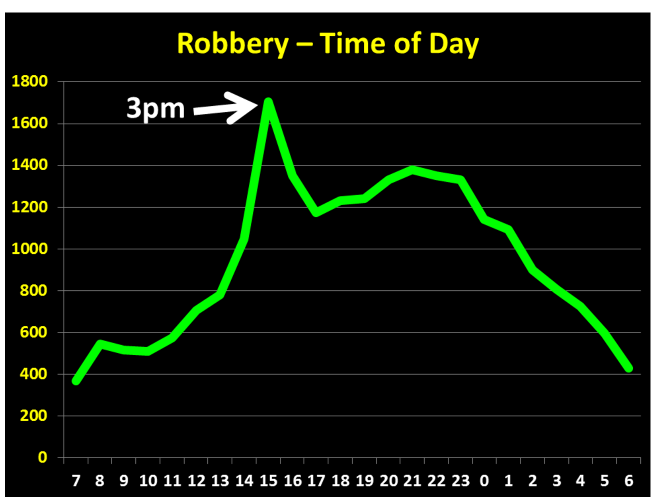


Figure 3.35: Robbery Time of Day temporal pattern. The scale is from 7am on the left to 6am on the right. Note that robbery has two peaks, a definitive 3pm peak and another late night (11pm) peak.

The robbery hour of day temporal pattern (figure 3.35) is much different than the hour of day temporal pattern for the other violent crimes (figure 3.34), where all of the other violent crimes are peaking at midnight-1am. Understanding that robbery is strongly spatially related to subway stations, the current day of week and hour of day temporal patterns also coincide with the decreasing ridership on subways on the weekends (see appendix). The sharp 3pm spike suggests a relationship between robbery, high school students (who are dismissed from school around 3pm), and subway stations (that are near subway stations).

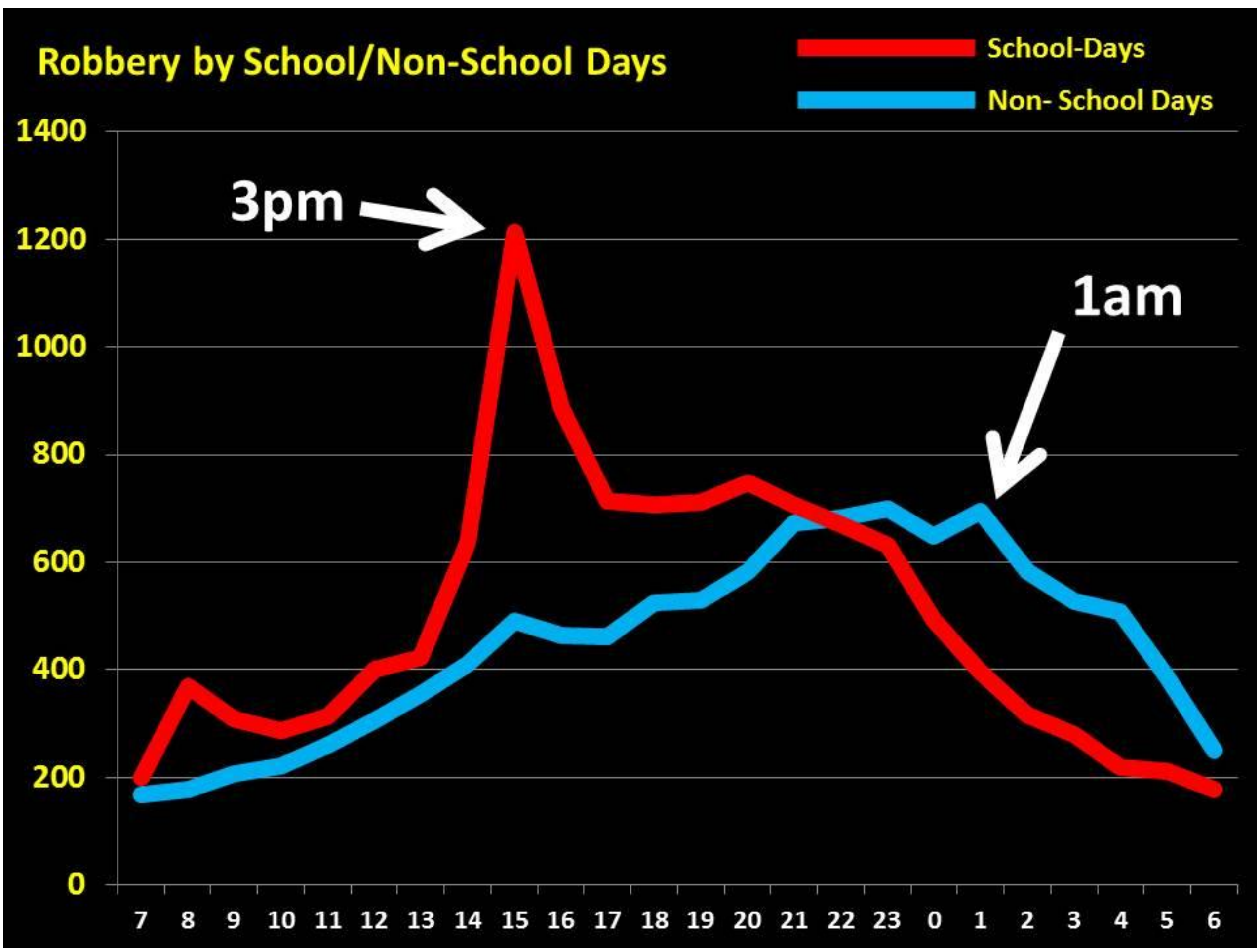


Figure 3.36: School-Day Robbery frequency and Non-School day Robbery frequency by Hour of Day. Note the two very different hourly temporal patterns and 3pm / 1am peaks.

When the robbery data is disaggregated (by week of year) according to the NYC Public School calendar (see the appendix for actual SQL query) – the red line indicates that school day robberies have a very distinct 3pm spike. This suggests that the 70,000 high school students in the Bronx probably play a significant role in 3pm robberies – either as motivated offenders, potential victims, or both. However, on non-school days (especially weekends), there is a considerable different and escalated nighttime robbery pattern occurring. The blue temporal line (figure 3.36) indicates the steady evening increase in robbery and the late night peak that occurs on non-school days between 11pm – 1am. This nighttime robbery trend follows a much more traditional violent crime temporal pattern and is similar to all of the other violent crime trends in this study (that also peak at midnight-1am, see figure 3.34).

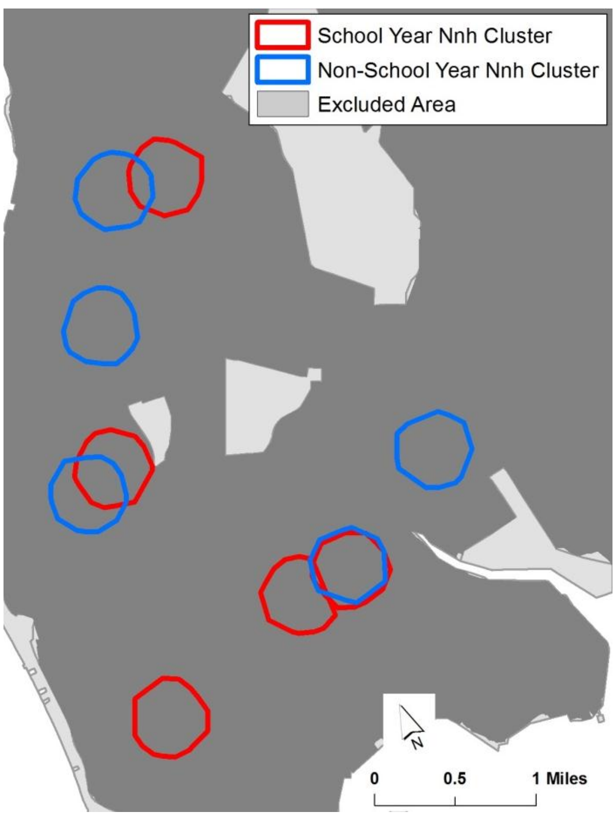


Figure 3.37: Nnh Robbery Clusters – School Day (red) vs. Non-School Day (blue)

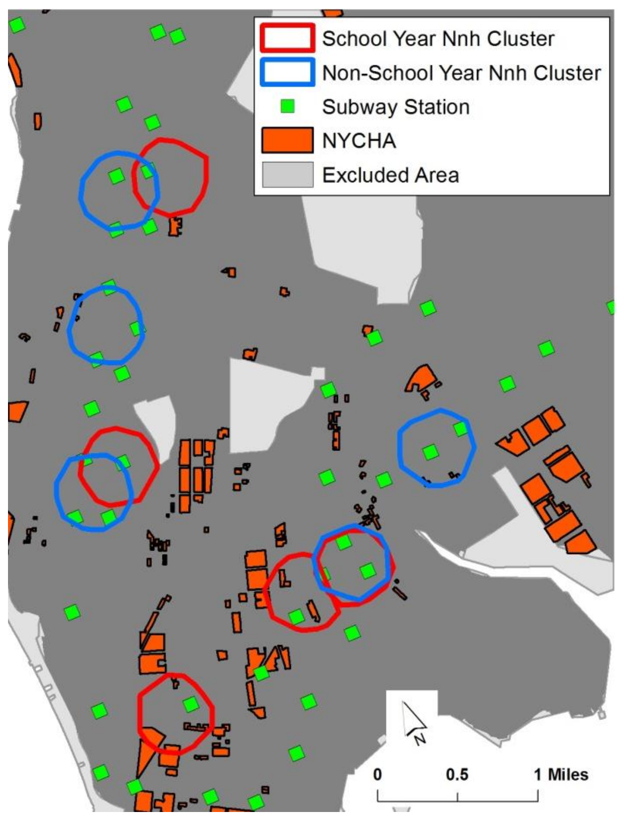


Figure 3.38: Nnh Robbery Clusters – School Day vs. Non-School Day (blue) and NYCHA Building Outlines (orange)

Figure 3.37 shows the robbery data when disaggregated based on the school-day / non-school day temporal query. While there is some overlap (and one complete overlap) between the clusters, there are also unique differences about the two sets of robbery clusters. When we add the subway stations and NYCHA building outlines (figure 3.38), we can note that all of the robbery clusters, regardless of school day or non-school day clustering, are still strongly spatially related to subway stations. If we substitute NYCHA building outlines for Bronx High School locations (black triangles), we can now note a spatial relationship between the school day clusters and high schools. Equally important is also the lack of spatial relationships between non-school day clusters and high schools.

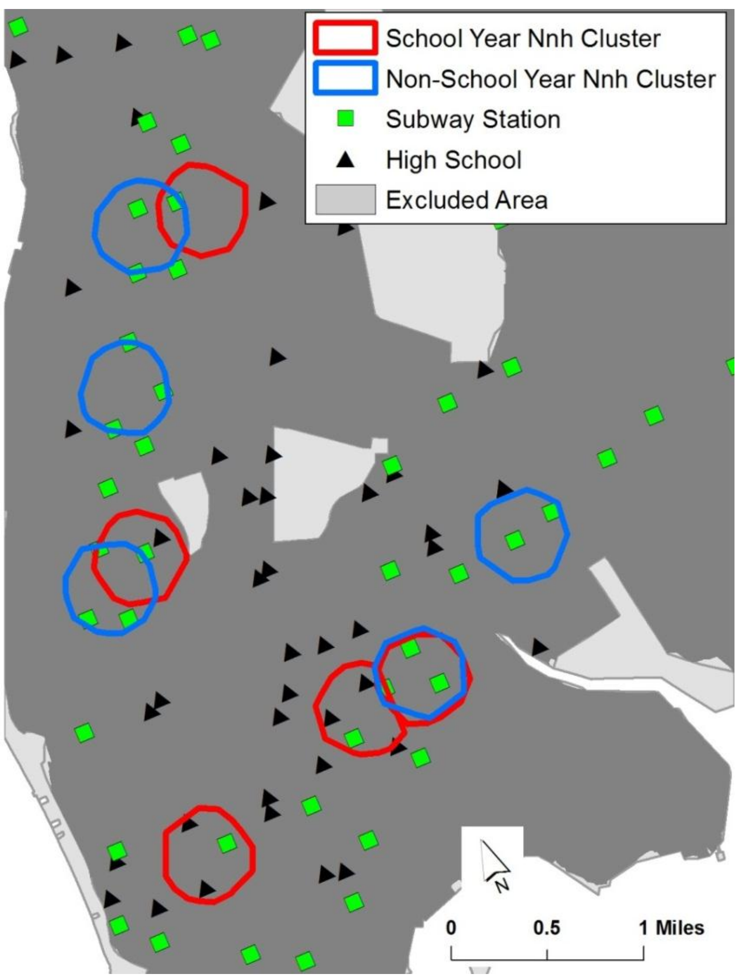


Figure 3.39: Nnh Robbery Clusters School Day/Non-School Day, NYCHA, and High Schools

Figure 3.39 shows that 3 out of the 5 school year clusters (red polygons) contain high schools (black triangles). Correspondingly, the 5 non-school year clusters (blue polygons) contain zero high schools.

Based on these new temporal results, another Nnh clustering routine was run using the robbery data, but this time, the data was queried by school day vs. non-school day *and* by hour of day prior to running the Nnh robbery model. The result of the data query was two subsets of data that contained robberies that occurred on the 3pm weekday peak (between 3pm-4pm) on school days (Mon-Fri) during the weeks that school was in session *and* robberies that occurred at 11pm (11pm-midnight) on weekends and weekdays when school was not in session (e.g. Thanksgiving break, Christmas/New Year break, February recess, Easter break, etc.). Not surprisingly, figure 3.37 shows the two very different spatiotemporal Nnh clusters that were constructed based on the 3pm school-day and 11pm non-school day robbery data subset. This not only illustrates variation by school day/ non-school day, but also by hour of day.

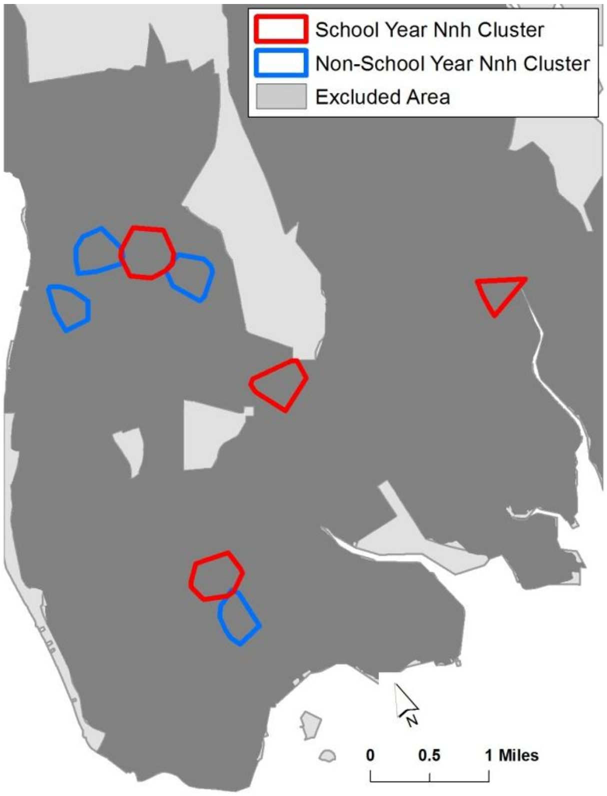


Figure 3.40: Nnh Assault Clusters – School Days and Non-School Days

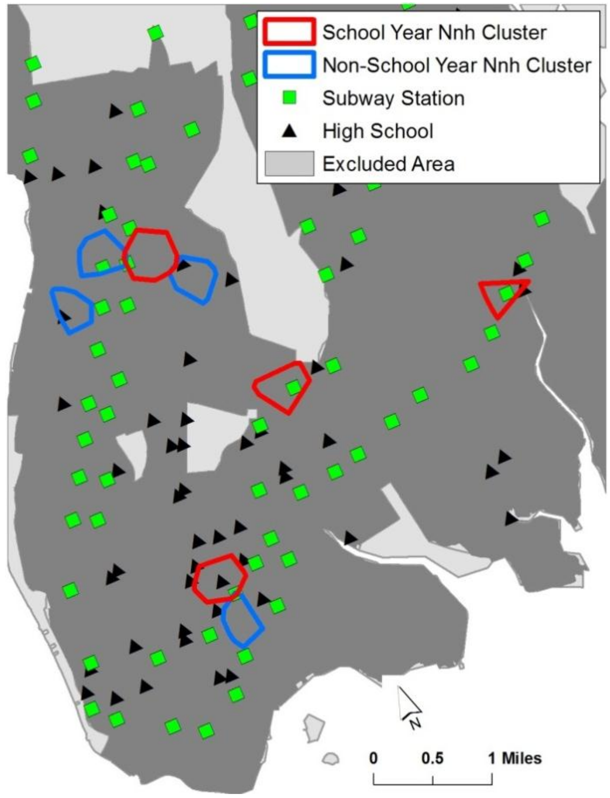


Figure 3.41: Nnh Assault Clusters – School Days, Non-School days, Subway Stations, and High Schools

While assault and robbery share similar frequencies, their spatial and temporal patterns have some variation, especially when compared to the other violent crimes in this study.

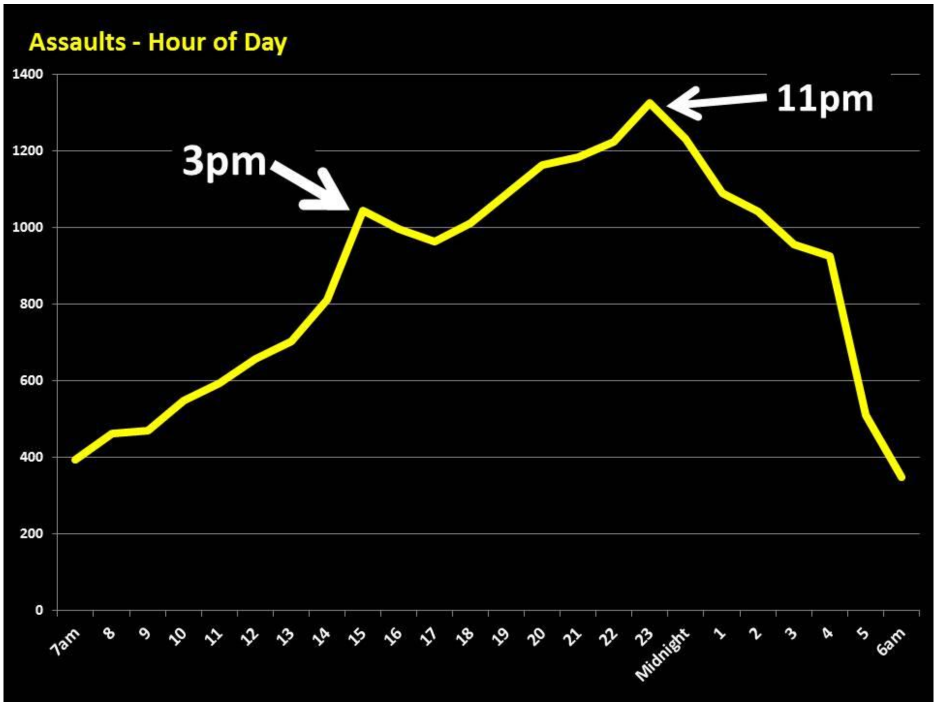


Figure 3.42: Temporal Analysis – Hour of Day Analysis for Assault

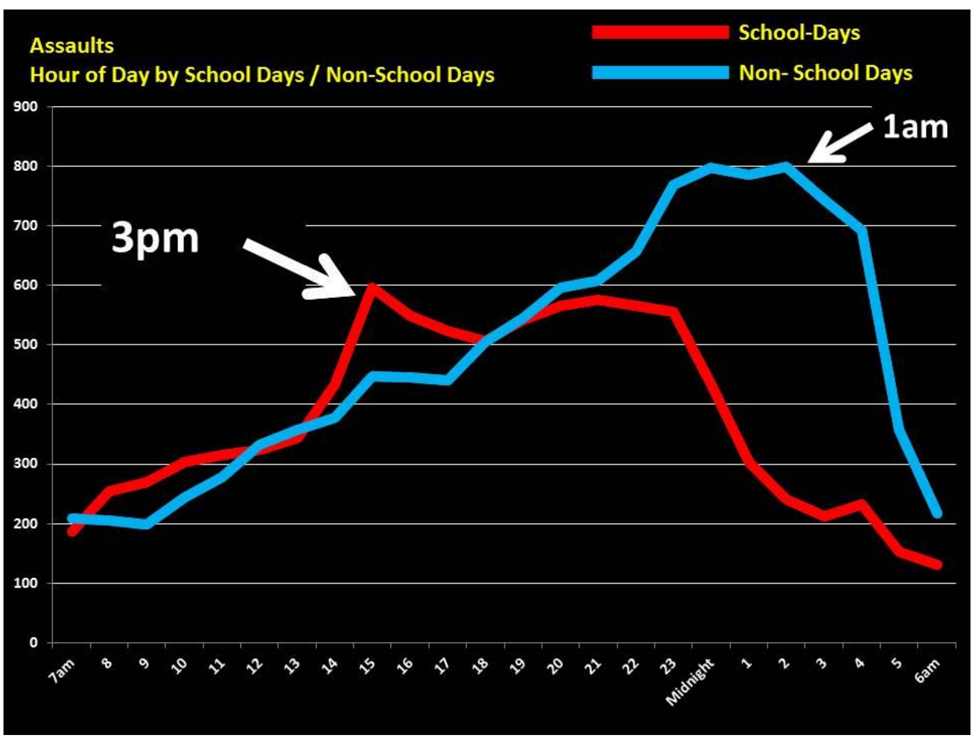


Figure 3.43 : Assault Hour of Day frequencies disaggregated by School day (red) vs. Non-School day (blue). Similar to the temporal pattern for robbery, there is a school day 3pm peak and a non-school day 1am peak.

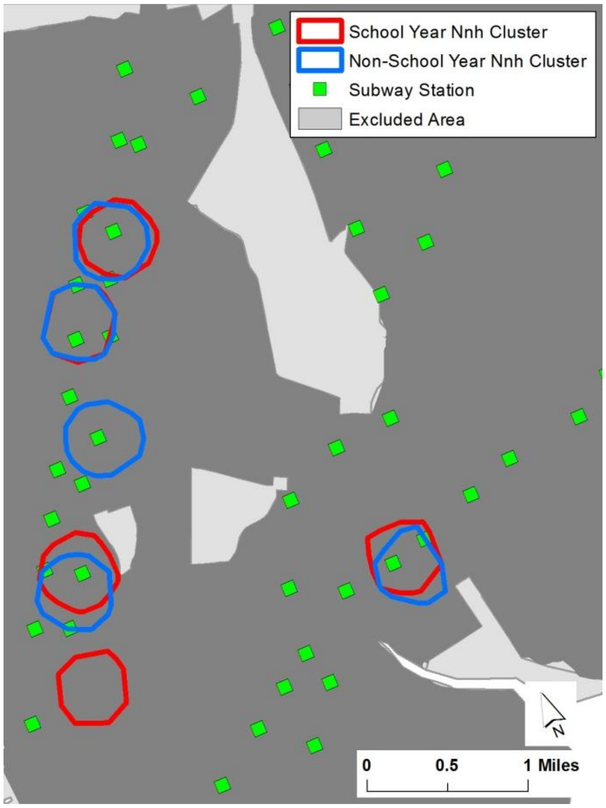


Figure 3.44: Nnh Assault Clusters School Day/Non-School Day and Subway Stations

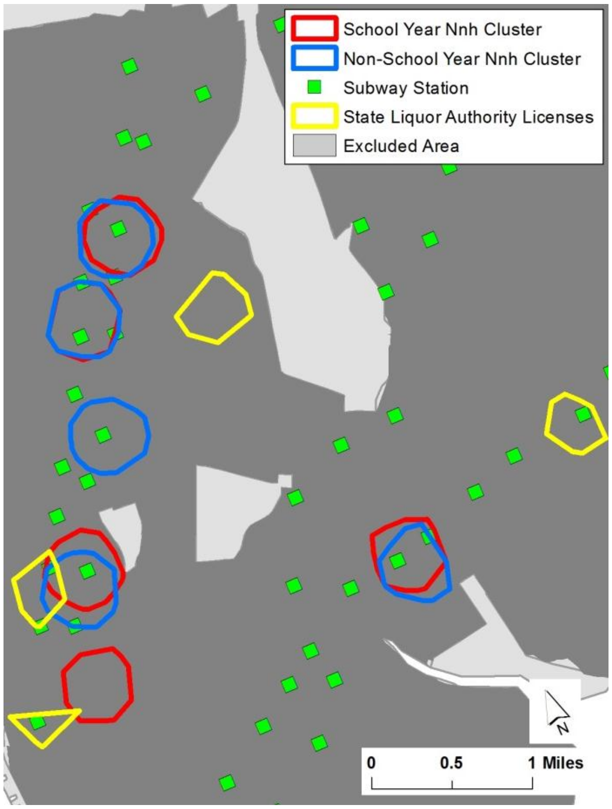


Figure 3.45: Nnh Assault Clusters, Nnh SLA Liquor Clusters, and Subway Stations

Another interesting violent crime temporal pattern can be viewed in the assault spatiotemporal clusters above (figures 3.44 and 3.45). Figure 3.44 shows the overlap between the school day and non-school day assaults. 4 out of 5 of the assault clusters overlap one another. Many of the assault clusters show little spatial variation from one another. Figure 3.45 also adds the clustering of New York State Liquor Authority retail licenses (yellow clusters).

With the exception of some overlap in the southwestern clusters, there appears to be little relationship between assault clusters and SLA liquor clusters, when disaggregated by school days/non-school days. However, an hour of day temporal analysis (figure 3.46) notes significant temporal variation between these two sets of assault clusters.

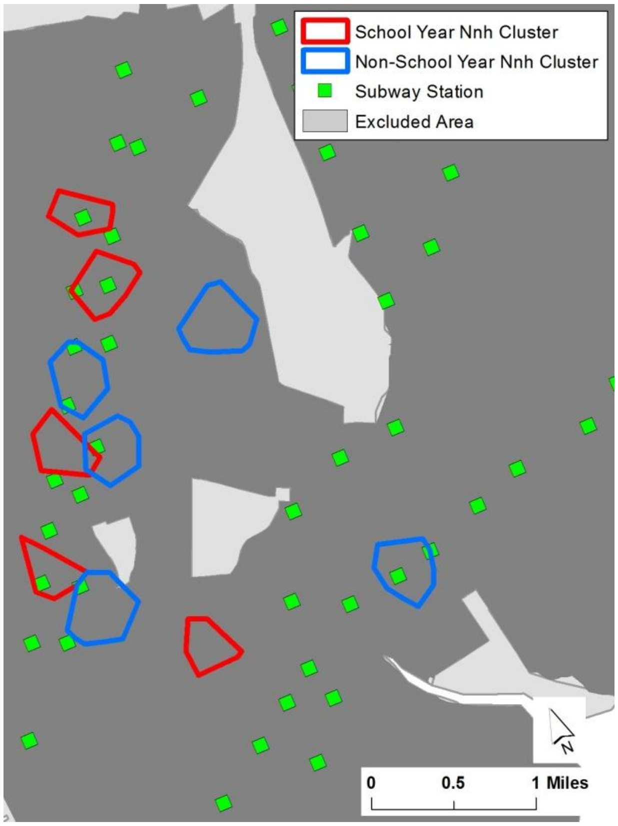


Figure 3.46: Nnh Assault Clusters by hour of day
3pm School Day Nnh Assault Clusters (red),
1am Non-School Day Clusters (blue), and
Subway Stations

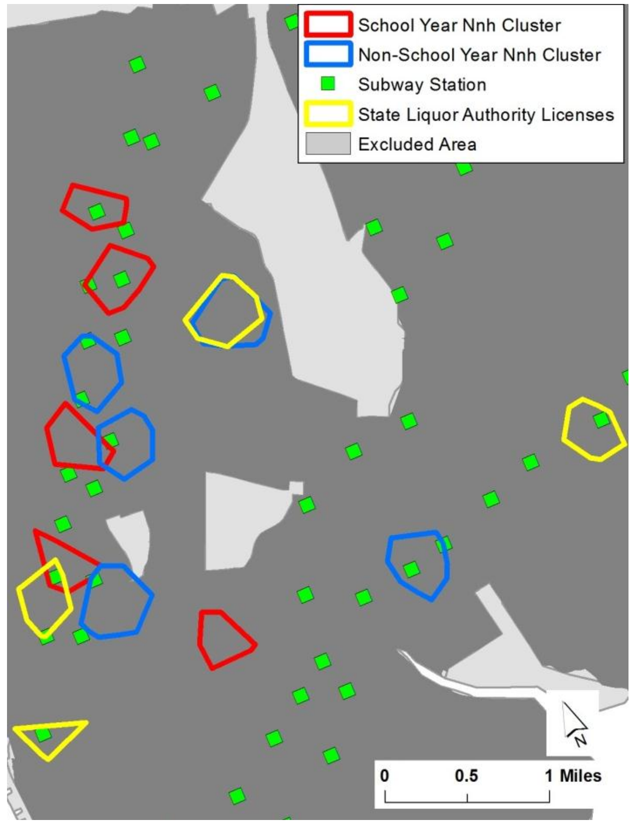


Figure 3.47: Nnh Assault Clusters by hour of day,
3pm School Day Nnh Clusters (red),
1am Non-School Day Clusters (blue), and
Nnh SLA Liquor Retail clusters (yellow)

Figure 3.46 shows the 3pm school day (red) and the 2am non-school day (blue) assault clusters. If you compare these clusters to the clusters in Figure 3.47, you will notice that there is some spatiotemporal variation between the two sets of Nnh clusters (figure 3.46 shows the 3pm/1am hourly peaks from figure 3.47). While there was no significant relationship between the assault clusters and SLA retail license clusters in figure 3.46, when the assault data was queried and clustered by peak time of day, a significant pattern emerges. There is a 2am assault (blue) cluster (figure 3.47) that completely overlaps an SLA retail license cluster (yellow).

The violent crime and land-use relationships are not always evident, but environmental criminology guided ESDA and MLUA provides an excellent opportunity to explore the various spatiotemporal patterns.

3.3 BUSINESS ESTABLISHMENT/PREMISES TYPE ANALYSIS

Crime	Risky Businesses - Results Summary
Murder	• Overall, murder hot spots are not (spatially) related to businesses, they are related to NYCHA public housing • Murder premises indicate that bars & night Clubs are the highest business type for murder location
Rape	• There are several businesses that fall within the rape clusters • Rape premises data indicate hotels/motels are the highest business type for rape locations
Robbery	• The robbery clusters contain the highest number of businesses compared to all other violent crimes • Subway stations, Bodegas, and playgrounds are the highest business type of robbery locations
Assault	• The assault clusters contain more businesses than the other violent crimes, except for robbery. • Bars & Night Clubs, Schools, and Bodegas are the highest business type for assault locations.
Shooting	• Shooting clusters do contain businesses, but not as many as robbery and assault • Bars & Night clubs, Bodegas, and Fast Food restaurants are the highest business type for shooting locations

Table 3.19: Risky Businesses – Results Summary

Business establishment and premises type analyses are better able to explain the actual violent crime locations in much more detail, since there is information on each crime location in the violent crime datasets. The Hot Spot analyses in the previous section are designed to explain the areas encompassing the violent crime concentrations (using the different hot spot methods) and provide a much better 'big picture' of crime locations.

