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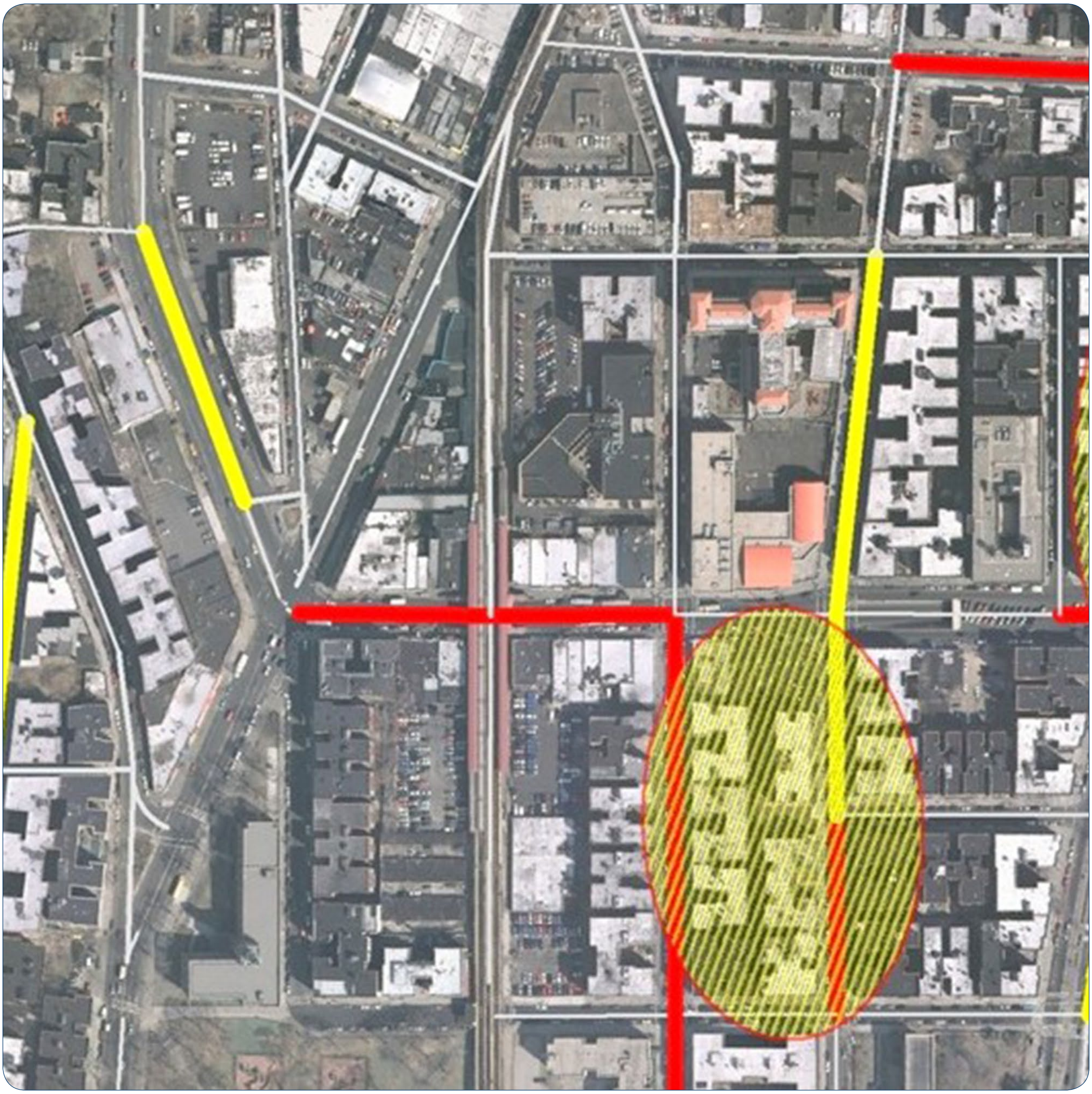

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The dynamics of robbery and violence hot spots

Christopher R. Herrmann*

Abstract

This paper examines how hot spots shift by hour of day and day of week. Hot spot analysis is more likely to have a substantial impact on crime patterns if spatiotemporal shifts are incorporated into the crime analysis process. Even in some of the highest crime neighborhoods in Bronx County (NY), not all micro-level geographies (e.g. street segments and property lots) contain substantial (if any) amounts of crime over the 5-year study period. Moreover, while there are 168 h in a week, even the hottest hot spots do not contain crime 24 h a day, 7 days a week, and 52 weeks a year. Hot spots shift by both space and time and it is important to illustrate these dual shifts when researching and analyzing different levels of geographies and/or hot spots. Spatiotemporal crime analyses are appearing much more frequently in our academic literature in recent years and have become a principal contributor to the progression of routine activities, crime pattern theory, place-management and situational crime prevention. In addition, spatiotemporal hot spots provide important subject and opportunity context and can help answer some of the questions about what specific types of crime opportunities are available inside of hot spots based on land-use and people's movement patterns. When studying geographical hot spots, it becomes important to measure and illustrate the interrelated temporal shifts within each of the specific hot spots (i.e. not all hot spots are the same) that are generated. Similarly, when studying temporal hot spots, it is important to measure and illustrate the interrelated spatial shifts within each of the temporal frame(s) that are examined. Examples of space–time and time–space hot spot analysis are provided using violent crime data from the New York City Police Department. Key findings of this research include significant shifting of hot spots from weekday to weekend and afternoon to evening, as well as decisive spatiotemporal pattern variations between school-day robberies vs. non-school day robberies.

Keywords: Robbery, Violence, Crime analysis, Spatiotemporal, Routine activities, Hot spots

Background

The crime science and crime analysis communities have become proficient in creating, tracking, and handling hot spots of crime (Chainey and Ratcliffe 2005). Current research (Weisburd et al. 2012; Groff et al. 2010; Bernasco and Block 2011; Brantingham et al. 2009; Weisburd et al. 2009) indicates that as crime scientists 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, building outlines), sizes, and spatiotemporal patterns.

By developing a more comprehensive understanding of the spatial and temporal variations within violent crime hot spots at the micro-level, crime prevention and crime control specialists can have a greater impact on apprehending criminals, police resource allocation and planning, crime modeling and forecasting, and evaluation of crime prevention and crime control programs (Boba 2001; Townsley et al. 2003; Ratcliffe 2004; Johnson et al. 2007). In our continuing state of shrinking government operating budgets, crime scientists and crime analysts need to consider the interrelatedness of spatial and temporal shifts in crime patterns when creating, tracking, and handling crime hot spots.

