

# Chapter 4

## Street-Level Spatiotemporal Crime Analysis: Examples from Bronx County, NY (2006–2010)

Christopher R. Herrmann

**Abstract** The objective of this chapter is to illustrate how different geographic scales of violent crime analyses vary and can benefit from spatiotemporal analyses within a geographic information science framework. Geographic clusters of violent crime, typically referred to as ‘hot spots’, can be very difficult to interpret and address at small geographic scales. Incorporating various temporal resolutions to small-scale crime analysis, such as ‘hot streets’ of violent crime, provides law enforcement with a much more robust understanding of small-scale crime patterns. These small-scale street patterns can assist police departments in developing improved geospatial models for targeted police patrols and provide a more comprehensive understanding of the complex relationships between crime and place.

In the first part of this chapter, I illustrate several popular ways that ‘hot spots’ are typically generated and demonstrate how hot spots vary using several violent crime types and temporal analysis. In the second part of the chapter, I establish the importance of exploring crime hot spots at small geographic scales (e.g., streets) and demonstrate several spatiotemporal methods for ‘hot streets’.

**Keywords** Crime mapping • Crime analysis • Micro-level • Hot spots • Hot streets • Small-scale

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## 4.1 Introduction

This chapter illustrates how complex issues in crime analysis can benefit from small-scale exploration within a geographical information system framework. Understanding both spatial and temporal variations in violent crime at the street level can have direct implications on apprehending criminals, police resource allocation & planning, crime modeling & forecasting, and evaluation of crime prevention & crime control programs (Ratcliffe 2004a; 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 crime patterns into consideration when identifying, exploring, and managing crime ‘hot spots’. If Sherman’s concept of ‘wheredunit’ (1989) for hot spots was the foundation for crime mapping and crime analysis between 1990 and 2010, I propose we consider a combination of ‘whendunit’ & ‘wheredunit’ at smaller geographic scales for 2011 and beyond.

## 4.2 Hot Spots

The crime analysis and crime mapping communities have become very proficient in locating, tracking, and managing ‘hot spots’. This iterative crime analysis and crime control process has resulted in a steady ebb and flow of statistical and spatial crime patterns throughout many geographic levels (i.e., neighborhoods, police precincts, census tracts). Current research (Weisburd et al. 2009; Groff et al. 2010; Block 2011) indicates that as we drill down into the small-scales of geography (e.g., streets, tax lots, buildings), crime hot spots start to form new shapes (i.e., lines, points), sizes, and patterns.

In my experience as a crime analyst with the New York City Police Department, not all violent crime hot spots act the same and (almost) all hot spots have significant internal spatiotemporal variance – especially at small-scales (Ratcliffe 2004a, b, c, 2006; Groff et al. 2010). Crime analysts and researchers 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. What (specifically) is generating the hot spot? On what days of the week and at what times of day are the problem(s) occurring within the 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 stationary? Are the problem areas diffused, focused, acute? Are the trends increasing, decreasing, remaining flat? (Ratcliffe 2004a, b, c).

The idea of hot spots (Sherman et al. 1989; Block RL and Block CR 1995; Levine 1999; Weisburd and Green 1995; Peuquet 1994; Ratcliffe 2002; Ratcliffe 2004a, b, c) has been the fuel for much of the interest in our current ‘crime and place’ research. Ever since the Sherman et al. article (1989), there has been a substantial body of literature that supports this concept of hot spots and crime concentrations. Hot spots can be calculated many different ways (Nearest Neighbor Hierarchical

**Table 4.1** Review of hot spot policing programs

| Hot spot study  | Program elements   |
|---|--|
| <b>Minneapolis (MN) RECAP</b><br>Sherman et al. (1989)                              | Problem-oriented policing to control crime at high-activity addresses; interventions comprised mostly traditional enforcement tactics with some situational responses  |
| <b>Minneapolis (MN) hot spots</b><br>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   |
| <b>Jersey City (NJ) DMAP</b><br>Weisburd and Green (1995)                           | Well-planned crackdowns on street-level drug markets followed by preventive patrol to maintain crime control gains   |
| <b>Jersey City (NJ) POP at violent places</b> 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   |
| <b>St. Louis (MO) POP in three drug areas</b> Hope (1994)                           | Problem-oriented policing to prevent crime at three high-drug activity addresses; interventions comprised mostly traditional enforcement tactics with some situational responses   |
| <b>Kansas City (MO) crack house raids</b> Sherman and Rogan (1995a)                 | Court-authorized raids on crack houses conducted by uniformed police officers  |
| <b>Kansas City (MO) Gun project</b><br>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  |
| <b>Houston (TX) targeted beat program</b> 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 |
| <b>Beenleigh (AUS) Calls for service project</b> 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  |

clusters, Getis-Ord  $G_i^*$  statistics, Kernel Density Estimation, Standard Deviation Ellipses, K-Means Clustering, Local Moran's  $I$  statistics), however, none of these methods take the temporal aspect of crime into consideration during calculation.<sup>1</sup>

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. Table 4.1 reports the cities where hot spot studies have been reported on and their associated program elements.

<sup>1</sup> For information on spatiotemporal clustering methods, see Kulldorff (1997) and Hardisty and Klippel (2010).

In his systematic review of hot spot interventions, Braga (2008) 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. Moreover, Clarke and Weisburd (1994) indicate that there is routinely a 'diffusion of benefits' that results from these types of police hot spot interventions. Not only does crime decrease throughout the targeted hot spot area as a result of the applied intervention, 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, none of the studies focused specifically on spatiotemporal clusters of crime, but rather traditional (spatial) hot spots.

Throughout the study of crime and place, criminologists have examined the various relationships between crime and social forces at various geographic scales. There have been numerous studies of crime at higher level geographies; such as countries (Weir and Bang 2007; Gartner 1990), states (Rosenfeld et al. 2001; Faggiani et al. 2001), countries (Block and Perry 1993; Baller et al. 2001), cities (Martin et al. 1998; Cork 1999), and neighborhoods (Elffers 2003; Tita and Cohen 2004). Many of these studies have indicated various relationships between crime and socioeconomic factors (e.g., poverty, race, education, etc.). However, all of the socioeconomic and environmental criminology factors that are of interest to crime analysts and criminologists also vary 'beneath the surface' (Maantay et al. 2007).

In the past 30 years, there has been a renewal in interest in crime at smaller scales. 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 smaller-scales (Taylor 1998; Weisburd et al. 2009; Groff et al. 2010). One of the current trends in crime and place research is small-scale geographies, where small-scale is defined as street segments, properties, or buildings. Most of this renewed interest is a result of small-scale research conducted in Minneapolis (Sherman et al. 1989), Baltimore (Taylor 2001), Seattle (Weisburd et al. 2004), and Jersey City (Weisburd and Green 1994).

Few of the previous macro-level (large scale) studies indicate that there is significant variation beneath the unit of analysis that is central to the research. However, as GIS analysts, we know 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. This research simply continues this process of 'zeroing in' on crime problems, beyond the neighborhood, census tract, and census block group levels.

### 4.3 Cones of Resolution

Brantingham et al. (1976) defined this process of zooming in to small-scale geographies as moving downward through different geographical ‘cones of resolution’. “The mapping of variables into areal aggregates limits comparative analysis to variables which have been mapped into similar levels of aggregation and further limits the questions that can be validly asked of the data” (Brantingham et al. 1976, p.261).

Figure 4.1 shows the different spatial and temporal levels of analysis that are typically used in crime analysis research today. It is important to note that as we drill down to smaller spatial units of analysis, it also becomes essential to correspondingly drill down on the temporal units of analysis. Small-scale hot spots (i.e., streets, properties, buildings) vary by space and time much more so than large-scale hot spots (census tracts, neighborhoods, police precincts).

For example, residential buildings/streets that contain crime problems do not have high crime problems 24 h a day and 7 days a week. Residential buildings/streets have a unique temporal pattern, based on the occupancy of the residents in the building. If residents work a traditional work/school week (Mon-Fri), during the daytime (6 am – 6 pm), there is more likely to be criminal activity in the evening (6 pm–midnight) on ‘workdays/schooldays’ (Mon–Thur). However, we would expect to see a shift from evening (6 pm–midnight) to nighttime (midnight–4 am) on Fridays and Saturdays, since most of the working residents would not be going to work (or school) in the morning on the following day. This day of week and time of day pattern is very evident in the Bronx violent crime patterns (Figs. 4.2 and 4.3).