The following tables will explain how each of the hot spot methodologies explains the relationship(s) between business establishments, premises types, and the five violent crimes. The appendix has the comprehensive list of premises types for each of the violent crimes.

<u>Risky Businesses – Murder Analysis</u>

Murder Cluster ID	# of Murders	Business Establishments in Murder Cluster	Murder Location Premises Types
1	9	Grocery, Church, Beauty Salon, Cleaners, Barber	56% Apartment 44% Street
2	9	None	89% Apartment 11% Other
3	7	Chinese Restaurant, Bodega, Barber	43% Public Housing 43% Street 14% Bodega
4	6	None	67% Public Housing 17% House 17% Street
5	6	Liquor	100% Public Housing
6	6	Laundry, Funeral Home, Nail Salon, Barber Shop,	50% Apartment 17% Merchant 17% Street 17% Park

Table 3.20: Risky Businesses – Nnh Murder Clusters, Business Types, and Premises Types

Table 3.20 shows each of the six murder clusters and the business establishments and premises types within each cluster. Since the clustering methodology is standardized based on a minimum number of murders (n=5) and size (.1 mile area), each of the clusters is spatially comparable. Each of the murder clusters has a somewhat different business establishment and premises type structure. Barber shop is the most common business establishment link between the murder clusters, although this is one of the more popular business establishment types (n=249) in the Bronx.

The Premises Type data details the murder location premises within each of the murder clusters. The Premises Type is the most accurate descriptor for each of the violent crime locations, since it is provided by the reporting NYPD officer. The premises type data indicates a very strong relationship between murder locations and public housing complexes (NYCHA), residential apartment complexes, and streets.

Risky Businesses – Rape Analysis

Table 3.21 shows each of the five rape clusters and the business establishments and premises types within each rape cluster. Since the clustering methodology is standardized based on a minimum number of rapes (n=10) and area (.1 mile area), each of the clusters is comparable. Each of the rape clusters has a somewhat different business establishment and premises type makeup, however beauty salons (SIC# 723106) are in 4 out of 5 of the clusters. Similar to barber shops, beauty salons (n=904) are one of the more popular business establishment types in the Bronx.

Rape Cluster ID	Number of Rapes	Businesses in Rape Cluster	Rape Location Premises Types
1	12	Beauty Salon, Pharmacy, Fast Food, Supermarket, Bodega, School, Church, Laundry	92% Apartment House 8% House
2	11	Beauty Salon	100% Apartment House
3	11	Beauty Salon, Church, Check Cashing	100% Apartment House
4	11	Hotel, Daycare, Barber, Beauty Salon, Restaurant, Jewelers,	73% Apartment House 27% Hotel / Motel
5	11	Child Care, Bodega	100% Apartment House

Table 3.21: Risky Businesses – Nnh Rape Clusters, Business Types, and Premises Types.

The Premises Type data details the rape location premises within each of the rape clusters. The premises type data indicates a very strong relationship between rape locations and residential areas (apartment houses, houses, and hotel/motels). Apartment houses contained 93% of the rapes within the rape clusters. As the hot spot methods indicated, there is a significant spatial relationship between rape and locations with higher population densities.

Risky Businesses – Robbery Analysis

Table 3.22 shows each of the five robbery clusters and the business establishments and premises types within each robbery cluster. Since the Nnh clustering methodology is standardized based on a minimum number of robberies (n=160) per area (.1 mile area), each of the clusters is comparable. Each of the robbery clusters is located in a much more commercial area, when compared to the murder, rape, and shooting cluster areas. It is also evident that the majority of the robberies inside the robbery clusters occurred outside on the street, versus inside residential units for murder and rape.

Robbery Cluster ID	Number of Robberies	Businesses in Cluster	Robbery Location Premises Types
1	185	100+ Businesses NYCHA, Clothing, Restaurants, Banks, Park, Cell Phone, Pharmacy, Shoes, Barber, Check Cashing, Music, Jewelry	55% Street 12% Subway 9% Apartment House 7% Bank 2% Clothing Store 2% Fast Food 2% Restaurant 11% Misc.
2	182	175+ Businesses Health Center, Library, Health Services, Social Services, Fast Food, Drug Rehab, Clothing, Banks, Pawn Shop, Cell Phone	68% Street 4% Apartment House 3% Bank 3% Subway 3% Bus Stop 20% Miscellaneous

3	165	250+ Businesses NYCHA, Hospital, Banks, Social Services, High School, Restaurants, Drug Rehab, Child Care, Cell Phone, Jewelry, Nail Salon	56% Street 19% Subway 4% Bank 4% Apartment House 2% Public Facility 15% Miscellaneous
4	164	100+ Businesses Hospital, Elementary School, Fast Food, Clothing, Banks, Western Union, Cell Phone, Check Cashing, Laundromat, Liquor, Nail Salon, Grocery	54% Street 16% Apartment House 13% Subway 3% Check Cashing 3% Bodega 2% Bank 9% Miscellaneous
5	160	150+ Businesses Elementary School, Grocery, Sporting Goods, Fast Food, Pharmacy, Cell Phone, Barber, Check Cashing, Pawn Broker	53% Street 12% Apartment House 11% Subway 4% Fast Food 3% Chain Store 2% Bank 15% Miscellaneous

Table 3.22: Risky Businesses – Nnh Robbery Clusters, Business Types, and Premises Types

Risky Businesses – Assault Analysis

Table 3.23 shows each of the five assault clusters and the business establishments and premises types within each assault cluster. Since the clustering methodology is standardized based on a minimum number of assaults (n=120) and area (.1 mile area), each of the clusters is comparable. Similar to robbery, each of the assault clusters is located in a much more commercial area, when compared to the murder, rape, and shooting cluster areas. It is also evident that there is significant variance between clusters, both in the commercial density (number of businesses) per assault cluster and the percentage of assaults occurring outside on the streets versus inside apartment houses. The primary difference between the assault cluster businesses and the robbery cluster businesses is the number of licensed alcohol establishments within the assault clusters. Additionally, the Bronx Criminal Court is highlighted as the primary 'hot lot' within assault cluster #5.

Assault Cluster ID	Number of Assaults	Businesses in Cluster	Assault Location Premise Types
1	158	40+ Businesses Alcohol x 3, NYCHA Furniture, Restaurants, Schools, Church, Grocery, Beauty Salon, Barber, Pawn Broker, Check Cashing	48% Apartment House 42% Street 4% House 1% Bodega 1% Public Building 4% Miscellaneous
2	145	75+ Businesses Alcohol x 2, Subways x 2 Supermarket, Restaurants, Cell Phone, Dry Cleaners, Salon/Barber, Liquor, Check Cashing, Pharmacy, Mental Health	57% Street 25% Apartment House 4% Restaurant 3% Bar/Night Club
3	129	90+ Businesses Subways x 2, Alcohol x 2, Hospital, Elementary School, Fast Food, Clothing, Beauty Salon, Cell Phone, Pharmacy, Mental Health, Barber, Jewelry,	54% Street 39% Apartment House 2% Bodega 5% Miscellaneous
4	127	60+ Businesses Subway x 1, Alcohol x 2 Restaurants, Deli, Check Cashing, Beauty Salon, Grocery, Bodega, Music,	54% Apartment House 35% Street 4% House 4% Bodega
5	121	125+ Businesses Bronx Criminal Court, Probation Children's Clothing, Restaurant, Pharmacy, Fast Food, Electronics, Shoes/Sneakers, Legal/Attorney Offices,	38% Public Building (Bronx Criminal Court) 19% Street 10% Commercial 10% Apartment House 4% Park / Playground 4% Parking Lot

Table 3.23: Risky Businesses – Nnh Assault Clusters, Business Types, and Premises Types

Risky Businesses – Shooting Analysis

Shooting Cluster ID	Number of Shootings	Businesses in Cluster	Shooting Location Premise Types
1	38	40+ Businesses NYCHA, Subway x 1 Restaurants, Nail Salon, Travel Agency, Grocery, Cell Phone, Beauty Salon, Fast Food,	45% Street 40% Apartment House 11% House 4% Miscellaneous
2	35	60+ Businesses Alcohol x 2, Subways x 2 Church, Grocery, Restaurants, Mosque, Beauty Salon, Liquor, Bodega,	91% Street 9% Apartment House
3	26	10+ Businesses NYCHA, High School, Elementary/Middle School. Community Center, Restaurants, Beauty Salon, Bodega,	50% Public Housing 46% Street 4% Public School
4	25	10+ Businesses NYCHA, Alcohol x 1 Restaurants, Pet Store, Furniture, Bodega,	60% Street 24% Apartment House 16% Public Housing
5	24	10+ Businesses NYCHA, Alcohol x 1 Beauty Salon, Laundromat, Restaurant,	58% Public Housing 42% Street
6	24	25+ Businesses Subway x 2, Alcohol x 1 Men's Clothing & Shoes, Grocery, Restaurants, Fast Food, Laundry, Cell Phone, Pharmacy, ,8/	64% Street 36% Apartment House

Table 3.24: Risky Businesses – Nnh Shooting Clusters, Business Types, and Premises Types

Table 3.24 shows each of the six shooting clusters and the business establishments and premises types within each shooting cluster. Since the clustering methodology is standardized based on a minimum number of shootings (n=24) and area (.1 mile area), each of the clusters is comparable. Similar to murder, the shooting clusters contain a mix of streets, apartment houses, and public housing. It is also evident that there is significant variance between the shooting clusters, both in the commercial density (number of businesses), types of businesses per shooting cluster and the percentage of shootings occurring outside on the streets versus inside apartment houses and public housing.

3.4 MICRO-LEVEL CRIME ANALYSIS

Zeroing In on Crime ? Why We Need to Move to the Micro-Level

The current trend in studying crime and place at the micro-level is simply a continuation of our historical interest in crime and place. If we continue to see clustering of crime at lower geographical levels, then we need to recognize that there are significant benefits of studying crime and place at these micro-levels. First and foremost, micro-level clusters provide easy 'targets' for directed police patrols and situational crime prevention strategies. It is much easier to target properties and street segments on specific times of day and days of the week, than it is to target entire neighborhoods for larger periods of time.

This is especially true when developing foot patrol strategies (Ratcliffe, 2011). If micro-level clusters of properties and street segments are responsible for a majority of the crime within an entire neighborhood, certainly a targeted foot patrol strategy would have a much more significant crime prevention / crime control benefit than police randomly patrolling entire neighborhoods using patrol vehicles. Moreover, incorporating temporal trends into spatial micro-level strategies maximizes prevention and control impact and outcomes. Second, this type of micro-level research provides a much better understanding of the social, structural, and opportunity factors that are related to crime and micro-level places.

One of the objectives in current environmental criminology and crime analysis is 'drilling down' on typical hot spot geographies that are generated by density and cluster maps. Using longitudinal crime data, it is now possible to zoom in to the micro-levels of geography and determine the actual cause(s) of the hot spots. This is the reason we map crimes to begin with –

to discover why crime patterns occur consistently at the same areas/places over time and to develop programs to intervene with these consistent crime patterns or problem areas. However, when we analyze hot spots and disaggregate the data within, several unique patterns begin to develop. Every hot spot does not act the same way. In fact, as was illustrated earlier, few crime hot spots behave similarly.

Hot Streets, Crime Streets, and Zero Crime Streets

Part of this dissertation research was devoted to finding out the variance of violent crimes at more macro-levels (tracts and neighborhoods) and explaining the spatiotemporal relationships of violent crimes within and between hot spots and street segments. One consistent result of the MLUA process that became very interesting along this dissertation pathway was the percentage of streets that contained zero crime, some crime, and a significant amount of crime (contained in a small percentage of streets). Table 3.25 shows how the MLUA process accentuates the amount of zero crime streets (streets with no reported violent crime between 2006-2010).

Crime	Crimes	Crimes per Street (Range)	Number of Crime Streets	% of Streets with Zero Crimes	Points of Interest
Murder	623	0 - 5	538	10,006 (95%)	13% of murder streets contain 25% of total murders
Rape	1,349	0 - 8	999	9,545 (91%)	7% of rape streets contain 18% of total rapes
Robbery	22,674	0 - 61	5,343	5,201 (49%)	14% of robbery streets contain 47% of total robberies
Assault	20,729	0 - 85	4,855	5,689 (54%)	9% of assault streets contain 38% of total assaults
Shootings	2,791	0 - 24	1,276	9,268 (88%)	26% of shooting streets contain 56% of total shootings
***4046 (38%) streets have zero violent crime over the 5-year study period**					

Table 3.25: Violent Crime, Number of Violent Crimes, Range of Crimes at the Street Level, Number of Crime Streets, Number and Percent of Zero Crime Streets, and Points of Interest

4. DISCUSSION & CONCLUSION

With police department budgets dwindling more and more during these difficult financial times, it is becoming vital for police departments to 'do more, with less'. New York City Mayor Michael Bloomberg eloquently stated this economic reality as the ability "to provide the service you need and then do it as efficiently as you can" (CBS Radio, 2011). With estimates of a 2-4% NYPD budget cut looming in 2011-2012, now more than ever is it important for the NYPD (and other police departments) to efficiently analyze, model, and utilize geospatial technologies.

4.1 DISCUSSION

Just as there is (almost) always significant spatial clustering with violent crime data, there is also (usually) significant temporal variation between and within violent crime data. This spatiotemporal realism is accentuated even more at the micro-level. Not all violent crimes act the same way and even the same crime(s) has significant internal temporal variations. As indicated earlier in the cones of resolution, when moving downward on the spatial cone of resolution, it becomes essential to correspondingly move down the temporal cone of resolution.

We should consider the temporal variations of crime at the higher spatial levels (block groups, tracts, and neighborhoods) a result of the dominant land uses (e.g. commercial, residential, recreational, transportation, vacant, etc.). According to the routine activities theory (Cohen & Felson, 1979), we would expect to see more daytime violence patterns in geographical areas where large groups of people congregate (e.g. commercial, recreational, transportation areas) or where groups of people are intermingling (e.g. transportation hubs, restaurants/bars).

Nighttime violence patterns in geographical areas may be dominated by areas with higher percentages of vacant land, public transportation hubs near high-density residential areas, or commercial areas (with late-night / 24-hour businesses, especially those serving alcohol) that lack effective place managers.

The micro-level crime analysis process (MLUA) that was developed for this dissertation research identifies spatiotemporal micro-level concentrations of crime, tracks these violent crime hot spots over time, and consistently monitors micro-level geographical units (i.e. properties and street segments) for changes in violent crime trends, land-use categories, business types, and population estimates. A significant contribution of this micro-level crime analysis process was the development and utilization of a micro-level population estimate (CEDS), which allows census tract population data to be disaggregated to micro-level units (i.e. tax lots) and then re-aggregated to higher level geographies (i.e. street segments).

One of the inherent problems in micro-level crime analysis research, such as this, is that it is difficult to categorize findings or generalize results. While there are results for each of the 10,544 Bronx street segments, not all of the street segment(s) findings are worth noting. The principal findings of this research are various spatiotemporal relationships between violent crime, land-use categories, & business type establishments.

Murder

For the crime of murder and non-negligent manslaughter, the results indicate that almost half of the murders occurred outside on the street or in some other location that would be considered ‘in public view’. Murder hot spots were related to specific public housing (NYCHA) projects in the southern section(s) of the Bronx. Since there are 90+ NYCHA housing projects in the Bronx, this is a significant finding because it identifies both the location (i.e. definitive sections/locations of specific housing projects) and when (i.e. day of week and time of day patterns) the murder problem exists within Bronx public housing. All of the murder hot spots were located on street segments in largely residential land-use areas (versus commercial or other dominant land-use categories). In the five neighborhoods that contained the highest number of murders (2006-2010), 9% of the street segments contained 100% of the murders (i.e. 91% of the street segments in the top 5 murder neighborhoods contained zero murders).

Rape

The spatiotemporal relationships between rape and land-use indicate that 87% of rape incidents occurred inside residential buildings (i.e. 64% apartments, 12% private house, 11% public housing). Just 5% of the rapes (2006-2010) occurred on the street or other 'outdoor' venue. As such, the crime of rape is much more of an 'indoor residential' violent crime compared to all of the other violent crimes studied whereas a significant percentage of the other violent crimes (i.e. murder, robbery, assault, and shootings) occurred on streets or other outdoor locations. All 5 of the Nnh rape clusters were located in smaller 'walk-up' apartment buildings, compared to larger elevator apartment buildings or NYCHA public housing. It should be noted that some of the rape HD zones contained NYCHA public housing, but this was also concentrated on public housing projects in the south Bronx (again, the high density zones are larger in size and more inclusive when compared to the Nnh clusters). In the five neighborhoods that contained the highest number of rapes (2006-2010), 15% of the street segments contained 100% of the rapes (i.e. 85% of the street segments in the top 5 rape neighborhoods contained zero rapes over the 5-year study period)

Robbery

Robbery continues to be the most prominent violent crime in the Bronx and the crime that NYPD allocates the most analytical resources on. The spatiotemporal relationships between robbery and land-use indicate that 60% of robberies occur on the streets or in other outdoor venues. The crime of robbery is much more of an outdoor public crime, compared to an indoor residential crime, like rape. The five Nnh robbery clusters indicated strong relationships to streets, especially those near subway stations. Streets that contained higher percentages of mixed residential-commercial buildings were also located within the Nnh robbery clusters. In the five neighborhoods that contained the highest number of robberies (2006-2010), 69% of the street segments contained 100% of the robberies (i.e. 31% of the street segments in the top 5 robbery neighborhoods contained zero robberies over the 5-year study period).

The most significant finding for robbery was the spatiotemporal relationship between robbery and subway stations based on the public school calendar. When the robbery data was temporally disaggregated based on the public school calendar, a very interesting daytime/nighttime temporal pattern emerged. There was a significant peak at 3pm, but only on schooldays when high school students were in school. However, when high school students were not in school (i.e. school holidays, weekends, summer break), the temporal pattern for robbery followed a traditional violent crime temporal pattern which peaks at midnight-1am. Overall, there are two very different, very distinct spatiotemporal patterns for robbery in the Bronx.

Assault

Interestingly, the temporal patterns for assault were similar to that of robbery. When the assault data was temporally disaggregated by the public school calendar, there were also two distinct assault patterns that emerged, a 3pm school day pattern and a 1am non-school day pattern. Moreover, many of the assault HD zones overlapped the robbery HD zones, however, there are noted differences between the 3pm and 1am HD zones for each of the respective crimes. The Nnh assault clusters indicate that streets, apartment houses, and the area in and around the Bronx Criminal Court are the primary assault locations. In the five neighborhoods that contained the highest number of assaults (2006-2010), 63% of the street segments contained 100% of the assaults (i.e. 37% of the street segments in the top 5 assault neighborhoods contained zero assaults over the 5-year study period).

Shootings

One of the more interesting findings of this micro-level research was the temporal analysis of shootings. The neighborhood of Mott Haven is undoubtedly the highest crime neighborhood of the 37 neighborhoods that comprise the Bronx. Mott Haven contains the highest number of rape, robbery, assault, & shootings (it was also the second highest neighborhood in murders). Over 60% of the shootings (n=177) in the Mott Haven neighborhood occurred during two 1-hour time periods (of the 168 hours of the week), between midnight-1am on Saturdays and Sundays.

Unfortunately, almost 70% of the street premise type data for shootings was ‘missing’. This made it difficult to determine the location type for many of the shootings (note, it did not impact the geocoding of the data). 40% of the shootings in the Bronx occurred on the streets. The shooting Nnh clusters were located on street segments that were in residential (multi-family walk-up and multi-family elevator) areas. The shooting HD zones identified several NYCHA public housing projects that contained high densities of shootings. 30% of the Bronx shootings occurred in the five neighborhoods that contained the highest number of shootings (2006-2010).

However, only 19% of the street segments in the top 5 shooting neighborhoods contained 100% of the shootings (i.e. 81% of the street segments in the top 5 shooting neighborhoods contained zero shootings over the 5-year study period).

<u>Violent Crime Streets</u>

This research indicates that there are numerous benefits to studying crime at the street segment level. One of the most interesting findings of this research was the significant percentage of streets in the highest crime neighborhoods that contained zero crime over the 5-year study period. By focusing on high crime streets, police can more effectively allocate their patrol and investigative resources and have a more substantial impact on violent crime.

Another benefit of analyzing and allocating patrol and investigative resources based on crime streets (versus neighborhoods) is that a significant number of the highest crime streets do not fall within the highest crime neighborhoods. By focusing on the highest crime streets, police can identify and target the few problem properties (i.e. risky facilities) on the high crime streets. Moreover, once identified, these risky facilities can be tracked if they move to other Bronx neighborhoods or areas within New York City.

4.2 CONCLUSION

Continuing advances in the fields of environmental criminology and geographical information sciences are facilitating place-based research. One of the current trends in environmental criminology is the focus on micro-level 'places' including street segments, property lots, and specific kinds of buildings and facilities in understanding crime patterns and the opportunity structure that permits crime. Despite important findings on the concentration of crime in urban areas, there continues to be substantial gaps in our knowledge about micro-level spatiotemporal patterns of crime. These gaps in micro-level environmental criminology research have primarily been a result of the lack of access to data, availability of ancillary data (land-use & business establishment data), accuracy of geocoded crime data, and availability of existing theory and methods to study crime at micro-levels.

Interestingly, many studies indicate that crimes are clustered at neighborhood level, but the entire neighborhood is rarely (if ever) criminogenic and only specific parts of neighborhoods contain high concentrations of crime. Prior studies incorrectly assume that the relationships between crime, population, land-use, and business establishment types are both homogenous and spatially stationary. Environmental criminologists using Pareto's 80/20 concept pointed out that not all parks are full of drug users/dealers, not all high schools have high rates of delinquency, not all bars contain high rates of assault, and not all parking lots have high rates of auto theft. In fact neighborhoods contain hot spots (high density crime areas) and cold spots (low density crime areas), bad streets and good streets, and good and bad businesses.

By undertaking a micro-level spatiotemporal framework, this dissertation research is intended to promote understanding of the patterns of violent crimes and the opportunity factors that contribute to these crimes in neighborhoods, street segments, property lots and business establishment types. The integration of environmental criminological theory and novel spatial analyses at the street segment and property lot level should help criminology/criminal justice scholars and practitioners to better understand the spatial and temporal processes in the 'magma' that fuels today's hot spots.

This study integrates data compiled by the NYPD about the types, extent, and magnitude of violent crime at the micro level (n= 49,582 major violent crimes including murder, rape, robbery, shooting and assaults at the address level in Bronx, one of the five boroughs in NYC), with new micro-level census population estimates, as well as detailed spatial land-use data by the New York City Department of City Planning and Finance, and business establishment type data from InfoUSA. It therefore constitutes a study that makes unique contributions in understanding crime patterns at the micro level and in informing future research and policies for designing out crime in micro-level places.

For the purposes of this present study, violent crime was measured using a micro-level unit aggregation process that sums each individual crime location (point) to street segments, census tracts, and neighborhoods. Traditional hot spot methodologies, including nearest neighbor hierarchical clustering, kernel density estimation, and Gi* hot spot statistics were used for each violent crime and related to land-use categories and business establishment types. This assisted in evaluating the strengths and weaknesses of each of the above hot spots analytical tools/techniques.

The results of this research suggest that there are numerous (complex) spatiotemporal relationships between violent crime types, land-use categories, and business establishment types, which vary over both space and time. It is important to note that a small percentage of street segments in the highest crime neighborhoods in the Bronx are responsible for a majority of the crime in those neighborhoods, while most of the street segments in high crime neighborhoods have zero crimes on them over the 5-year study period (2006-2010). Several crime specific relationships are noteworthy: robbery hot spots are strongly associated with subway stations (at certain days of the week and times of day); temporal assault hot spots are associated with clusters of licensed alcohol outlets; and murders and shootings are associated with some public housing complexes. This comprehensive micro-level ecological framework is capable of continuously identifying spatiotemporal patterns of crime, monitoring micro-level estimates of population, land-use categories, and tracking 'risky facilities' (e.g. businesses with crime problems) over time.

In sum, the shifting trends in criminology from offender-based theories to place-centered research have resulted in considerable reductions in crime throughout the USA and elsewhere. This research will assist law enforcement crime control strategies, advancement of environmental criminology theories at the micro-level, and expansion of existing crime prevention frameworks.

Crime Control Strategies

One way the NYPD currently achieves efficient crime prevention and crime control is by continuously analyzing crime and developing prevention and control strategies at both the macro (county, precinct) and micro-levels (police sectors, streets). The NYPD CompStat system was designed to analyze crime patterns at the precinct, patrol borough, and county levels on a weekly/bi-weekly basis. The newer 'Operation Impact' system is a much more dynamic crime analysis management system, which continuously analyzes crime patterns and trends at the street and (police) sector level on a day-to-day basis. Under Operation Impact, hundreds of uniformed and plain-clothes police officers that are (foot) patrolling high crime areas one day can be redeployed to completely different micro-level areas the following day/week. Both CompStat and Operation Impact are utilized by NYPD, but both operate at different spatiotemporal levels and have different goals/objectives.

If the emerging trend within local government agencies is ‘doing more, with less’ (resources), then we need to understand the importance of advancing crime analysis, while also advancing our understanding of crime prevention and control strategies. New analyses, especially those at micro-level geographical scales will generate a wealth of new data for police to analyze, plan with, and respond to. As such, large scale information sharing initiatives, such as crimesolutions.gov and the POP Center (www.popcenter.org) become more important. These information sharing websites have become a repository for accepted research and confirmed crime prevention and control initiatives.

This research hopes to benefit both policing strategies that focus on crime prevention and crime control by providing a much more comprehensive ‘look’ at crime, while also identifying micro-level areas that would benefit from prevention and control initiatives. One distinct improvement that this type of micro-level crime analysis has for future prevention and control initiatives is an efficient continuous analysis process, as well the ability to track and monitor changes in crime over small areas and short periods of time. As such, the results from the micro-level analyses will provide a better of understanding to crime prevention and control specialists of ‘what works, what doesn’t work, and what needs to be changed’.

Advancing Environmental Criminology at the Micro-Level

One of the current themes in environmental criminology is the focus on micro-level areas and the inherent opportunity structures that are created at crime locations & places (Natarajan, 2011). Traditional macro-level studies of crime have focused on the social and economic features of neighborhoods and communities (Sampson & Groves, 1989; Bursik & Grasmick, 1993). The predominant theories in the criminology of place include routine activities (Cohen and Felson, 1979; Felson, 2001), crime pattern theory (Brantingham & Brantingham, 1993), and situational crime prevention (1995). Criminologists can benefit from a better understanding of the immediate setting(s) where crime takes place, as well as an improved understanding of the interaction between the offender, victim, and the actual crime setting. An example of this may include the varying opportunity structures that exist for assaults that frequently occur at a bar.

A bar's occupants (both type of occupant and number of occupants) will vary significantly by both time of day and day of week. The reason(s) for fights that happen on a Monday night football night may differ from fights that occur on Thursday night ladies night, which also may differ from fights that happen on Saturday or Sunday afternoons during the baseball or scocer playoffs. All three of these examples indicate different opportunity structures for the same crime (i.e. assaults) that occur within the exact same place setting. As Clarke has noted (1980, 1995), it is much easier to change the situations and reduce opportunities at a business by using techniques of situational crime prevention.

Besides a better understanding of the opportunity structures necessary to commit crime, there also needs to be increased knowledge on how the routine activities (Cohen and Felson, 1979) of people and places (Eck & Weisburd, 1995) contributes to crime at the micro-level. Similarly to the variance within opportunity structures for crime, there is considerable change in the population (both type of people and number of people) at places based on the time of day and day of week. While the routine activity approach was developed to describe predatory crime interactions, it also does a superb job of classifying the changes in population(s) at places over time and how these population changes impact victimization (Felson & Poulsen, 2003).

This dissertation research offers a unique framework for criminologists because it provides a more micro-level understanding of 'crime places', since it incorporates both the opportunity structures for crime to occur based on specific land-use / business types, while taking the routine activities of people (over time) into consideration (Felson, 2002). In order for us to better understand crime (not criminality), we must first understand the similarities between opportunity and motive and how these two important concepts interact with both space and time at micro-level places.

There are several advantages for using street segments as a micro-level unit of analysis when conducting geospatial modeling and mapping for crime analysis. As was illustrated earlier, there is considerable internal spatiotemporal variation(s) when conducting traditional hot spot analyses and neighborhood level crime analyses. Understanding that crime is clustered in both space and time is not a new finding, however, this research highlights some of the benefits of utilizing street segments as micro-level units of analysis, including identification of hot streets and detection of spatiotemporal patterns at the micro-level.

It is important to note that the identification of spatiotemporal patterns of crime streets provides significant 'actionable intelligence' for police departments. Understanding that a small percentage of streets are responsible for a significant percentage of violent crime is an important finding of this research. Likewise, the significant percent of street segments with zero crime or very low crime (over time) is equally important. Both of these findings can assist in the development of street level crime prevention and control strategies that can save police departments considerable resources (patrol and investigative resources, time, money) and provide police with a much better understanding of the relationship between crime and opportunity at the street level.

Expansion of Crime Prevention and Control Strategies

This dissertation research studies crime at the micro-level (i.e. property lots and street segments), which provides a wealth of new information that can be used for crime prevention and control strategies (Clarke & Eck, 2007). The idea of micro-level crime analysis research (using land-use and business establishments) can assist police by providing information on specific types of facilities (e.g. assaults at bars), as well as identifying those specific risky businesses that fall within each problematic land-use/business type (e.g. fights at Bar X on Thursday nights, Bar Y on Saturday nights, etc.).

Typical hot spot analyses are (usually) unable to identify the various types of facilities that are actually generating crimes in an area (especially within larger areas, like neighborhoods and counties). Hot spot analyses identify areas (e.g. Nnh clusters, density zones) that contain high concentrations of crime when *compared* to the rest of the study areas. One significant shortcoming of hot spots is that high-crime properties and high-crime street segments may simply fall under the threshold that identifies the area as a hot spot.

This problem was highlighted in this research when analyzing the patterns of violent crime at the street level. More than 65% of the highest crime street segments did not fall inside of the highest crime neighborhoods. The micro-level analysis process developed for this dissertation is better able to identify any/all of the problem properties and / or high crime street segments within the study area.