Many studies indicate that crimes are clustered at the neighborhood level, but the entire neighborhood is rarely (if ever) criminogenic and only specific parts of neighborhoods contain high concentrations of crime (Taylor 1997; Fagan and Davies 2000; Groff et al. 2010). Prior studies

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incorrectly assume that the relationships between crime, population, land-use, and business establishment types are both homogenous and spatially stationary (Shaw and McKay 1969; Bursik and Grasmick 1993; Sampson et al. 1997; Morenoff and Sampson 1997). Even at the neighborhood level, crime is highly clustered and the highest crime neighborhoods have significant percentages of low or zero crime streets within the neighborhood(s).

A substantial body of research has identified that a small percentage of crime locations (i.e. hot spots) contain a significant percentage of crime (Sherman et al. 1989; Block and Block 1995; Eck and Weisburd 1995; Brantingham and Brantingham 1999). One of the current trends in environmental criminology and crime analysis 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. Part of this concept of micro-level analysis is known as the 80/20 rule or Pareto's Principle (Eck et al. 2007; Weisburd et al. 2012), and reigns true not only in crime prevention and crime control, but other areas of the criminal justice field as well [this concept has also been branded as the 'law of crime concentrations' by Weisburd et al. (2012)].

The 80/20 rule suggests that by targeting or focusing on the highest 20 % of crime hot spots can have a dramatic influence on the majority (approximately 80 %) of total crime in the study area. According to the 80/20 rule, the net impact of crime prevention and crime control strategies targeting the 20 % would be much higher than attempting to target an entire neighborhood (or whatever the larger study area is that is being examined).

Environmental criminologists using Pareto's 80/20 rule have pointed out that not all parks are full of drug users/dealers (Wilcox et al. 2004; Eck et al. 2007; Groff and McCord 2012), not all high schools have high rates of delinquency (Wikstrom et al. 2012; Glover 2002; LaGrange 1999), not all bars contain high rates of assault (Ratcliffe 2012; Newton and Hirschfield 2009; Eck et al. 2007; Gorman et al. 2001), and not all parking lots have high rates of auto theft (Rengert 1997; Clarke and Goldstein 2003). In fact, even 'high crime' neighborhoods contain hot spots (high density crime areas) and cold spots (zero/low crime areas), high crime streets and zero/low crime streets, and both 'good' (i.e. crime protectors) and 'bad' (i.e. crime generators) streets and businesses.

Violent crime (i.e., murder, rape, robbery, assault, and shootings) has declined 73 % in the Bronx since 1990 (NYPD Compstat 2010). In his 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 spot policing, zero tolerance, stop and frisk) and community crime interventions (including 'gun buyback' and drug violence reduction programs). Shifting hotspots 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 micro-levels (e.g. street segments and risky facilities) will help crime scientists, police departments, and policy makers better understand the spatial and temporal processes in the 'magma' that fuels today's crime hot spots.

Data and methodology

The objective of shifting hot spots research is to explore, measure, and illustrate the various spatiotemporal shifts that occur within and between violent crime hot spots. Specifically, this research focuses on spatiotemporal crime shifts within violent crime 'hot spots' in the Bronx. The Bronx was selected because it contains a higher per capita violent crime rate (crimes per 1000 residents), as well as a higher crime density (crimes per square mile), compared to the other four counties that comprise the City of New York. While much of the spatiotemporal variation(s) or hot spot 'shiftiness' occurs as a result of routine activities and land-use heterogeneity-very few hot spots (if any) appear to be both spatially and temporally stationary.

The research area and data for this study are comprised of various Geographic Information Systems (GIS) datasets for Bronx County, including violent crime datasets (2006–2010) from the New York City Police Department. The Bronx is geographically organized into 38 neighborhoods (note, 36 of the 38 neighborhoods are 'residential', the other two are categorized as parks/open space and industrial), 12 Police Precincts, 355 Census Tracts, 987 Census Block Groups, 10,781 street segments, 89,211 tax/property lots, and 101,307 buildings (NYC Department of City Planning 2010; NYPD 2010; NYC Department of Finance 2010; NYC City Department of Buildings 2010). The Bronx is 42 square miles in area, which makes it 14 % of New York City's total geographical land area (NYC Department of City Planning 2010). According to the US Census (2000), the population of the Bronx is 1,332,650 which comprises 17 % of the total New York City population.

One of the reasons the Bronx is an ideal place to study crime is because it is the third most densely populated county in the United States (behind Manhattan & Brooklyn) and about a quarter of its land area is uninhabited open space or industrial areas. Interestingly, the US 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 US Census (2010), if two Bronx residents are randomly selected, 90 % of the time they would be of a different race or ethnicity (Newsweek 2009).

As Table 1 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). 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. NYPD crime data is geocoded to property lots or intersections, which can then be aggregated up to street segments based on a very accurate, but rather complex, composite address geolocators developed and maintained by the NYC Department of City Planning and the NYC Department of Information Technology and Telecommunications.

Research questions

The methods set forth below are designed to address the following research questions.

- How do violent crime hot spots shift from weekday to weekend?
- How do violent crime hot spots shift from daytime to evening/nighttime?
- Are there temporal shifts within and/or between violent crime hot spots?

Hot spots can be calculated many different ways, including Nearest Neighbor Hierarchical clusters, Getis-Ord Gi* statistics, Kernel Density Estimations, Standard Deviation Ellipses, K-Means Clustering, and Local Moran's I statistics. While any geographic cluster of crime can typically be referred to as a hot spot, not all hot spots are created equal. It should be noted that none of these hot spot methods take temporal trends into consideration, which is an important function of crime analysis (for more on space–time clustering methods, see Kulldorff 2001).

For this paper, the analysis of violent crime data will include hot spot analysis using the nearest neighborhood hierarchical (Nnh) clustering methodology. Nnh hot spots were selected because they generate a specific type of hot spot map which clearly 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; Mitchell 2005).

The nearest neighbor hierarchical clustering (Nnh) routine (in CrimeStat) is simple to understand, runs very quickly on most computers, and is one of the customary hot spot methodologies for identifying groups or clusters of incidents that are spatially 'near' to one another (Harries 1999; Eck et al. 2005; Chainey and Ratcliffe 2005). The Nnh hot spot routine assembles crimes (points) together based on a pre-defined search criterion (typically, the minimum number of points over a specified geographical area). The clustering routine is then repeated until either all points are grouped into a single cluster or the clustering criterion fails.