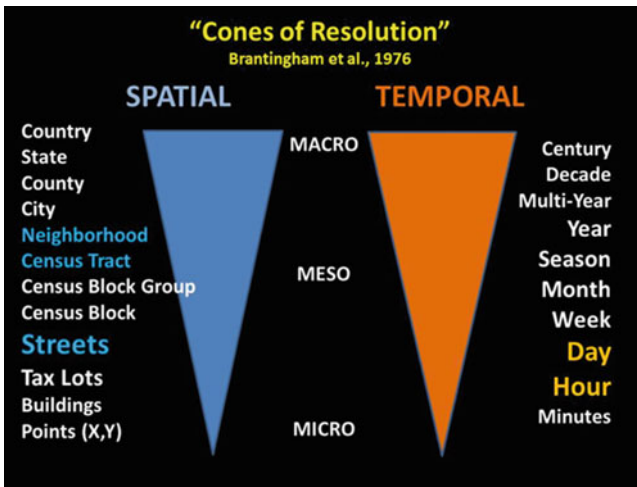


Fig. 4.1 Spatial and temporal units of crime analysis

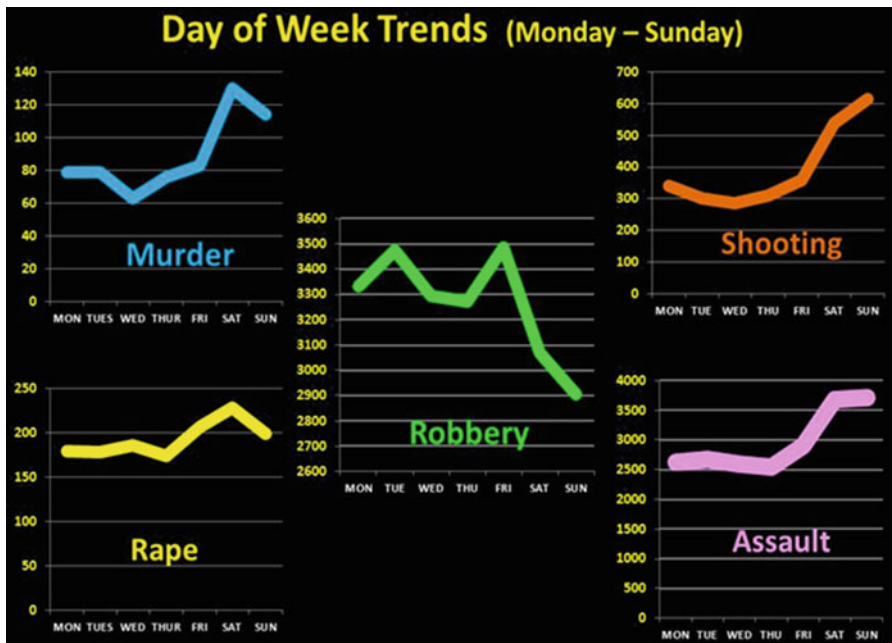


Fig. 4.2 Violent crime trends for the Bronx (2006–2010) by day of week

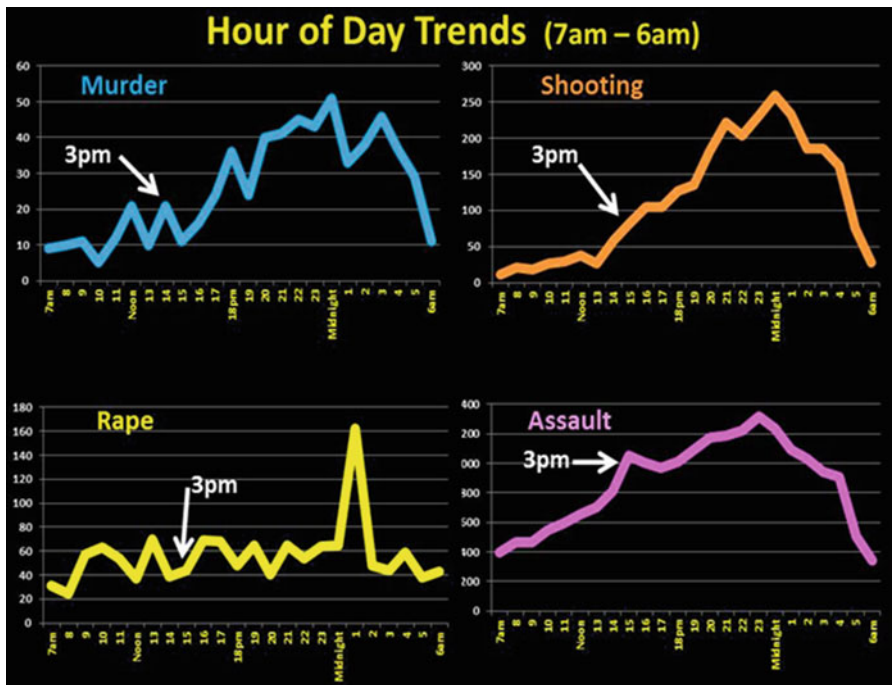


Fig. 4.3 Violent crime trends for the Bronx (2006–2010) by hour of day

If hot spot geographies ‘move’ based on the day of week and/or time of day, such as high crime Nearest Neighbor hierarchical (Nnh) clusters, they will also vary much more temporally when these Nnh clusters are constructed at smaller scales. If you query out crime data by hour of day and/or day of week and run the same Nnh clustering parameters, you will most likely obtain very different locations for the small-scale clusters. A very beneficial analysis is to do this over a 24-h period, to find out how each crime ‘moves’ over the course of one day. You can also query out crime by day of week to find out how the Nnh cluster locations vary day to day.

#### 4.4 The Move to the Micro-level

One of the current trends in studying crime and place at smaller scales is simply a continuation of our historical interest in crime and place. If we continue to see clustering of crime at smaller geographic levels, then we need to recognize that there are significant benefits of studying crime and place at smaller scales. First and foremost, small-scale clusters provide easy ‘targets’ for directed police patrols. It is much easier for the police to target patrols at properties and street segments, than it is to target entire neighborhoods or police precincts. This is especially true when developing foot patrol strategies (Ratcliffe et al. 2011).

Moreover, if small-scale clusters of properties and street segments are responsible for a majority of the crime within an entire neighborhood, certainly a targeted patrol strategy would have a much more significant crime prevention/crime control benefit than police randomly patrolling entire neighborhoods. Problem-Oriented Policing (POP) strategies are much more effective when they target specific small-scale areas. Again, it is important to recognize that small-scale areas are not 24×7 problem areas. In order to effectively address small-scale crime hot spots, we must incorporate temporal trends into our small-scale crime prevention and control strategies. Not only would this small-scale place+time process maximize police impact and outcomes, it would also manage police resources much more effectively than ‘random’ 24×7 patrols. Furthermore, this type of small-scale research provides better understanding of the social, structural, and opportunity factors that are related to crime and small-scale places.

One of the current objectives in environmental criminology and crime analysis is drilling down/zooming in on typical hot spot geographies that are generated by density maps. Using longitudinal crime data, it is now possible to zoom in to the small-scale units 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. 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, few crime hot spots behave similarly.



## 4.5 Welcome to the Bronx

The research area and data for this study comprise of various Geographic Information Systems (GIS) datasets for Bronx County, New York; as well as several violent crime datasets for the Bronx from the New York City Police Department (NYPD). 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 1970s (New York City Department of City Planning 2010). The GIS datasets include Bronx County (Borough), Bronx Neighborhoods (n=37), Bronx Census Tracts (n=355), Census Block Group (n=957), street segments (n=10,544), and property lot data (n=89,812) from the New York City Department of City Planning (NYC-DCP) and the New York City Department of Finance (NYC-DOF).

The neighborhood boundaries of the Bronx are defined by NYC-DCP to contain small area population projections of at least 15,000 people and the boundaries are designated according to historical geographic and sociocultural data (NYC-DCP, 2010). The resulting 37 neighborhoods shapefile contains entire census geographies that were subdivisions of New York City Public Use Microdata Area (PUMA) datasets. Within the 37 unique neighborhoods, Bronx County is further disaggregated into 355 census tracts, 957 census block groups, 10,097 street segments, 89,812 property lots, and 101,307 buildings.

While this chapter promotes advances in small-scale (geographical units below the block group level) crime analysis techniques, it does not intend to concentrate on the inherent problems that occur in most studies of crime and space; most notably the issues related to census unit boundaries (Rengert and Lockwood 2009; Hipp 2007), the modifiable areal unit problem (MAUP) (Openshaw 1984; Chainey and Ratcliffe 2005), and the issue(s) surrounding ecological fallacy (Robinson 1950; Subramanian 2009).

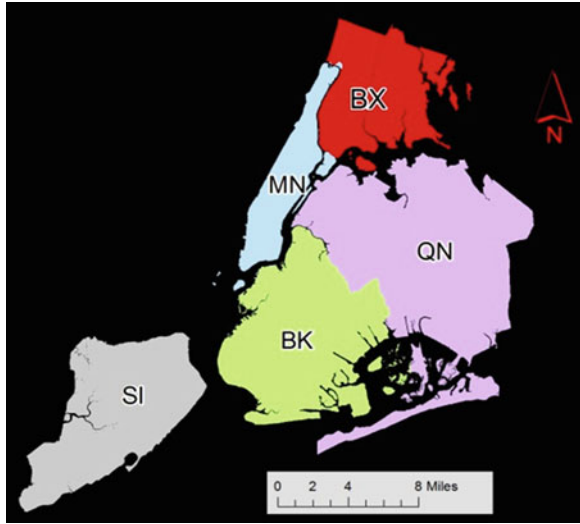
## 4.6 The New York City Police Department and GIS

The NYPD has been using GIS since the early 1990s, primarily for use in its innovative COMPSTAT process (Bratton 1996). The violent crime datasets for this research include traditional Uniform Crime Report (UCR) violent crime categories murder, rape, robbery, and assault records that were exported out of the NYPD Crime Data Warehouse (NYPD Computer File, 2011). In addition to UCR data, shooting incidents, where shooting locations are confirmed by evidence of a shooting (one or more credible witnesses, one or more shooting victims, gun shell casings, bullet holes, etc.) were also included in the violent crime dataset. All of the violent crime data were geocoded to the property lot level and then aggregated up to street segments and higher-level geographies (i.e., census tracts and neighborhoods).