In addition to identifying problematic land-uses and business-types and their spatiotemporal relationships to crime, this micro-level crime analysis process can also identify high-crime properties within land-use/business type establishment categories (e.g. identify those subway stations with higher rates of robbery compared to all other subway stations). This is important because it provides police with an easy explanation as to why a specific property / business was targeted for crime prevention and control strategies (e.g. if bar X has an assault rate 5 times higher than the other bars in the area).

One strategy that I would like to promote as a result of this research is a 'top 100' list of spatiotemporal high crime streets (on a county level) or a 'top 10 crime streets' for each of the 37 Bronx neighborhoods. A 'top 10 crime street list' would provide police with easy to understand temporal targets for crime prevention and control programs. Since street segments (i.e. places) do not move over time, police could then focus solely on the opportunity structures or routine activities of victim(s) and / or offender(s) at these high crime micro-level areas. Again, this micro-level analysis process allows for progress of prevention and control programs to be consistently monitored over time, successes and failures can be noted, and strategies can be constantly reassessed and modified as needed.

4.3 RESEARCH LIMITATIONS

This research promotes advances in micro-level (geographical units below the census block group level) crime analysis techniques. One of the significant shortcomings of this research is the census data that was disaggregated using the CEDS process (Maantay et al, 2007). The only census data that was available at the beginning of this research was the year 2000 census. However, at the end of this research, the 2010 census data became available. Since this research analyzes violent crime from 2006-2010, it would have been ideal to also disaggregate the 2010 census data to the 2010 property lots. This would have allowed me to calculate the change in micro-level populations between the two decennial census periods. In addition, approximately one percent of the property lots in the Bronx change shape, ownership, or land-use category each year. The urban backcloth is a continuously evolving landscape and this process used crime data for 2006-2010 and property lot data for 2008 only. Understandably, the change in population and land-use / business type can have a significant impact on micro-level crime rates.

Another research limitation that should be noted is a dual concept of endogeneity and the inherent micro-macro relationships between properties and neighborhoods. When studying street segments and property lots, one cannot overlook the importance or impact of the larger 'macro' levels (neighborhoods, counties) on the more micro level units. Similarly, not only does the larger geographical unit(s) 'push their influence downward' on the micro-level units, but it is difficult to determine what specific role the macro-level units have on the micro-level units (i.e. does a high-crime neighborhood generate crime problems for properties or is it problem properties that create a high-crime neighborhood, or is it some combination of the two) (Elffers, 2003). In addition to the micro-macro links between properties and neighborhoods is the change of properties and neighborhoods over time and the impact both of these have on one another. Example – crime may increase in a neighborhood, which discourages some people from moving in and encourages some people to move out of the neighborhood. In addition, businesses may move out of a neighborhood if crime begins to increase, thus leaving a vacant business/empty building that would then attract crime.

4.4 FUTURE RESEARCH

In order to alleviate some of the limitations mentioned throughout this dissertation, there are some additional datasets, methods, and analyses that could be employed in future research. The incorporation of multilevel modeling would provide a method to measure the impact of the macro-micro link within and between neighborhoods and their respective street segments. Utilizing two or more years of land-use category data, as well as business establishment types, would provide better insight as to the impact in the change of land-use/business type and its temporal impact on micro-level crime patterns and trends.

It would be interesting to include different types of qualitative data into this type of spatiotemporal micro-level crime analysis. This might provide some insight into the impact of broken windows type variables (i.e. quality of life offenses) on small-scale crime places. It would also be interesting to determine the various linear trends of crime at street segments over a longer time period (5 years, 10 years, 20 years). This would require a wealth of data, as well as historical street centerline files that can account for changes in the street network(s) over time.

NYPD has been investing significant financial resources into closed-circuit television and other types of surveillance technology (i.e. red light cameras, mobile & fixed license plate readers, radiological sensors, etc.). It would be interesting to incorporate the surveillance technology into the micro-level crime analysis model (i.e. how could this technology assist with micro-level crime analysis).

4.5 FINAL STATEMENT

This dissertation has confirmed and elaborated upon a well-known environmental criminology observation – that a small percentage of places are responsible for a significant percentage of violent crime. In examining Bronx data on violent offenses , a substantial percentage of streets contain zero violent crimes over the 5-year study period – which has important implications for policing and the public's sense of security. The association between specific violent crimes and land-use/business establishment type was also established. In the case of the Bronx, several NYCHA housing projects were identified as multiple violent crime problem locations in specific parts of the county - the South Bronx. Subway stations were another focus of violent crime – especially robbery, but only during certain hours of the day and days of the week. Assaults also contained a unique spatiotemporal signature and were related to several clusters of licensed-alcohol retail locations.

Finally, this dissertation has demonstrated that spatiotemporal analysis at the micro-level can be extremely beneficial in our understanding of crime and place. In addition, by incorporating land-use category and business type establishment data, micro-level geospatial analysis provides a more comprehensive description of spatial patterns of all types of crime. These results reinforce the power of geospatial analysis and temporal mapping in criminology, but they also open the way to studies in many other disciplines concerned with urban life in America (e.g. sociology, anthropology, urban planning, and public health) – and suggest the importance of geography as a fundamental literacy issue in our curricula throughout higher education.

5. APPENDIX

PILOT STUDY / PRELIMINARY ANALYSIS

The following pages contain preliminary analyses that were completed on the 44th Precinct of the Bronx. Originally, this was done to determine the feasibility of this line of research. It is being included in this background section to introduce the primary issues between neighborhood level and micro-level crime analysis. I created several maps to illustrate the importance and need for more micro-level crime research. The maps also illustrate some of the theoretical and methodological issues that are inherent in neighborhood level research and how micro-level analyses may improve on these issues. The 44th Precinct was selected simply because it contains the highest amount of violent crime in the Bronx from 2000–2009 (n= 13,074). The 44th Precinct contains various sections of four neighborhoods (Concourse, High Bridge, Mount Eden, and Concourse Village). The fact that the precinct does not incorporate or overlaps four different neighborhood boundaries identifies the first significant problem.

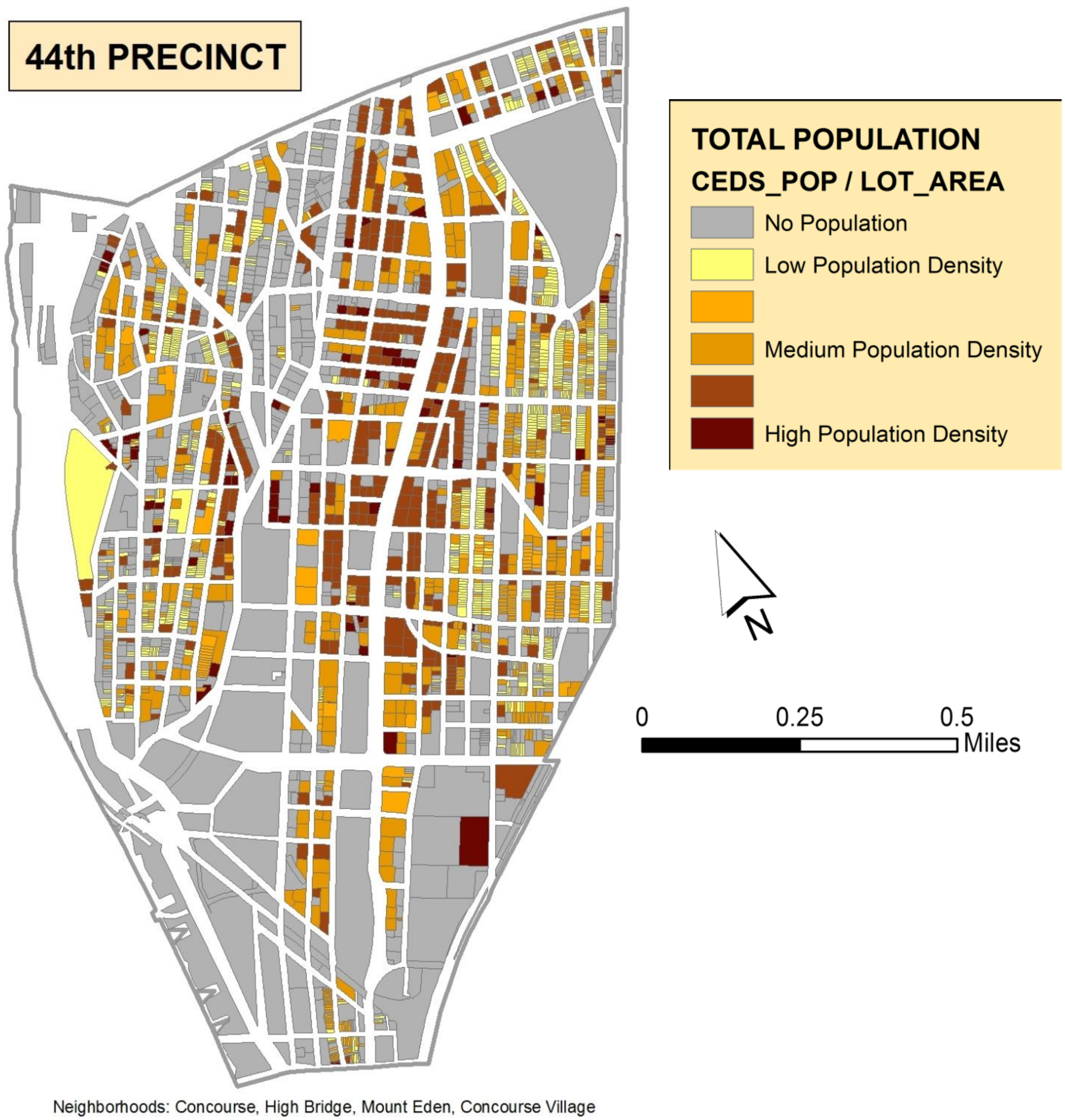
Each of the following maps will illustrate significant variance of crime, population density and distribution, land use, and business establishments throughout the 44th Precinct. Few studies, if any, take this statistical and spatiotemporal variance into consideration when they examine & quantify relationships, construct statistical & spatial models, and develop crime prevention, control, and public policy programs (Eck, J., 2002; Elffers, H., 2003; Groff et al., 2010). Preliminary average Nearest Neighbor Analysis (Nna) also indicates that crime, residential properties, and business establishments are all ‘clustered’ at both the county and the 44th precinct level. However, most crime clusters simply overlap residential (high population density) areas. When crime clusters do not contain high population densities, something else is fueling these non-residential crime clusters/hot spots.

These maps also start to outline several explanations why micro-level research will provide substantial new ideas for our understanding of crime and place. If we are able to collect, organize, and analyze data at the micro-level, we should be able to better understand the social, economic, and opportunity structures that generate our current crime trends/patterns.

MAP 1. POPULATION DENSITY

Utilizing a new and innovative census population estimation dataset you can clearly see that population density is not homogenous throughout the 44th Precinct properties. If population density is not homogenous, we should also assume that crime rates and crime trends are not homogenous throughout this area.

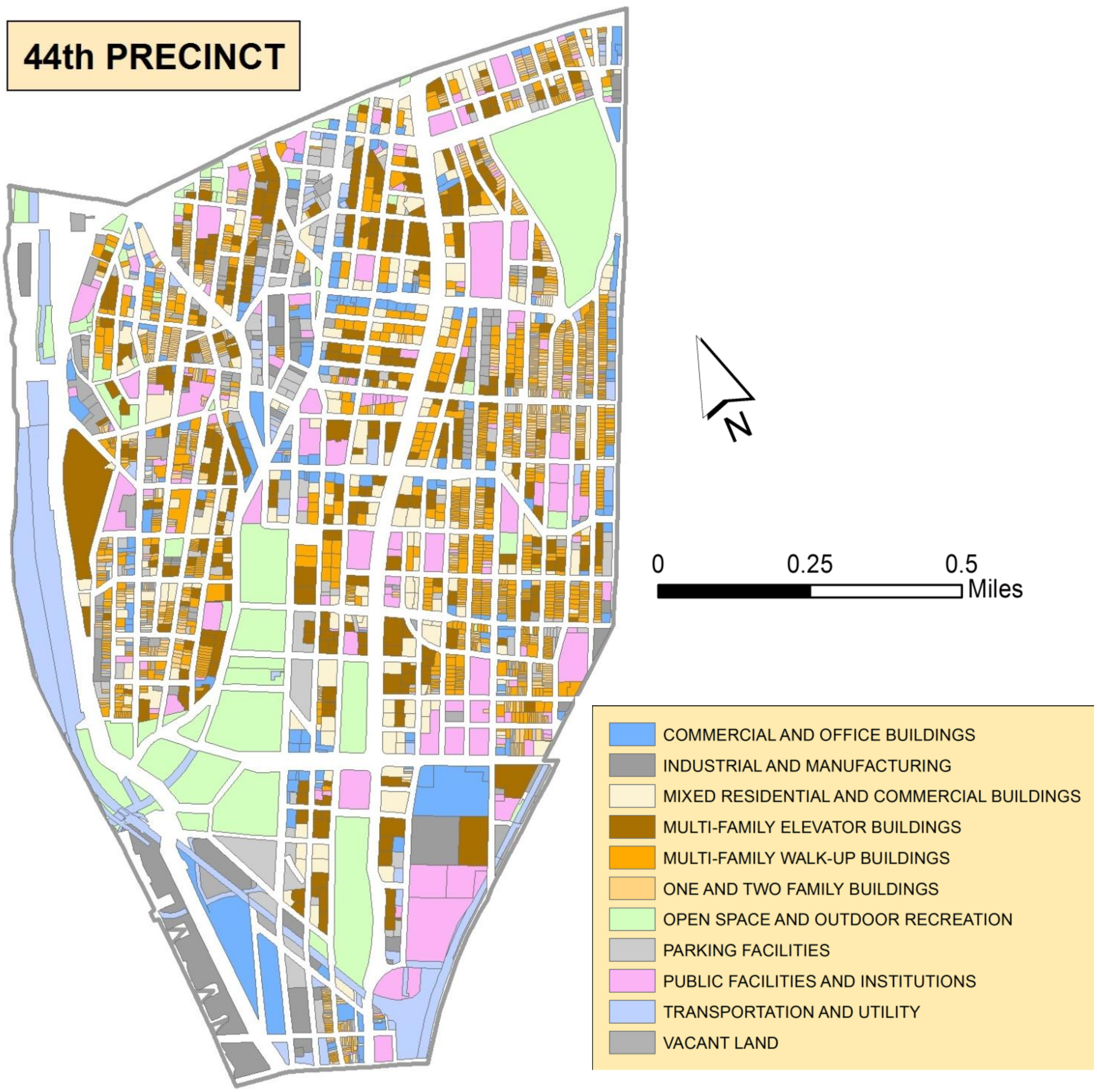
Additionally, the 44th Precinct of the Bronx incorporates four different 'neighborhoods'. As a result of the population density variance throughout the precinct (and neighborhoods), it is important that we examine crime at the lowest possible level (property-level or street-segment if possible). Aggregating spatial data increases error to any model(s), which can only cloud the picture (or worse, give you an entirely different story).



MAP 2. LAND-USE CATEGORIES

This map shows that land-use categories are not homogenous throughout the 44th Precinct.

Theory suggests that some land-use categories are more criminogenic than others (ie. assaults at bars). If this is correct, we would assume that crime rates and crime trends would vary throughout the precinct, simply based on land-use and business types.



Neighborhoods: Concourse, High Bridge, Mount Eden, Concourse Village

MAP 3. BUSINESS ESTABLISHMENT TYPES

Each point on this map represents a business establishment (this includes 'home and personal businesses'). This might be the first time an extensive business listing dataset is used in this type of micro-level environmental criminology research. The business dataset contains 2,800+ businesses within the 44th precinct. Each business 'point' can be categorized by its respective business type (ie. SIC code). The businesses in the 44th Precinct are comprised of more than 60 different business 'types'.

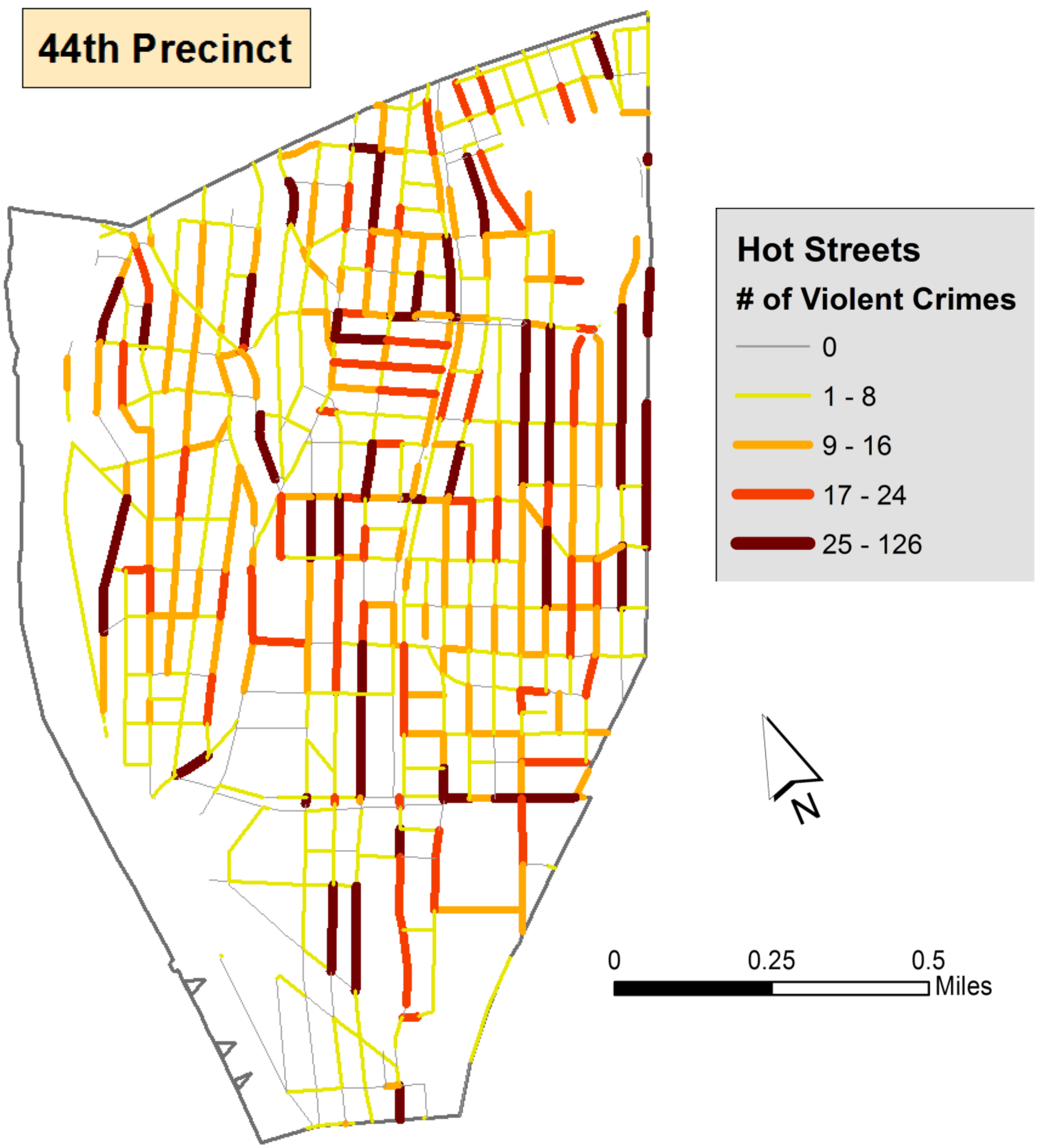
Research question: what business types are generating the various violent crime rates and crime trends ? What is creating the differences in crime rate/trends, both within & between business types ?

MAP 4. VIOLENT CRIME "HOT STREETS"

This map shows how violent crime, when aggregated to the street segment level, is not evenly distributed throughout the 44th Precinct street network.

Theory suggests that when motivated offenders and suitable targets converge, in the absence of capable place managers, crime will occur. As is illustrated, some street segments are much more criminogenic than others.

Research question: what is creating the variance in crime rates and crime trends at the street segment level ? Is it population, land-use, business types ?



Neighborhoods: Concourse, High Bridge, Mount Eden, Concourse Village

MAP 5. VIOLENT CRIME "HOT PROPERTY LOTS"

This map shows how violent crime, when aggregated to the property lot level, is not homogenous throughout the 44th Precinct.

Research question: what is creating the variance in crime rates and crime trends at the property lot level ? Which specific properties contain high/low amounts of (specified) crime ? Can we determine why specific crime (e.g. Assaults) occurs at specific locations (e.g. Bars) and not at other locations ?

MAP 6. ORTHOIMAGERY
This map shows an 'aerial view' of the 44th Precinct. The 2008 orthoimagery for New York City is extremely detailed (4 band digital, .5 foot resolution). As you can see, there are several easily identifiable locations within the 44th Precinct [Yankee Stadium (lower left); high-density public housing (left side, along the river); a NYC transit subway station / maintenance facility; and several bridges into Manhattan]

Neighborhoods: Concourse, High Bridge, Mount Eden, Concourse Village

Geographic Levels	Bronx	Dissertation Study Area
Tax / Property Lots	89,211	88,993
Streets	10,781	10,544
Block Groups	987	951
Tracts	355	343
Neighborhoods	38	36

CRIME	Bronx Crime (2006-2010)	Dissertation Study Area Crimes
Murder	657	623
Rape	1512	1349
Robbery	23018	22674
Assault	21564	20729
Shootings	n/a	2791

Murder Cluster ID	Number of Murders	Neighborhoods	Tracts	Streets
1	9	2	3	10
2	9	1	2	5
3	7	1	1	5
4	6	1	3	5
5	6	1	2	3
6	6	1	2	7

Murder Clusters

Rape Cluster ID	Number of Rapes	Neighborhoods	Tracts	Streets
1	12	2	5	7
2	11	2	2	6
3	11	2	3	2
4	11	1	2	4
5	11	2	3	5

Rape Clusters

Robbery Cluster ID	Number of Robberies	Neighborhoods	Tracts	Streets
1	185	2	4	17
2	182	1	5	18
3	165	2	3	27
4	164	2	2	22
5	160	3	4	19

Robbery Clusters

Assault Cluster ID	Number of Assaults	Neighborhoods	Tracts	Streets
1	158	1	1	11
2	145	2	3	21
3	129	2	3	22
4	127	1	3	22
5	121	2	3	17

Assault Clusters

Shooting Cluster ID	Number of Shootings	Neighborhoods	Tracts	Streets
1	38	2	3	6
2	35	2	3	15
3	26	2	3	8
4	25	1	4	9
5	24	2	2	9
6	24	2	2	7

Shooting Clusters

Neighborhood Name	Hood ID	Population	Murder	Rape	Robbery	Assault	Shooting
Morrisania/Melrose	1	31185	28	46	756	720	126
Parkchester	2	29958	7	16	452	297	19
Mott Haven Port Morris	4	49311	38	68	1299	1323	175
West Farms Bronx River	5	30548	12	39	589	620	59
Fordham South	6	24606	17	34	647	559	78
Van Cortlandt Village	7	50376	15	25	621	539	52
Woodlawn/Wakefield	8	43473	19	37	517	419	58
Norwood	9	40585	12	34	643	621	61
Claremont/Bathgate	10	26622	19	39	577	599	84
East Tremont	11	39312	20	54	1064	853	135
Pelham Bay/City Island	12	26923	1	16	132	120	5
University Heights Morris Heights	13	54162	25	51	956	898	139
Soundview/Castle Hill	14	45558	18	56	798	735	98
East Concourse Concourse Village	15	62681	39	66	1112	1231	154
Spuyten Duyvil Kingsbridge	16	29099	1	14	233	174	12
Co-Op City	17	40217	8	27	474	272	48
Westchester /Unionport	18	25510	5	16	356	308	18
Bedford Park Fordham North	19	54360	28	54	1037	837	105
Longwood	20	23833	24	31	609	564	101
Mount Hope	21	53357	37	66	966	928	158
Riverdale/Fieldston	22	27550	3	4	65	50	3
Van Nest/Morris Park	23	28728	11	28	516	401	35
Kingsbridge Heights	24	35092	13	30	719	537	37
Belmont	25	24125	10	40	520	413	33
Highbridge	26	33162	19	45	501	677	80
Melrose South Mott Haven North	27	28752	32	59	1014	782	148
Pelham Parkway	28	30213	5	13	324	201	34
Williamsbridge Olinville	29	52850	34	68	830	1065	175
West Concourse	30	41109	26	57	894	866	164
Soundview/Bruckner	31	34938	14	41	553	615	76
Eastchester/Baychester	32	36360	25	27	474	464	90
Crotona Park East	33	18956	16	22	428	376	44
Schuylerville Throgs Neck	34	40374	7	25	269	304	29
Allerton/Pelham Gardens	35	27839	9	25	348	232	33
Bronxdale	36	29857	13	28	594	403	46
Hunts Point	37	23274	13	48	787	726	79

Neighborhood Name	Hood ID	Population	% NHWH	% NHBL	% HISP	% POV	% NOHS
Morrisania/Melrose	1	31185	1	46	51	43	47
Parkchester	2	29958	6	45	39	20	27
Mott Haven Port Morris	4	49311	1	24	73	45	54
West Farms Bronx River	5	30548	4	27	62	31	41
Fordham South	6	24606	1	30	64	47	51
Van Cortlandt Village	7	50376	14	17	56	28	35
Woodlawn/Wakefield	8	43473	21	57	13	13	24
Norwood	9	40585	15	18	55	30	33
Claremont/Bathgate	10	26622	1	43	54	51	54
East Tremont	11	39312	2	31	65	46	49
Pelham Bay/City Island	12	26923	78	1	16	9	23
University Heights Morris Heights	13	54162	1	40	55	40	46
Soundview/Castle Hill	14	45558	3	38	57	32	37
East Concourse Concourse Village	15	62681	2	45	50	40	47
Spuyten Duyvil Kingsbridge	16	29099	58	7	25	11	18
Co-Op City	17	40217	15	58	24	9	19
Westchester /Unionport	18	25510	12	16	59	18	33
Bedford Park Fordham North	19	54360	12	18	59	35	41
Longwood	20	23833	2	21	75	46	55
Mount Hope	21	53357	2	27	66	38	50
Riverdale/Fieldston	22	27550	71	7	14	7	12
Van Nest/Morris Park	23	28728	40	8	41	18	32
Kingsbridge Heights	24	35092	5	23	65	39	45
Belmont	25	24125	24	17	53	46	50
Highbridge	26	33162	2	35	61	40	45
Melrose South Mott Haven North	27	28752	2	23	71	41	57
Pelham Parkway	28	30213	48	8	30	15	23
Williamsbridge Olinville	29	52850	5	71	19	23	33
West Concourse	30	41109	2	26	67	40	50
Soundview/Bruckner	31	34938	3	24	65	39	46
Eastchester/Baychester	32	36360	4	73	20	22	30
Crotona Park East	33	18956	1	36	61	39	50
Schuylerville Throgs Neck	34	40374	62	6	28	13	28
Allerton/Pelham Gardens	35	27839	36	30	25	11	28
Bronxdale	36	29857	24	27	42	21	33
Hunts Point	37	23274	1	22	75	46	57

Neighborhood Name	Hood ID	Avg. Weekday Subway Ridership	Avg. Weekend Subway Ridership	HS Enrollment	Male HS Enrollment	Female HS Enrollment
Morrisania/Melrose	1	2593	2901	2412	880	1532
Parkchester	2	6228	5825	0	0	0
Mott Haven Port Morris	4	34183	36239	2600	1598	1002
West Farms Bronx River	5	0	0	511	361	150
Fordham South	6	28868	35558	0	0	0
Van Cortlandt Village	7	12763	11811	3785	1786	1999
Woodlawn/Wakefield	8	6058	5932	0	0	0
Norwood	9	7391	7602	0	0	0
Claremont/Bathgate	10	0	0	2114	929	1185
East Tremont	11	4688	4237	695	343	352
Pelham Bay/City Island	12	7442	5647	0	0	0
University Heights Morris Heights	13	0	0	108	60	48
Soundview/Castle Hill	14	0	0	1053	411	642
East Concourse Concourse Village	15	13176	16738	959	529	430
Spuyten Duyvil Kingsbridge	16	15260	17138	1572	693	708
Co-Op City	17	3300	2477	3406	1893	1513
Westchester /Unionport	18	1878	1388	4288	2439	1849
Bedford Park Fordham North	19	20116	19752	0	0	0
Longwood	20	14061	14528	1016	464	552
Mount Hope	21	25453	28181	0	0	0
Riverdale/Fieldston	22	0	0	1327	682	645
Van Nest/Morris Park	23	8081	6543	464	290	174
Kingsbridge Heights	24	0	0	440	209	231
Belmont	25	0	0	1949	793	1156
Highbridge	26	0	0	0	0	0
Melrose South Mott Haven North	27	4196	4296	1859	1460	399
Pelham Parkway	28	7775	7247	361	216	145
Williamsbridge Olinville	29	14018	14197	735	486	249
West Concourse	30	50363	50824	1120	365	755
Soundview/Bruckner	31	27802	29865	0	0	0
Eastchester/Baychester	32	3325	2116	0	0	0
Crotona Park East	33	11984	12944	1868	969	899
Schuylerville Throgs Neck	34	0	0	0	0	0
Allerton/Pelham Gardens	35	7727	5044	268	194	74
Bronxdale	36	7544	7869	450	186	264
Hunts Point	37	16070	16513	0	0	0

Neighborhood Name	Hood ID	% LU-1 Lot Area	% LU-2 Lot Area	% LU-3 Lot Area	% LU-4 Lot Area	% LU-5 Lot Area	% LU-6 Lot Area
Morrisania/Melrose	1	15	19	18	9	3	5
Parkchester	2	6	5	13	4	9	0
Mott Haven Port Morris	4	7	7	10	6	5	19
West Farms Bronx River	5	27	35	16	4	6	1
Fordham South	6	7	24	19	16	15	1
Van Cortlandt Village	7	11	8	16	4	1	0
Woodlawn/Wakefield	8	58	12	18	2	4	3
Norwood	9	13	19	16	9	9	1
Claremont/Bathgate	10	7	9	2	8	7	13
East Tremont	11	10	13	4	4	6	1
Pelham Bay/City Island	12	30	6	13	2	3	1
University Heights Morris Heights	13	16	12	12	6	4	2
Soundview/Castle Hill	14	21	7	16	2	6	2
East Concourse Concourse Village	15	7	18	11	12	8	5
Spuyten Duyvil Kingsbridge	16	19	5	8	4	9	2
Co-Op City	17	8	2	2	0	22	2
Westchester /Unionport	18	38	12	10	3	9	17
Bedford Park Fordham North	19	14	23	9	10	10	0
Longwood	20	14	20	17	10	8	2
Mount Hope	21	11	20	15	14	9	4
Riverdale/Fieldston	22	29	2	30	0	1	0
Van Nest/Morris Park	23	31	12	17	5	11	3
Kingsbridge Heights	24	12	16	22	4	7	2
Belmont	25	8	15	17	7	7	1
Highbridge	26	8	15	26	10	6	4
Melrose South Mott Haven North	27	10	17	2	7	10	2
Pelham Parkway	28	23	4	3	2	4	6
Williamsbridge Olinville	29	42	19	2	3	5	0
West Concourse	30	1	7	5	8	11	6
Soundview/Bruckner	31	22	28	56	4	9	2
Eastchester/Baychester	32	29	7	22	1	3	5
Crotona Park East	33	18	13	32	4	10	10
Schuylerville Throgs Neck	34	39	5	18	1	4	1
Allerton/Pelham Gardens	35	70	7	3	5	8	0
Bronxdale	36	24	16	19	5	9	1
Hunts Point	37	2	3	0	1	2	26