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 kilometer) of crime events over a specified geographic area. Levine (1999) advises that higher frequency crimes (e.g. assault, robbery, auto theft) usually have a much lower threshold distance when compared to lower frequency crimes (e.g. murder, rape, arson) which contain higher threshold distances. Crime clusters can be calculated as convex hulls or ellipses and

Table 1 Violent crime, land area, population, and the percentages for each of the 5 boroughs of New York City by County, for 2006–2010

Violent crime (2006–2010)	Bronx	Brooklyn	Manhattan	Queens	Staten island	Citywide
Murder	657 (25 %)	1074 (41 %)	371 (14 %)	434 (17 %)	86 (3 %)	2622
Rape	1512 (23 %)	1873 (28 %)	1388 (21 %)	1624 (24 %)	278 (4 %)	6675
Robbery	23,018 (22 %)	36,616 (35 %)	21,745 (21 %)	22,029 (20 %)	2181 (2 %)	105,589
Assault	21,564 (26 %)	28,958 (34 %)	16,015 (19 %)	15,486 (18 %)	2240 (3 %)	84,263
Shooting	2791 (31 %)	3613 (40 %)	1094 (12 %)	1311 (15 %)	222 (2 %)	9031
Land area (in sq. miles)	42.41	71.46	22.78	109.67	58.50	304.82
Percentage of NYC land area	14 %	23 %	8 %	36 %	19 %	100 %
Population	1,332,650	2,465,326	1,537,195	2,229,379	443,728	8,008,278
Percentage of NYC population	17 %	31 %	19 %	28 %	5 %	100 %

Source: NYPD Compstat; NYPD Office of Management, Analysis, and Planning; 2012 Census 2000 a resulting shapefile can be exported from within the Crimestat software. The primary difference between convex hull and ellipse boundaries are that convex hull boundaries incorporate all of the points within the geographical boundary whereas standard deviational ellipses are a spatial statistical summary and may not incorporate all of the actual points included in the Nnh cluster. In practice, the convex hull selection is ideal when defining hot spot boundaries, while the standard deviational ellipses provide an excellent analysis including the directionality of the hot spot(s).

As a result of the availability, popularity, comprehensive instruction manual, 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 science and 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 (Chainey and Ratcliffe 2005). While the Nnh clustering analysis provides an excellent clustering technique, it does not provide crime scientists with a statistical test of clustering significance (i.e. Getis-Ord Gi* statistic).

Additionally, there is another free software package that takes temporal values into spatial clustering analysis (SatScan), however this software package is much more complex to learn and is not as widely used in the field of crime analysis (for more on SaTScan, see http://www.satscan.org).

Space–time hot spots vs. time–space hot spots

There are two relatively easy processes to construct, examine, and geovisualize the temporal aspects of Nnh hot spots. The first, is a 'space–time' analysis, where crime scientists conduct routine spatial hot spot analysis and then ascertain the temporal patterns within each of the hot spots. By querying, clipping, and exporting the crime data within each of the spatial hot spots that are generated (import into SPSS or Excel, for example), researchers can detect temporal patterns that are significant to each spatial hot spot. The results of the temporal analysis *after* the initial spatial hot spot analysis can further assist crime scientists and analysts in determining what types of targets/victims are present at these hot spots and more importantly, how these targets/victims vary over different time periods (hour of day, day of week, month of year, etc.). In addition, temporal analysis can help delineate different types/groups of offenders that may be operating at these locations, as well as expose various offender techniques/modus operandi.

The other way to construct, examine, and geovisualize hot spots is to begin by conducting a temporal analysis first, *before* constructing the spatial Nnh hot spots. By defining and analyzing the temporal trend(s) first, crime scientists can identify temporal patterns within the data and then query, clip, and geovisualize these temporal 'slices' or aggregates of time data into different hot spot analyses based upon the temporal aspect(s) of interest (e.g. specific days of week, hours of day, weekday vs. weekend). By conducting the temporal analysis before the spatial hot spot analysis, researchers can determine the temporal stability (or variance) of crime patterns and decide more appropriate prevention and control responses according to the temporal (and spatial) clustering.

Temporal trends are becoming increasingly relevant, since this type of data/information provides a much needed crime opportunity context for crime places where crime prevention and control programs are needed, as well as a more structured way of understanding the routine activity patterns of people's movements based on land-use and business establishment types within micro-level geographies. There are many times where crime patterns correlate more with a temporal routine activities trend, as opposed to the spatial clustering relationships that are normally examined and geovisualized without any further temporal analysis (Felson and Boba 2009; Lersch and Hart 2011).

Results and discussion

This section presents the primary findings of the research, as well a dialogue of the results.

Day of week shifts

Much of the impetus for this time–space research process began with the following day of week and time of day temporal trend analysis (see Figs. 1, 2). For the day of week charts, the days of the week are on the bottom (x-axis) and range from Monday to Sunday and the frequency of crime is located on the left (y-axis).

As you can see from Fig. 1, the violent crimes of murder (blue line), shootings (red line), and assaults (yellow line) all follow a very similar day of week pattern—smaller numbers of crime on weekdays and then a noticeable shift increase on Friday, Saturday, and Sunday (weekends).

The day of week analysis for robbery is much different from the other day of week violent crime temporal trends. As you can see from Fig. 2 (robbery, green line), robbery has a much higher amount of robbery on weekdays and a very noticeable shift decrease in robbery on Friday, Saturday, and Sunday (weekends). After reviewing many incident reports, it became apparent that there were two very different spatiotemporal patterns emerging, not only in day of week shifts, but also shifts in time of day.