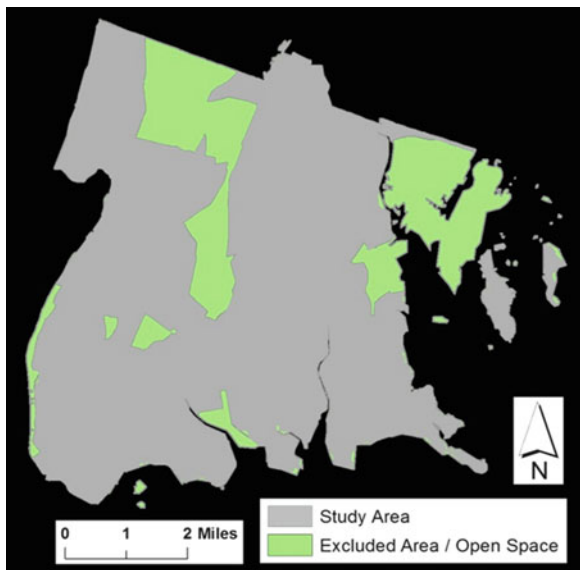
This research takes place in Bronx county (shown in red, Fig. 4.4), the northernmost county of the five counties that make up New York City. The Bronx is 42 square



**Fig. 4.4** New York city map



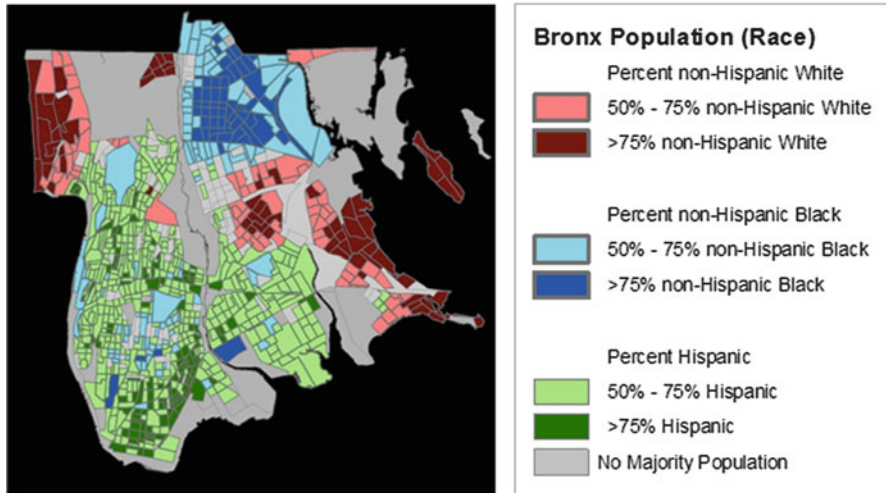
**Fig. 4.5** Bronx study area and open space



miles in area, which makes it 14% of New York City’s total geographical area. Even though the Bronx is the third most densely populated county in the United States (behind Manhattan & Brooklyn), about a quarter of its land area (shown in Fig. 4.5 in green) is uninhabited open spaces. These uninhabited open spaces include the largest park in New York City (Pelham Bay Park), the Bronx Zoo & Botanical Gardens, large cemeteries, industrial, and waterfront areas.

**Table 4.2** New York City and Bronx violent crime between 2006 and 2010 (NYPD 2011)

| Crime    | NYC     | Bronx  | Bronx as % of NYC |
|----------|---------|--------|-------------------|
| Murder   | 2,622   | 657    | 25                |
| Rape     | 6,944   | 1,510  | 23                |
| Robbery  | 105,788 | 23,069 | 22                |
| Assault  | 84,541  | 20,732 | 25                |
| Shooting | 7,998   | 2,256  | 28                |

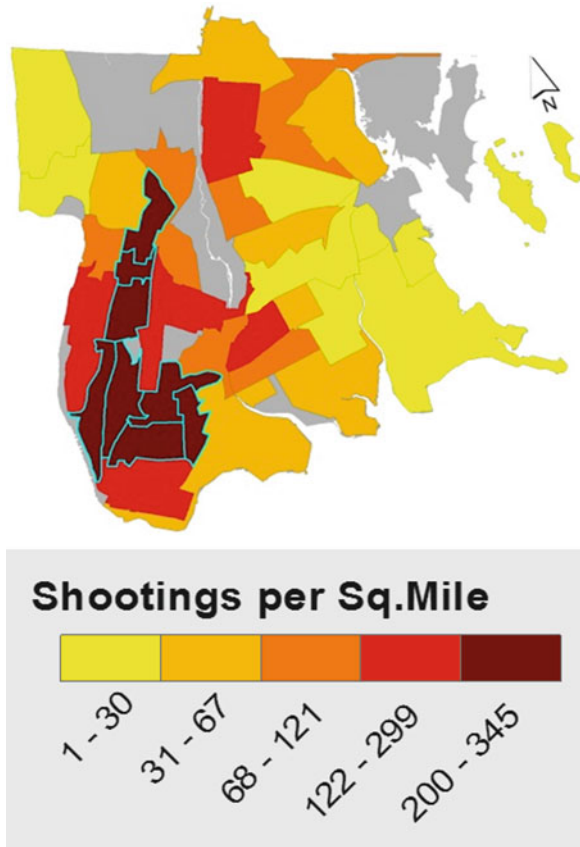


**Fig. 4.6** Census tract by race

The Bronx is an ideal place to model human behavior (such as crime) because it is one of the smallest (in area), one of the highest in population density, it is the most diverse in ethnic/racial composition, and it has a substantial amount of violent crime (between 2006 and 2010). As Table 4.2 indicated, the Bronx contains a disproportionate amount of violent crime while considering its size (14% of NYC’s total land area) and population (17% of NYC’s total population).

The population of the Bronx is 1.4 million (U.S. Census, 2010). Figure 4.6 shows the population distribution by race throughout the Bronx. The Bronx River runs north/south thru the middle of the Bronx and separates the east/west parts of the Bronx. The US Census 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 US Census, if you randomly selected two Bronx residents, 90% of the time they would be of a different race or ethnicity (Newsweek 2009). Figure 4.7 shows the population distribution by race at the census tract level. As you can see, not only is the Bronx extremely diverse, but it is also very segregated by race.

**Fig. 4.7** Shooting density by neighborhood



#### 4.7 Why Police Departments Must Focus on Small-Scale Crime Analysis

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 any other police departments facing budget cuts) to efficiently analyze, model, and utilize geospatial technologies.

One way the NYPD achieves efficient crime prevention and crime control is by continuously analyzing crime and developing prevention and control strategies at both large-scales (county, precinct) and small-scales (police sectors, streets, properties). The NYPD COMPSTAT system was designed to analyze crime patterns at larger-scales – precincts, patrol boroughs (i.e. Manhattan, Brooklyn, and Queens

Counties are each split into two patrol boroughs based on north/south geography) and county levels on a weekly/monthly 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 levels on an hourly/day-to-day basis (police sectors at NYPD are very similar in size to census block groups). 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 small-scale areas the following day or week. Both COMPSTAT and Operation Impact are utilized by NYPD, but both operate at different spatiotemporal levels and have different goals/objectives.

There is (almost) always significant spatial clustering with violent crime data. Moreover, there is also (usually) significant temporal variation between and within violent crime data. This spatiotemporal realism is accentuated even more at smaller-scales. Not all violent crimes act the same way and even the same crime(s) have significant internal temporal variations.

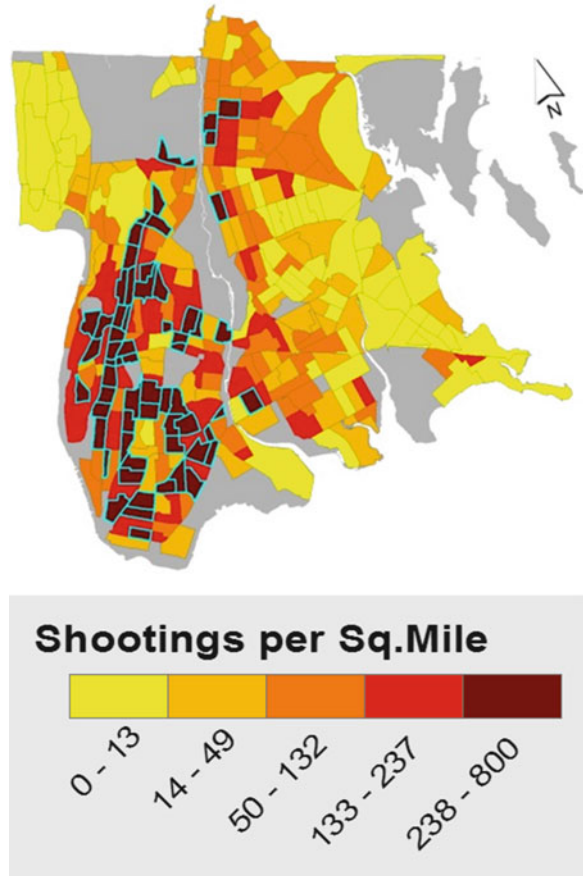
We should consider the temporal variations of crime at higher spatial levels (neighborhood, tract, block group) primarily as a result of the dominant land uses (e.g., commercial, residential, recreational, transportation, vacant, etc.). According to the routine activities theory (Cohen and Felson 1979), we would expect to see more daytime violence patterns in geographical areas where large groups of people congregate (e.g., commercial, recreational, transportation) or where groups of people are intermingling (e.g., transportation hubs). Evening and nighttime violence patterns in geographical areas may be dominated by areas with higher percentages of vacant land, public transportation hubs, high-density residential areas, or commercial areas (especially those with late-night/24-h businesses serving alcohol) that lack effective place managers.

