

A Microspatial Analysis of Robbery: Prospective Hot Spotting in a Small City

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Abstract

With the greater availability of crime data geocoded to the incident level and the general accessibility of the tools for spatial analysis, it has become possible to complete successful microspatial analysis of crime. Robbery is a crime uniquely suited to this type of study. It is a volume crime committed with both instrumental and expressive motivations. Further, most robberies (even those occurring consonant with other illegal activity) tend to get rapidly reported to the police. All robberies reported to the police in a small city over a four-year period were geocoded and a first- and second-order spatial analysis identified hot spots. These hot spots were analyzed for accuracy and predictive accuracy using the Predictive Accuracy Index. Implications for crime control strategy are discussed.

Street robbery is unique in that the targets (people) are frequently mobile rather than static as in the case of burglary where the target is typically stationary. Robbery is also a crime with a high enough volume (36% of all violent crime) to both make applied research useful to public safety and without encountering some of the problems of studying more rare crimes such as rape (6% of all violent crime) or homicide (1.5% of all violent crime). And unlike aggravated assault (56.6% of violent crime), robbery is much more likely to represent the intentional, rational behavior of the motivated offender. These figures are based on an analysis of official Uniform Crime Reports data for the period 1960 through 2007 (Bureau of Justice Statistics (website), n.d.)

Sherman (1992) noted that because robbery is such a significant proportion of all violent crime it is easier to predict by place. It is a volume crime, occurring with enough frequency to make it amenable to statistical and spatial analysis. Sherman, Gartin, and Buerger (1989), analyzed police calls in 1986 in Minneapolis and found that only three percent of the places produced fifty percent of the calls. Robbery tends to cluster in a limited number of places making it particularly useful in the study of hot spot analysis.

In this context, robbery is an ideal crime type for the study of routine activities theory (Cohen & Felson, 1979; Groff, 2007; 2008). Of necessity, the robber engages in specific wayfinding behavior (Golledge, 1999) that is designed to bring him in contact with potential targets. Wayfinding behavior

is the sum total of the manner in which a person utilizes sensory cues and cognitive maps derived from the built environment to maneuver from place to place. People engage in wayfinding behavior to move about in their activity space, and routine activities theory informs us that where there is overlap in the activity spaces of offender and targets the probability of a crime occurring increases in those locations (Cohen & Felson, 1979; Cohen, 1987; Sherman et al., 1989). This probability increases substantially when the wayfinding behavior of the motivated robber crosses the path of an attractive victim in a place where there is a general lack of effective guardianship. If this space is such that it frequently combines qualities that are desirable to robbers, this location is likely to become a robbery hot spot (Sherman, et al., 1989).

Unlike the other high volume violent crime, aggravated assault, robbery is generally an intentional crime with the offender engaging in *à priori* decision making to enjoin an active hunt for a suitable victim, or at the very least to be ready should the opportunity to rob present itself. This implies a higher order of utilitarian rationality to the predation of the typical robber as compared to the perpetrator of assault. Therefore, given a mobile target, the robber must select a hunting ground with a high density of suitable targets, a lack of effective guardianship, and comports with the least effort principle (Zipf, 1950). The least effort principle states that given multiple possible hunting grounds, all other things being equal, the robber is most likely to choose the one requiring the least travel costs. If the robber engages in either a hunter- or poacher-style of search and attack behavior, the offense is more likely to occur in the most a suitable location which is close to home or work (Block, Galary, & Bice, 2007; Rossmo, 2000; Van Koppen & Jansen, 1998). Places with a concentration of motivated offenders, suitable targets, and the social and physical geography of a good hunting area are prone to becoming robbery hot spots.

BACKGROUND

In their pattern theory of crime, Brantingham and Brantingham (1984; 1993; 2008) described places that are crime attractors and other places that are crime generators. Crime attractive places tend to be locations that draw a lot of people for work, shopping, or recreation and where there is a relative lack of effective or consistent guardianship. A crime attractor is a target-rich environment that may exist only at certain times of the day when businesses other attractions are open to draw the people to that location. Such places are typically characterized by a high density of commercial land use and a low density of residential land use. People, including offenders, generally move to such locations.