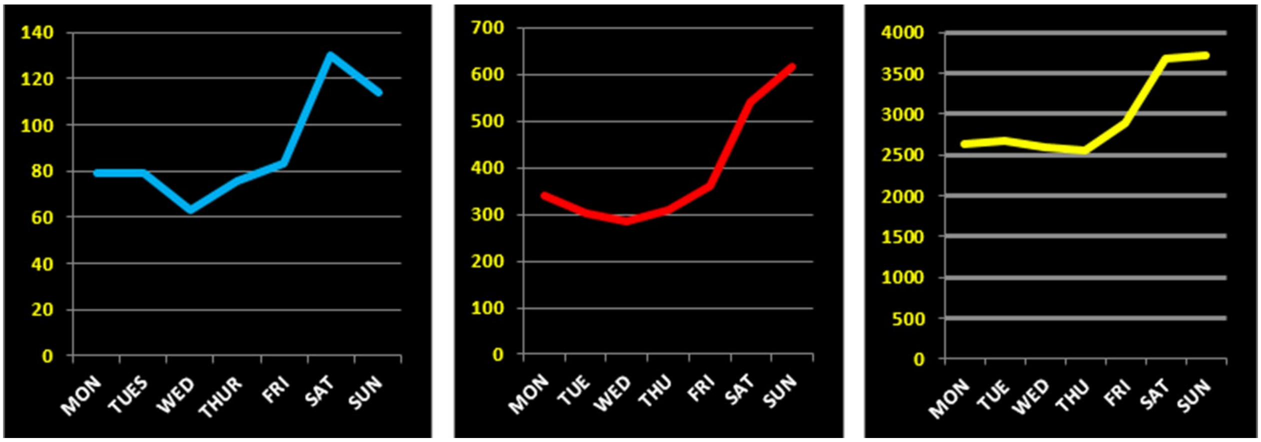

Fig. 1 Day of week trend for murder. Day of week trend for shootings. Day of week trend for assaults

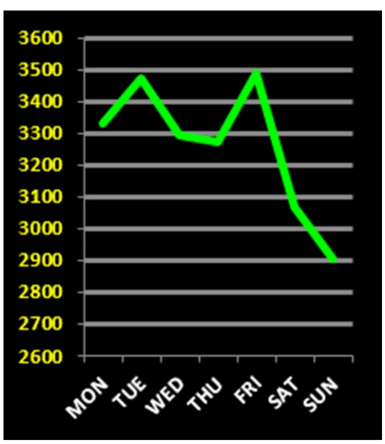

Fig. 2 Day of week trend for robbery

Time of day shifts

For the time of day figures (Figs. 3, 4), the hour of day is at the bottom (x-axis, ranges from 7 am on the left to 6 am on the right) and the frequency of crime is on the left side (y-axis).

As you can see in Fig. 3, there is a noticeable increasing hour of day trend in murder (blue line) and shootings (yellow line), which begins around 12 pm/noon and escalates until 12 am/midnight, after which, there is a noticeable decline in crime until it levels out around 6 am.

Figure 4 shows that the assault (red line) hour of day trend is very similar to the murder (blue line) and shooting (yellow line) hour of day trends, which increases throughout the daytime, peaks at midnight, and then declines very sharply until it levels out around 6 am. Robbery (green line), on the other hand, has a completely different and very abnormal hour of day trend, which steadily increases from 10 am until its highest peak at 3 pm. Then there is a noticeable shift/decline from 3 pm until 5 pm, after which it slowly increases again until 11 pm, after which it declines sharply and levels off around 6 am.

Further analysis of the NYPD robbery reports indicated two very opposing crime patterns (offenders/victims and targets/places). It became evident after reading thru the narratives of many crime reports that the 3 pm robbery spike was largely a result of school-age offenders, school-age victims, not surprisingly, near schools and subway stations, on 'school-days', and the primary targets were small electronics (e.g. cell phones, tablets, iPods and headsets). The other interesting peak that was noted was a more traditional 12 am/midnight–1 am peak (mostly on weekends). This weekend-nighttime trend mirrored the other traditional violent crime temporal trends noted previously, with the exception that these hot spots were also connected to subway stations (see Fig. 5 below). The nighttime-weekend robbery hot spots also varied significantly from the daytime-weekday pattern offenders/victims and targets/places. The nighttime-weekend robbery offenders were late teens—early 30's, the victims were late teens—early 40's, and the targets were wallets/purses, jewelry, and cell phones.

As a result of the relationship between offenders, victims, and places/schools for the 3 pm crime peak, a time–space analysis was conducted and the total robbery points data was disaggregated, by school weeks (weeks when public schools are in session vs. weeks when public schools are not in session), over the 5-year study period. The results indicate a much different 'temporal-spatial landscape', than the original (aggregated) robbery map (Fig. 6). The resulting robbery data was then 'queried and clipped' into two peak time periods, the 3 pm school-day robbery points and the 1 am non-school day robbery

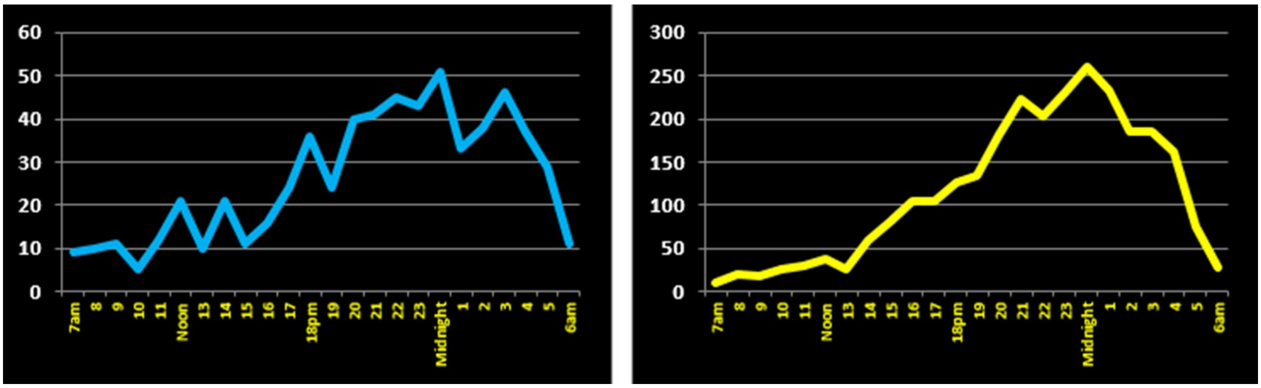

Fig. 3 Time of day (hours) trend for murder. Time of day (hours) trend for shootings