## 4.8 Bronx Shootings

Geospatial analysis was conducted on 2,752 shooting incidents throughout the Bronx between 2006 and 2010. Shooting locations were geocoded to the property lot level and then aggregated up to the street segment, census block group, census tract, and neighborhood levels. Shooting aggregates were divided by the polygon area (in square miles) which created a shooting density for each geographical unit. The shooting classes were then symbolized using a quintile classification method, where the dataset is split into five groups, each with an equal number (approximately 20%) of areal units. This quintile method works well with neighborhood and census level data in New York City because it allows comparison of geographical units that are similar in size and population. However, one of the weaknesses of quintile classification is that it masks some of the outlier classes because the values are grouped by an ordinal ranking system (Maroko et al. 2009).

The shooting maps (Figs. 4.7, 4.8, and 4.9) illustrate several problems that typically occur when analyzing crime densities at comparatively coarse geographies.

**Fig. 4.8** Shooting density by census tract

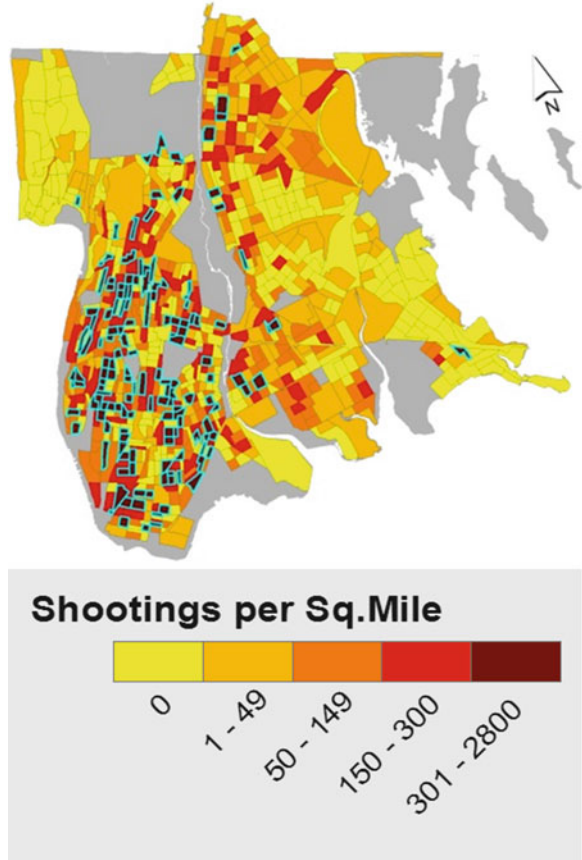


The neighborhood (Fig. 4.7), census tract (Fig. 4.8), and census block group (Fig. 4.9) level maps all illustrate how shooting densities vary significantly at each geographic level. When starting at the neighborhood level (Fig. 4.7), each subsequent geographic level indicates increased spatial variation.

Table 4.3 indicates the small-scale street variations within the higher level geographies – neighborhoods, census tracts, and census block groups. Overall, as we drill down through the spatial cone of resolution (from neighborhood to block group level); the number and percentage of shootings that occur within the top (20%) quintile (outlined in blue) increases and the number and percentage of street segments within the top quintile decreases. Likewise, the number and percentage of streets that have zero shootings on them decreases as we move from higher level to lower level geographies.

It is important to note that almost 80% of the street segments within the highest quintile shooting neighborhoods have zero reported shooting incidents on them. Therefore, even within the highest quintile shooting density neighborhoods, shooting incidents are highly clustered which indicates a need to examine shootings at smaller

**Fig. 4.9** Shooting density by block group



**Table 4.3** Bronx shooting frequencies and percentages within top quintile class

| Bronx Shootings 2006–2010<br>n=2,752         | # of Total shootings in top quintile | % of Total shootings in top quintile | # of total streets in top quintile | % of total streets in top quintile | # of zero shooting streets in top quintile | % of zero shooting streets in top quintile |
|--|--------------------------------------|--------------------------------------|------------------------------------|------------------------------------|--|--|
| High shooting neighborhoods<br>(8 out of 36) | 1,006                                | 37                                   | 1,820                              | 18                                 | 1,430                                      | 79   |
| High shooting Tracts (62 out of 329)         | 1,268                                | 46                                   | 1,591                              | 16                                 | 1,137                                      | 72   |
| High shooting block groups (144 out of 924)  | 1,286                                | 47                                   | 1,047                              | 10                                 | 643  | 61   |

scales. Similarly, at the census tract level, almost half of the total reported shootings occur in the top 20% of tracts and the majority (72%) of street segments contain zero shootings. Even at the block group level, the majority (61%) of streets have zero reported shooting incidents within the highest (quintile) block groups.

## 4.9 Bronx Robbery

Robbery is the most common form of violent crime in New York City and one that many researchers consider to be the best indicator of street-level and neighborhood ‘safety’ (Kennedy and Baron 1993; Groff 2007; Block and Bernasco 2011). The New York City Police Department uses robbery as their primary violent crime indicator for the creation and development of its crime reduction “impact zone” program. Impact zones are small geographical areas, similar to clusters of street segments, that experience consistent high or sharply increasing rates of robbery (and/or other violent crimes). At a recent symposium on the “Understanding the Crime Decline in New York” (John Jay College 2011), Zimring noted that impact zones and destruction of outdoor drug markets were two NYPD initiatives that have helped reduce robbery 30% since 2000.

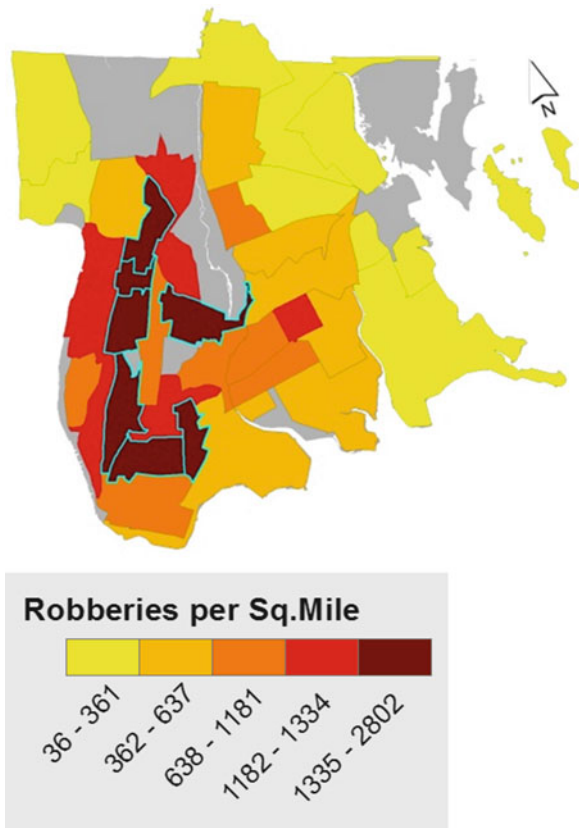
Spatiotemporal analysis was conducted on 22,824 robbery incidents that were reported in the Bronx between 2006 and 2010. Robbery locations were geocoded to the property lot level and then aggregated to the street segment, census block group, census tract, and neighborhood levels. Robbery aggregates were divided by the polygon area (in square miles) which created a robbery density for each geographical unit. The robbery classes were then symbolized using a quintile classification method, where the dataset is split into five groups, each with an equal number (approximately 20%) of areal units.

The robbery maps (Figs. 4.10, 4.11, and 4.12) illustrate many of the similar problems exhibited by the previous shooting maps. As was observed in the neighborhood (Fig. 4.10), census tract (Fig. 4.11), and census block group (Fig. 4.12) level maps – robbery densities vary significantly at each geographic level. When starting at the neighborhood level (Fig. 4.10), each subsequent geographic level indicates increased spatial variation.