Neighborhood Name	Hood ID	% LU-7 Lot Area	% LU-8 Lot Area	% LU-9 Lot Area	% LU-10 Lot Area	% LU-11 Lot Area
Morrisania/Melrose	1	1	15	4	6	7
Parkchester	2	1	12	2	3	1
Mott Haven Port Morris	4	3	9	12	6	3
West Farms Bronx River	5	1	9	4	2	1
Fordham South	6	1	9	3	5	2
Van Cortlandt Village	7	1	23	33	1	2
Woodlawn/Wakefield	8	1	7	4	3	3
Norwood	9	1	17	7	5	2
Claremont/Bathgate	10	1	16	10	7	4
East Tremont	11	1	8	39	3	3
Pelham Bay/City Island	12	0	14	27	0	3
University Heights Morris Heights	13	1	18	12	5	6
Soundview/Castle Hill	14	2	6	20	1	11
East Concourse Concourse Village	15	1	20	1	4	6
Spuyten Duyvil Kingsbridge	16	1	19	9	2	4
Co-Op City	17	2	15	3	4	7
Westchester /Unionport	18	3	6	2	3	4
Bedford Park Fordham North	19	1	13	7	3	1
Longwood	20	0	16	10	3	4
Mount Hope	21	2	11	3	6	3
Riverdale/Fieldston	22	0	19	10	0	5
Van Nest/Morris Park	23	1	26	3	4	3
Kingsbridge Heights	24	0	25	8	2	7
Belmont	25	0	51	1	5	1
Highbridge	26	2	10	6	8	8
Melrose South Mott Haven North	27	0	22	4	5	6
Pelham Parkway	28	1	19	28	1	2
Williamsbridge Olinville	29	0	8	14	2	2
West Concourse	30	3	9	29	9	1
Soundview/Bruckner	31	2	7	3	2	2
Eastchester/Baychester	32	5	6	31	1	3
Crotona Park East	33	4	10	6	4	7
Schuylerville Throgs Neck	34	0	11	22	1	6
Allerton/Pelham Gardens	35	1	6	0	1	2
Bronxdale	36	1	10	1	1	2
Hunts Point	37	20	3	2	4	14

Neighborhood Name	Hood ID	# of Tracts in Hood	% of Tracts with Zero Murder	% of Tracts with Zero Rape	% of Tracts with Zero Robbery	% of Tracts with Zero Assault	% of Tracts with Zero Shootings
Morrisania/Melrose	1	9	0	0	0	0	0
Parkchester	2	5	20	0	0	0	20
Mott Haven Port Morris	4	16	31	19	6	6	13
West Farms Bronx River	5	8	13	0	0	0	0
Fordham South	6	3	0	0	0	0	0
Van Cortlandt Village	7	8	25	13	0	0	0
Woodlawn/Wakefield	8	17	65	41	0	0	18
Norwood	9	7	14	0	0	0	0
Claremont/Bathgate	10	8	25	0	0	0	0
East Tremont	11	13	15	0	0	0	0
Pelham Bay/City Island	12	5	80	20	0	0	40
University Heights Morris Heights	13	12	25	17	0	0	8
Soundview/Castle Hill	14	14	36	14	7	0	7
East Concourse Concourse Village	15	10	10	10	0	0	0
Spuyten Duyvil Kingsbridge	16	8	88	25	0	0	38
Co-Op City	17	3	33	0	0	0	0
Westchester /Unionport	18	8	50	13	0	0	13
Bedford Park Fordham North	19	10	30	0	0	0	0
Longwood	20	5	0	0	0	0	0
Mount Hope	21	13	23	0	0	0	0
Riverdale/Fieldston	22	11	73	82	27	18	73
Van Nest/Morris Park	23	14	64	14	0	0	36
Kingsbridge Heights	24	7	29	14	0	0	14
Belmont	25	5	40	20	0	0	0
Highbridge	26	7	14	0	0	0	0
Melrose South Mott Haven North	27	8	0	0	0	0	0
Pelham Parkway	28	8	63	38	0	0	25
Williamsbridge Olinville	29	20	25	0	0	0	5
West Concourse	30	8	0	13	0	0	0
Soundview/Bruckner	31	8	13	0	0	0	13
Eastchester/Baychester	32	9	11	11	0	0	0
Crotona Park East	33	7	14	0	0	0	0
Schuylerville Throgs Neck	34	16	69	56	0	0	56
Allerton/Pelham Gardens	35	14	57	57	0	0	50
Bronxdale	36	7	29	0	0	0	14
Hunts Point	37	13	46	38	0	0	8

Neighborhood Name	Hood ID	# of Streets in Hood	% of Streets with Zero Murder	% of Streets with Zero Rape	% of Streets with Zero Robbery	% of Streets with Zero Assault	% of Streets with Zero Shooting
Morrisania/Melrose	1	255	91	87	31	29	80
Parkchester	2	148	95	91	33	47	91
Mott Haven Port Morris	4	441	93	89	45	47	83
47West Farms Bronx River	5	215	94	87	41	42	83
Fordham South	6	111	86	79	22	30	75
Van Cortlandt Village	7	192	92	89	32	41	86
Woodlawn/Wakefield	8	477	97	94	54	57	91
Norwood	9	184	94	86	30	35	83
Claremont/Bathgate	10	226	92	88	39	46	84
East Tremont	11	335	94	86	28	39	84
Pelham Bay/City Island	12	463	100	98	83	83	99
University Heights Morris Heights	13	247	91	87	30	35	74
Soundview/Castle Hill	14	407	96	90	52	57	89
East Concourse Concourse Village	15	275	88	83	30	35	78
Spuyten Duyvil Kingsbridge	16	243	100	95	63	74	97
Co-Op City	17	240	97	92	55	63	91
Westchester /Unionport	18	295	98	95	58	63	95
Bedford Park Fordham North	19	233	91	84	22	25	79
Longwood	20	148	86	84	23	24	70
Mount Hope	21	312	90	83	31	35	81
Riverdale/Fieldston	22	363	99	99	88	91	99
Van Nest/Morris Park	23	403	98	94	53	61	95
Kingsbridge Heights	24	108	90	82	15	23	83
Belmont	25	157	94	82	25	40	88
Highbridge	26	201	91	83	35	33	76
Melrose South Mott Haven North	27	253	91	83	28	36	80
Pelham Parkway	28	293	99	96	67	77	94
Williamsbridge Olinville	29	446	94	87	37	33	80
West Concourse	30	276	93	87	41	46	82
Soundview/Bruckner	31	141	91	80	27	29	82
Eastchester/Baychester	32	409	94	94	55	60	89
Crotona Park East	33	167	93	90	35	49	86
Schuylerville Throgs Neck	34	825	99	98	83	81	98
Allerton/Pelham Gardens	35	430	98	97	64	76	96
Bronxdale	36	181	93	86	27	41	86
Hunts Point	37	444	97	93	64	64	92

The following tables report the number of crimes and the number of neighborhood, tract, and streets that the respective violent crime clusters intersect. As you can see, one of the strengths of point pattern analysis is that it transcends higher level geographical boundaries.

Murder Cluster ID	Number of Murders	Neighborhoods	Tracts	Streets
1	9	2	3	10
2	9	1	2	5
3	7	1	1	5
4	6	1	3	5
5	6	1	2	3
6	6	1	2	7

Murder Cluster ID	Land-Use	Primary Land Use in Cluster	Businesses in Cluster	Murder Location Premise Types
1	LU1: 3% LU2: 37% LU3: 30% LU4: 15% LU8: 15%	Multi-Family Walk-up	Grocery, Church, Beauty Salon, Cleaners, Barber	56% Apartment 44% Street
2	LU1: 16% LU2: 31% LU3: 36% LU4: 11% LU7: 4% LU9: 1% LU10: 1%	Multi-Family Elevator	None	89% Apartment 11% Other
3	LU1: 4% LU2: 7% LU3: 66% LU4: 6% LU5: 3% LU9: 13% LU10: 1% LU11: 1%	Multi-Family Elevator	Chinese Restaurant Bodega Barber	43% Public Housing 43% Street 14% Bodega
4	LU1: 43% LU2: 57%	Multi-Family Walk-up	None	67% Public Housing 17% House 17% Street
5	LU3: 42% LU4: 42% LU5: 8% LU8: 8%	Multi-Family Elevator	Liquor	100% Public Housing
6	LU2: 8% LU3: 10% LU4: 23% LU5: 15% LU8: 2% LU9: 38% LU11: 3%	Open Space	Laundry, Funeral Home, Nail Salon, Barber Shop,	50% Apartment 17% Merchant 17% Street 17% Park

Rape Cluster ID	Number of Rapes	Neighborhoods	Tracts	Streets
1	12	2	5	7
2	11	2	2	6
3	11	2	3	2
4	11	1	2	4
5	11	2	3	5

Rape Cluster ID	Land-Use	Primary Land Use in Cluster	Businesses in Cluster	Rape Location Premises Types
1	LU1: 13% LU2: 29% LU3: 12% LU4: 13% LU5: 5% LU8: 22% LU9: 2% LU10: 2%	Multi-Family Walk-up	Beauty Salon, Pharmacy, Fast Food, Supermarket, Bodega, School, Church, Laundry,	92% Apartment House 8% House
2	LU2: 12% LU3: 66% LU4: 17% LU5: 3% LU11: 2%	Multi-Family Elevator	Beauty Salon	100% Apartment House
3	LU1: 7% LU2: 38% LU3: 24% LU4: 16% LU5: 2% LU8: 7% LU10: 1% LU11: 3%	Multi-Family Walk-up	Beauty Salon Church	100% Apartment House
4	LU1: 43% LU2: 57%	Multi-Family Walk-up	Hotel, Daycare, Barber, Beauty Salon, Restaurant, Jewelers,	73% Apartment House 27% Hotel / Motel
5	LU1: 6% LU2: 48% LU3: 17% LU4: 8% LU5: 12% LU9: 9%	Multi-Family Walk-up	Child Care, Bodega	100% Apartment House

Robbery Cluster ID	Number of Robberies	Neighborhoods	Tracts	Streets
1	185	2	4	17
2	182	1	5	18
3	165	2	3	27
4	164	2	2	22
5	160	3	4	19

Robbery Cluster ID	Land-Use	Primary Land Use in Cluster	Businesses in Cluster	Robbery Location Premises Types
1	LU1: 19% LU2: 8% LU4: 18% LU5: 37% LU8: 4% LU9: 8% LU10: 4% LU11: 2%	Commercial & Office Buildings	100+ NYCHA, Clothing, Restaurants, Banks, Park, Cell Phone, Pharmacy, Shoes, Barber, Check Cashing, Music, Jewelry,	55% Street 12% Subway 9% Apartment House 7% Bank 2% Clothing Store 2% Fast Food 2% Restaurant 11% Misc.
2	LU2: 12% LU3: 66% LU4: 17% LU5: 3% LU11: 2%	Multi-Family Elevator Buildings	175+ Health Center, Library, Health Services, Social Services, Fast Food, Drug Rehab, Clothing, Banks, Pawn Shop, Cell Phone,	68% Street 4% Apartment House 3% Bank 3% Subway 3% Bus Stop 20% Miscellaneous
3	LU1: 7% LU2: 38% LU3: 24% LU4: 16% LU5: 2% LU8: 7% LU10: 1% LU11: 3%	Multi-Family Walk-Up Buildings	250+ NYCHA, Hospital, Banks, Social Services, High School, Restaurants, Drug Rehab, Child Care, Cell Phone, Jewelry, Nail Salon,	56% Street 19% Subway 4% Bank 4% Apartment House 2% Public Facility 15% Miscellaneous
4	LU1: 43% LU2: 57%	Multi-Family Walk-Up Buildings	100+ Hospital, Elementary School, Fast Food, Clothing, Banks, Western Union, Cell Phone, Check Cashing, Laundromat, Liquor, Nail Salon, Grocery,	54% Street 16% Apartment House 13% Subway 3% Check Cashing 3% Bodega 2% Bank 9% Miscellaneous
5	LU1: 6% LU2: 48% LU3: 17% LU4: 8% LU5: 12% LU9: 9%	Multi-Family Walk-Up Buildings	150+ Elementary School, Grocery, Sporting Goods, Fast Food, Pharmacy, Cell Phone, Barber, Check Cashing, Pawn Broker,	53% Street 12% Apartment House 11% Subway 4% Fast Food 3% Chain Store 2% Bank 15% Miscellaneous

Assault Cluster ID	Number of Assaults	Neighborhoods	Tracts	Streets
1	158	1	1	11
2	145	2	3	21
3	129	2	3	22
4	127	1	3	22
5	121	2	3	17

Assault Cluster ID	Land-Use	Primary Land Use in Cluster	Businesses in Cluster	Assault Location Premise Types
1	LU1: 7% LU2: 49% LU3 : 16% LU4: 17% LU5: 8% LU8 : 1% LU10: 2% LU11: 1%	Multi-Family Walk-Up Buildings	40+, Alcohol x 3, NYCHA, Furniture, Restaurants, Schools, Church, Grocery, Beauty Salon, Barber, Pawn Broker, Check Cashing	48% Apartment House 42% Street 4% House 1% Bodega 1% Public Building 4% Miscellaneous
2	LU1: 7% LU2: 24% LU3 : 34% LU4: 18% LU5: 10% LU8 : 2% LU10: 3% LU11: 2%	Multi-Family Elevator Buildings	75+, Alcohol x 2, Subways x 2 Supermarket, Restaurants, Cell Phone, Dry Cleaners, Salon/Barber, Liquor, Check Cashing, Pharmacy, Mental Health	57% Street 25% Apartment House 4% Restaurant 3% Bar/Night Club
3	LU2: 27% LU3: 17% LU4: 26% LU5: 18% LU8: 11% LU11: 1%	Multi-Family Walk-Up Buildings	90+, Subways x 2, Alcohol x 2, Hospital, Elementary School, Fast Food, Clothing, Beauty Salon, Cell Phone, Pharmacy, Mental Health, Barber, Jewelry,	54% Street 39% Apartment House 2% Bodega 5% Miscellaneous
4	LU1: 21% LU2: 36% LU3: 20% LU4: 11% LU5: 3% LU8: 7% LU11: 2%	Multi-Family Walk-Up Buildings	60+, Subway x 1, Alcohol x 2 Restaurants, Deli, Check Cashing, Beauty Salon, Grocery, Bodega, Music,	54% Apartment House 35% Street 4% House 4% Bodega
5	LU3: 11% LU4: 17% LU5: 56% LU7: 2% LU8: 10% LU10: 3%	Commercial & Office Buildings	125+, Bronx Criminal Court, Probation Children's Clothing, Restaurant, Pharmacy, Fast Food, Electronics, Shoes/Sneakers, Legal/Attorney Offices,	38% Public Building (Bronx Criminal Court) 19% Street 10% Commercial 10% Apartment House 4% Park / Playground 4% Parking Lot

Shooting Cluster ID	Number of Shootings	Neighborhoods	Tracts	Streets
1	38	2	3	6
2	35	2	3	15
3	26	2	3	8
4	25	1	4	9
5	24	2	2	9
6	24	2	2	7

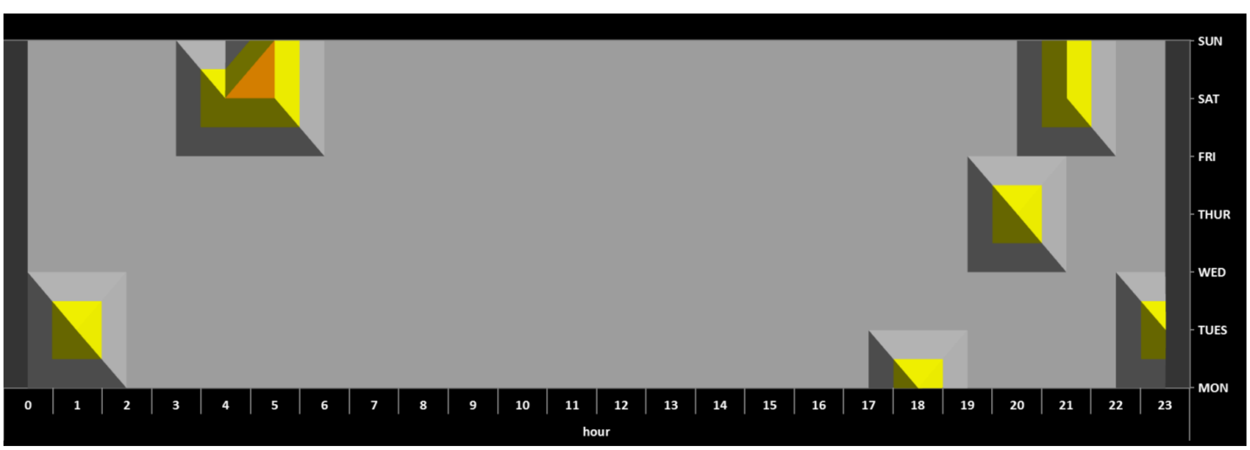
Shooting Cluster ID	Land-Use	Primary Land Use in Cluster	Businesses in Cluster	Shooting Location Premise Types
1	LU1: 1% LU2: 61% LU3 : 15% LU4: 7% LU5: 11% LU10: 5%	Multi-Family Walk-Up Buildings	40+, NYCHA, Subway x 1 Restaurants, Nail Salon, Travel Agency, Grocery, Cell Phone, Beauty Salon, Fast Food,	45% Street 40% Apartment House 11% House 4% Miscellaneous
2	LU1: 7% LU2: 29% LU3 : 26% LU4: 16% LU5: 12% LU8 : 3% LU9: 1% LU10: 3% LU11: 2%	Multi-Family Walk-Up Buildings	60+, Alcohol x 2, Subways x 2 Church, Grocery, Restaurants, Mosque, Beauty Salon, Liquor, Bodega,	91% Street 9% Apartment House
3	LU1: 9% LU2: 14% LU3: 18% LU4: 1% LU5: 1% LU8: 52% LU11: 5%	Public Facilities & Institutions	10+, NYCHA, High School, Elementary/Middle School. Community Center, Restaurants, Beauty Salon, Bodega,	50% Public Housing 46% Street 4% Public School
4	LU1: 14% LU2: 22% LU3: 21% LU5: 17% LU8: 20% LU10: 2% LU11: 4%	Multi-Family Walk-Up Buildings	10+, NYCHA, Alcohol x 1 Restaurants, Pet Store, Furniture, Bodega,	60% Street 24% Apartment House 16% Public Housing
5	LU1: 3% LU2: 14% LU3: 65% LU4: 3% LU5: 1% LU8: 1% LU10: 3% LU11: 9%	Multi-Family Elevator Buildings	10+, NYCHA, Alcohol x 1 Beauty Salon, Laundromat, Restaurant,	58% Public Housing 42% Street
6	LU1: 3% LU2: 14%	Multi-Family Elevator	25+, Subway x 2, Alcohol x 1 Men's Clothing & Shoes, Grocery,	64% Street 36% Apartment House

	LU3: 65% LU4: 3% LU5: 1% LU8: 1% LU10: 3% LU11: 9%	Buildings	Restaurants, Fast Food, Laundry, Cell Phone, Pharmacy, ,8/	

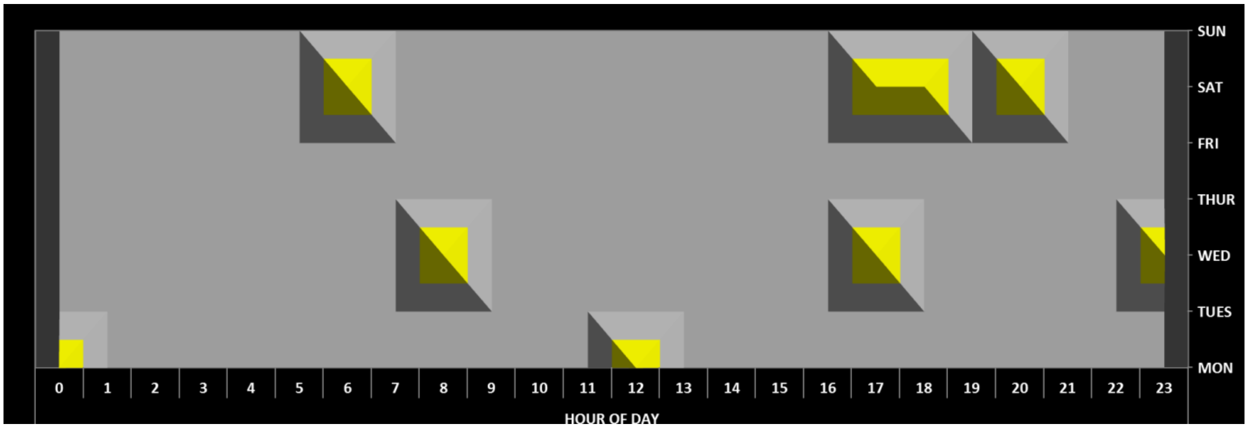
Murder Cluster ID	Total Population in Cluster	Percent NHWH	Percent NHBL	Percent HISP	Percent POV	Percent NOHS
1	2,086	18	20	54	32	43
2	1,744	32	20	45	47	43
3	621	3	26	69	31	61
4	148	1	48	49	39	45
5	2,555	8	40	50	40	37
6	311	42	18	38	15	26

Population Characteristics inside Murder Clusters

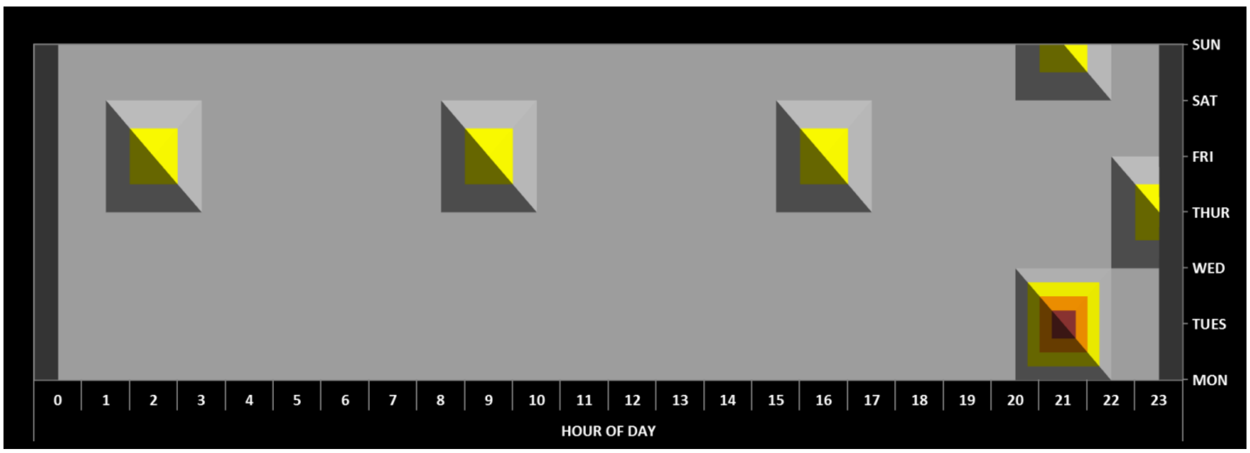
One advantage that micro-level Nnh clustering techniques has over KDE and GI* is that it allows for efficient temporal analysis of the violent crimes within each cluster. The figures below illustrate the temporal patterns of murder in each of the 6 clusters.



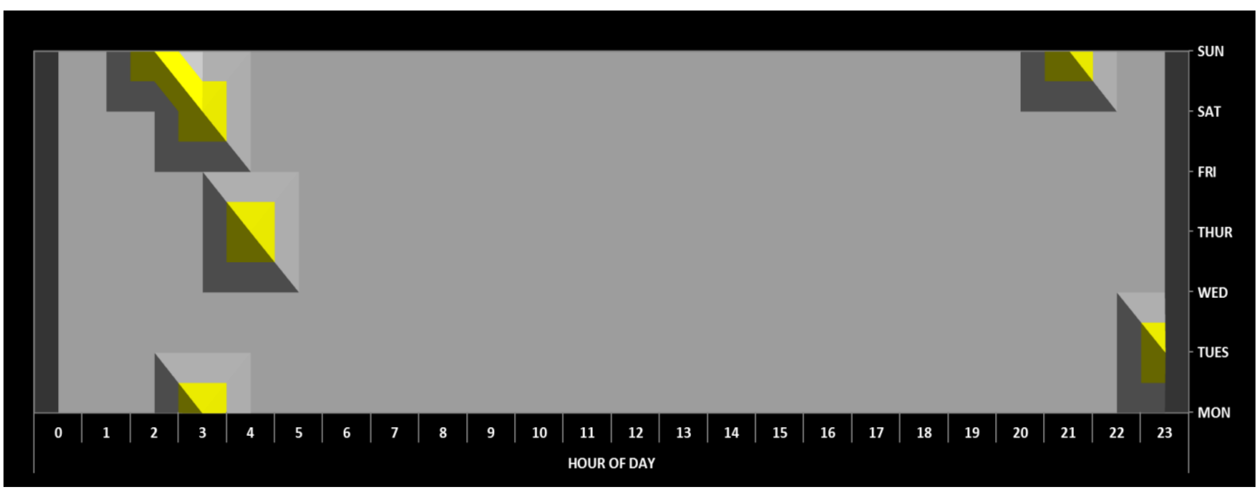
Temporal Analysis of Murder Cluster #1. Gray areas indicate no reported murder. Yellow areas indicate low murder counts. Orange areas indicate higher murder counts. In this cluster, most of the murders occur in the evening / nighttime and on the weekends.



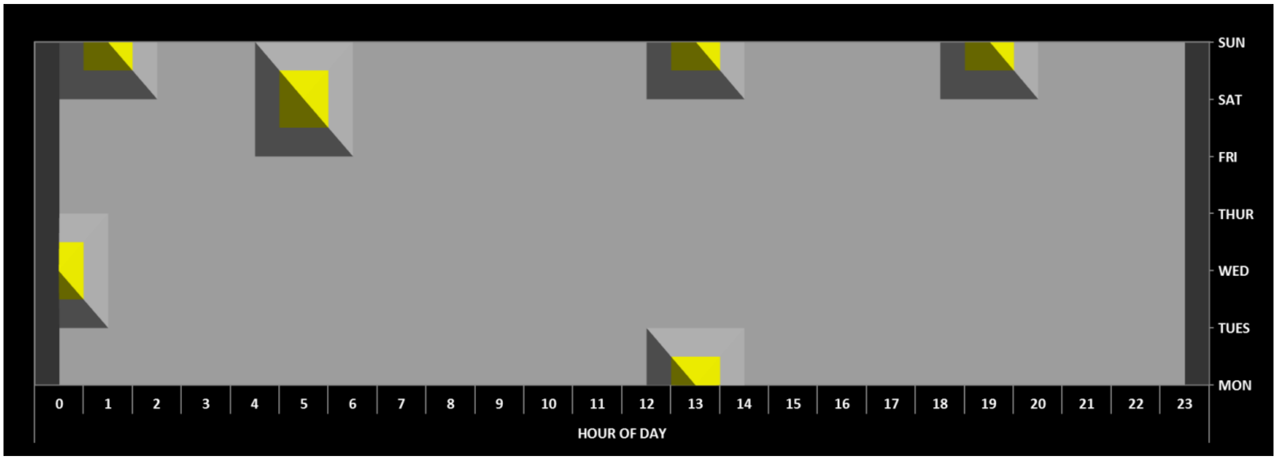
Temporal Analysis of Murder Cluster #2. Gray areas indicate no reported murder. Yellow areas indicate low murder counts. In this cluster, some of the murders occur in the evening / nighttime and on the weekends, while other murders occur on Mondays & Wednesdays.



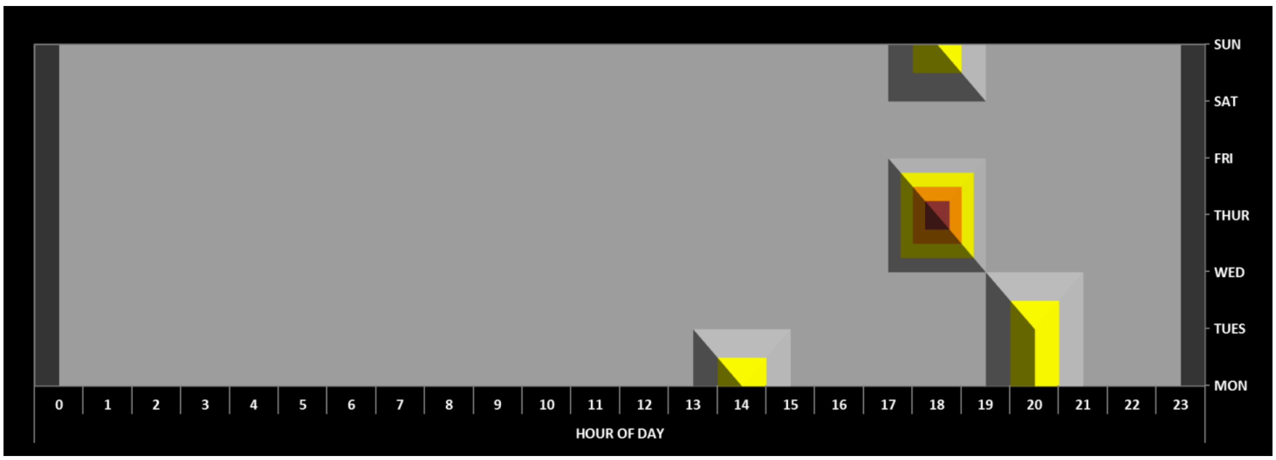
Temporal Analysis of Murder Cluster #3. Gray areas indicate no reported murder. Yellow areas indicate low murder counts. Orange and Red areas indicate high amounts of murder. In this cluster, there is a very high number of murders occurring on Monday nights at 9pm. All of the other murders are occurring on the weekend.



Temporal Analysis of Murder Cluster #4 Figure XXX: Gray areas indicate no reported murder. Yellow areas indicate low murder counts. Orange and Red areas indicate high amounts of murder. In this cluster, most of the murders occur on the weekend, in the evening/nighttime. The other murders are occurring on Tuesday evening.