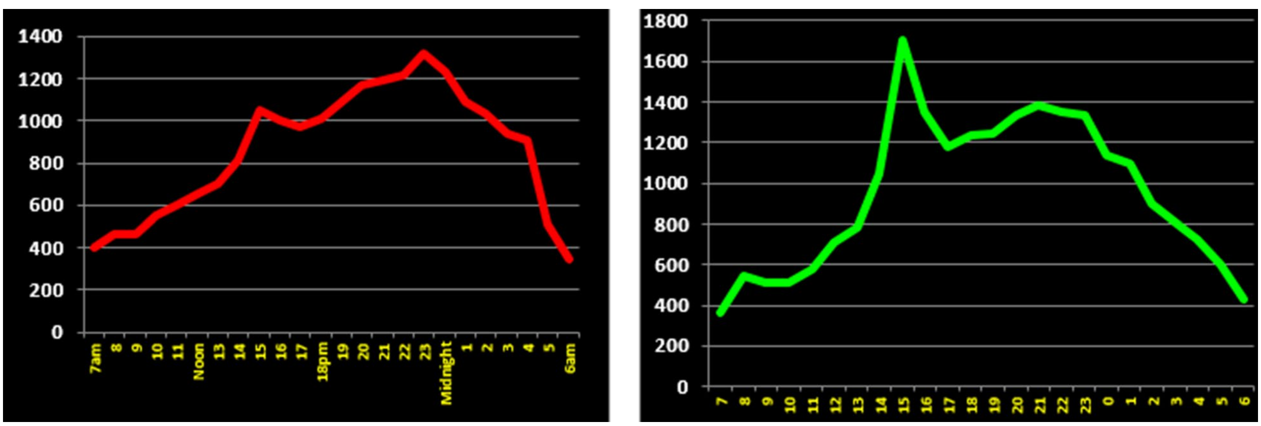

Fig. 4 Time of day (hours) trend for assaults. Time of day (hours) trend for robberies. Note the 3 pm peak which varies significantly from the other violent crimes

points, and then exported out of ArcGIS. After this process, the two disaggregated point files were imported into Crimestat, the Nnh clustering routine was run again (using the same 0.10 mile parameters) and a time–space hot spots shapefile was created for each of the 3 pm and 1 am time periods, which were then mapped (see Fig. 7).

The resulting map is Fig. 7, which indicates the temporal-spatial shifts in robbery hot spots. As you can see, all of the 3 pm school-day robbery hot spots are connected to subway stations. There is an individual 1 am non-school day robbery hot spot that is not connected to a subway station (further analysis indicates that this hot spot is a high population density residential complex).

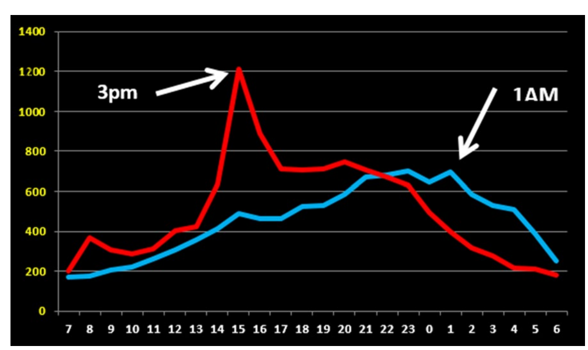

Fig. 5 Time of day temporal shifts between school-day robberies (*red*, peaks at 3 pm) vs. non-school day robberies (*blue*, peaks 1 am)

Violent crime hot spots in the Bronx

In this section of the research, Nnh clusters (convex hulls) were constructed for all robbery and assaults (the top 2 violent crimes, which comprise 90 % of total violent crime). The parameters used were fixed distance (0.10 square miles); minimum number of points (varies by violent crime type, see Table 2), and 100 Monte Carlo simulation runs. The minimum number of points was selected based on an iterative process where the top three highest hot spots were selected for each violent crime per

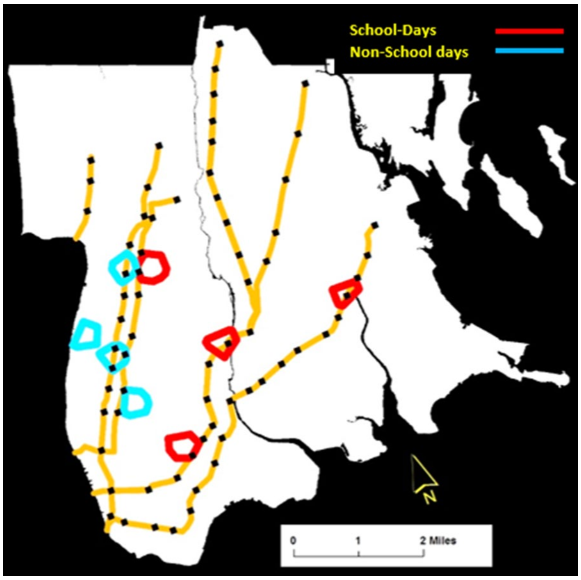

Fig. 6 Robbery hot spots. Robbery hot spots and subway stations

approximated 0.10 square mile area (note: a 0.10 square mile area was used because this provides NYPD foot post officers with a much more manageable area to monitor, this is also a similar parameter that NYPD uses for CCTV camera placement 'zones').

The 'top 3 hot spots' approach was used to clearly illustrate the spatiotemporal shifts between the two violent crimes. Spatiotemporal crime comparison analyses are important to determine any apparent overlapping (spatial and/or temporal) hot spots. The Monte Carlo simulation (Levine 2010; Barnard 1963; Dwass 1957) was used to conduct a significance test for the resulting Nnh clusters. The Monte Carlo simulation randomly assigns N cases to a rectangle with the same area as the Bronx County shapefile and measures the number of Nnh clusters as per the defined parameters (Levine 2010). Table 2 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.

Temporal analysis of robbery clusters

Robbery is the most common of the violent crimes in this study. Robbery is also the violent crime that many researchers consider to be the best indicator of street-level and neighborhood 'safety' (Kennedy and Baron 1993; Groff 2007; Bernasco and Block 2011). Moreover, robbery hot spots continue to be the primary 'target' for many of NYPD's (street-level) crime control strategies. Figure 6 shows how all of the robbery hot spots in this analysis are connected to subway stations, this finding is important to note and will be examined further in the discussion section.

Figures 8, 9 and 10 illustrate the temporal analysis that was completed on each of the three highest robbery

Fig. 7 Robbery time-space hot spots. *Red* hot spots are school days at 3 pm. *Blue* hot spots are non-school days at 1 am

Table 2 Total number of crimes analyzed, minimum number of crimes per hot spot, and number of hot spots generated for the total number of crimes analyzed

Crime	Number of crimes (2006–2010)	Minimum number of crimes per cluster	Number of resulting clusters
Robbery	22,674	165	3
Assault	20,729	125	3

Source: New York City Police Department (2011), IBM Data Warehouse/COGNOS

clusters (minimum number of robberies per hot spot was 165/0.10 square mile). As you will see, there were significant temporal shifts within each of these robbery hot spots. The temporal analysis was completed using robbery point data that was 'queried, clipped, and exported' from each individual cluster and then analyzed in Microsoft Excel (i.e. surface chart).