Table 4.4 indicates similar micro-level street variations throughout the coarser level robbery geographies. Since robbery is more than nine times as prevalent and widespread (robbery is still clustered countywide, but it has a much larger spatial distribution) than shootings, the data showing the number/percentage of robberies in the highest quintile class does not suggest as much of a difference between the neighborhood/tract and tract/block group levels. The percentage of streets in the top quintile for robbery is almost the exact same as the percentage of streets in the top quintile for shootings. However, the differences in the percentage of top quintile streets demonstrates the primary difference between the two crimes. Again, it is important to note that even in the top quintile robbery areas, 26% of streets have fewer than 2 robberies and more than 20% of street segments contain zero robbery incidents



**Fig. 4.10** Robbery denisty by neighborhood



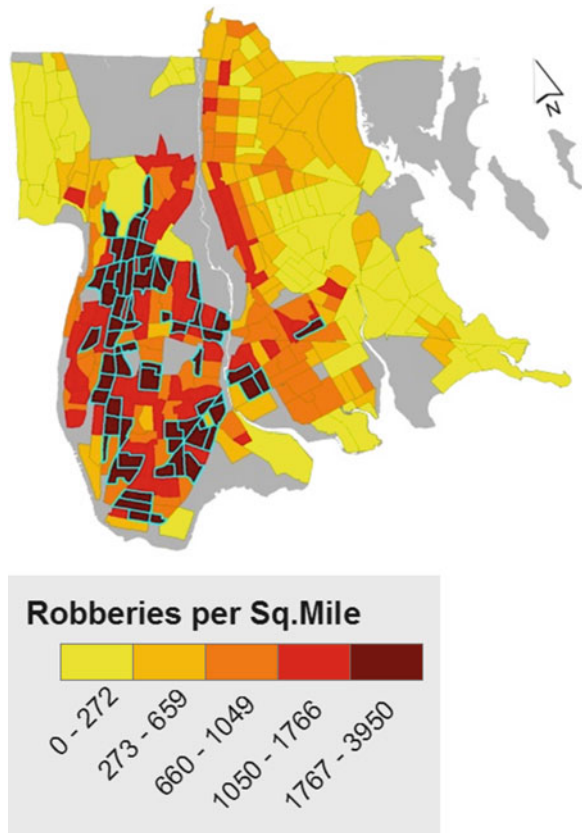
over the 5-year study period. Even with the most widespread violent crime in the Bronx, almost 50% of the streets contain less than the average number of robberies. Again, this suggests a need for analyzing crime at finer spatial resolutions.

### 4.10 Bronx Assault

Assault is the second most common form of violent crime in New York City. The New York City Police Department also uses assault as a secondary violent crime indicator for its crime reduction “impact zone” program.

Analysis was conducted on 20,726 assault incidents that were reported in the Bronx between 2006 and 2010. Similarly to shootings and robberies, assault points were geocoded to the property lot level and then aggregated to the street, census block group, census tract, and neighborhood levels. Assault aggregates were divided by the polygon area (in square miles) which created an assault density for each geographical unit. The assault classes were then symbolized using a quintile

**Fig. 4.11** Robbery by census tract

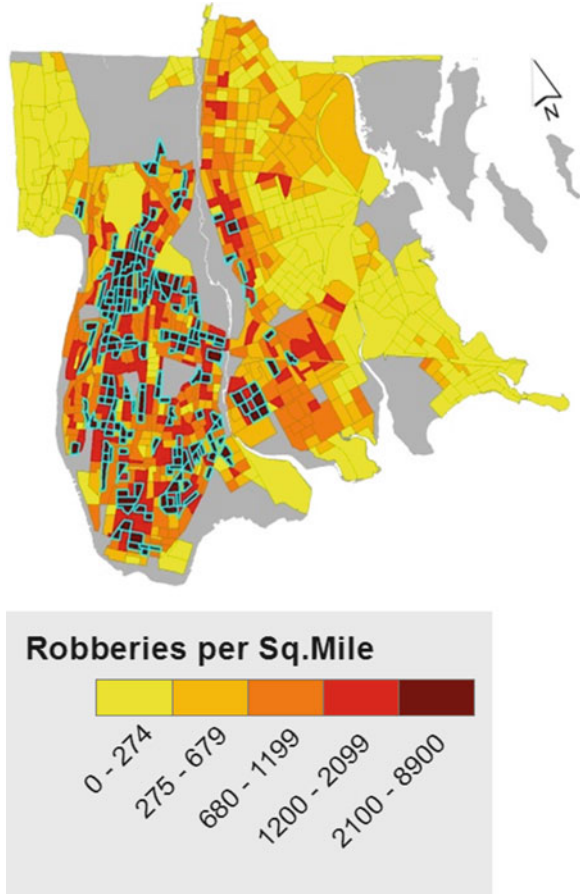


classification method, where the dataset is split into five groups, each with an equal number (approximately 20%) of areal units.

The assault maps (Figs. 4.13, 4.14 and, 4.15.) illustrate similar problems exhibited by the previous shooting and robbery maps. As you can see in the neighborhood (Fig. 4.13), census tract (Fig. 4.14), and census block group (Fig. 4.15) level maps – assault densities vary at each geographic level. When starting at the neighborhood level (Fig. 4.13), each subsequent geographic level indicates increased spatial variation.

Table 4.5 indicates similar micro-level street variations throughout the coarser level assault geographies. Since assault is also (7.5 times) more prevalent and widespread than shootings, the data showing the number/percentage of assaults in the highest quintile classes do not suggest as much of a difference between the neighborhood/tract and tract/block group levels. The percentage of streets in the top quintile for assault is similar to the percentage of streets in the top quintile for robberies. Again, it is important to note that even in the top quintile robbery areas; 22% of street segments at the block group level, 26% of street segments at the tract

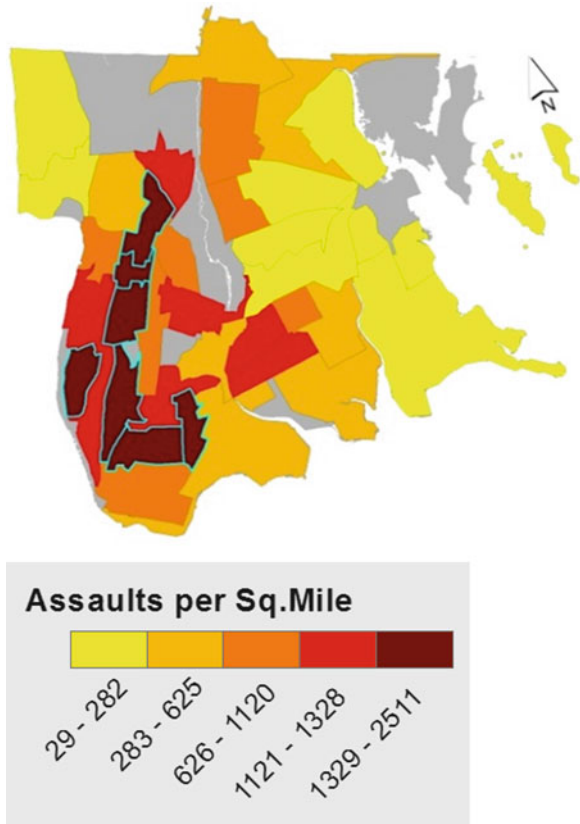
**Fig. 4.12** Robbery by census block group



**Table 4.4** Robbery frequencies and percentages within the top quintile class

| Bronx Robbery 2006–2010<br>n=22,824        | # of Total robberies in top Quintile | % of total robberies in top quintile % | # of total streets in top quintile | % of total streets in top quintile | # of zero robbery streets in top quintile | % of zero robbery streets in top quintile |
|--|--------------------------------------|--|------------------------------------|------------------------------------|---|---|
| High robbery neighborhoods (7 out of 37)   | 6,630                                | 29                                     | 1,656                              | 16                                 | 446                                       | 27  |
| High robbery tracts (64 out of 329)        | 8,495                                | 37                                     | 1,635                              | 16                                 | 345                                       | 21  |
| High robbery block groups (169 out of 924) | 6,953                                | 31                                     | 1,047                              | 10                                 | 229                                       | 22  |

**Fig. 4.13** Assault Density by neighborhood

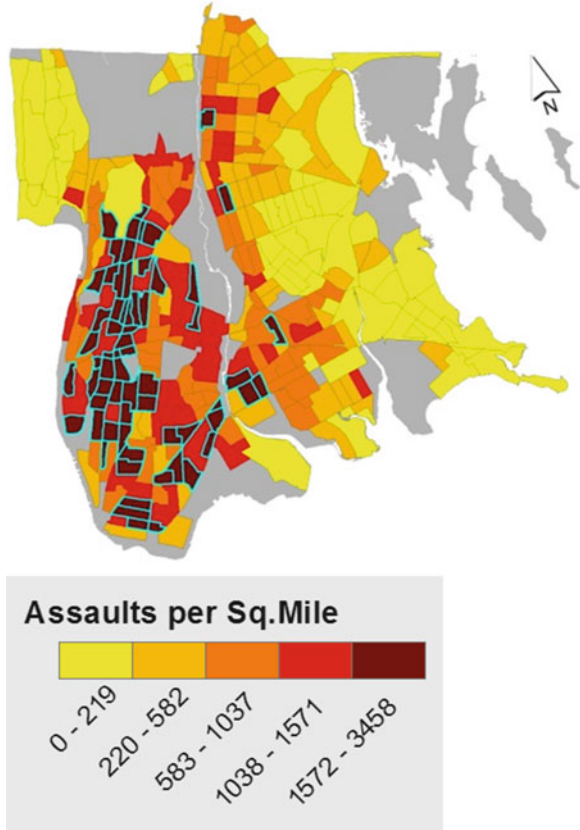


level, and 31% of street segments at the neighborhood level contain zero assault incidents over the 5-year study period. Again, this suggests a need for analyzing crime at finer spatial resolutions.