A crime generator, by comparison, is a location that tends to be conducive to criminal enterprise and activity due largely to its social and physical geography. Crime tends to flourish in areas with high levels of social disorganization (Bursik, 1988; Sampson & Groves, 1989; Taylor, 1997), residential instability (Osgood, 2000; Sampson, Raudenbush, & Earls, 1997) and mixed land use (Groff, 2007; Hirschfield & Bowers, 1997; Taylor, Koons, Kurtz, Greene & Perkins, 1995). People, including offenders, tend to move about in (rather than moving to) such locations. Crime attractors are more likely to attract a poacher-type of offender and a crime generator is more likely to be the operational environment for a hunter-style robber. The poacher type offender moves to a location and ranges out from a search or activity base to locate available targets. The hunter type of offender bases their search from a stable or static location such as their home (most likely according to Rossmo, 2000) or their place of employment. Ultimately the identification of any location as a crime attractor or a crime generator is based largely on qualitative interpretations of the place description and the movement patterns of the offenders and the victims. However, both attractors and generators contribute to the spatial clustering of crime.

Places where crimes occur are far more predictable than is the individual behavior of people who commit the crimes (Sherman, 1992). Sherman et al. (1989) define place in two different ways: geographically and sociologically. From a geographical perspective, place is defined as “a

fixed environment that can be seen completely and simultaneously, at least on its surface, by one's naked eye" (Sherman et al., p. 31). Sociologically, place is "the social organization of behavior at a geographic place" (Sherman et al., p. 32).

Although the contemporary popularity of hot spot analysis can largely be attributed to Sherman et al. (1989), since the early work of Guerry (1833) and Quetelet (1842) criminologists have understood that crime is neither randomly nor intuitively distributed in the environment. These statisticians, using thematic mapping to identify areas of differential crime concentration, showed that crime clustered consistent with the underlying social and demographic characteristics of French enumeration districts. Contrary to Willie Sutton's famous quote ("Because that's where the money is"), thievery in 19th century France did not cluster in the wealthiest districts. In fact, similar to the findings of current environmental criminologists, crime tended to cluster in the poorer districts. This early mapping analysis serves as foundational guidance for the study of crime as a spatially non-random phenomenon.

Over the last thirty years there has been an exponential growth in the mapping analysis of crime and the wide availability of tools for geospatial analysis allowed for the more finely grained study of where crime occurs. The mapping and analytic capabilities of geographic information systems and the increasing availability of data that can be mapped to the incident location allowed for the microspatial analysis of crime at the neighborhood, block, and even street level. We are now able to study the ecology of crime empirically, at the microspatial (specific places, small areas, or neighborhoods), mesospacial (cities, counties or metropolitan statistical areas), and macrospatial (state, regional, or national) level because of the wide availability of rich data and the ready availability of the necessary tools for this analysis. Each level of study provides a unique contribution to the general understanding of this complex, multi-causal phenomenon.

The robber's selection of location is dependent on a number of factors including the offender's motivation, the robbery site, and the nature of the target (Van Koppen & Jansen, 1998). The cost of travel is well documented and offenders exhibit behavior consistent with the least effort principle traveling relatively short distances to commit their crimes (Brantingham & Brantingham, 1981; Rengert, 2004). When the opportunity surface close to home is not suitable, the travel cost to commit the crime increases. As a result, offenders tend to commit most of their crimes closer to home to minimize that cost. While it may not always hold in the case of the individual offender, the distance decay function of the journey-to-crime demonstrates this phenomenon in a general sense (Van Koppen & De Keijser, 1997; Rengert, Piquero, & Jones, 2006).

Neighborhood characteristics such as disadvantage and instability also influence the offender's choice of place (Stretesky, Schuck, & Hogan, 2004). Neighborhoods with impacted poverty that are socially or physically isolated from more mainstream neighborhoods encourage the proliferation of crime in those neighborhoods. As Zenous (2003) points out, a person is more likely to commit a crime if his peers are also committing crimes. The localized tacit support for criminal behavior tends to contribute to the proliferation and clustering of crime in certain neighborhoods (Keizer, Lindenberg, & Steg, 2008). Land use characteristics, such as the transportation infrastructure, the amount of street traffic, zoning, and density of commercial activity, all affect the offender's decision to commit an offense in a given neighborhood (Duffala, 1976). Certain business establishments, like bars or taverns, have long been associated with the occurrence of robberies in proximity to those locations (Sherman, 1992).