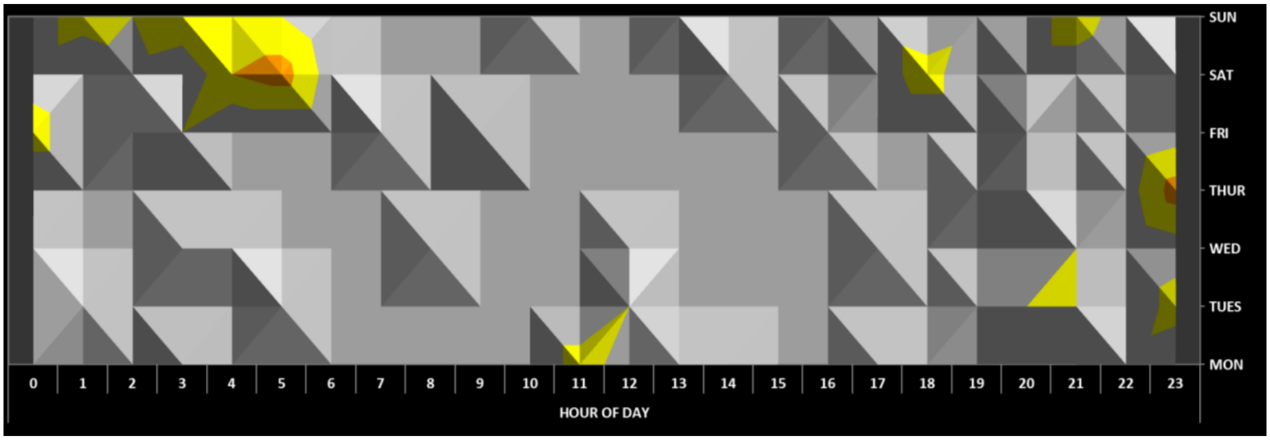


Temporal Analysis of Murder Cluster #5. In this cluster, as with the others, most of the murders occur on the weekend, however, some of them occur on Sunday afternoon.



Temporal Analysis of Murder Cluster #6. In this cluster, orange and red areas indicate higher amounts of murder. Most of the murders occur on Thursday evening, between 5pm-7pm. While this is very different from the other murder clusters, this is also the only cluster with a very different land-use (primarily open space & outdoor recreation).

Murder HD Zones



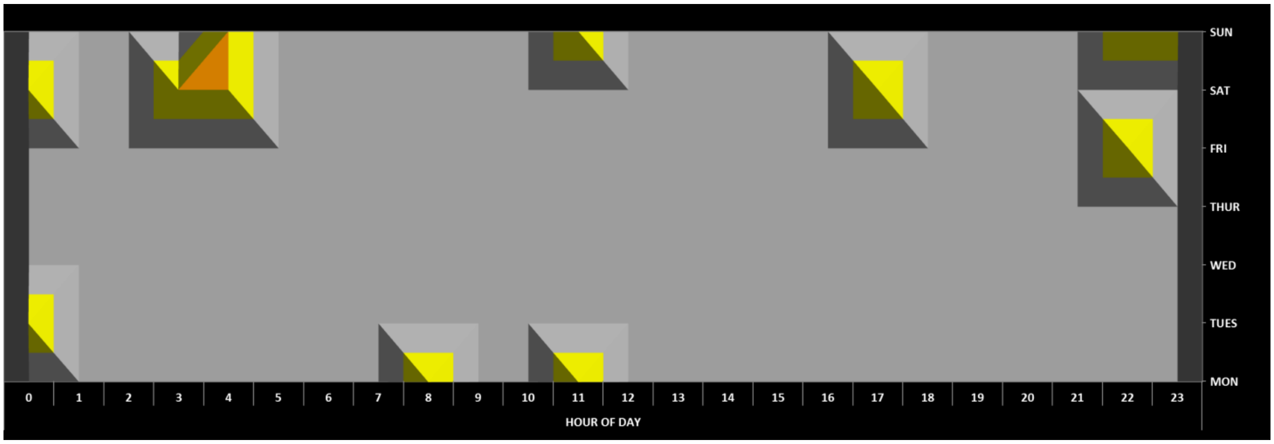
Temporal Analysis of Murders inside Murder HD Zones shows the primary pattern is a nighttime weekend pattern (upper left) and a lesser weekday afternoon/early evening pattern (right side of the graph).

Rape Clusters

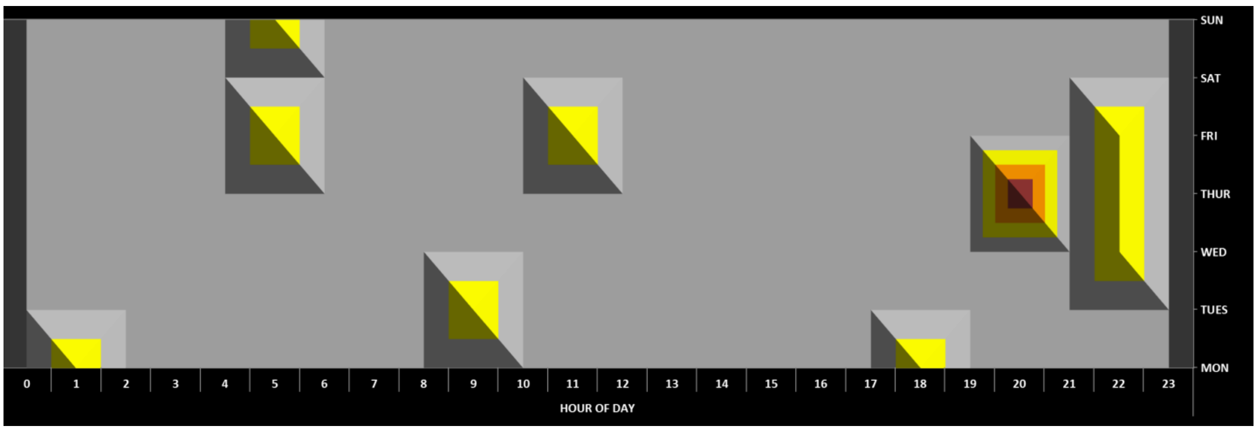
Rape Cluster ID	Population in Cluster	Percent NHWH	Percent NHBL	Percent HISP	Percent POV	Percent NOHS
1	6,002	9	24	67	40	46
2	5,094	6	28	65	37	43
3	7,320	12	24	44	23	24
4	6,867	3	25	71	56	54
5	6,324	4	20	74	47	52

Population Characteristics inside Nnh Rape Clusters. Total population, percent non-Hispanic White, percent non-Hispanic black, percent Hispanic, percent below poverty, percent of adults > 25-years-old without a high school diploma.

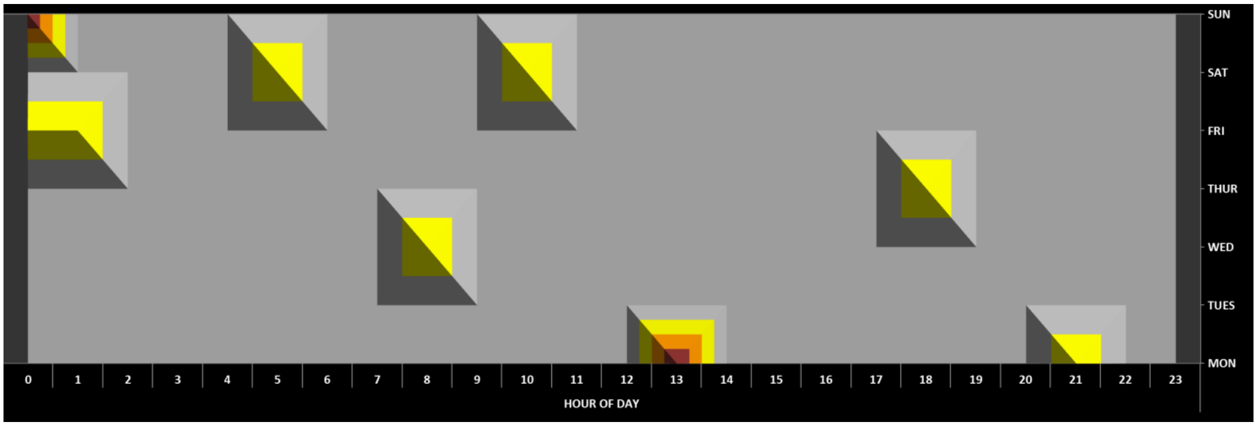
Temporal analysis of rape clusters suffers from the same problem that temporal analysis of murder clusters has, low frequency of crimes within each of the micro-clusters makes it difficult to detect discernible patterns. While temporal patterns are not as definitive, there are still (somewhat) noticeable temporal patterns within each cluster. Previous research (NCVC, 1991; Kilpatrick and Acierno, 2003) indicates that one of the significant crime reporting issues related to rape is that victims wait for a period of time before notifying the police (or victims do not report the crime to the police at all).



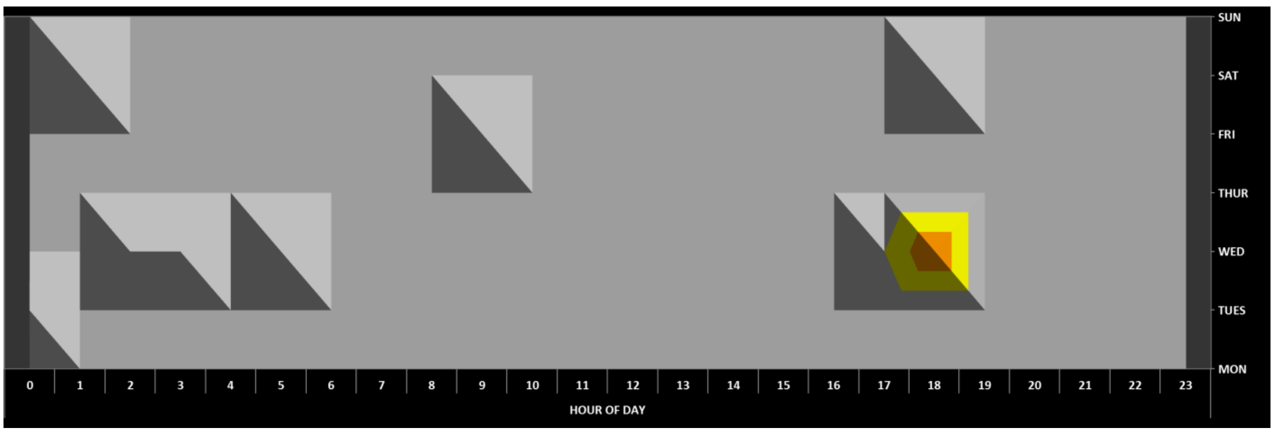
Temporal Analysis of Rape Cluster #1 shows that the majority of the rapes in this cluster occur on the weekend and in the evening / nighttime.



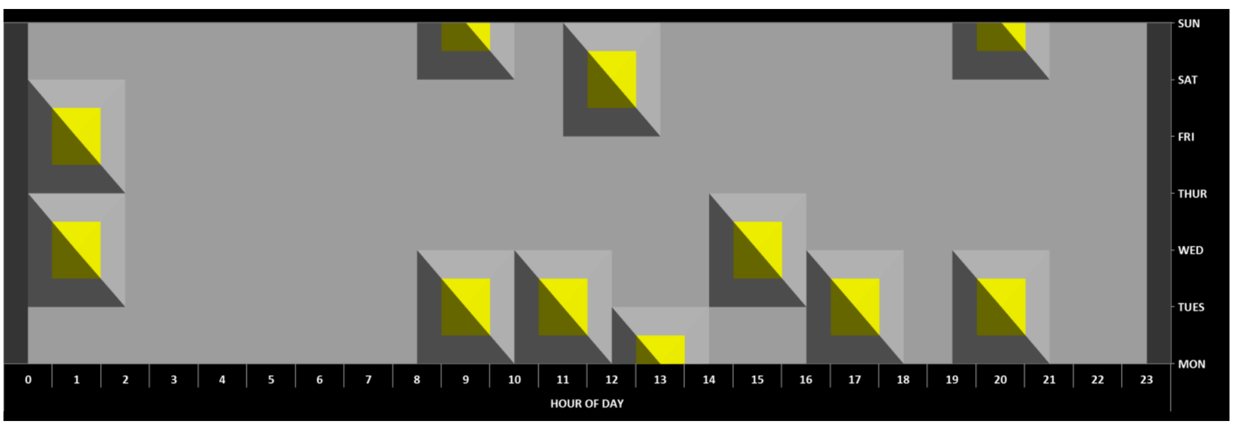
Temporal Analysis of Rape Cluster #2 indicates an interesting evening 8pm-10pm pattern on weekdays and a late night pattern on the weekends.



Temporal Analysis of Rape Cluster #3 shows a weekend nighttime and early morning pattern, as well as a Monday afternoon pattern.

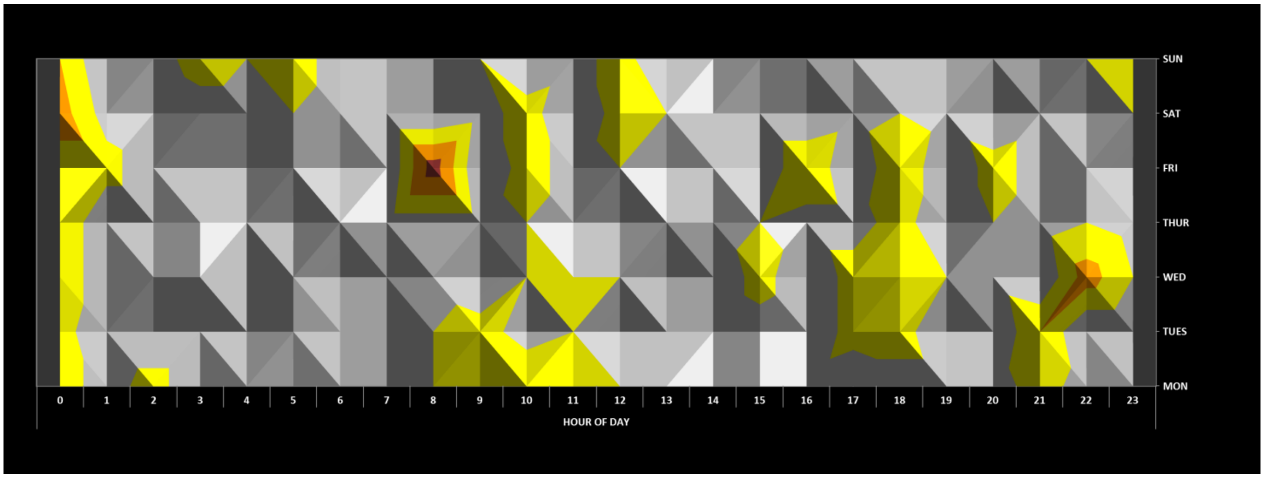


Temporal Analysis of Rape Cluster #4 shows an weekday evening pattern is the primary rape problem for this cluster.



Temporal Analysis of Rape Cluster #5 does not show any definitive temporal pattern. Again, this is probably a result of the low number of rapes in this particular micro-cluster.

RAPE Gi*



Temporal Analysis of Rape HD Zones (KDE) indicates several temporal peaks on weekend nights 11pm-1am, Friday mornings 7am-9am, and weekday evenings 9pm-11pm.

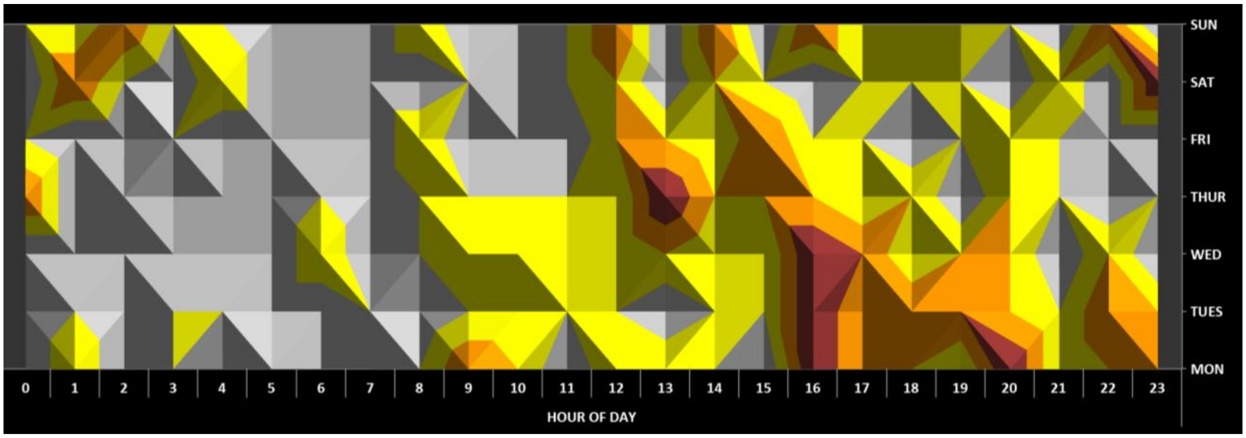
ROBBERY

Robbery Cluster ID	Population in Cluster	Percent NHWH	Percent NHBL	Percent HISP	Percent POV	Percent NOHS
1	2,470	5	24	70	23	28
2	5,450	6	29	63	18	23
3	2,612	22	15	50	12	20
4	6,811	6	24	65	28	33
5	1,239	8	21	63	21%	25%

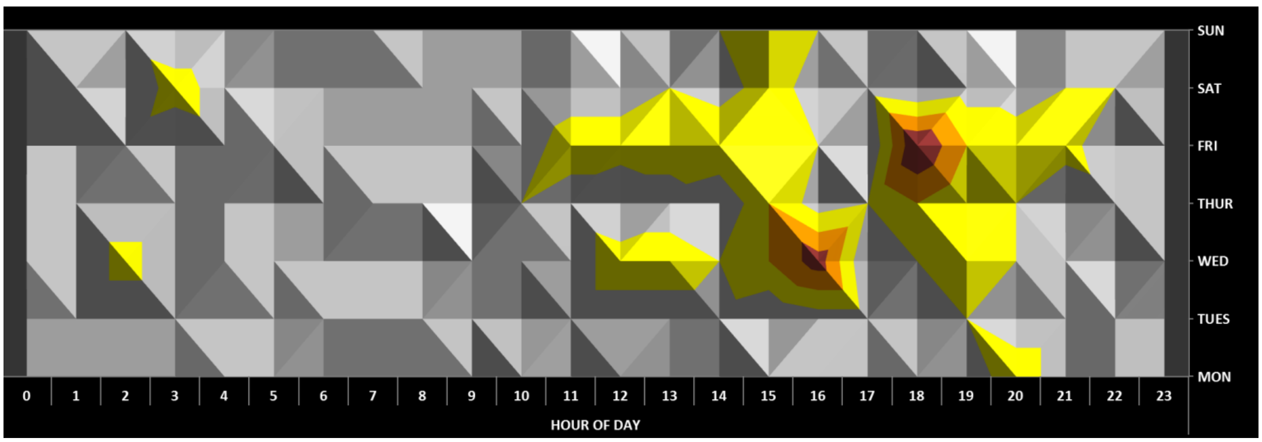
Population Characteristics inside Robbery Nnh Clusters

The table above indicates that robbery clusters contain much lower population counts when compared to murder and rape clusters. About half as many people reside in robbery clusters when compared to murder and rape clusters. Since all of the violent crime Nnh clusters are the same size (.1 square miles), this shift in land-use pattern is the notable difference between robbery and all other violent crimes.

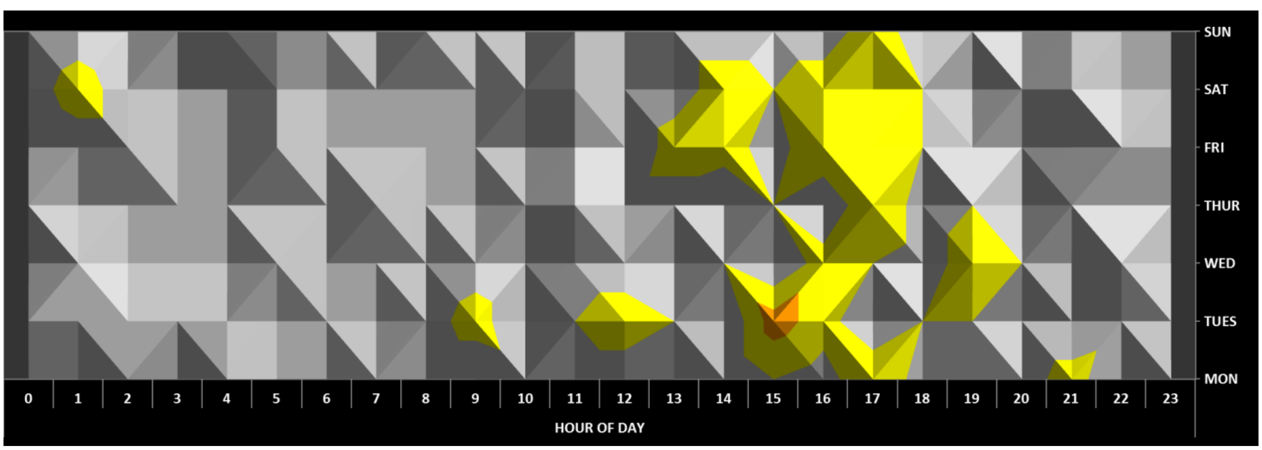
Temporal Analysis of Robbery Clusters



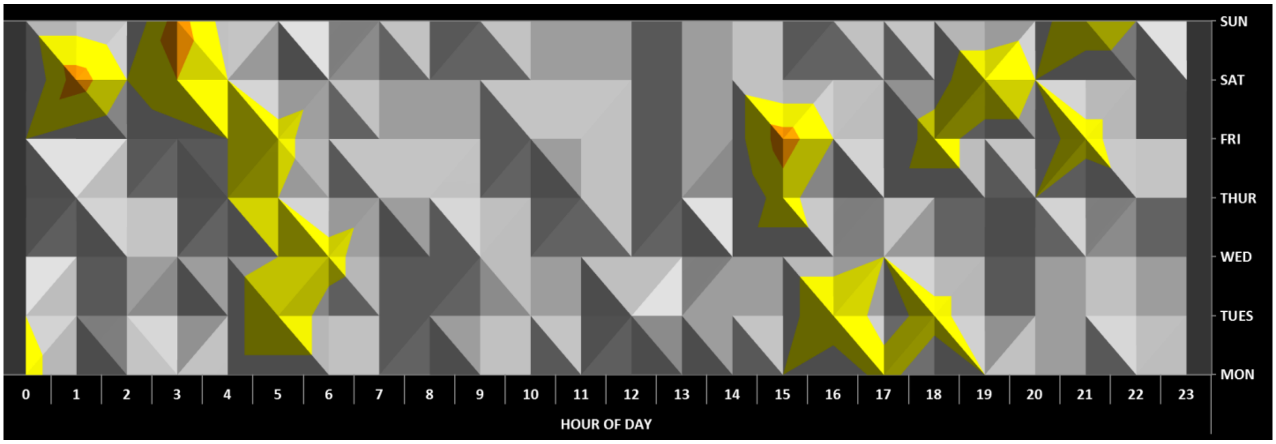
Temporal Analysis of Nnh Robbery Cluster #1, where gray is no/little robbery, yellow/orange is medium amounts of robbery, and dark red is high counts of robbery. This cluster indicates a significant weekday and daytime temporal pattern that is much different than the previous violent crime clusters that have been analyzed.



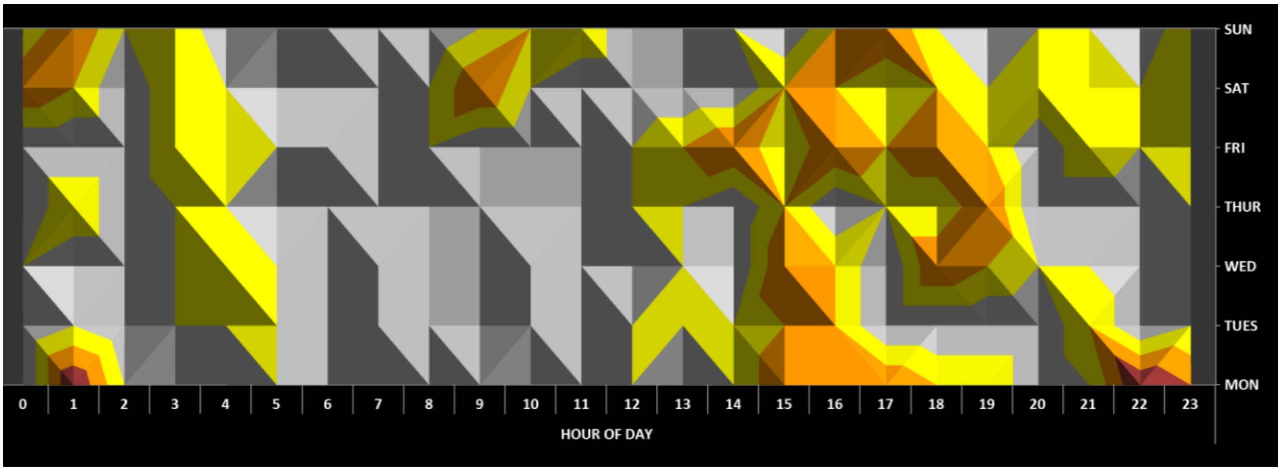
Temporal Analysis of Robbery Cluster #2 shows a 5pm-7pm Friday and Saturday peak, as well as a weekday afternoon peak. Two distinct temporal patterns usually indicates two separate land-use robbery relationships or two separate groups of robbery offenders.



Temporal Analysis of Robbery Cluster #3 is different from previous robbery clusters, since it shows that weekday afternoon robberies are the primary problem in this cluster. There is no significant weekend or evening / nighttime pattern, with the exception of a very small Saturday/Sunday, Midnight-2am pattern.

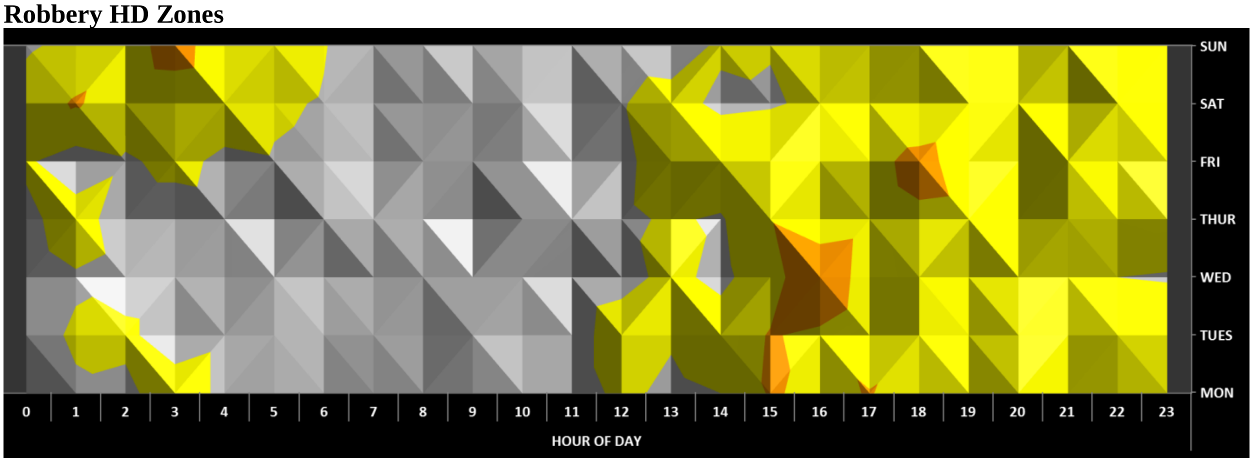


Temporal Analysis of Robbery Cluster #4 shows two very distinct patterns, a weekday afternoon/early evening pattern (right side) and a nighttime weekend pattern (left side).



Temporal Analysis of Robbery Cluster #5 is very similar to robbery cluster #4, since it also shows two very distinct patterns, a weekday afternoon/early evening pattern (right side) and a nighttime weekend pattern (left side). The primary difference between these two clusters is that cluster #5 has more weekend and nighttime robberies than cluster #4.

Robbery HD Zones

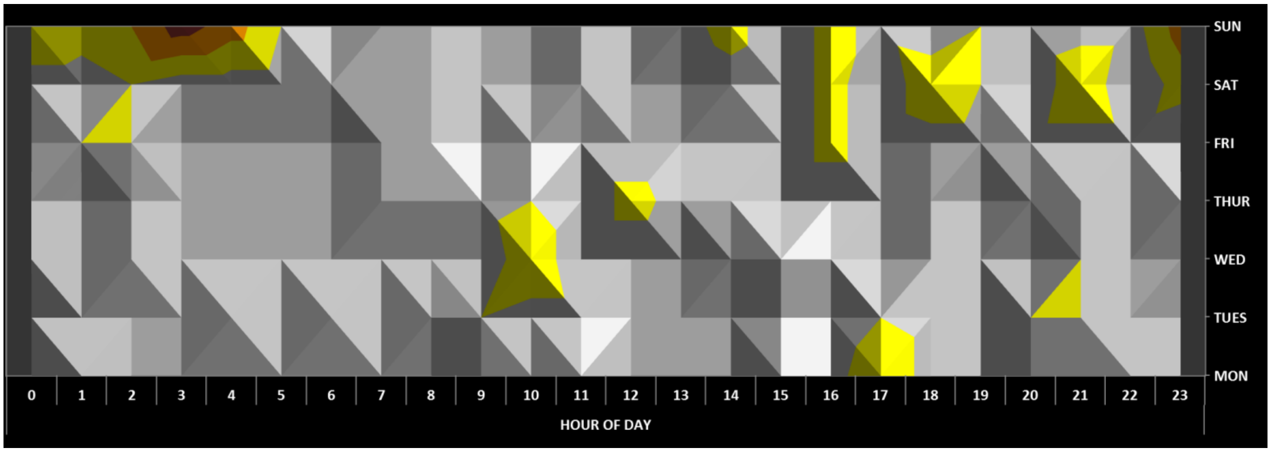


Temporal Analysis of Robbery HD Zones clearly illustrates the two separate patterns. The left side of the chart indicates a nighttime, primarily weekend robbery pattern. The right side of the chart shows an afternoon/evening peak temporal pattern, primarily on weekdays.