#### 4.11 Crime Clusters and Crime Densities

There appears to be a continuously growing number of ways that police departments analyze crime clusters and crime densities today (especially if we consider a priori knowledge of analysts/officers). If we refer back to the cones of resolution (Fig. 4.1), we can see that there are at least 12 different geographic levels of resolution, almost all of which would produce different size, shape and strength crime clusters or crime densities. If we incorporated the concepts of scale, temporal trends, input parameters, and classification methods into this cluster/density analysis process, there would appear to be an exponential number of ways to analyze crime.

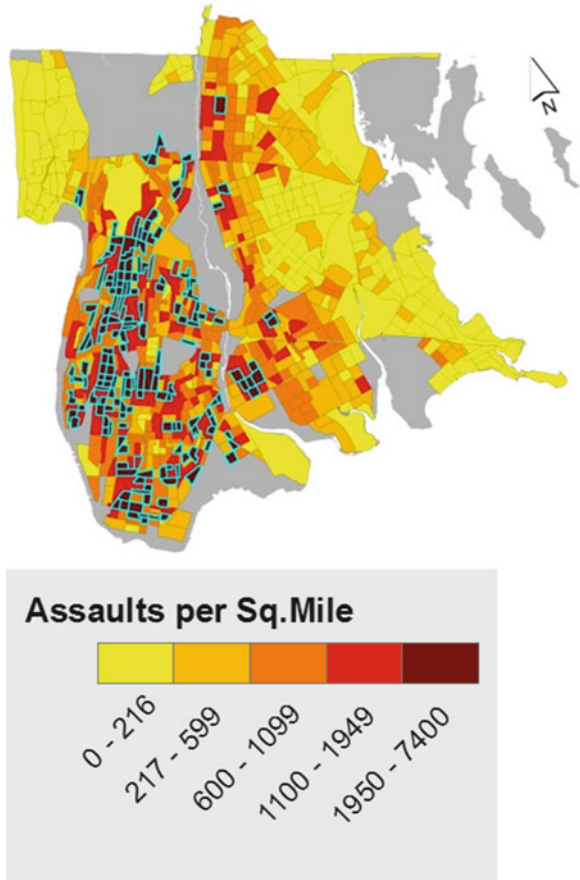
**Fig. 4.14** Assault density by census tract



Furthermore, there also appears to be a growing number of geospatial analysis methods that are being used to analyze crime (ie. Nearest Neighbor Hierarchical clusters, Getis-Ord  $G_i^*$  statistics, Ripley’s ‘K’ Statistic, Single/Dual Kernel Density Estimation, LISA, Standard Deviation Ellipses, K-Means Clustering, Spatial and Temporal Analysis of Crime [STAC], Geary’s ‘C’, Anselin’s Local Moran’s I statistics, SatScan, etc.). While each method/tool has advantages and disadvantages, several geospatial methods have become prevalent throughout the crime analysis community.

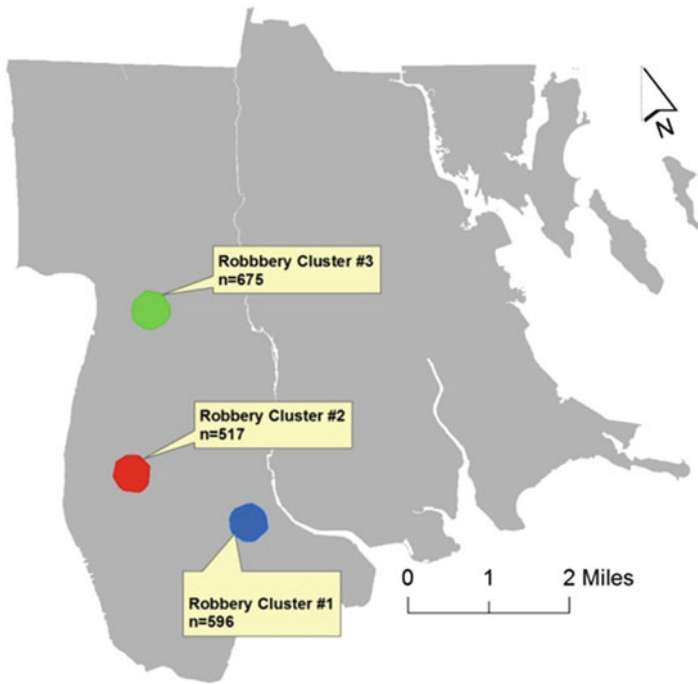
Perhaps the most common geospatial analysis methods used in crime analysis today are nearest neighbor hierarchical spatial clustering (using CrimeStat), Hot Spots/Getis-Ord  $G_i^*$  (using the ArcGIS Hot Spot tool), and Single/Dual Kernel Density Estimation (using CrimeStat or ArcGIS Spatial Analyst) (McGuire and Williamson 1999; Chainey et al. 2002; Eck 2002a, b; Chainey and Ratcliffe 2005). While each of these popular geospatial methods does an excellent job of generating clusters/densities, none of these geospatial methods incorporate temporal trends into the analysis process. The primary objective of these clustering/density methods

**Fig. 4.15** Assault density by census block group



**Table 4.5** Assault frequencies and percentages within top quintile class

| Bronx Assault 2006–2010<br>n=20,726        | # of total assaults in top quintile | % of total assaults in top quintile | # of total streets in top quintile | % of total streets in top quintile | # of Zero assault streets in top quintile | % of zero assault streets in top quintile |
|--|-------------------------------------|-------------------------------------|------------------------------------|------------------------------------|---|---|
| High assault neighborhoods (7 out of 37)   | 5,643                               | 27                                  | 1,507                              | 15                                 | 460                                       | 31  |
| High assault tracts (60 out of 329)        | 7,912                               | 38                                  | 1,625                              | 16                                 | 421                                       | 26  |
| High assault block groups (167 out of 924) | 7,737                               | 37                                  | 1,335                              | 13                                 | 293                                       | 22  |



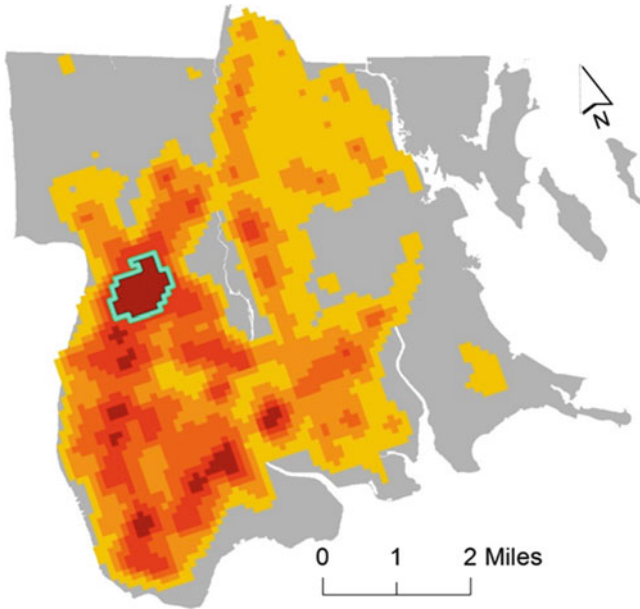
**Fig. 4.16** Quarter-mile robbery clusters

is to isolate geographical areas of high/low concentration(s) so police departments can focus their resources on these areas and analysts can gain a better understanding of the complex relationship(s) between crime and place.

Figure 4.16 shows a typical nearest neighbor hierarchical cluster robbery map. The clustering routine was generated in CrimeStat III (Levine 1999) & ArcGIS using an iterative process with a fixed input parameter of a quarter mile and a minimum number of robbery points (greater than 500). My objective was to find the three ‘highest’ quarter mile robbery clusters. Figure 4.17 shows a single kernel density estimation map that was also generated in CrimeStat III & ArcGIS, using a quartic method of interpolation, fixed interval tenth-mile bandwidth, and relative densities output. While the two maps utilize the same exact robbery data, as you can see, there are several noteworthy differences between the two maps.