HOT SPOT ANALYSIS

The use of hot spot methods to study crimes such as robbery has grown in popularity and utility over the last twenty years (Anselin, Griffiths, & Tita, 2008; Block et al., 2007; Block, Daddoub, & Fregly, 1995; Bowers, Johnson, & Pease, 2004; Ratcliffe & McCullagh, 1999; Sherman et al., 1989;). However, the precise and accurate use of hot spotting methodologies lacks a widely accepted

standard (Chainey & Racliffe, 2005; Chainey, Reid, & Stuart, 2002; Eck et al., 2005; Ratcliffe & McCullagh, 2001; Weir & Bangs, 2007). There are essentially three main classes of hot spotting methods: Thematic mapping using administrative boundaries or quadrat grids, point-pattern analysis producing ellipses or convex hulls, and kernel density interpolation methods. Each represents the underlying phenomenon in a slightly different manner and therefore each method changes the meaning of the phenomenon being studied. Because all hot spotting methods involve a level of aggregation, there is also a net loss of real information as the data are transformed by the hot spotting method. There is inevitably a tradeoff between accuracy and precision based solely on the method of analysis chosen (Chainey, Tompson, & Uhlig, 2008a; Levine, 2008).

Until very recently there was not any metric for evaluating the effectiveness of a hot spotting method that would also allow for the comparison of different approaches at different locations. Ultimately, the objective of hot spot mapping is not to inform about what has happened, but to anticipate where and when crime will happen. There has only been limited work in prospective hot spot analysis, at least in part because of the subjectivity of the hot spot methods currently available (Bowers et al., 2004). One early effort was reported by Liu and Brown (2003) in which they developed a predictive algorithm using a transition density model based on criminal preferences derived from an analysis of past events. These authors report the model was successful, but it has not generally seen wide acceptance in the crime analysis community due to the proprietary nature of the underlying algorithm. Bowers and her colleagues (2004) have also used a measure called the Search Efficiency Rate which is based on the density of crimes per unit of area. The weakness of this method is that while it performs well in localized prediction, it does not consider the entire study region (e.g., jurisdiction, city).

Chainey et al., (2008a) have recently proposed a metric for evaluating the effectiveness of different hot spotting methods that shows great promise. The Predictive Accuracy Index (PAI) is specifically designed to consider the localized hot spot against the larger study region in a form that allows direct comparison of hot spot prospective accuracy between different study regions. The PAI is derived from a ratio of the hit rate (the number of crimes in the hot spot compared to the region) to the area percentage (proportion of the region represented by the hot spot). In their research, Chainey et al. reported on the evaluation of three different general techniques of hot spot mapping: Thematic mapping, nearest-neighbor derived ellipses, and kernel density estimation. Using baseline data they predicted the accuracy of the different methods in predicting "future" crime in those areas identified as hot spots. These authors concluded that the kernel density estimation method was superior to the other two based on their analysis of different crime types from two enumeration districts in London.

While the conclusions on the best hot spotting methods arrived at by these authors is not without controversy (Chainey, Tompson, & Uhlig, 2008b; 2008c; Levine, 2008; Pezzuchi, 2008) the utility of the PAI as a method for the objective evaluation of hot spot methods is an important contribution to crime analysis and crime mapping research. The PAI provides an objective criterion with which to evaluate the accuracy of a hot spot from either measured or predicted crimes. In his response to Chainey et al., (2008), Levine (2008) suggests complementing the PAI with a measure he calls the Recapture Rate Index (RRI). The RRI measures the recapture of prospective crime incidents by comparing the rate of change from a measured time period to a predicted time period. In essence, the RRI complements the PAI by providing a measure of the precision of the hot spot method as well as an estimate of the accuracy.

In this research we evaluate the efficiency of several popular hot spotting methods using robbery data from the City of Roanoke, Virginia. Roanoke is the largest urban area in predominantly rural southwest Virginia. The city, at the center of a metropolitan statistical area with a population base of slightly more than 209,441, reported a 2007 census of slightly more than 92,000 individuals. Roanoke covers approximately 43 square miles in southwest Virginia, at the very southern end of the Shenandoah Valley. The city is located in the Roanoke Valley region, which is made up of the City

of Roanoke, Roanoke County, and the adjoining independent city of Salem. Roanoke experienced a net loss of 1.96% in population from the 2000 census through 2007. By way of comparison, the surrounding county experienced a net growth of 6.4% and the city of Salem a moderate growth of 1.7% in population. The business leaders of the city are currently engaged in an active campaign to recruit young professionals, the demographic group exhibiting the greatest exodus from the area.