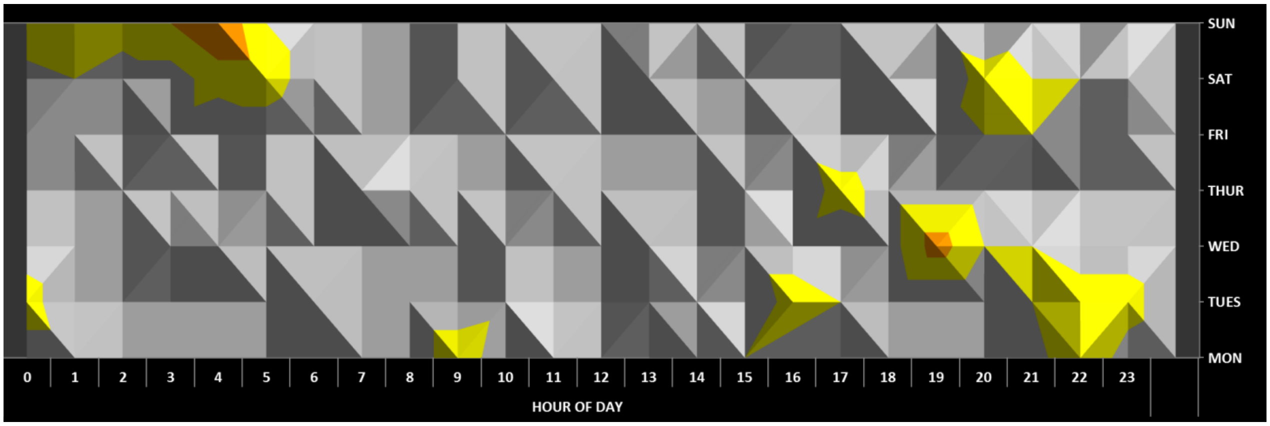
Assault Clusters

Assault Cluster ID	Population Estimate in Cluster	Percent NHWH	Percent NHBL	Percent HISP	Percent POV	Percent NOHS
1	10,555	5	25	62	29	32
2	7,546	8	32	58	33	32
3	5,781	5	20	68	28	33
4	7,991	3	30	60	39	38
5	2,260	9	28	58	10	12

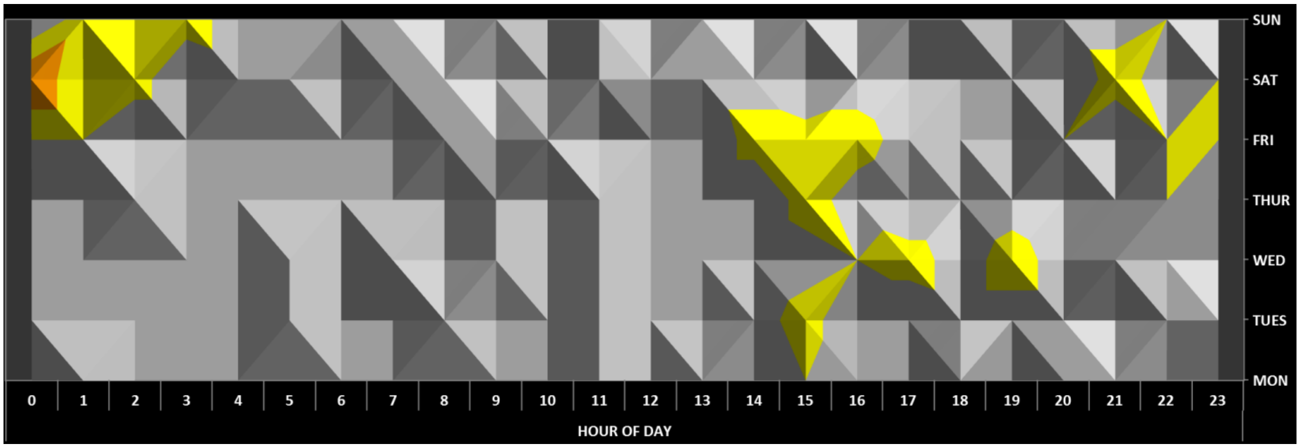
Assault Cluster ID, Population, Percent non-Hispanic White, non-Hispanic Black, Hispanic, Percent of Households in Poverty, and Percent of Adults >25 Year olds with no high school diploma.



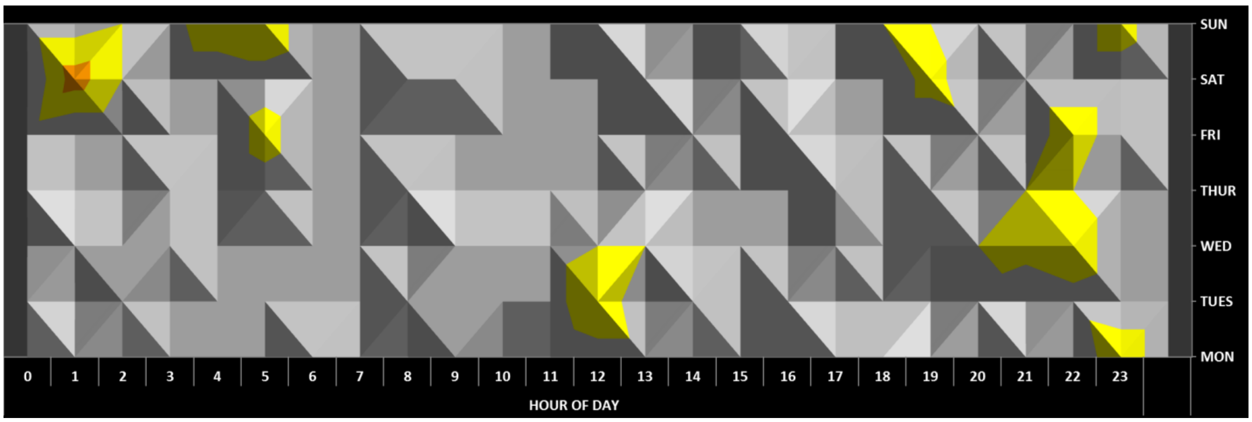
Temporal Analysis of Assault Cluster #1 shows primarily weekend and evening / nighttime patterns



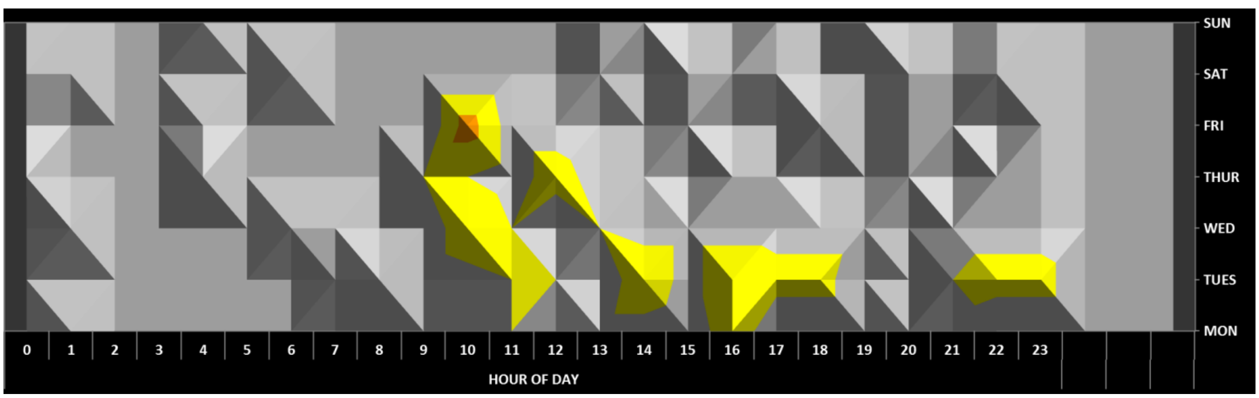
Temporal Analysis of Assault Cluster #2 shows some weekday afternoon and evening patterns, but the primary pattern is weekend and nighttime (2am-5am).



Temporal Analysis of Assault Cluster #3 indicates two separate patterns, a weekday afternoon 3pm-5pm pattern and a weekend nighttime 10pm-2am pattern.

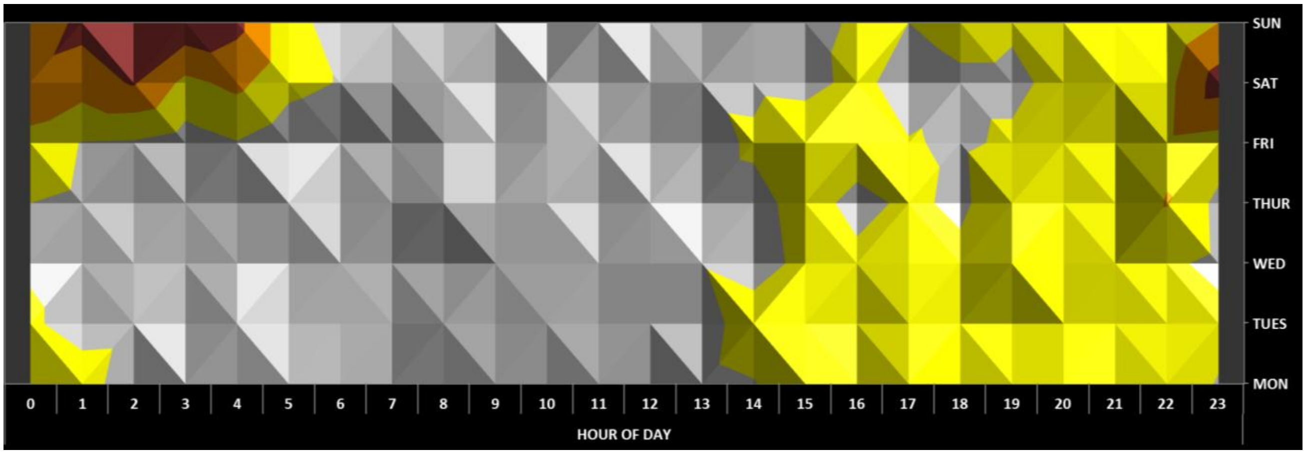


Temporal Analysis of Assault Cluster #4 shows a varied weekday daytime pattern and weekend nighttime pattern.



Temporal Analysis of Assault Cluster #5 shows a definitive weekday afternoon pattern, which is much different than the other assault clusters.

Assault HD Zones

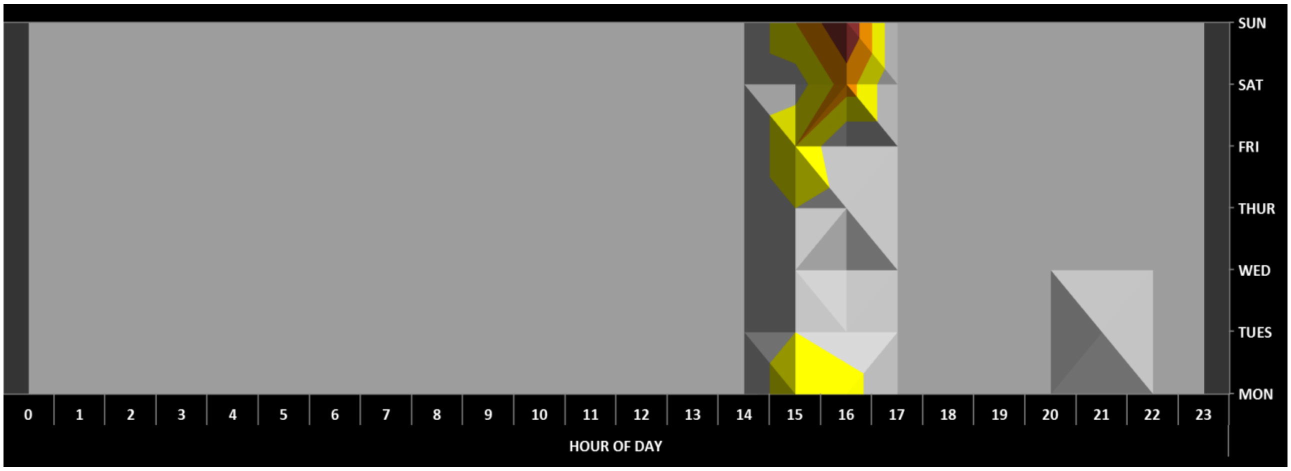


Temporal Analysis of Assaults within Assault HD Zones provides a much better illustration of the weekday / daytime temporal pattern and the weekend / nighttime temporal pattern.

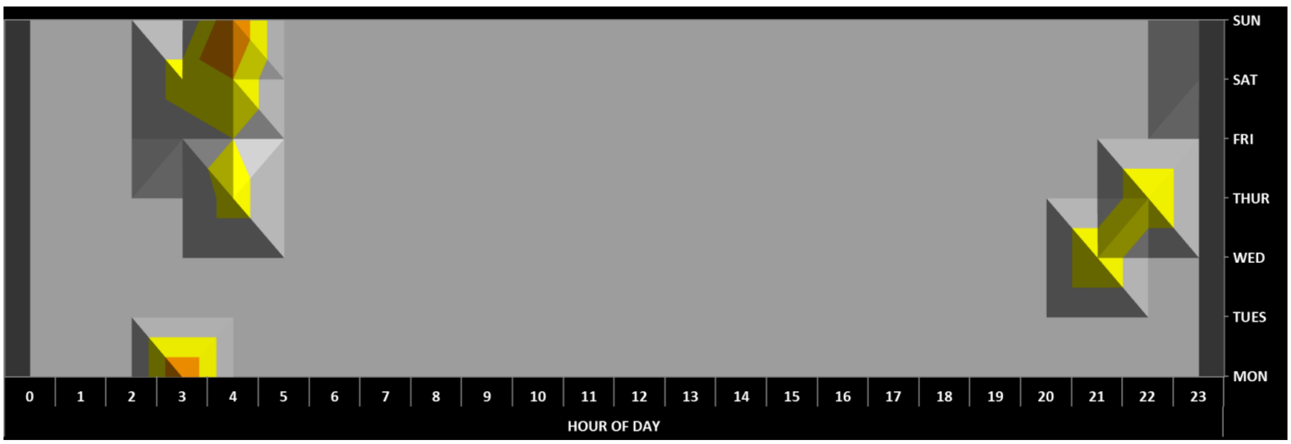
SHOOTINGS

Temporal Analysis of the shooting clusters is not as comprehensive as robbery and assault because of the low frequency of shootings per cluster. Nevertheless, there are distinct temporal patterns in the shooting clusters that are worth noting.

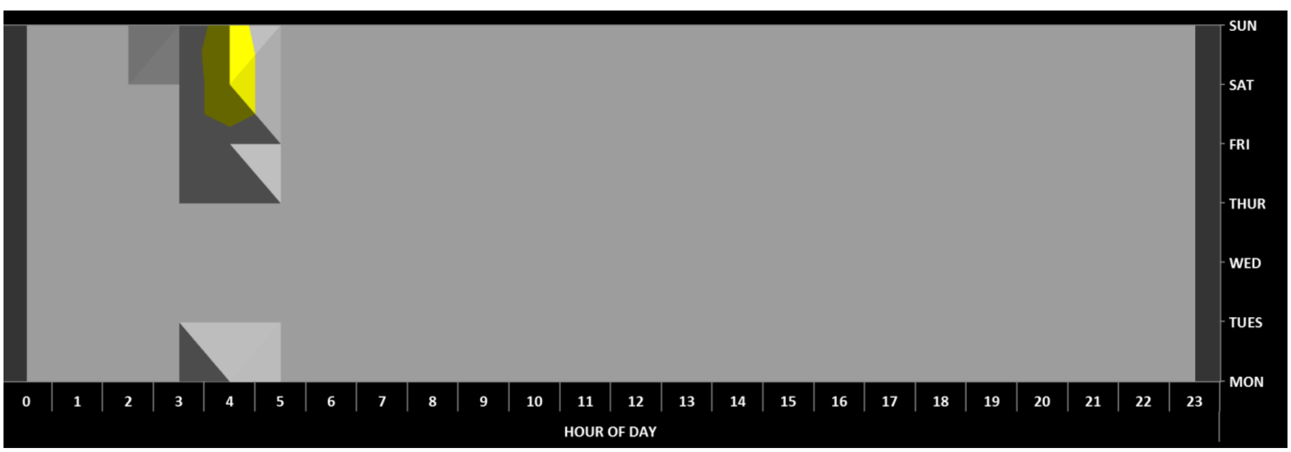
Shooting Cluster ID	Population Estimate in Cluster	Percent NHWH	Percent NHBL	Percent HISP	Percent POV	Percent NOHS
1	6,055	6	28	65	35	42
2	5,309	4	29	61	36	35
3	2,134	3	40	54	40	45
4	2,608	2	48	48	51	45
5	3,377	4	33	61	50	51
6	4,897	4	20	67	30	37



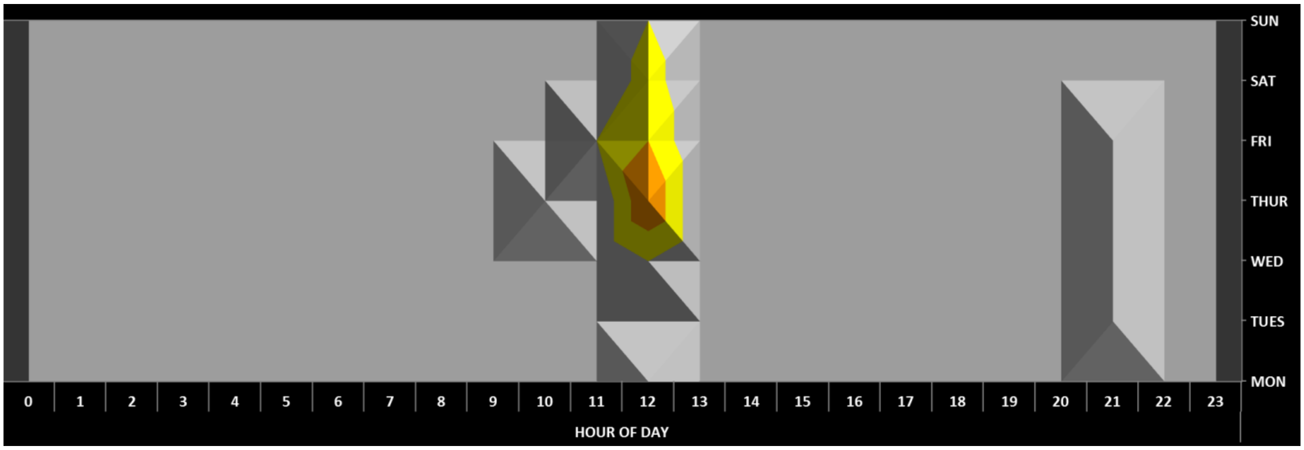
Temporal Analysis of Shooting Cluster #1indicates a very distinct afternoon 2pm-5pm pattern that peaks on the weekends



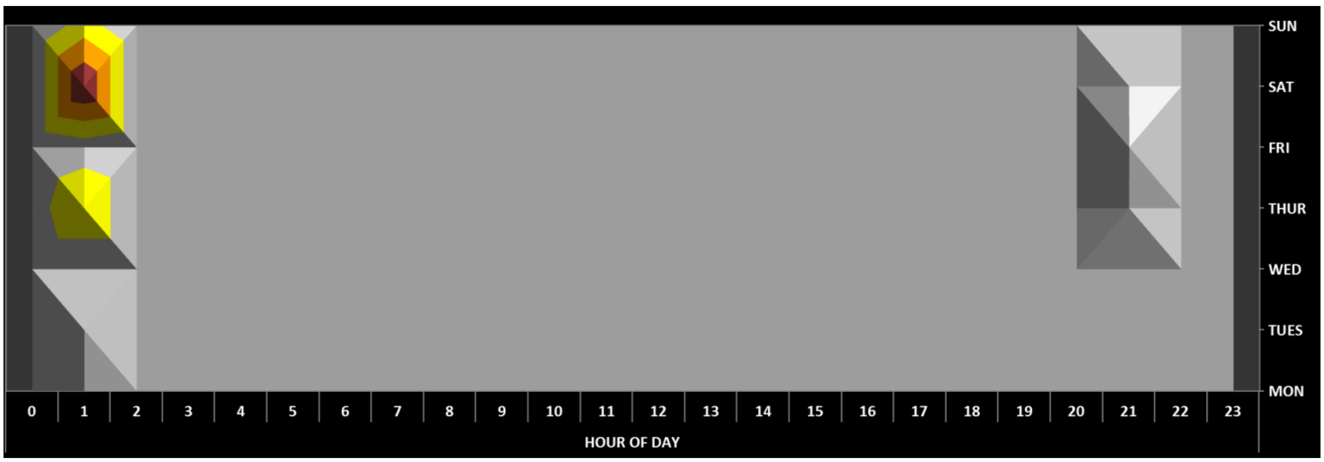
Temporal Analysis of Shooting Cluster #2 indicates a weekend evening / nighttime pattern



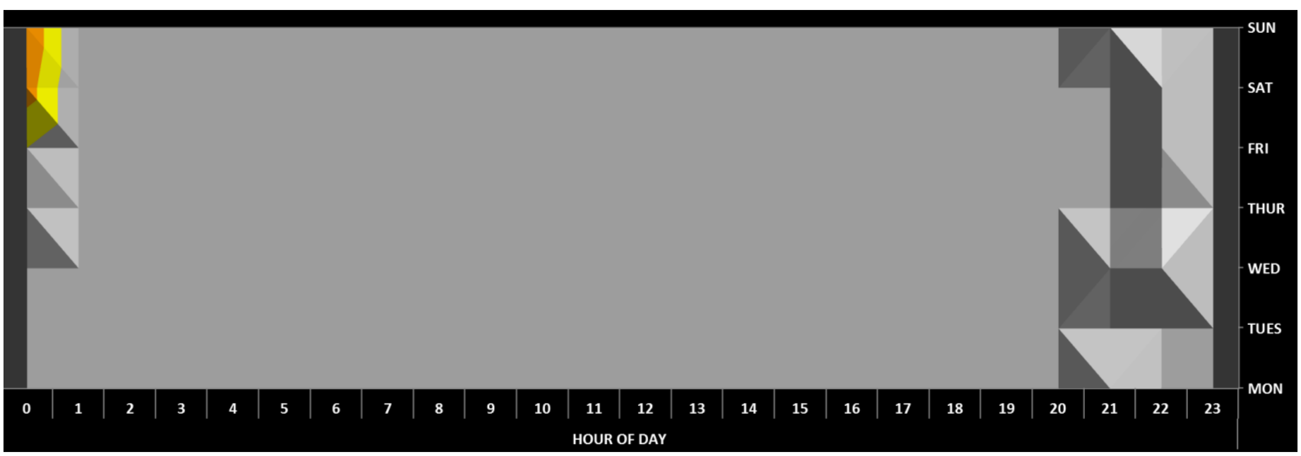
Temporal Analysis of Shooting Cluster #3inidicates a definitive weekend nighttime 2am-4am pattern.



Temporal Analysis of Shooting Cluster #4indicates a very distinct afternoon 11am – 2pm weekday pattern

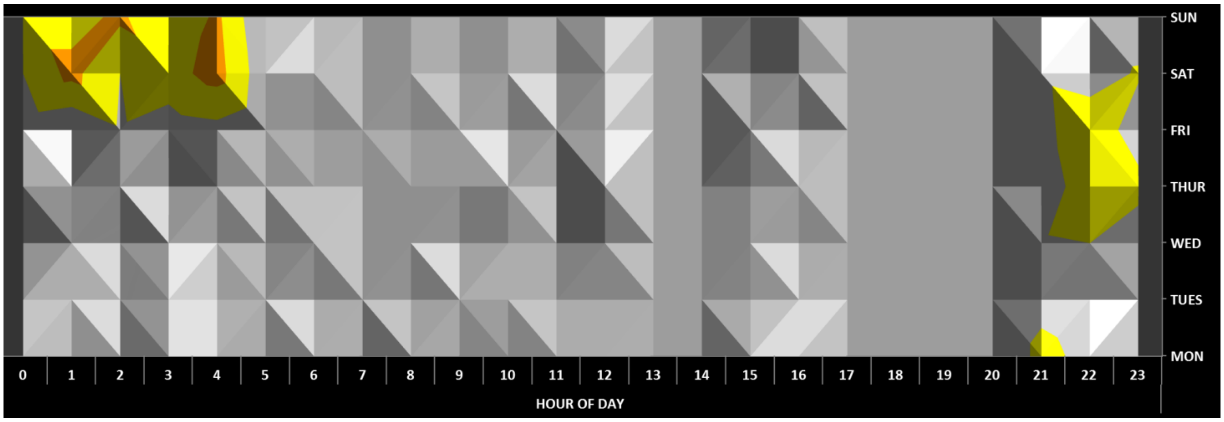


Temporal Analysis of Shooting Cluster #5 shows a very distinct nighttime weekend pattern.



Temporal Analysis of Shooting Cluster #6 also shows a very distinct nighttime weekend pattern (very similar to shooting cluster #5)

SHOOTING HD Zones



Temporal Analysis of the (KDE) Shooting HD Zones. There is a very similar temporal pattern with the other violent crimes which indicate a weekday evening pattern, as well as a weekend nighttime pattern.

Land-Use Categories

(1) One and Two Family Buildings

(2) Multi-Family Walk-up Buildings

(3) Multi-Family Elevator Buildings

(4) Mixed Residential and Commercial Buildings

(5) Commercial and Office Buildings

(6) Industrial and Manufacturing

(7) Transportation and Utility

(8) Public Facilities and Institutions

(9) Open Space and Outdoor Recreation

(10) Parking Facilities

(11) Vacant Land

School Year Query:

"YEAR" =2006 AND "DOW" <=5 AND ("WEEK" >= 1 AND "WEEK" <= 6 OR "WEEK" >= 9 AND "WEEK" <= 15 OR "WEEK" >= 18 AND "WEEK" <= 25 OR "WEEK" >= 37 AND "WEEK" <= 51) OR "YEAR"=2007 AND "DOW" <=5 AND ("WEEK" >= 1 AND "WEEK" <= 7 OR "WEEK" >= 10 AND "WEEK" <= 13 OR "WEEK" >= 16 AND "WEEK" <= 25 OR "WEEK" >= 37 AND "WEEK" <= 51) OR "YEAR"=2008 AND "DOW" <=5 AND ("WEEK" >= 1 AND "WEEK" <= 6 OR "WEEK" >= 9 AND "WEEK" <= 16 OR "WEEK" >= 19 AND "WEEK" <= 25 OR "WEEK" >= 37 AND "WEEK" <= 51) OR YEAR= 2009 AND "DOW" <=5 AND ("WEEK" >= 1 AND "WEEK" <= 7 OR "WEEK" >= 10 AND "WEEK" <= 15 OR "WEEK" >= 18 AND "WEEK" <= 26 OR "WEEK" >= 37 AND "WEEK" <= 51) OR YEAR=2010 AND "DOW" <=5 AND ("WEEK" >= 1 AND "WEEK" <= 6 OR "WEEK" >= 10 AND "WEEK" <= 15 OR "WEEK" >= 18 AND "WEEK" <= 26 OR "WEEK" >= 37 AND "WEEK" <= 51)

MURDER - PREMISES TYPE	COUNT
STREET	255
RESIDENCE - APT. HOUSE	186
RESIDENCE - PUBLIC HOUSING	82
RESIDENCE-HOUSE	28
PARK/PLAYGROUND	15
OTHER	14
BAR/NIGHT CLUB	8
GROCERY/BODEGA	4
RESTAURANT/DINER	4
MISSING	3
PARKING LOT/GARAGE (PRIVATE)	3
PARKING LOT/GARAGE (PUBLIC)	2
TRANSIT - NYC SUBWAY	2
BRIDGE	1
CLOTHING/BOUTIQUE	1
COMMERCIAL BUILDING	1
DEPARTMENT STORE	1
DRY CLEANER/LAUNDRY	1
FAST FOOD	1
FOOD SUPERMARKET	1
GAS STATION	1
HIGHWAY/PARKWAY	1
HOSPITAL	1
HOTEL/MOTEL	1
MARINA/PIER	1
OPEN AREAS (OPEN LOTS)	1
SMALL MERCHANT	1
STORAGE FACILITY	1
STORE UNCLASSIFIED	1
TAXI (LIVERY LICENSED)	1

RAPE - PREMISES TYPE	COUNT
RESIDENCE - APT. HOUSE	860
RESIDENCE-HOUSE	165
RESIDENCE - PUBLIC HOUSING	142
HOTEL/MOTEL	54
STREET	49
OTHER	17
PARK/PLAYGROUND	14
MISSING	12
HOSPITAL	7
PUBLIC BUILDING	5
ABANDONED BUILDING	4
OPEN AREAS (OPEN LOTS)	4
PARKING LOT/GARAGE (PRIVATE)	3
COMMERCIAL BUILDING	2
PARKING LOT/GARAGE (PUBLIC)	2
BRIDGE	1
CONSTRUCTION SITE	1
DOCTOR/DENTIST OFFICE	1
GROCERY/BODEGA	1
PUBLIC SCHOOL	1
SMALL MERCHANT	1
SOCIAL CLUB/POLICY	1
STORE UNCLASSIFIED	1
TRANSIT - NYC SUBWAY	1

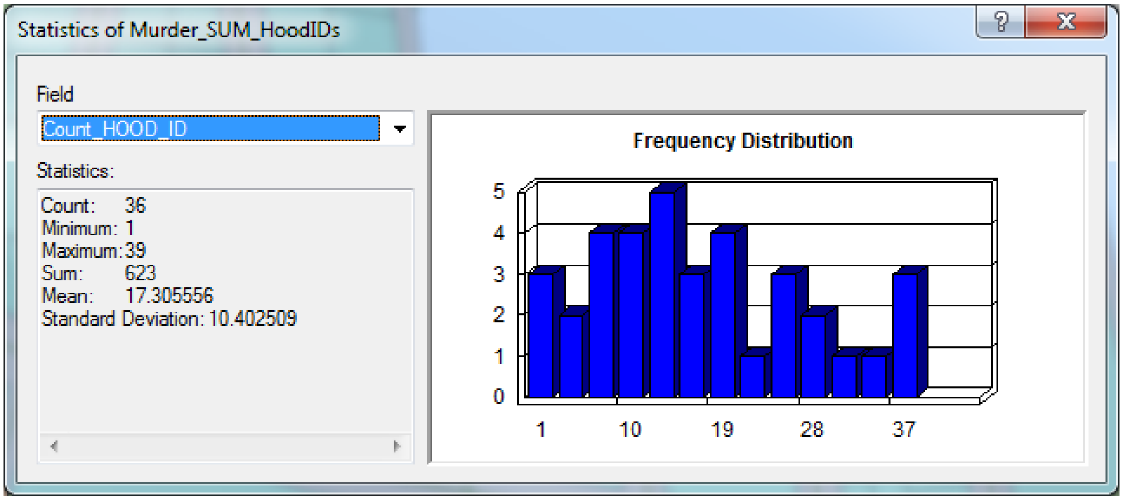
ROBBERY – PREMISES TYPE	COUNT
STREET	13056
RESIDENCE - APT. HOUSE	3288
RESIDENCE - PUBLIC HOUSING	1149
TRANSIT - NYC SUBWAY	778
OTHER	453
GROCERY/BODEGA	440
PARK/PLAYGROUND	383
RESIDENCE-HOUSE	365
COMMERCIAL BUILDING	159
PUBLIC SCHOOL	158
BANK	156
FAST FOOD	144
CHAIN STORE	143
BUS (NYC TRANSIT)	124
GAS STATION	120
TAXI (LIVERY LICENSED)	117
RESTAURANT/DINER	106
STORE UNCLASSIFIED	92
MISSING	91
PUBLIC BUILDING	86
OPEN AREAS (OPEN LOTS)	84
BUS STOP	82
PARKING LOT/GARAGE (PUBLIC)	81
CANDY STORE	77
SMALL MERCHANT	70
DRUG STORE	66
FOOD SUPERMARKET	64
BEAUTY & NAIL SALON	63
CLOTHING/BOUTIQUE	63
DRY CLEANER/LAUNDRY	60
PARKING LOT/GARAGE (PRIVATE)	60
BAR/NIGHT CLUB	51
TAXI/LIVERY (UNLICENSED)	51
DEPARTMENT STORE	43
CHECK CASHING BUSINESS	41
BRIDGE	33
TELECOMM. STORE	23
BUS (OTHER)	22
VARIETY STORE	21
JEWELRY	19