First, the clustering map (Fig. 4.16) provides a very easy, focused illustration of the areas that contain the highest number of robberies. The area of each cluster is approximately .18 miles, which makes it an ideal candidate for foot patrol or stationary foot post(s). The clustering routine can show you where the smallest areal units (which you can define) contain the highest number of points (which you can also define). On the other hand, the density map (Fig. 4.17) provides you with a much broader illustration of where robbery is/is not, since the method provides





**Fig. 4.17** Tenth-mile robbery densities with highest density area highlighted

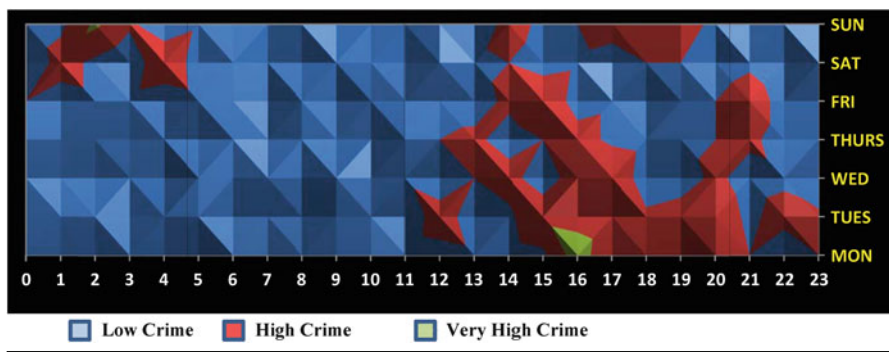
an estimate for all parts of the study region. In this case, it highlights what areas of the Bronx have high/medium/low/no amounts of robbery. Density maps are great for providing a look at ‘the big picture’ of crime. (If you would like more detailed information and examples on clustering or density methods, please see Chaps. 6, 7, and 8 in the CrimeStat III manual).

## 4.12 Internal Temporal Variation Issues with Cluster and Density Methods

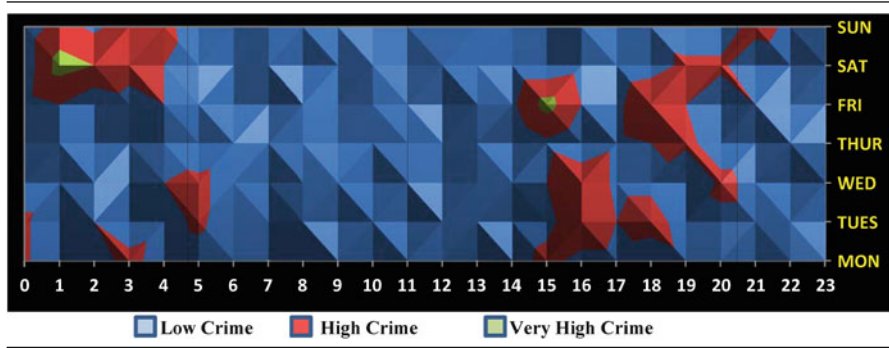
When we start to use cluster and density routines to ‘zero in’ on micro-level crime areas (streets, properties, buildings), we must also consider the temporal variation that will also occur at the micro-level. For example, when the robbery points that are used to generate the robbery cluster map (Fig. 4.16) are queried, exported, and analyzed in Microsoft Excel 3d contour charts, you can observe that there is significant variation by the day of the week (y-axis) and also by the time of day (hour of day, located on the x-axis) for the three distinct quarter-mile robbery clusters.

Robbery Cluster #1 (Fig. 4.16, blue cluster) contains 596 robberies. Table 4.6 illustrates the distinct day of week and hour of day temporal variations throughout this robbery cluster. The 3D contour chart is a very helpful illustration because it

**Table 4.6** Robbery Cluster #1 – day of week and hour of day temporal variations



**Table 4.7** Robbery cluster #2 – day of week and hour of day temporal variations

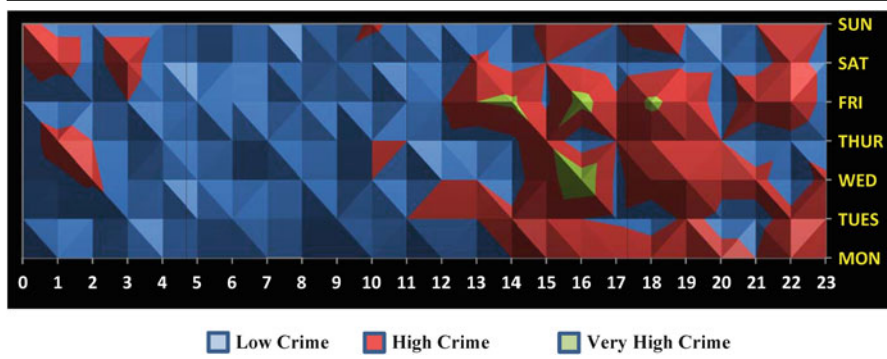


clearly identifies both day of week (y-axis) and hour of day (x-axis) patterns. As you can see, there are two robbery peaks (shown in green) – one on Mondays, around 1,600 h (4 pm) and another peak on Sundays at 0200 h (2 am).

Robbery Cluster #2 (Fig. 4.16, red cluster) contains 517 robberies. Table 4.7 illustrates the day of week and hour of day temporal variations throughout this robbery cluster. As you can see, there are two robbery peaks (shown in green) – one robbery peak on Fridays at 1,500 h (3 pm) and another robbery peak on Saturdays/Sundays between 0030 and 0200 h (12:30 am–2 am).

Robbery Cluster #3 (Fig. 4.16, green cluster) contains 675 robberies. Table 4.8 illustrates the distinct day of week and hour of day temporal variations throughout this robbery cluster. As you can see, this robbery cluster is more similar to robbery cluster #1, but very different from robbery cluster #2. There are two robbery peaks (shown in green) – one robbery peak on Fridays, between 1,300 h – 1,800 h (1 pm–6 pm) and another robbery peak on Tuesdays – Thursdays, between 1,500 h–1,700 h (3 pm–5 pm). Robbery clusters #1 and #3 are primarily weekday, afternoon patterns whereas robbery cluster #2 has distinct weekend, afternoon & late night temporal clustering.

Figure 4.17 shows the single kernel density estimation map that was generated in CrimeStat III & ArcGIS, using a quartic method of interpolation, fixed interval

**Table 4.8** Robbery cluster #3 – day of week and hour of day temporal variations

tenth-mile bandwidth, and relative densities output. The highest robbery density z-scores were queried using ArcGIS and a separate shapefile (polygon) was exported for the largest (and highest density) robbery area. This high density robbery zone has a geographical area of .51 square miles, which is almost three times as large as each of the clusters. There are 1,604 robbery points that fall within the high density robbery zone. The robbery zone contains 247 street segments, 51 of these street segments (21%) have no reported robberies on them. Even when using KDE, more than a fifth of the streets contain zero crime and the crime varies extensively based on time of day and day of week temporal trends.

### 4.13 Driving Crime Analysis Down to the Street (Level)

As this chapter has illustrated, crime continues to cluster as we move further down the cone of resolution to smaller and smaller geographic levels. This is great news for crime analysts, police officers, and police managers because clustering of crime at smaller areal units makes increased accuracy of targeted police patrols and management of ‘hot spots’ much easier. However, as Fig. 4.1 illustrated, as we move down the spatial cone of resolution, we must also move down the temporal cone of resolution. We noted significant internal temporal variations within both the quarter-mile clusters and the high density zone(s).

Ratcliffe (2004a, b, c), recognizing both the importance of spatiotemporal clustering and the temporal variance within hot spots, developed a brilliant framework for evaluating and targeting hot spots and called it a “hot-spot matrix”. The hot spot matrix incorporates both the spatial and temporal dynamics of hot spots into a manageable framework so police managers can optimize resource allocation and crime control strategies. Spatial events were classified into three spatial categories; dispersed, clustered, or hot points. Temporal events are also classified into three categories; *diffused*, *focused*, and *acute*. While this was originally developed for use with hot spots (polygons), I would like to propose that we transform this framework so it can also be used at the street segment level.

*Dispersed* spatial events are distributed throughout the hot street; there is no discernible intra hot street clustering. An example of a dispersed hot street pattern might be a street segment where there are a significant number of residential foreclosures. Each foreclosed (vacant) property attracts residential burglary, but no one individual property in particular is the cause of the burglary hot street. A hot street that is classified as *clustered* contains within hot street clustering at one or more points within the hot street. An example of this might be a strip mall parking lot, where cars are stolen at parking spaces near the entrances/exits at a much higher rate than other parking spaces in the parking lot. A *hot street* is exactly that, an individual street segment where crime consistently occurs over and over again. An example of a hot street might be parking spaces on a street near a bank (especially those with an outside ATM), where people get out of their car to take money out of the ATM and are robbed on the way back to their car.

*Diffused* temporal events have no discernible temporal pattern throughout the hot spot. There may be some temporal variation(s) within the hot spot, but nothing that creates a distinct temporal pattern. A *focused* temporal pattern may have one or more significant increasing trends throughout the day. These trends might require additional manpower, but are not quite considered an acute problem. *Acute* problems are confined to a much smaller period of time. If the majority of problems occur over a relatively short period of time, this is defined as an acute problem.

## 4.14 Creating Hot Streets

The street segment is becoming a more important unit of analysis in the crime analysis process as a result of the significant within-neighborhood crime variance. In addition, intra-hot spot temporal variation (as described in Figs. 4.16 and 4.17, Tables 4.6, 4.7, and 4.8) indicates significant temporal variation within crime clusters. The last part of this chapter will explain how hot streets are created, identified, analyzed and various methods to geovisualize hot streets.

Micro-level crime analysis begins like many other geospatial point pattern analyses, geocoding. The accuracy of geocoding becomes essential to any type of micro-level crime modeling and analysis. Crime locations that are unable to be geocoded or locations that are inaccurately geocoded can create significant problems for micro-level analyses by skewing statistical and/or spatiotemporal results.