While the City of Roanoke experienced a gradual loss in population over the last eight years, it simultaneously experienced an increase in robberies. The mean robbery rate for the most recent five-year period (2003-2007) is 219 per 100,000 citizens (Virginia State Police, 2007; 2006; 2005; 2004; 2003). The robbery rate increased by approximately 32 incidents per-100,000 persons per year during that period of time (slope of the trend line for the five year period). If it continues to increase at the same rate, robbery in 2008 will exceed 300 per 100,000 individuals. This is about twice the U.S. robbery rate of 149.4 for 2006 (Bureau of Justice Statistics, n.d.).

By comparison, Salem had a mean robbery rate of 44.9 and the county had a robbery rate of 17.4 for the same period. Further, while the trend increased for all three jurisdictions in the Roanoke Valley, the increase for Salem was 2.4 (per 100,000 per year) and for the county it was 2.3 (per 100,000 per year). The U.S. robbery rate showed an increasing trend of 2.49 (per 100,000 per year) for the years 2003-2006 (2007 data not yet available at the national level). The two jurisdictions surrounding the City of Roanoke had a growth trend roughly on par with the national trend in robbery.

Robbery in Roanoke exhibited a growth rate approximately 12 times the national trend for the same period. In the five-year period from 2003 to 2007 eight times as many robberies were reported to the police as the neighboring jurisdictions. The use of hot spot analysis of these robberies can serve to inform both community and policing responses to the problem. The current analysis is an attempt to identify the patterns and trends through the analysis of robberies for the most recent four year period for which complete data on all reported robberies is available, 2004 through 2007.

In order to analyze the trends and patterns of robbery in Roanoke, the evaluation of these incidents are conducted with several different hot spot methods. Through a convergence of hot spot methods, local areas (hot zones and hot points) within the larger study region are identified and evaluated. A comparison of hot spot methods addresses the question of which method serves which purpose best. By considering the convergence of hot spot methods, neighborhoods with the greatest robbery problem are identified and evaluated for the social and physical characteristics that may be conducive to robbery.

METHODS

One consistent criticism with the hot spot analysis of incident-level crime is that many of the parameters used to determine a hot spot are subjective (Chainey et al., 2002; Chainey et al., 2008a; Eck, Chainey, Cameron, Leitner & Wilson, 2005). Widely differing results may come from even small alterations in the definitional parameters of the analysis. When relying on thematic mapping techniques, the issue is compounded by the modifiable areal unit problem (MAUP), which results from spatial analyses conducted on areal units of varying size defined by administrative boundaries rather than the physical geography (Taylor, Gorad & Fitz, 2003).

To help control for these issues in analysis, we use an approach that relies on the convergent evaluation of multiple hot spot methods. By using several different methods and altering parameters within methods, including both point-pattern and lattice data, to address each hypothesis, we hope to find a convergence of results which can be used to clearly define a problem area. The use of convergent methodologies necessarily means that the unit of analysis varies with the particular method employed. However, all these analyses are ultimately based on the geocoded incident-level robberies reported to the police in the City of Roanoke for the years 2004 through 2007.

All robberies reported to the police and recorded in the records management system (RMS) were obtained for the period between 1 January 2004 and 31 December 2007. The records from the

RMS are not geocoded and the first step in this analysis was to prepare a point-pattern (pin) map by geocoding the locations for the reported robberies. The address locator was prepared from street centerline reference data prepared by the City of Roanoke GIS Department and downloaded from the public access website (City of Roanoke, 2008). This reference file is updated on a daily basis. The geocoding engine native to ArcGIS™ was used for this purpose and a nominal geocoding rate of 99% was achieved through a combination of automated and interactive geocoding of incident addresses. This exceeds the minimum acceptable hit rate recommended by Ratcliffe (2004). Addresses which could not be geocoded were inspected for any pattern which may have tended to introduce a systematic bias into the data and none were detected. An incident map (pin map) was produced for visual inspection of the pattern of robbery (see Figure 1 below).