PRIVATE/PAROCHIAL SCHOOL	18
HOTEL/MOTEL	16
TAXI (YELLOW LICENSED)	16
HOSPITAL	15
TUNNEL	15
HIGHWAY/PARKWAY	14
VIDEO STORE	10
ATM	9
TRANSIT FACILITY (OTHER)	9
CHURCH	8
FACTORY/WAREHOUSE	8
LIQUOR STORE	8
STORAGE FACILITY	8
CONSTRUCTION SITE	7
SOCIAL CLUB/POLICY	6
DOCTOR/DENTIST OFFICE	5
SHOE	5
CEMETERY	4
PHOTO/COPY	3
ABANDONED BUILDING	2
MARINA/PIER	2
OTHER HOUSE OF WORSHIP	2
BUS TERMINAL	1
SYNAGOGUE	1

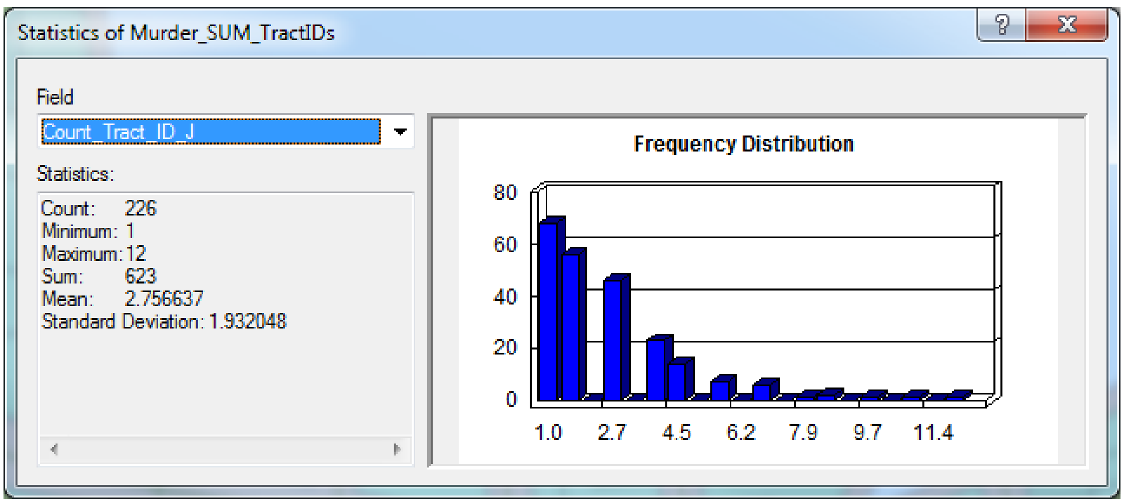
ASSAULT - PREMISES TYPE	COUNT
STREET	7998
RESIDENCE - APT. HOUSE	6478
RESIDENCE - PUBLIC HOUSING	1733
RESIDENCE-HOUSE	1283
OTHER	484
BAR/NIGHT CLUB	348
PUBLIC SCHOOL	302
GROCERY/BODEGA	241
PARK/PLAYGROUND	200
PUBLIC BUILDING	182
RESTAURANT/DINER	159
MISSING	149
TRANSIT - NYC SUBWAY	131
COMMERCIAL BUILDING	115
HOSPITAL	92
FAST FOOD	87
BUS (NYC TRANSIT)	59
PARKING LOT/GARAGE (PUBLIC)	53
PARKING LOT/GARAGE (PRIVATE)	50
STORE UNCLASSIFIED	44
SOCIAL CLUB/POLICY	42
CANDY STORE	40
CHAIN STORE	37
BEAUTY & NAIL SALON	31
DRY CLEANER/LAUNDRY	30
OPEN AREAS (OPEN LOTS)	30
GAS STATION	29
SMALL MERCHANT	29
FOOD SUPERMARKET	26
HIGHWAY/PARKWAY	23
BUS STOP	21
CLOTHING/BOUTIQUE	18
FACTORY/WAREHOUSE	18
BRIDGE	16
DEPARTMENT STORE	16
CONSTRUCTION SITE	14
HOTEL/MOTEL	12
DOCTOR/DENTIST OFFICE	11
GYM/FITNESS FACILITY	10
BUS (OTHER)	9

TAXI (LIVERY LICENSED)	9
PRIVATE/PAROCHIAL SCHOOL	8
TRANSIT FACILITY (OTHER)	7
VARIETY STORE	7
CHURCH	6
DRUG STORE	6
LIQUOR STORE	5
STORAGE FACILITY	5
TUNNEL	4
VIDEO STORE	3
CHECK CASHING BUSINESS	2
OTHER HOUSE OF WORSHIP	2
TAXI (YELLOW LICENSED)	2
TELECOMM. STORE	2
AIRPORT TERMINAL	1
ATM	1
BANK	1
BUS TERMINAL	1
CEMETERY	1
JEWELRY	1
MARINA/PIER	1
MOSQUE	1
SHOE	1
SYNAGOGUE	1
TAXI/LIVERY (UNLICENSED)	1

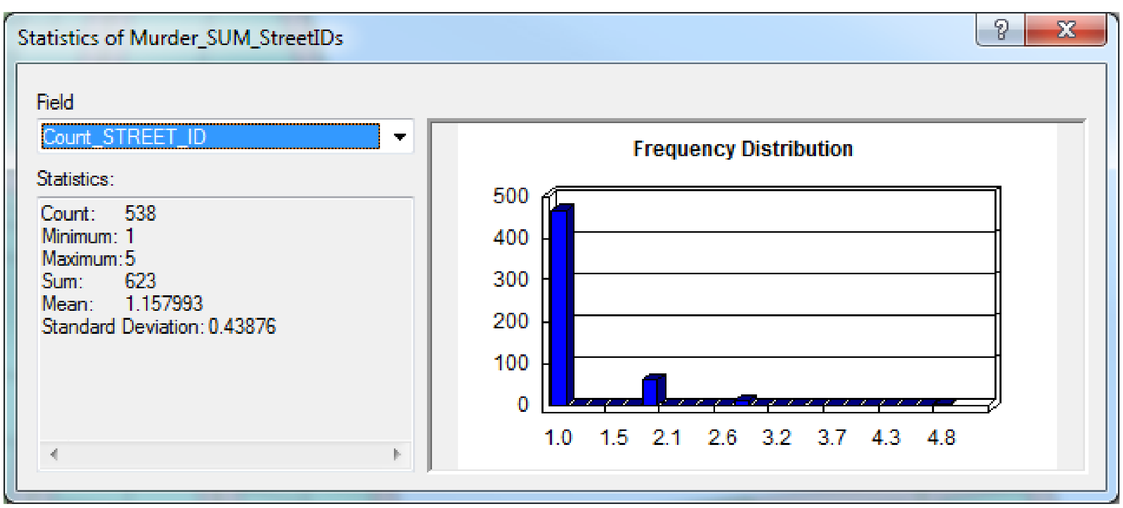
SHOOTING - PREMISE TYPE	COUNT
MISSING	1939
STREET	335
RESIDENCE - APT. HOUSE	235
RESIDENCE - PUBLIC HOUSING	149
RESIDENCE-HOUSE	37
BAR/NIGHT CLUB	17
GROCERY/BODEGA	10
FAST FOOD	9
PARK/PLAYGROUND	8
RESTAURANT/DINER	8
PARKING LOT/GARAGE (PRIVATE)	7
CANDY STORE	6
OTHER	5
HOSPITAL	3
PUBLIC BUILDING	3
PUBLIC SCHOOL	3
COMMERCIAL BUILDING	2
GAS STATION	2
GYM/FITNESS FACILITY	2
SMALL MERCHANT	2
BEAUTY & NAIL SALON	1
FACTORY/WAREHOUSE	1
FOOD SUPERMARKET	1
PARKING LOT/GARAGE (PUBLIC)	1
SOCIAL CLUB/POLICY	1
STORAGE FACILITY	1
STORE UNCLASSIFIED	1
SYNAGOGUE	1
TELECOMM. STORE	1



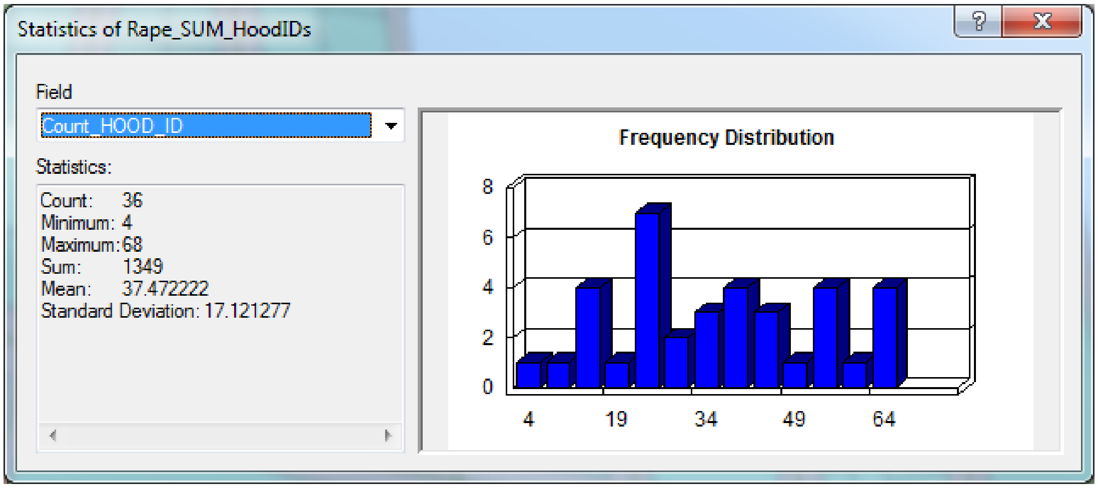
Murder Frequency Distribution by Neighborhood



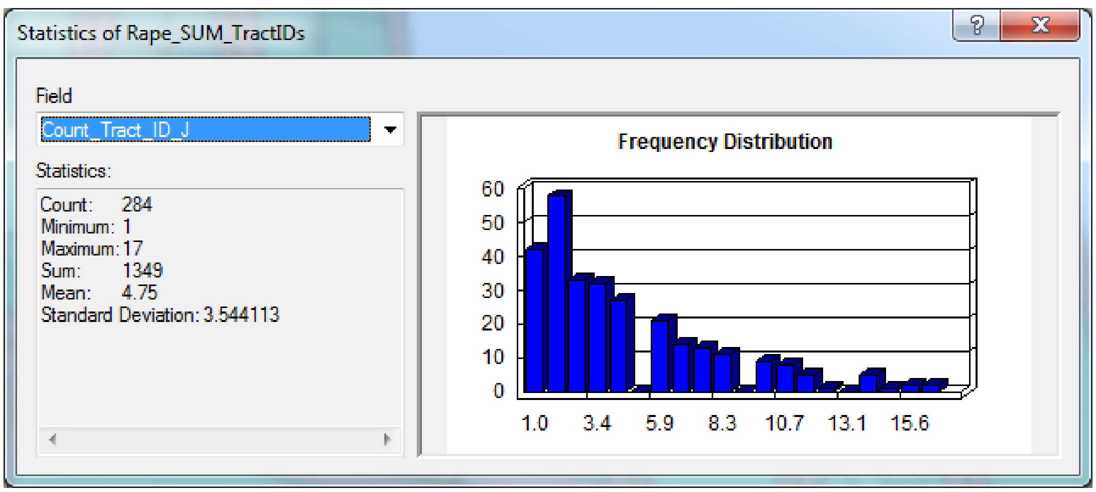
Murder Frequency Distribution by Census Tract



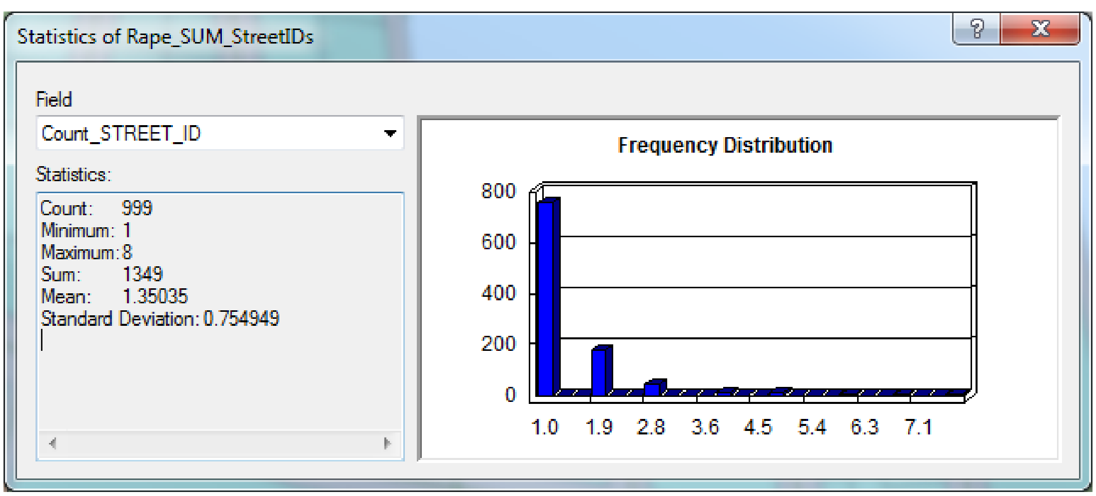
Murder Frequency Distribution by Street Segment



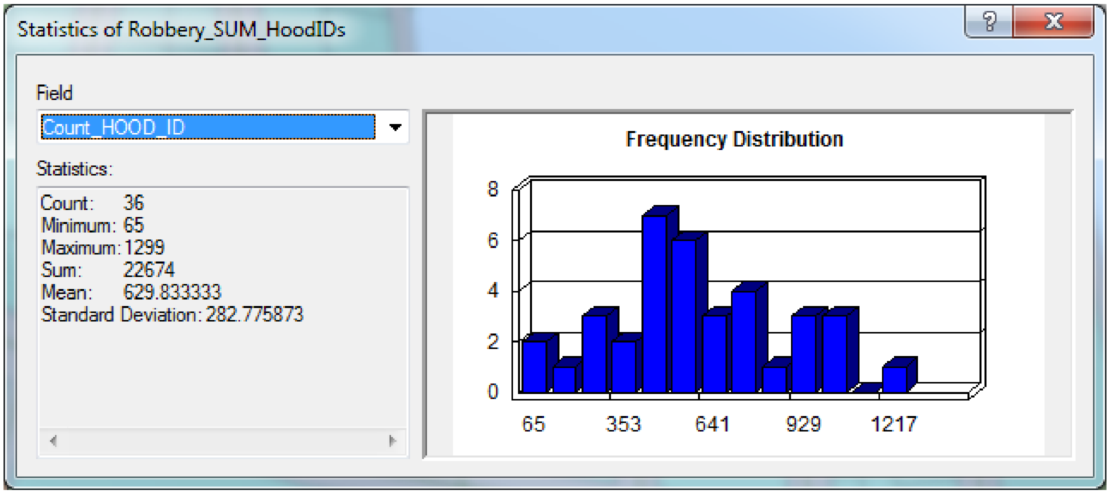
Rape Frequency Distribution by Neighborhood



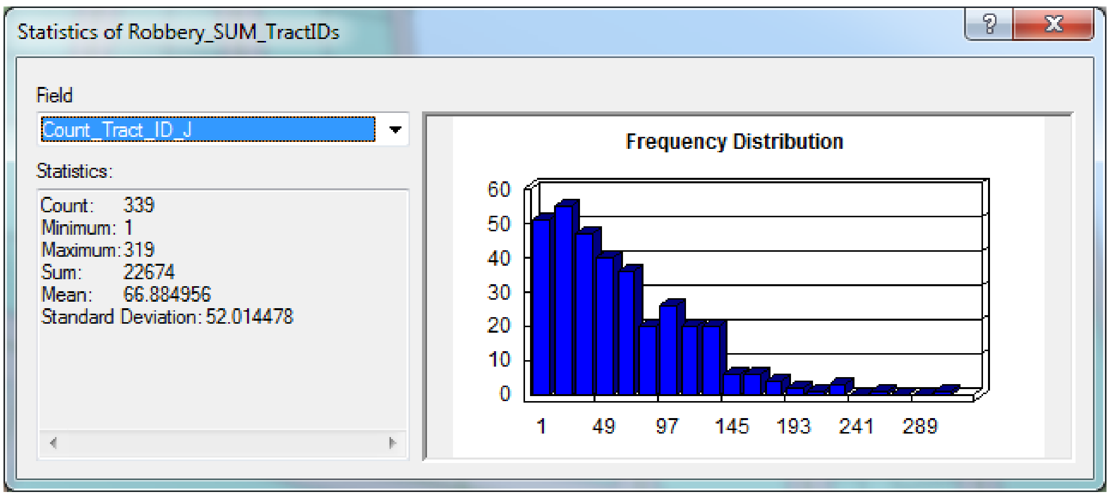
Rape Frequency Distribution by Census Tract



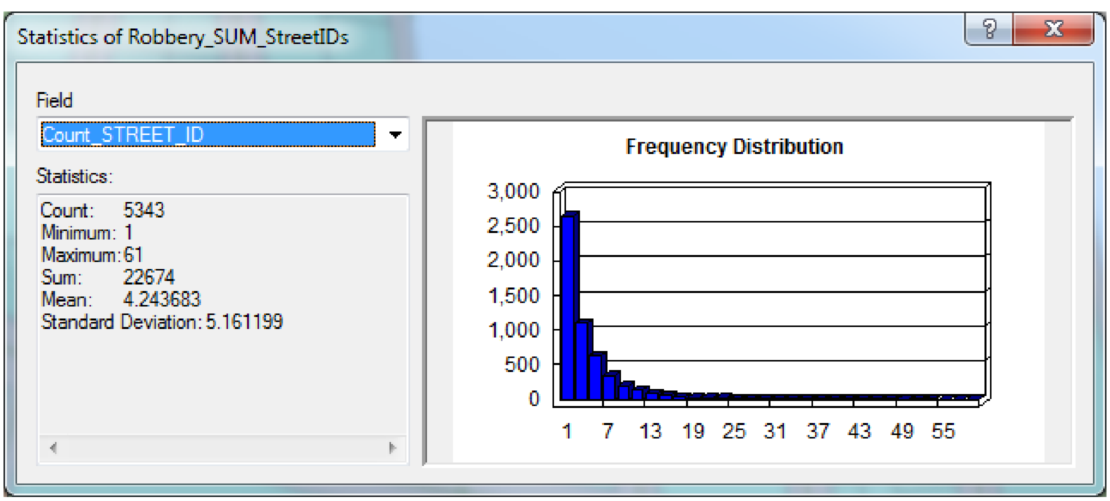
Rape Frequency Distribution by Street Segment