While geocoding continues to be an issue (Ratcliffe 2004a, b, c) for some police departments, other departments have made significant improvements in the way that crime locations are assigned an X/Y coordinate on the map. The New York City Department of City Planning (2010) developed an innovative geocoding application, called 'GBAT', that allows New York City GIS analysts to batch geocode address files to the property lot level. Once crime locations are properly geocoded, they can be spatially joined to higher-level geographies. There are several ways to complete this process in ArcGIS.

The most effective way to begin this aggregation process is a 'bottoms-up approach', where the street (line) file is spatially joined to the crime (point) file (i.e. lines to points)

AND the crime (point) file is also spatially joined to the street (line) file (i.e. points to lines). This aggregation process will allow calculation of crime (points) per street and also permit calculation of temporal (or other) attributes of crime (assuming your crime points have temporal/other attributes) for each street segment.

### 4.15 Spatiotemporal Variations Within Neighborhoods

As was illustrated earlier in this chapter (Figs. 4.16 and 4.17, Tables 4.6, 4.7, and 4.8), there was distinct spatiotemporal variation within crime hot spots (both kernel densities and clusters). For this neighborhood level analysis example, I analyzed two different violent crimes (shootings and robbery) within the Mott Haven neighborhood in the south Bronx. Mott Haven was selected because it contained the highest number of shootings and robberies (combined over the 5-year study period) compared to the other 36 neighborhoods in the Bronx.

As was similar to the internal variation observed within the hot spots (densities and clusters), visual inspection of Fig. 4.18 indicates considerable spatial variation between streets containing robberies in this neighborhood. Since robberies are the most frequent violent crime in the Bronx, it is expected that robbery would also be the most widespread violent crime at the neighborhood level. Figure 4.18 indicates that 41% of the streets in the neighborhood have zero robberies; 67% of the streets have less than 3 robberies per segment; and 5% of streets contain 35% of the neighborhood robbery.

Table 4.9 indicates the day of week/time of day temporal patterns of robbery incidents within the Mott Haven neighborhood. There are two noticeable temporal

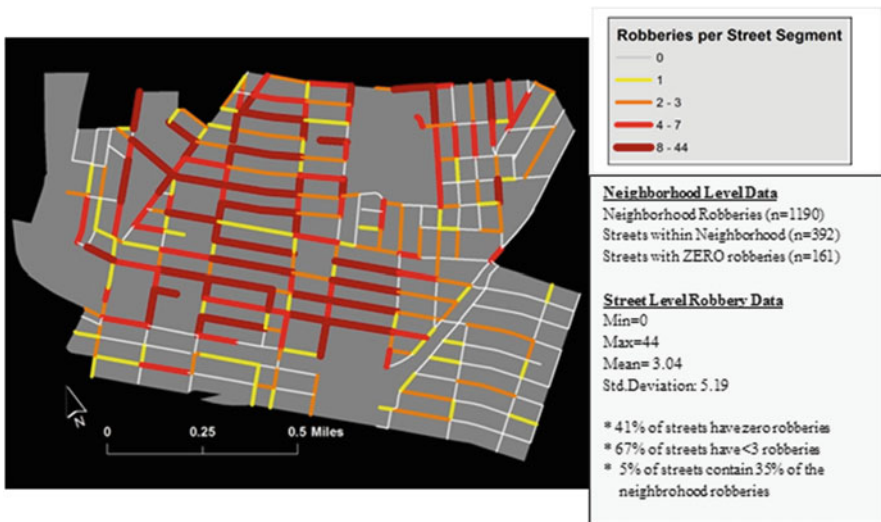
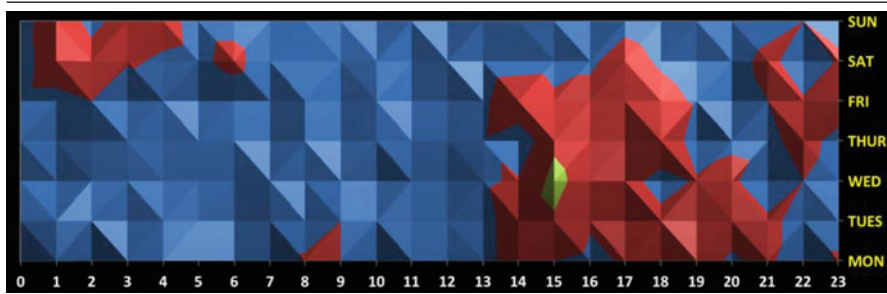
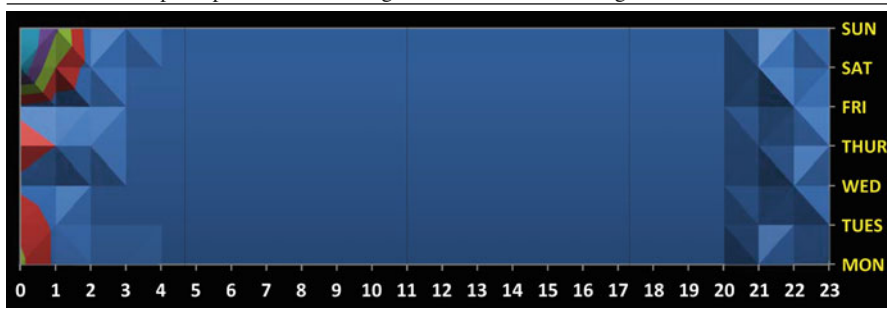


Fig. 4.18 Robbery streets in the neighborhood of Mott Haven

**Table 4.9** Temporal patterns of robbery incidents in a Bronx neighborhood**Table 4.10** Temporal patterns of shooting incidents in a Bronx neighborhood

trends that can be observed within this robbery dataset. First, we can note that there are two (red) time periods highlighted on the chart, a weekday afternoon (2 pm–7 pm) trend and a weekend nighttime (10 pm–4 am) robbery trend. The highest temporal peak for robbery in Mott Haven is Wednesday at 3 pm.

Table 4.10 illustrates the temporal variation between the neighborhood shooting incidents. This is a very interesting temporal crime pattern, since there are no reported shootings that occur between 4 am and 8 pm on any day of the week. 52% of the shootings occur within a 1-h time frame, between the hours of midnight and 1 am. When the shooting data is disaggregated further (by hour of day and day of week), we can observe more specifically that 30% of shootings within this neighborhood occur on Saturdays & Sundays, between midnight and 1 am.

As was similar to the intra-neighborhood spatial variation observed within the robbery hot streets, visual inspection of the shooting hot streets (Fig. 4.19) indicates considerable spatial variation between streets containing shootings in this neighborhood. Since shootings occur much less frequently than robbery, it is expected that lower frequency crimes (like murder, rape, shootings) would cluster more at the different geographic levels. Table 4.10 indicates that 83% of the Mott Haven streets have zero shootings and 5% of streets contain 62% of the neighborhood shootings.



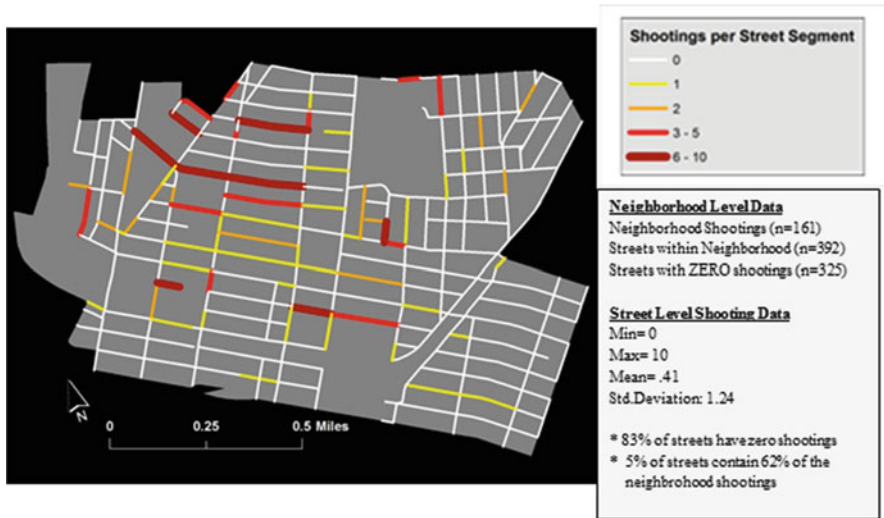


Fig. 4.19 Shooting streets in a Bronx neighborhood

## 4.16 Conclusion

This chapter identifies several unique advantages for using street segments as a small-scale unit of analysis when conducting geospatial modeling and mapping for crime analysis. As was illustrated earlier in the chapter, 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 chapter highlights some of the benefits of utilizing street segments as units of analysis including identification of hot streets and detection of unique temporal patterns, both of which can assist police departments in crime prevention and control strategies.

It is important to note that the identification of spatiotemporal patterns of hot 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. Equally important, although often overlooked, is the number and percentage of streets with zero crime over the study period. Developing street level crime prevention and control strategies can save police departments considerable resources (manpower, time, money) and provide police with a much better understanding of the relationship between crime and opportunity at the street level.

Future research on hot streets should incorporate analysis of land-use and business types to determine what the spatiotemporal relationship(s) are between hot streets, violent crime types, and the smaller-scale units ‘below’ the street segment level.



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