In the following temporal visualizations, the day of week is on the y-axis/right side of the chart (Monday at the bottom, Sunday at the top) and the time of day (midnight on the left, to 11 pm on the right) is located on the x-axis/bottom of the chart. The color ramp varies from gray (zero/very little crime), to yellow (low crime) to dark red (very high crime). Besides the obvious temporal shifts within each cluster, it is also important to note the amount of zero/very little crime that occurs throughout each of the hot spots. This indicates the very tight temporal clustering and trends that occurs within these micro-level spatial hot spots.

Assault hot spots

Robbery and assault are the most common forms of violent crimes in the Bronx and comprise 90 % of the violent crimes in this research. Figure 5 shows the spatial distribution of the three assault hot spots (each assault hot spot contains a minimum of 125 assaults per 0.10 square mile). Below is the spatial distribution of the three assault hot spots. Similar, but slightly different than robbery, it should be noted that some of the assault hot spots also intersect subway stations (Fig. 11).

Temporal shifts within assault hot spots

Figures 12, 13 and 14 illustrate the temporal analysis that was completed on each of the assault hot spots clusters (minimum number of assaults per hot spot was 125/per 0.10 square mile). Similar to the robbery hot spots, there are also temporal shifts within each of the assault hot spots. Overall, the assault hot spots have more weekend late night/early morning temporal trends compared the robbery trends, which occur more often on weekdays and afternoons/early evenings.

Conclusion

In New York City, previous analyses conducted with NYPD (Herrmann, 2003–2012) 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 *shift* over time, but if crime scientists and analysts conduct temporal analysis on large scale time periods (i.e. months and years), they will notice that

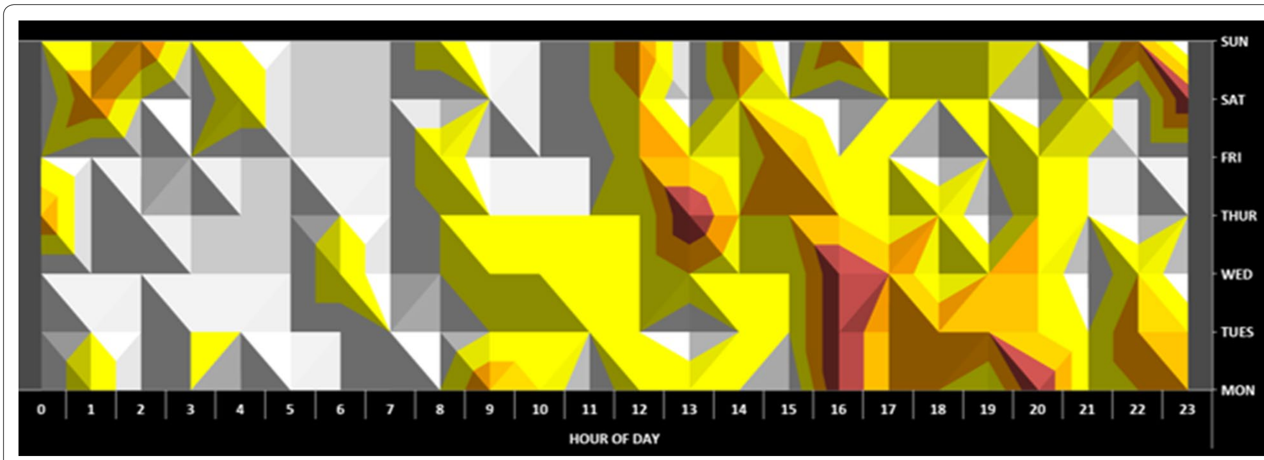

Fig. 8 Temporal analysis of robbery cluster #1 (n = 185 robberies), where *gray* is zero/very little robbery, *yellow/orange* is medium amounts of robbery, and *dark red* is high counts of robbery. This cluster indicates a significant weekday and daytime temporal pattern that is much different than the other violent crime clusters that are analyzed. There is a notable Monday–Thursday 3:30 pm–4:30 pm robbery peak, as well as Friday 1 pm peak. The weekend nighttime trend occurs between 11 pm–2:30 am, primarily on Friday and Saturday nights. These trends are different than robbery clusters #2 and #3

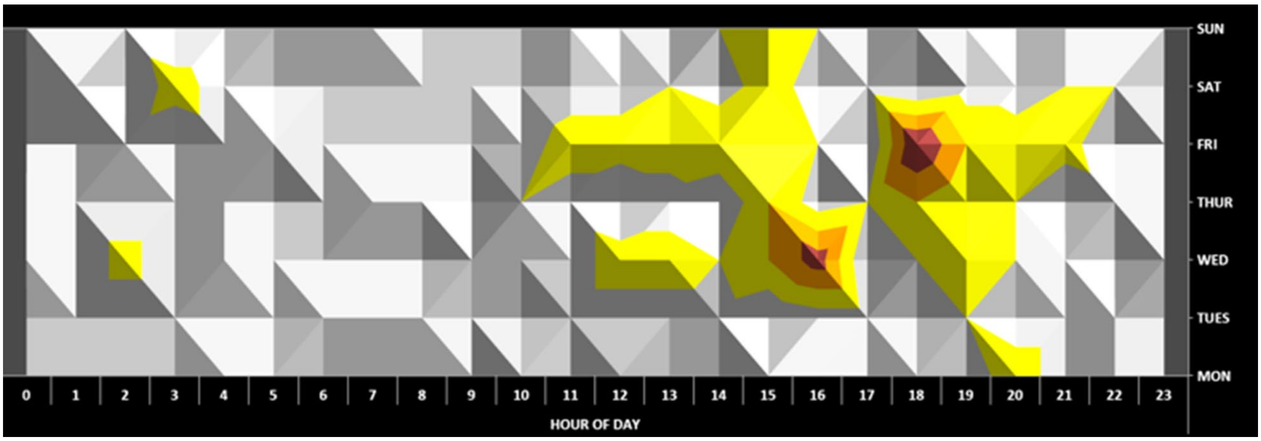

Fig. 9 Temporal analysis of robbery cluster #2 (n = 182 robberies) shows a 5 pm–7 pm Friday and Saturday peak, as well as a weekday Wednesday–Friday afternoon peak, between 2 pm–5 pm. Two distinct temporal patterns usually indicated two separate land-use/business establishment type robbery relationships or two separate groups of robbery offenders and/or targets. Friday are the longest crime trending days of the week, with stable trends form 1 pm–10 pm, with a prominent 5 pm–7 pm 'rush hour' peak