To test for global and local spatial clustering, convergent methodologies were employed. Point-pattern analyses for complete spatial randomness (CSR) were conducted using two different approaches: A Nearest Neighbor Analysis and a Ripley's K function. No edge correction was used for either point-pattern method. Individual incidents were aggregated to two different areal units for this analysis. A count of robberies per block group and a count of robberies per grid cell were used. Lattice data were tested for CSR using these two methods of aggregation and a Moran's I test for spatial autocorrelation was completed on each form of the areal data. For the Moran's I analysis, first order Rook spatial weights were used for both the quadrats and the block groups. The Moran's I statistics were evaluated for significance with three different methods: An assumption of normality (null tested against a normal distribution), an assumption of randomization (null tested against a random sample drawn from the data), and with a Monte Carlo simulation with 999 trials.

Robbery incident were aggregated to census block groups (n=82) and to a quadrat grid laid over the city boundaries. The quadrat grid size was determined by using Griffith & Amrhein's (1991) formula for determining quadrat size:

$$\text{Size of quadrat} = 2A/r \quad (1)$$

Where A is the size of the study area and r is the number of points in the incident distribution. This resulted in a recommended quadrat size of approximately 500 feet-square. To cover the surface of the city 5,068 individual quadrats were required. After aggregating the robberies to this grid it was discovered that there were 4,567 (90%) empty cells. The quadrat size was adjusted (to reduce the frequency of empty cells) to a 1000 foot-square grid. This resulted in 1,320 cells to cover the area, with 75% having zero-counts. Although this is still a very high number of empty cells, this size was preferable to the smaller cell size for both practical reasons and to reduce the zero-count cells.

Once the robberies were aggregated to the two different lattice units (census block group and 1000-foot grid), they were tested for global spatial autocorrelation with Moran's I. The test is of a null hypothesis of complete spatial randomness, with a significant finding indicating spatial clustering in the study region. For the data aggregated to the 1000-foot grid cells, the raw count was used because all the cells are of equal dimensions (0.04 square miles). This allows a direct comparison of raw frequency data. In effect, the count is a density function based on a standard grid cell size. However, for the data aggregated to the census block groups count data were transformed into location quotients or concentration indices for purposes of comparison and analysis (hereafter the term concentration index is used).

Concentration indices were computed for the variables representing frequency data according to the formula recommended by Brantingham and Brantingham (1997). The concentration index provides information about the relative concentration of a variable in a single areal unit compared to the spatial distribution of that variable across the study region. This index is calculated as a ratio of the proportion of the variable in a small area to the proportion of the variable distributed throughout the study region. This ratio is constructed such that a value of 1.0 indicates that the variable is present in the smaller areal unit (e.g. – the block group) with the same concentration across the study region. Values less than 1.0 indicate a lower concentration and values more than unity indicate a higher

concentration in the block group. For example, a concentration index of 1.33 would indicate that the variable was present in the smaller areal unit in a concentration 33% higher than would be expected based on the region-wide distribution. Correspondingly, a concentration index of 0.75 would indicate a concentration 25% lower than expected.

Concentration indices have a distinct advantage over the use of traditional crime rates in the study of crime aggregated to census units. This is particularly true of the microspatial analysis of crime within a single urban area. As noted above, one issue with census units is related to the MAUP. In the study of urban crime in an area that transitions from urban center to suburban areas, the population density per unit varies greatly. In the typical construction of census block groups, the size of the block group is a direct function of that population density. The result is that smaller block groups cluster in the urban center where population density is greatest, and larger areal units tend to be located at the periphery of the city (with a corresponding decrease in population density).

Crime rates, which are standardized per unit of population, are directly affected by the relative population density in a block group. It is not unusual for a block group with considerable land area and a small population density to result in a relatively higher, visually indicated, crime rate in a thematic map. Similarly, a high volume of crime occurring in a small area with a small residential population such as the city center or an industrial park results in a distorted crime rate even though the area itself is relatively small. When these rates are displayed in exploratory spatial data analysis as thematic maps, this distortion can result in a fundamental misunderstanding of where crime is concentrated. The residential population may also not accurately represent the population at risk. Andresen (2007) noted the superiority of concentration indices when considering the ambient nature of populations at risk. Crime rates unrealistically assume the population at risk is the same as the residential population in a census unit. This may be particularly inappropriate for the analysis of crime in small areas such as urban centers.