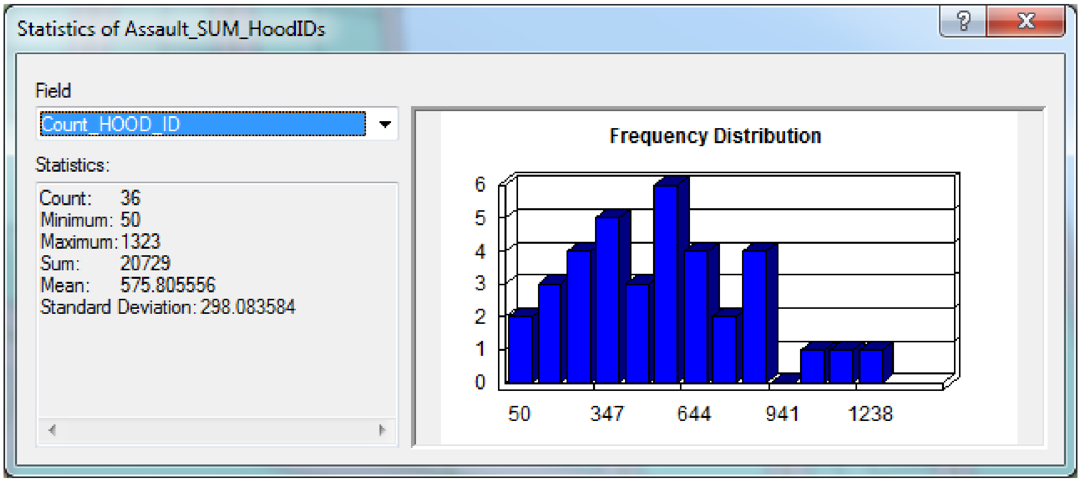
Robbery Distribution by Neighborhood



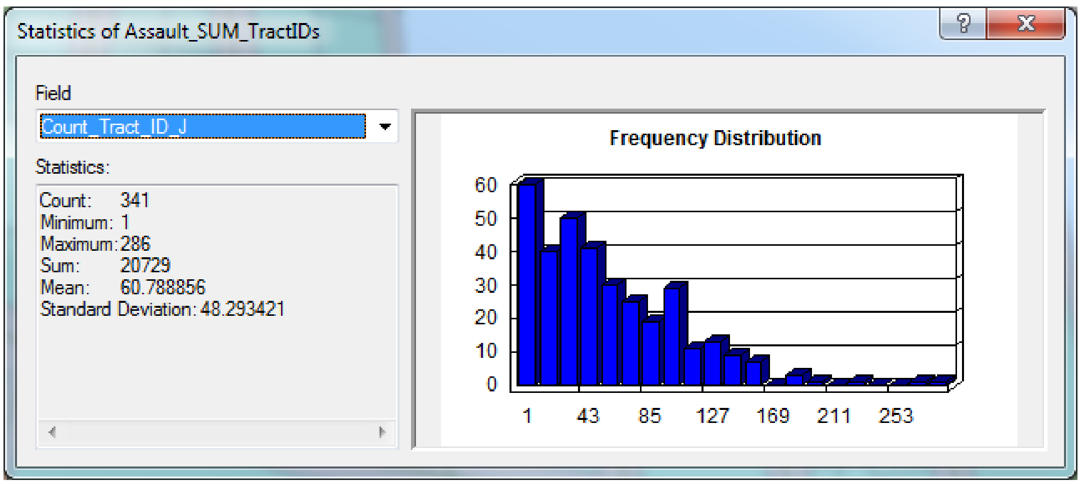
Robbery Distribution by Census Tract



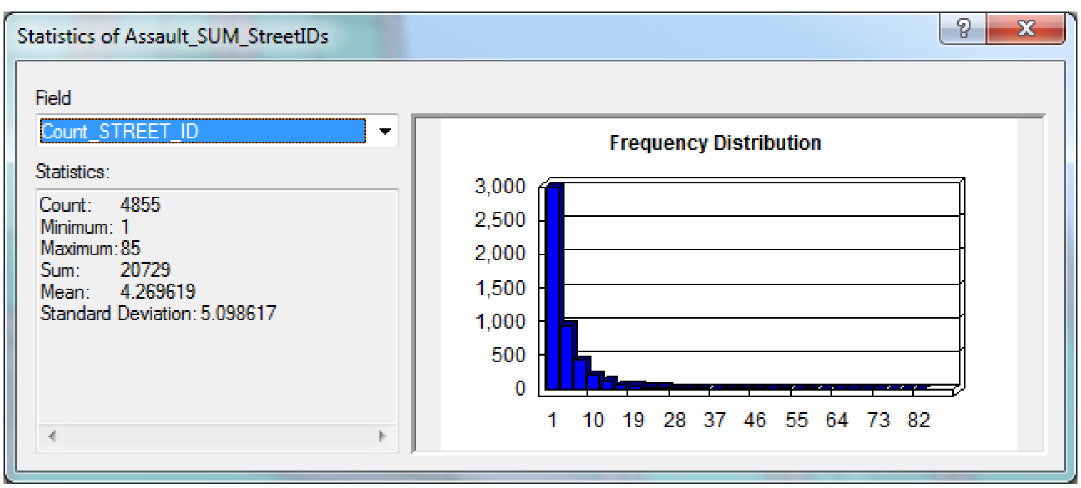
Robbery Distribution by Street Segment



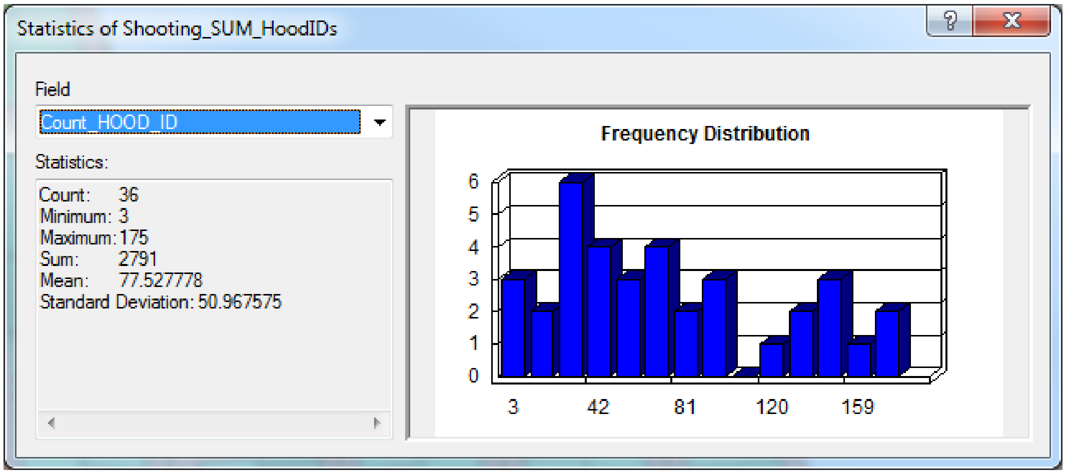
Assault Distribution by Neighborhood



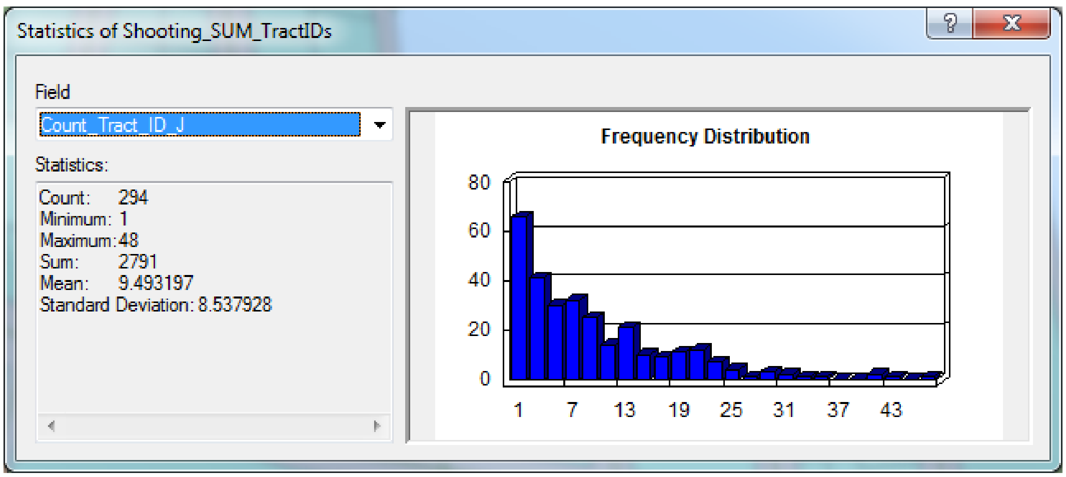
Assault Distribution by Census Tract



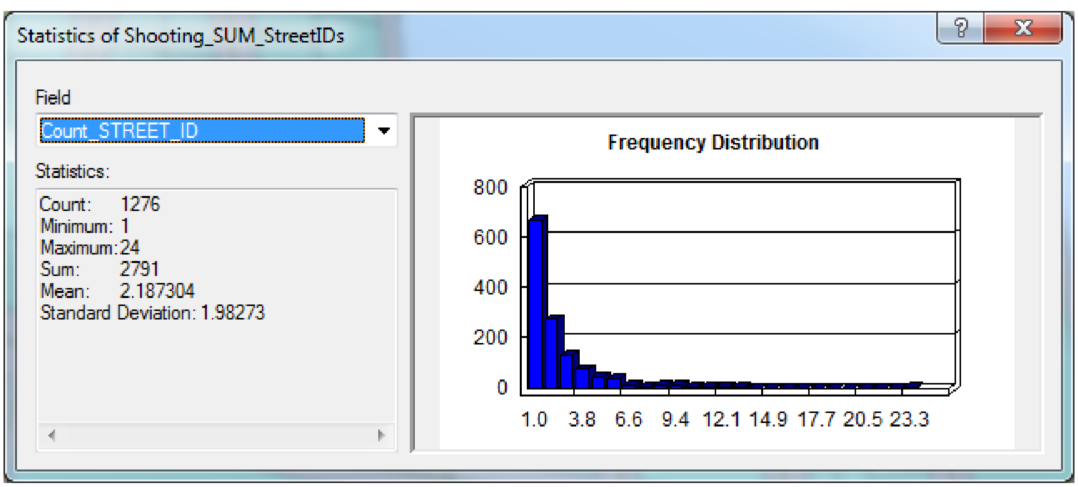
Assault Distribution by Street Segment



Shooting Distribution by Neighborhood

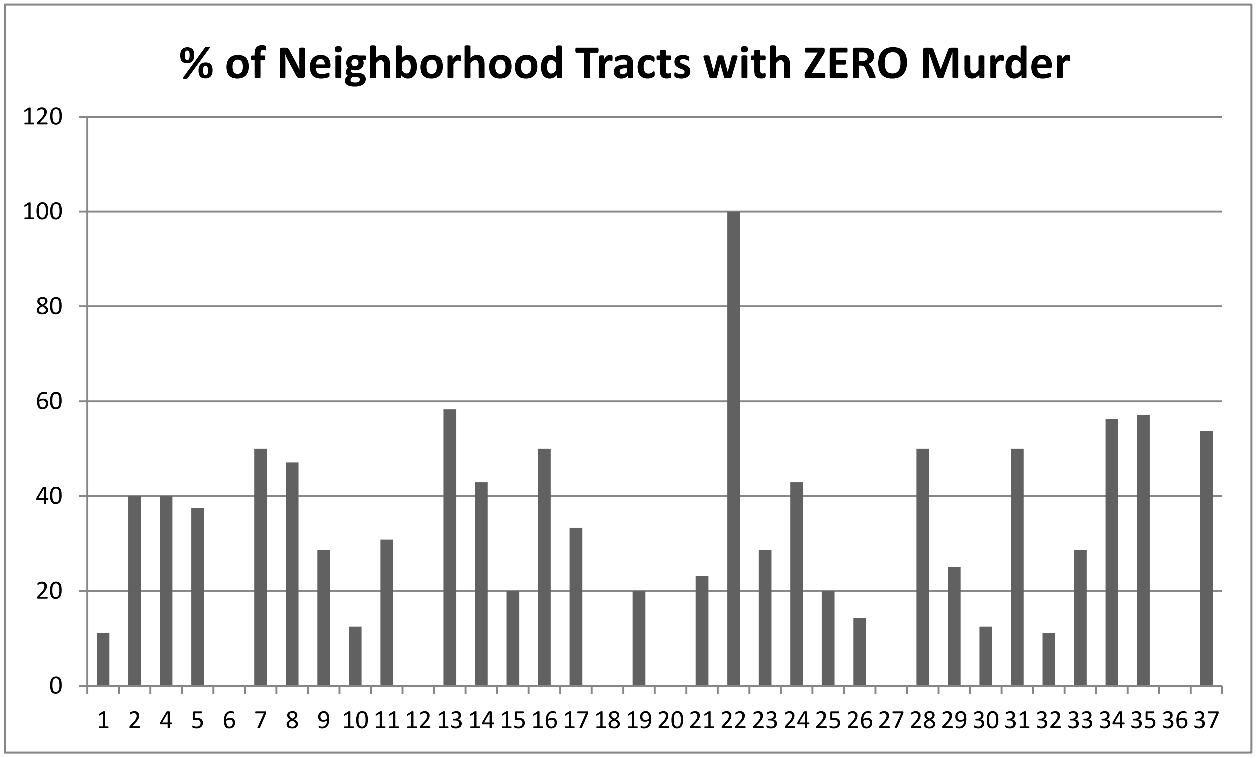


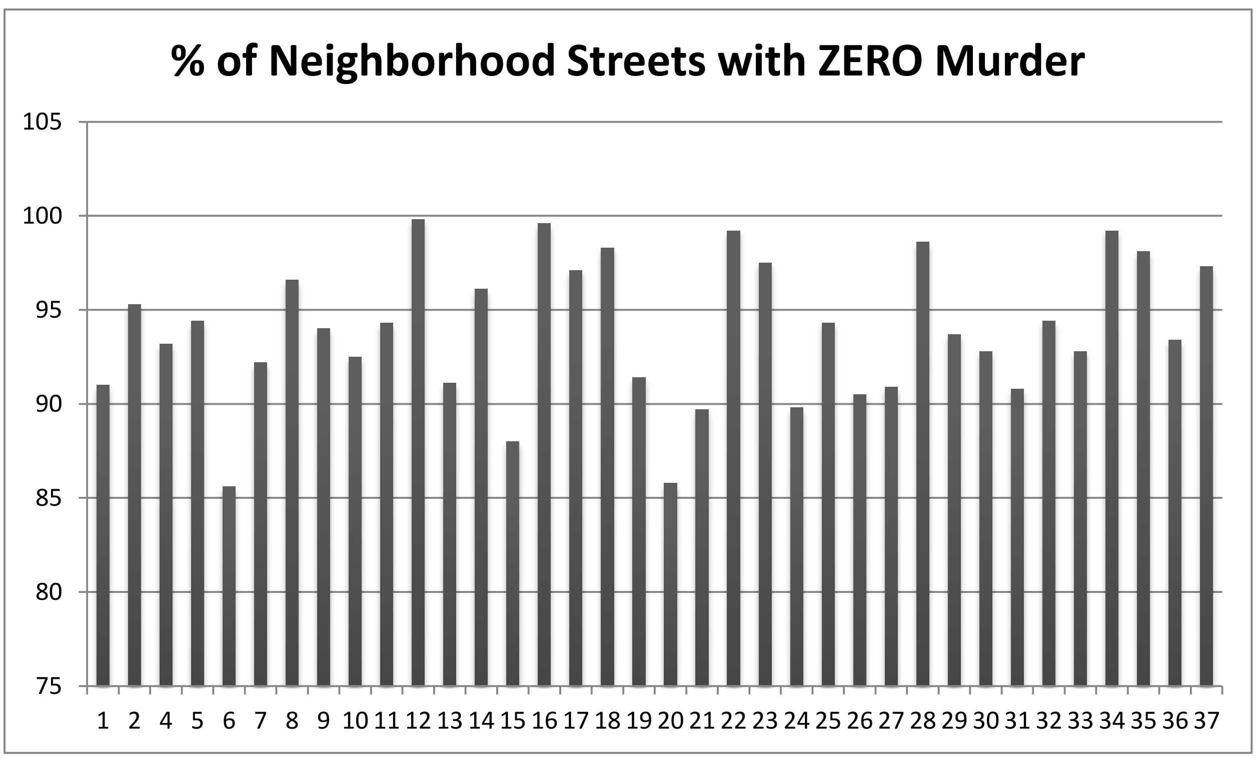
Shooting Distribution by Census Tract

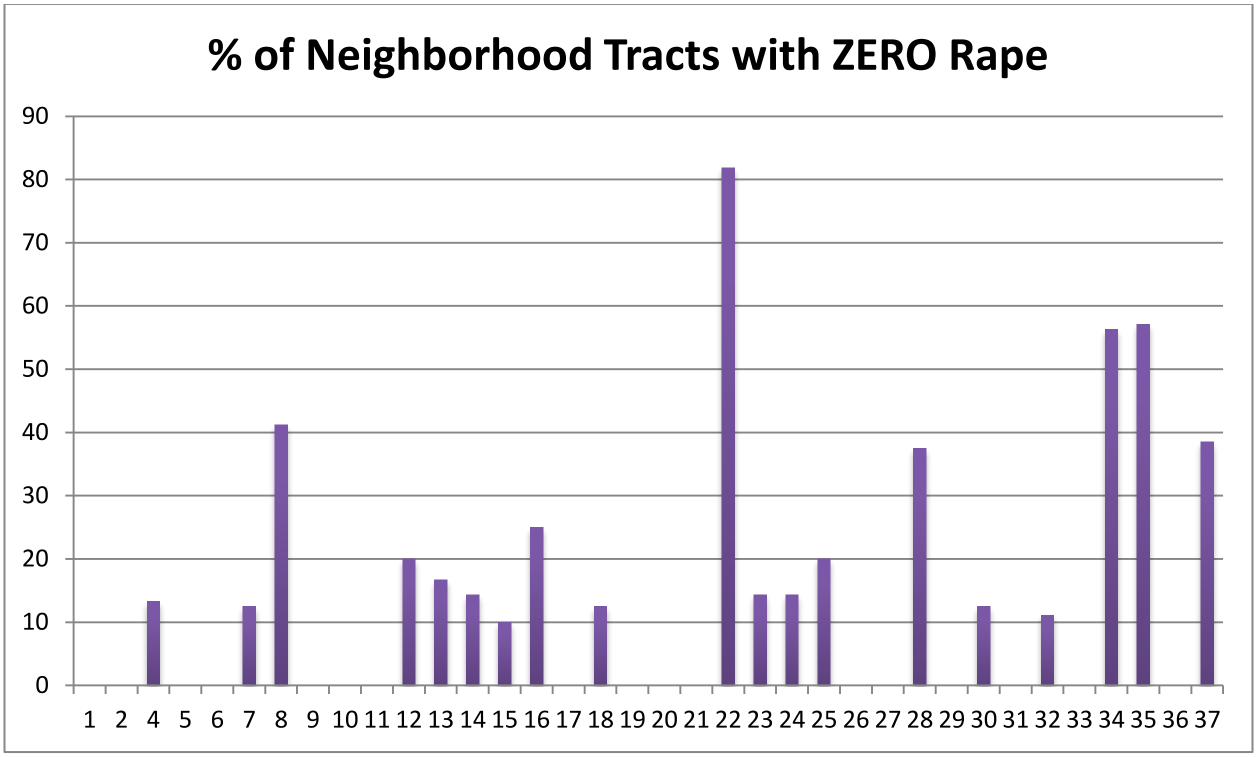


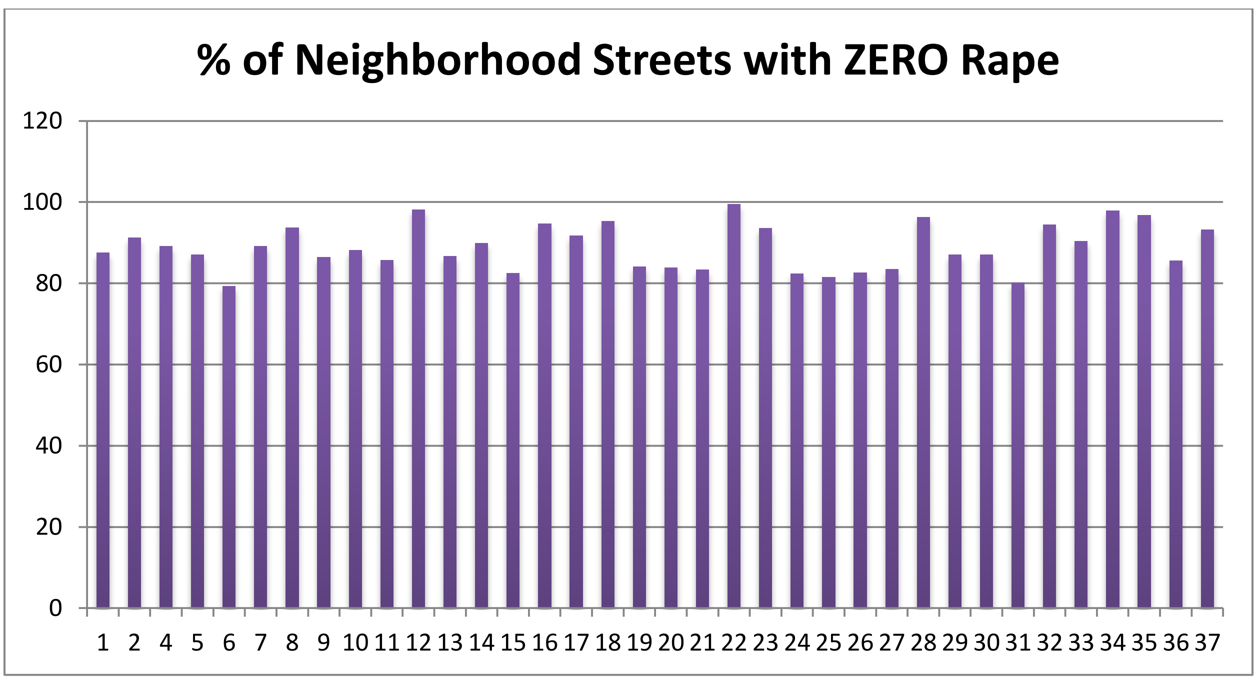
Shooting Distribution by Street Segment

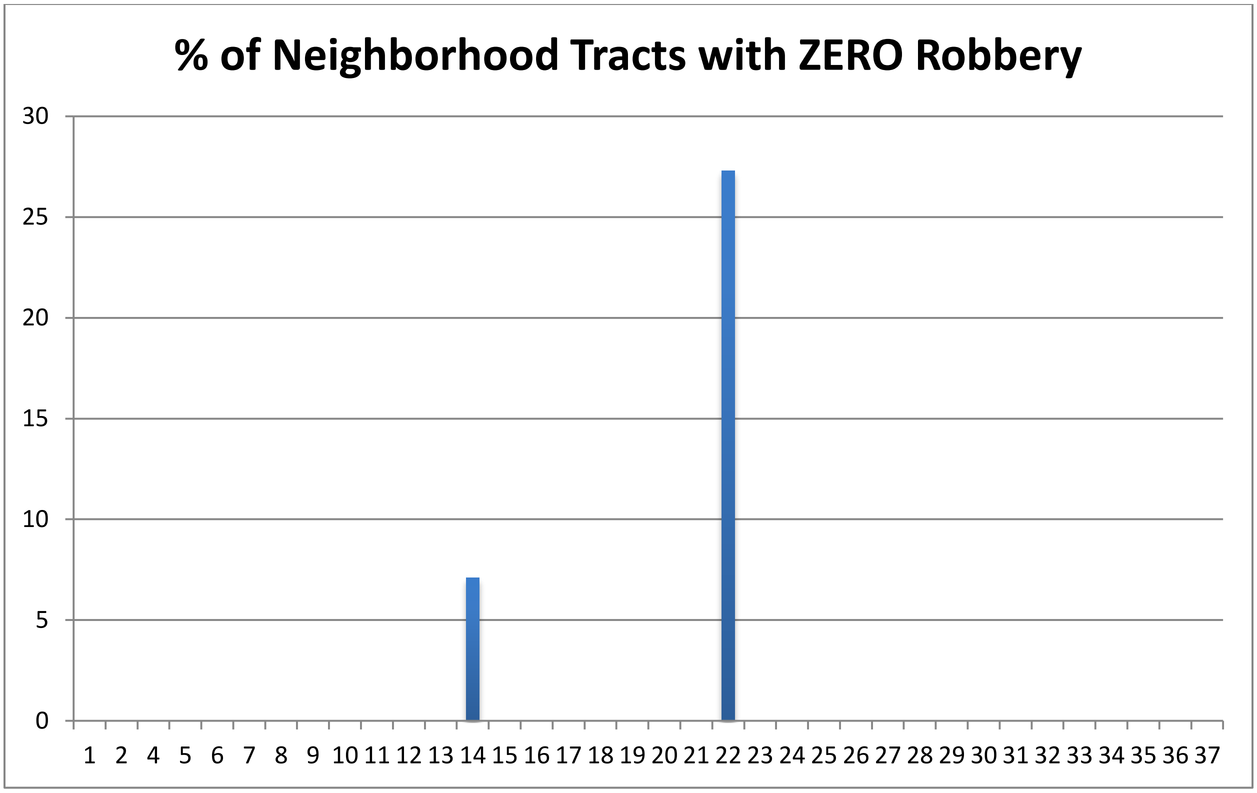
The following pages contain the percentage of tracts and streets with zero crimes by neighborhood. Neighborhood IDs are on the X-axis, Percentage of Tracts/Streets with Zero Crime is on the Y-Axis (taller bars indicate more tracts/streets with zero crimes over the 5-year study period. These type of charts can direct departments to better allocate their resources by neighborhood.

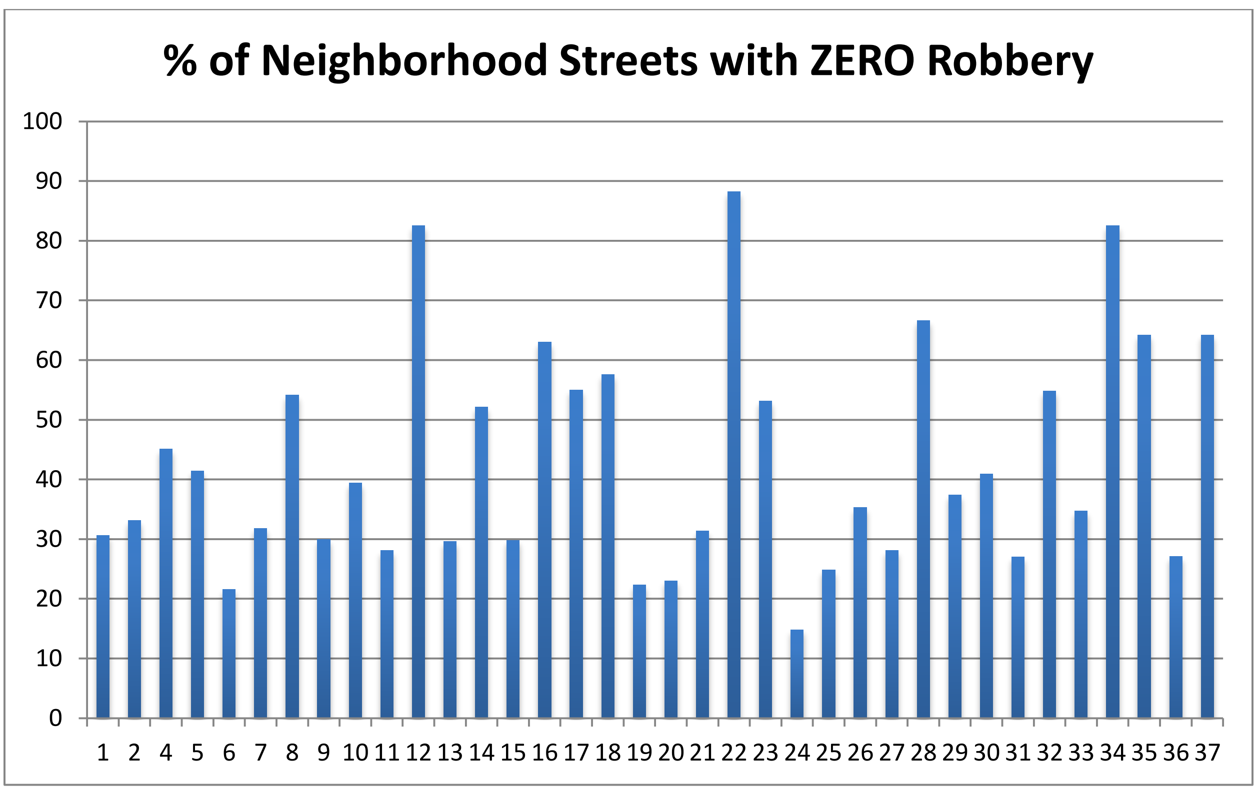


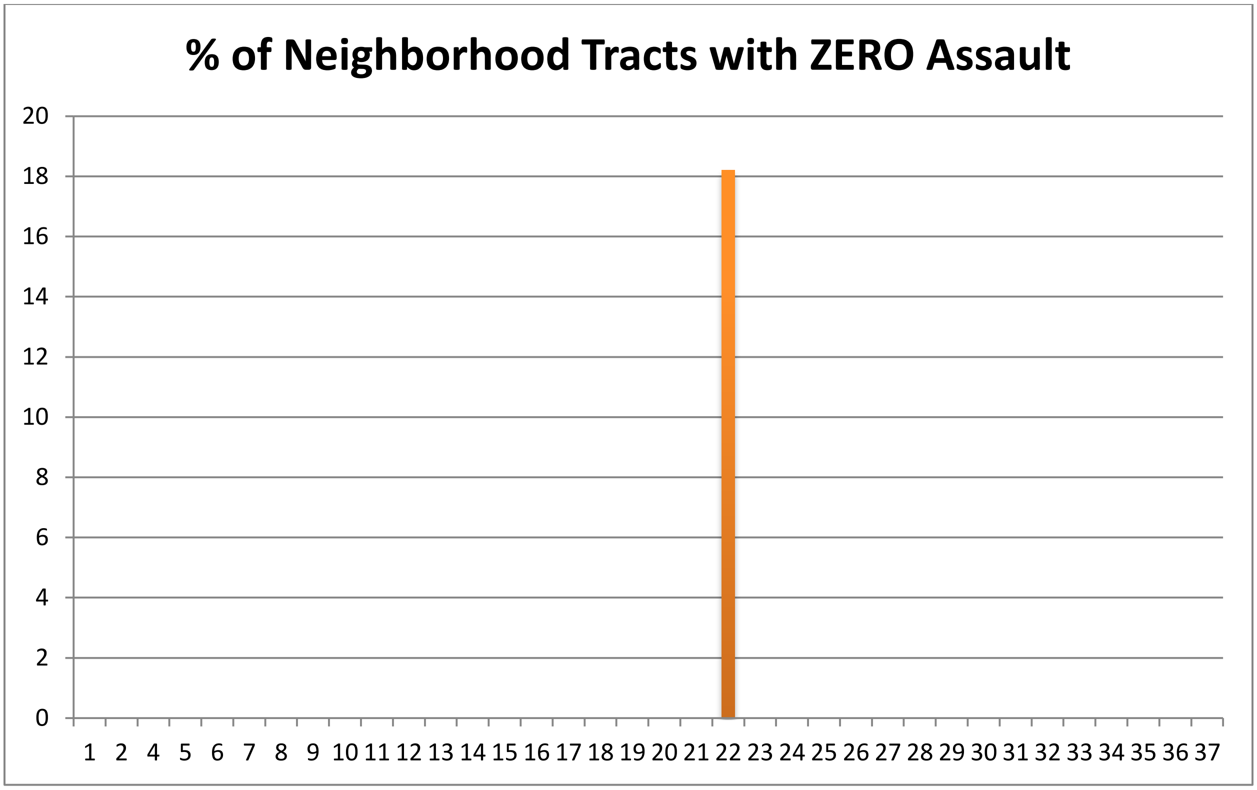


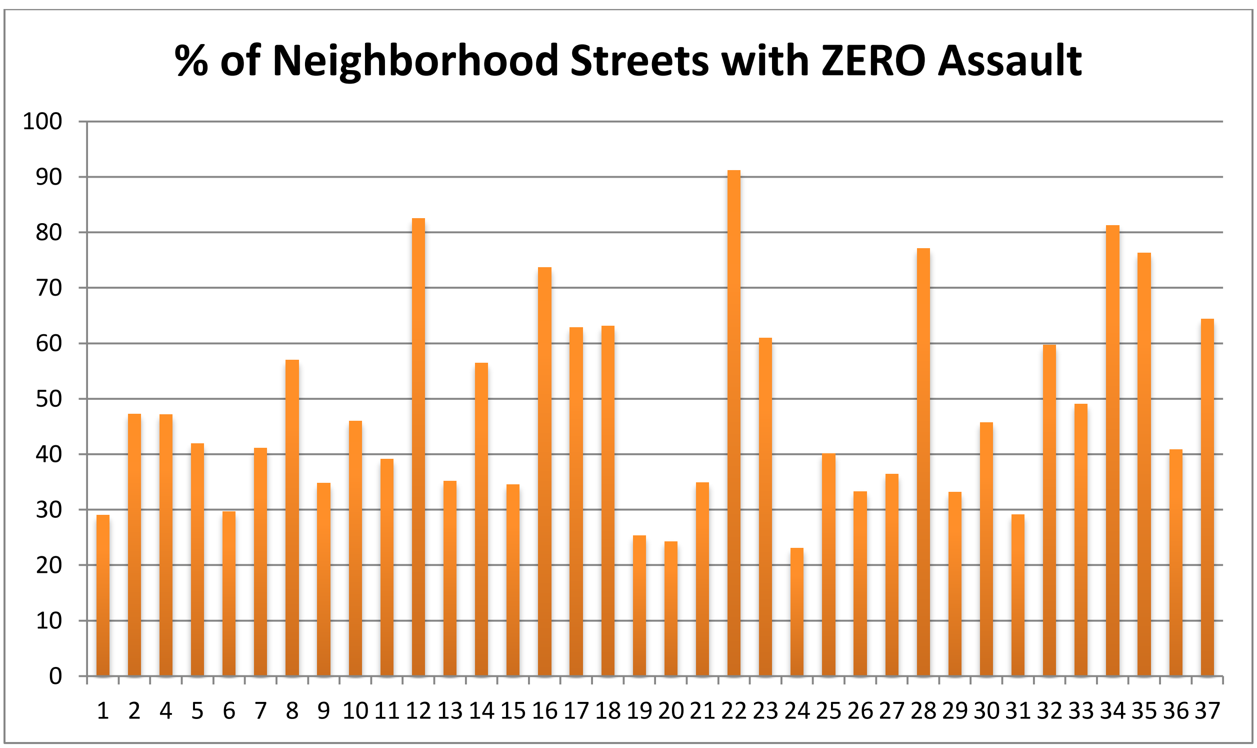

% of Neighborhood Tracts with ZERO Rape
90
80
70
60
50
40
30
20
10
0
1 2 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37

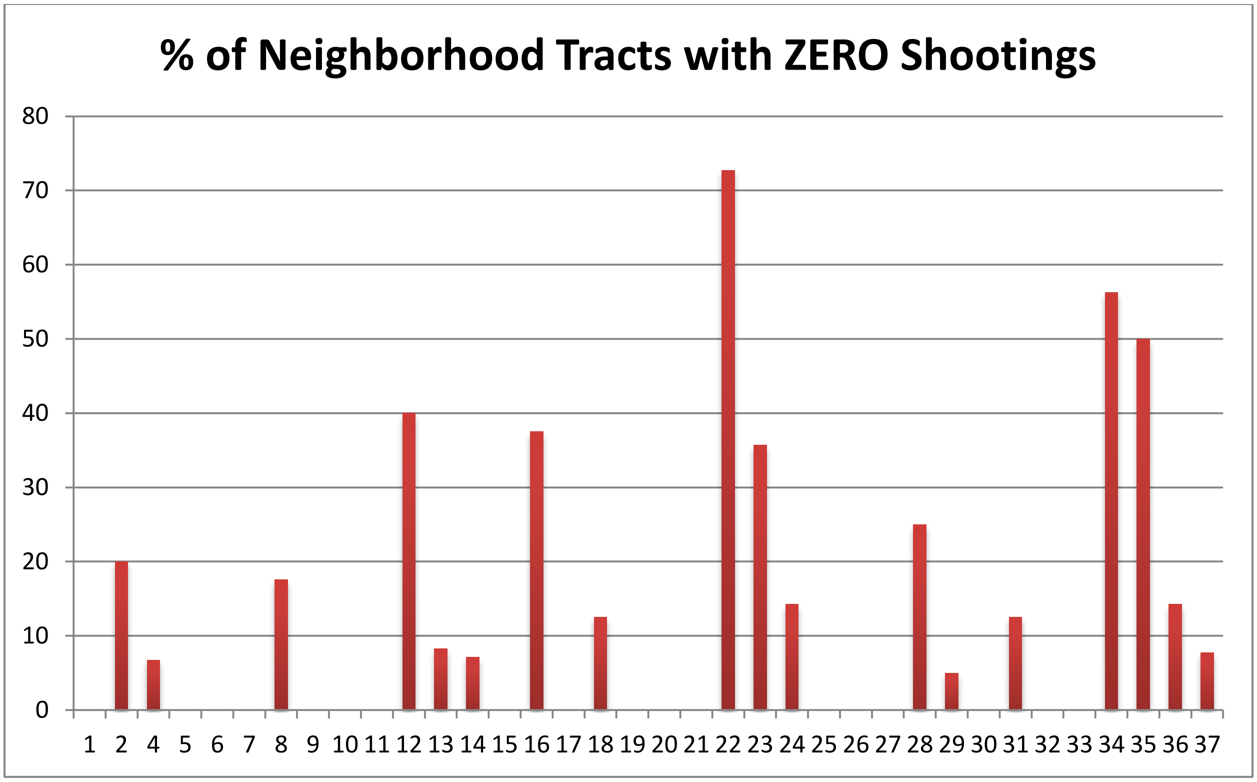

% of Neighborhood Streets with ZERO Rape
120
100
80
60
40
20
0
1 2 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37

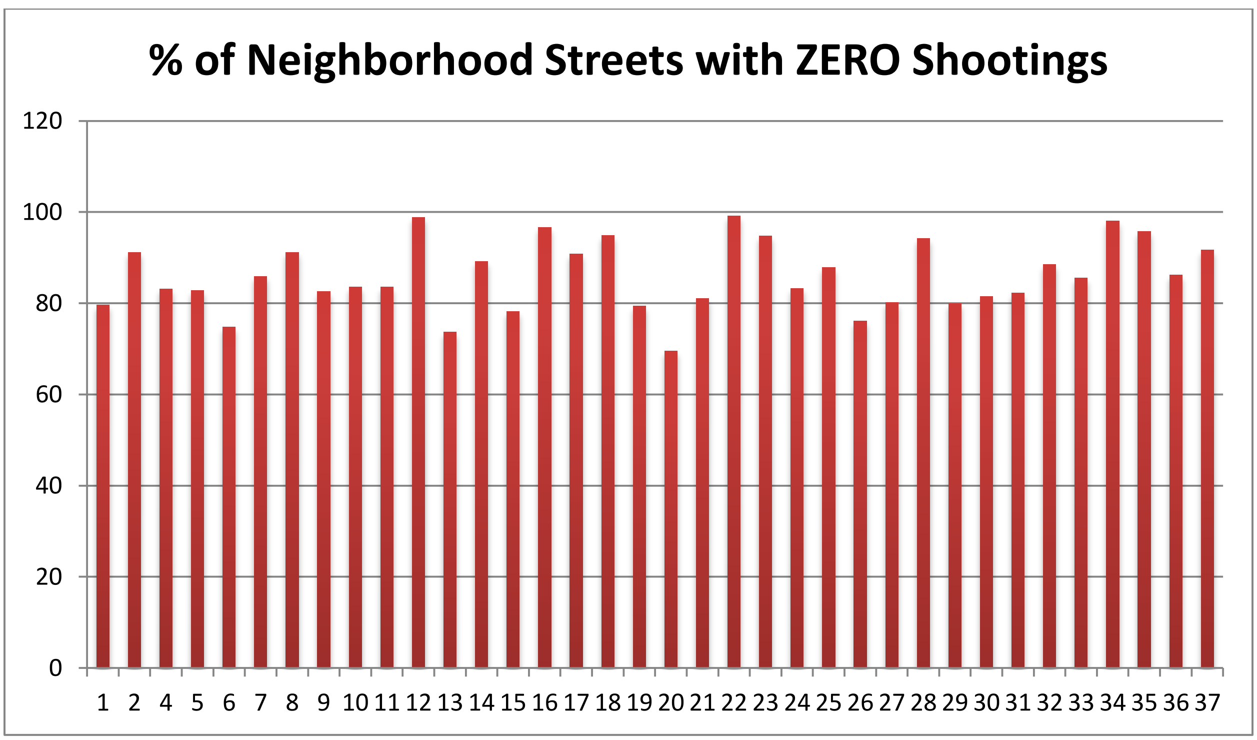

% of Neighborhood Tracts with ZERO Robbery
30
25
20
15
10
5
0
1 2 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37


% of Neighborhood Streets with ZERO Robbery
100
90
80
70
60
50
40
30
20
10
0
1 2 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37


% of Neighborhood Tracts with ZERO Assault
20
18
16
14
12
10
8
6
4
2
0
1 2 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37


% of Neighborhood Streets with ZERO Assault
100
90
80
70
60
50
40
30
20
10
0
1 2 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37


% of Neighborhood Tracts with ZERO Shootings
80
70
60
50
40
30
20
10
0
1 2 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37


% of Neighborhood Streets with ZERO Shootings
120
100
80
60
40
20
0
1 2 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37

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