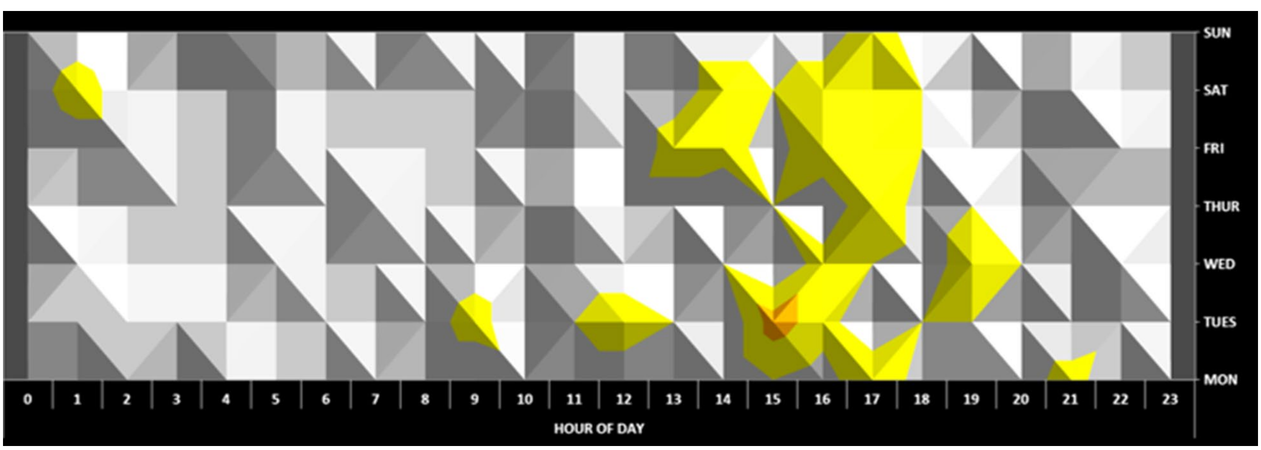

Fig. 10 Temporal analysis of robbery cluster #3 (n = 165 robberies) is different from previous robbery clusters, since it shows that weekday afternoon robberies are the primary problem in this cluster. There is no significant weekend or evening/nighttime shift pattern, with the exception of a very small Saturday/Sunday, Midnight-2 am pattern

crime hot spots have important temporal shifts within each hot spot. This intra-hotspot temporal variance is usually much more concentrated at more micro-levels (Ratcliffe 2004, 2006; Groff et al. 2010; Herrmann 2012).

According to the routine activities theory (Cohen and Felson 1979), crime scientists 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 population density residential areas, or commercial areas (with late-night/24-h businesses, especially those serving alcohol) that lack effective place managers. At more micro-levels (e.g. hot spots, hot streets, 'risky facilities'), the Pareto Principle still remains relevant and more research should focus on micro-level variations, since these can be very beneficial when developing and implementing crime prevention and control initiatives, especially resource allocation(s) and place-management approaches.

More complex temporal analyses, such as the aforementioned school-day vs. non-school day robbery analysis, can have immediate and significant operational and administrative impacts for both crime prevention and law enforcement control programs. While we assume that there would be differences in crime patterns for these

Fig. 11 Assault hot spots. Assault hot spots and subway stations

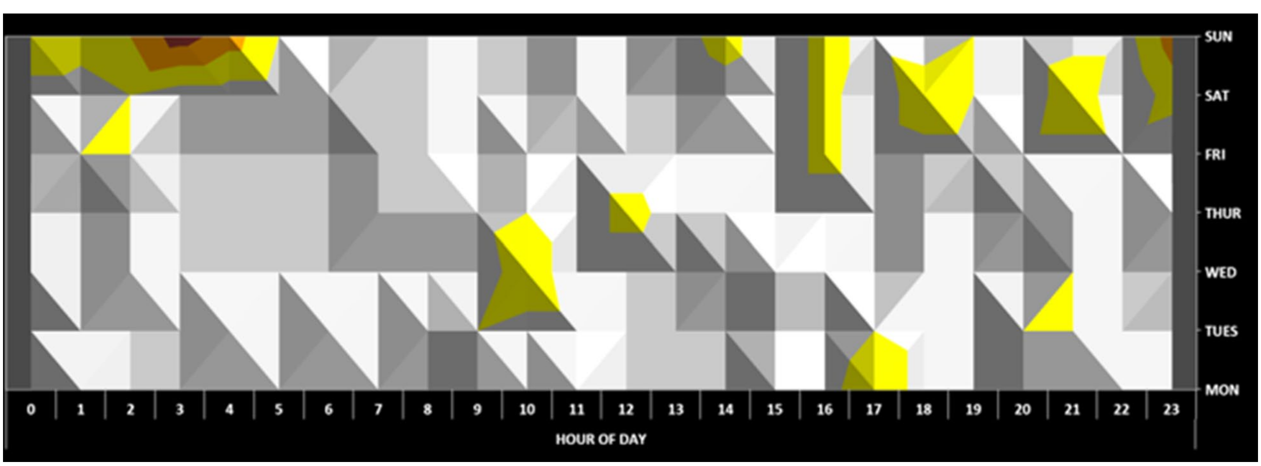

Fig. 12 Temporal analysis of assault cluster #1 (n = 158 assaults) where *gray* is zero/very little robbery, *yellow/orange* is medium amounts of robbery, and *dark red* is high counts of assaults. This cluster indicates a significant weekend and nighttime temporal pattern that is much different than assault cluster #3. There is a notable Saturday night/Sunday morning 2 am–4:30 am assault peak, as well as scattered Saturday and Sunday afternoon times. This cluster varies somewhat from #2 and #3, which have more weekday, afternoon trends (*yellow* areas)

two distinct time periods (school-day afternoons vs. non-school day nights) based upon routine activity and crime pattern theory, the time–space hot spot method clearly illustrates the essential component that temporal analysis plays in our understanding of crime hot spots, especially how hot spots shift (spatially) over time and how victims, targets, and offenders also vary according to these distinct time periods.