Crime rates also rely upon probabilistic reasoning to make sense of the relative risk. A crime rate is a probabilistic statement of risk (probability of victimization) of a particular crime, usually per 100,000 people. It is not an intuitively understandable statement of risk (Girgerenzer, 1991; Girgerenzer & Hoffrage, 1995) whereas the concentration index reports risk as a frequentist function in the form of a percentage increase (or decrease) in concentration (relative risk).

Another distinct advantage to the use of concentration indices in the study of crime is the flexibility of choosing different areal units for comparison. Crime can be compared based on the concentration per unit of area, or based on the comparison of a specific crime type to the concentration of all crime types. Crimes can be aggregated to polyline features and compared as a concentration per unit of length. In addition to crime-related variables, other frequency type data such as that typically found in census based files can be used to compute a concentration index. For example, if it is useful to derive information about crime in a non-standard areal unit such as a police patrol district, a concentration index can be calculated easily. However, population data is rarely available for such non-standard areal units making the computation of a crime rate impossible.

The use of concentration indices in the microspatial analysis of crime proves a very powerful tool for understanding events at this level of analysis (McCord & Ratcliffe, 2007; Ratcliffe & Rengert, 2008). The following formula is used to calculate a concentration index based on the study area:

$$LQ = \frac{C_{A_i}}{A_i} \bigg/ \frac{\sum_{n=1}^N C_{A_i}}{\sum_{n=1}^N A_i} \quad (2)$$

Where

C_{A_i} = the count of variable in the i -th area

A_i = the area in square miles of the i -th area

$\sum_{n=1}^N C_{A_i}$ = the sum of all variable counts in study region

$\sum_{n=1}^N A_i$ = the sum of all areas in study region

With the presumption that robbery is positively spatially autocorrelated, the next step in the analysis is to conduct convergent hot spot analyses to determine the neighborhoods where it is most strongly clustered. As noted above, we proceed with several different methods in three broad categories and look for a convergence of findings among those methods. The first approach is to use thematic mapping techniques based on Local Indicators of Spatial Association (LISA) (Anselin, 1995) to ascertain the clustering of high robbery concentration areas surrounded by high concentration areas. A critical parameter in thematic mapping is the threshold values used to define an area as “hot.” Chainey and colleagues (2002) stressed the importance of a having a statistically robust method for determining hot spot thresholds. LISA calculates a local spatial autocorrelation statistic, per individual areal unit (block group or grid square) and tests it for significance against the null of spatial randomness. The LISA statistic is then classified into one of five categories (non-significant, high-high, low-low, low-high, and high-low). We then use a high unit surrounded by other high units (High-High) to define the hot spots. The LISA analysis is next performed with both the 1000-foot grid aggregation using raw robbery counts as the intensity measure and with the census block groups using the robbery concentration index as the intensity measure to calculate the areas of high robbery concentration. The use of the LISA approach to define areal-unit based hot spots removes the necessity of making subjective decisions about the categorization of thematic display levels (Chainey et al., 2002).

Once the hot spots for the thematic maps are identified they are evaluated with the Predictive Accuracy Index (PAI) developed by Chainey et al. (2008a). The PAI is the ratio of the hit rate percentage (the percentage of robberies in the hot spot) to the area percentage (the percent of area in the hot spot in relation to the study region’s total area) for the identified hot spot. The following formula is used to derive the PAI:

$$PAI = \left(\frac{n}{N} \right) * 100 / \left(\left(\frac{a}{A} \right) * 100 \right) \quad (3)$$

Where n is the number of robberies in the hot spot and N is the total number of robberies in the study region, a is the area of the hot spot and A is the area (in square miles) of the study region. Both measured PAIs and predictive PAIs will be constructed. A measured PAI is based on the historical data and is a utility metric by which that particular hot spot technique can be compared to others. A predictive PAI is based on identifying the hot spot areas from historical data and then evaluating the predictive accuracy by counting the robberies from a subsequent (predicted) time period in the historically established hot spot. The basic PAI formula is modified thus:

$$PAI' = \left(\frac{n'}{N'} \right) * 100 / \left(\left(\frac{a}{A} \right) * 100 \right) \quad (4)$$

Where n' is the number of prospective robberies in the historically identified hot spot and N' is the total robberies in the prospective time period; and a and A are the respective areas of the historic hot spot.