There has been a renewed interest in this type of focus of crime at micro-level places, especially the role of place management within crime places, such as 'risky facilities'. In their place management research, Madensen and

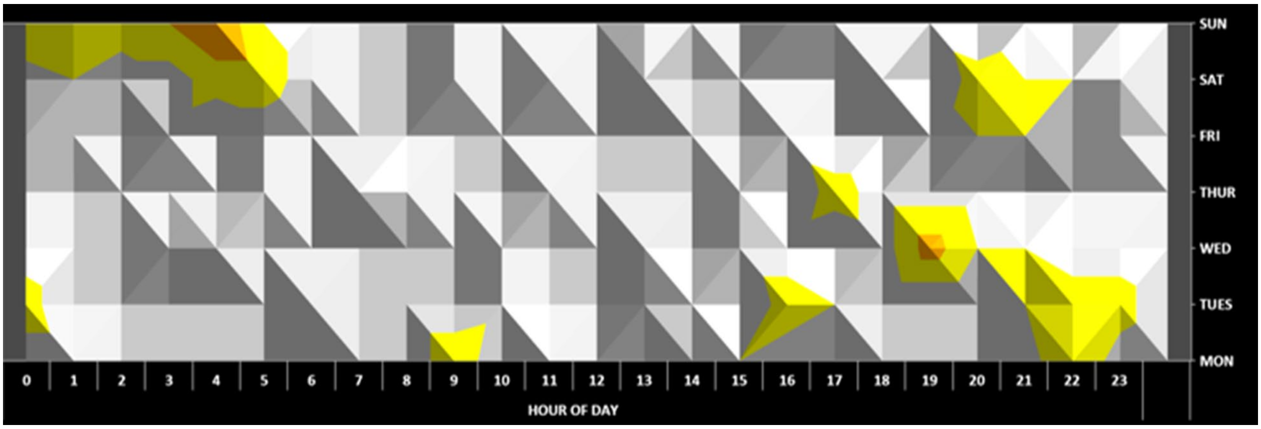

Fig. 13 Temporal analysis of assault cluster #2 (n = 145 assaults). This cluster indicates a significant weekend and nighttime temporal pattern that is similar to assault cluster #1. There are several weekday afternoon and early evening trends (between 3 pm–8 pm) trends that occur

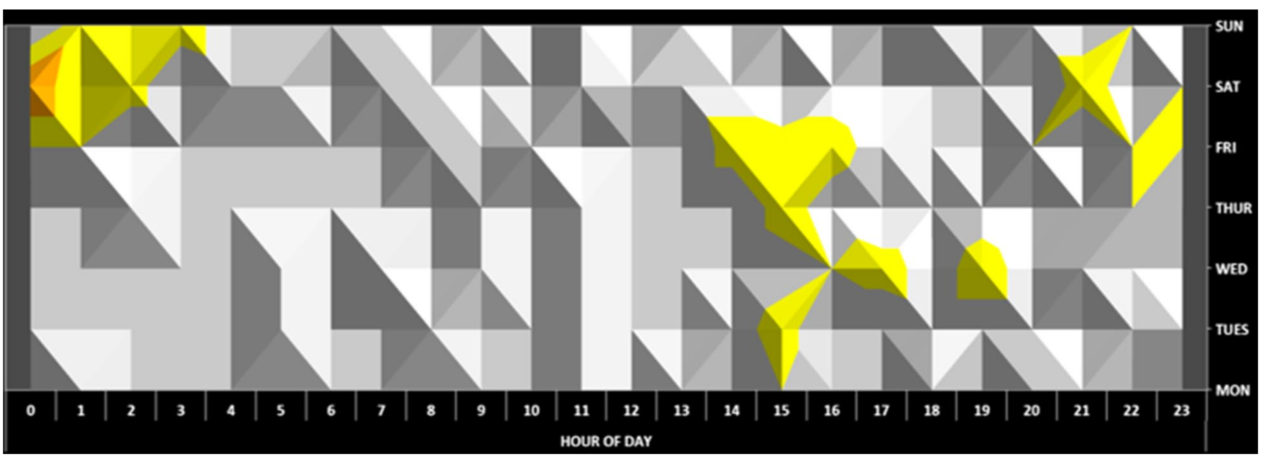

Fig. 14 Temporal analysis of assault cluster #3 (n = 129 assaults) indicates two separate patterns, a weekday afternoon 3 pm–5 pm and a weekend nighttime 10 pm–2 am pattern

Eck (2012), suggest three new descriptions of micro-level places that take into account the ownership (i.e. 'proprietary' nature of the business), the spatial clustering of places (i.e. 'proximal' relationships to other businesses), and the outermost boundaries or 'pooled' nature of the surrounding facility neighborhoods. Much of the current place management research suggests that effective place managers can have a considerable impact on the criminogenic nature of risky facilities and that several prevention and control efforts can have a direct impact on these 'convergent settings' (Felson 2003) that bring people together in both time and space. By utilizing time–space hot spot techniques, place management researchers can have a much more comprehensive understanding of the different targets/victims that are at risk and how they intersect/converge with potential offenders in both time and space.

Some considerations for future research include examining the strength of the temporal patterns using circular statistics, which takes into consideration the 'circular nature' of the 24-h time periods that are utilized in micro-level place-based research (Brunsdon and Corcoran 2006; Wuschke et al. 2013). The process of examining spatiotemporal variations and stabilities of micro-level crime clusters can also assist crime scientists in understanding how these micro-level place-based opportunities are more generally linked to theory, which in turn can promote more effective crime prevention and control strategies and better implementation configurations.

Many of the limitations of shifting hot spots research are similar to the more generalized limitations of hot spots research; namely, the geoprocessing of crime data, the various methods of constructing crime hot spots, and the generalizability of the 'findings' from within the hot spots. Geoprocessing of crime data typically includes selecting the type(s) of crime to include in the analyses, selecting the appropriate time period(s) to query and analyze the crime data, and defining the appropriate level(s) of geographic aggregation for geocoding the crime data. While the nearest neighbor hierarchical clustering method provides distinct geographical boundaries, this method can also exclude relevant crime data that falls marginally outside of the crime hot spot boundary, but is still considerably related to the phenomenon being studied. Lastly, a hot spot is not a hot spot is not a hot spot… not all crime hot spots behave the same way and generalizing the spatiotemporal shifts in hot spots should be crime specific, as well as location and time specific to each respective hot spot location.

Shifting hot spots research is an important issue that merits further research in crime science and crime analysis. Intra-hot spot variance is good news and bad news to crime scientists and crime analysts. The good news is that many hot spots have very specific temporal 'trends' or definitive patterns within them, usually based on routine activities, land-uses, facility types (especially 'risky facilities'), and victim/offender schedules that are active within each hot spot. When temporal analysis is conducted within each hot spot, a temporal trend can normally be identified and then an appropriate opportunity prevention framework, place management strategy, and/or police response can be developed and applied. However, the bad news is that if temporal analysis is not conducted on each hot spot, prevention resources and patrol efforts may be ineffective at best and 'wasted' at worst.

Competing interests
The author decalres that he has no competing interests.

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