For the lattice data, hot spots are developed for each year (time period) based on just the robberies occurring in that year, and hot spots are also developed for the overall time period (2004 to 2007). For each of the individual years the historic hot spot are used to predict robberies for the subsequent year. A measured PAI and a predictive PAI will be derived for each.

In each instance where a predictive PAI is calculated, a Recapture Rate Index (RRI, Levine, 2008) are also be generated. The RRI was developed by Levine to further assess the predictive ability of hot spot techniques. It is a recapture ratio comparing the hot spot crime density of time period 2 (predicted) to the hot spot crime density in time 1 (historical) standardized for the change in crime density for the study region from period 1 to period 2. In effect it is the ratio of the predictive PAI for time period 2 to the measured PAI for time 1:

$$RRI = PAI_t / PAI_{t-1} \quad (5)$$

Hot spot techniques that use any interpolative algorithm in their computation (e.g. – kernel density estimation) increase the likelihood that future incidents will be captured within the hot spot boundaries. This tends to make them more accurate (higher PAIs), but may do so at the cost of loss of precision (lower RRIs). In effect, the RRI serves as a reliability or consistency indicator and allows us to evaluate the hot spot method for both accuracy and consistency (precision). Levine provides an example of the dart thrower from Jessen (1978) to illustrate; the player who throws darts all over the board but whose mean center is the bull's eye is accurate but not precise.

The next approach to hot spot analysis is to use point-pattern methods based on nearest-neighbor clustering of hot spots. For each method (Spatio-temporal Analysis of Crime, STAC, and nearest neighbor hierarchal clustering, NNH) two different forms of hot spot output (ellipses and convex hulls) evaluated. Both the STAC (Block, 1995) and NNH methods are implemented using *CrimeStat III* (Levine, 2004). Ellipses and convex hulls are developed for each method (STAC and NNH), for each year, and for combined years to use in the prospective analysis. The different methods are then evaluated with both the PAI and the RRI.

In evaluating the predictive ability of the different methods it is important to recognize that the use of ellipses to represent a hot spot is an abstraction based on the underlying data drawn on a major directional axis rotated through the underlying distribution with an orthogonal minor axis. Depending on the algorithm used to construct the ellipse it may or may not (usually not) include all the incidents comprising the hot spot. For this reason the PAI is computed based on the incidents that actually fall within the ellipse. Alternatively, convex hulls are drawn by connecting the outer most incidents included in the hot spot to make a polygon and include all the crimes in the cluster.

Again, the hot spots produced by these methods are sensitive to the parameter settings. The parameters set by the analyst include the number of locations making up a hot spot and the search radius (or bandwidth) for inclusion of points. Manipulation of these parameters can cause the identification of hot spots to vary widely. The decision on the search parameters should be informed by both the theoretical and the practical aspects of the crime clusters (Eck et al., 2005). Ideally, the parameter setting should consider the real world geography of the region and the crime under study. Given this guidance, these parameters should be set as part of an *a priori* decision by the analyst. With the volume of robberies being analyzed ($N=904$) and the physical and social geography of the city, the general search parameters for this analysis are set at fifteen (15) offenses per cluster for the total incidents for the four year period. For the creation of single-year hot spots, this count was reduced to seven (7) incidents per cluster, and for two-year hot spots the method was evaluated at 7, 10, and 15 incidents per cluster. The decision was made to use a search radius of 1320 feet (a quarter-mile). This search radius roughly represents the distance a person travels by foot before seeking an alternative means of transportation (Agrawal, Schlossberg, & Irvin, 2008). This is the distance a person walking

at a comfortable pace (3 mph) can traverse in 5 minutes (Bohannon, 1997). This distance is chosen because it approximates a “neighborhood” foot-travel range and is consonant with the study region’s total area (42.91 square miles).

The final hot spot method was the use of kernel density estimation to generate an interpolated density surface based on the existing crimes in a measurement time period. There are two parameters that affect the computation of the interpolated cell densities, the cell size and the kernel bandwidth. Cell size affects the overall appearance of the map layer generated and the number of cells for which the actual incident data must be smoothed. Necessarily, the smaller the cell size, the more the data must be interpolated to generate the density for each cell. Since interpolation is a mathematical smoothing process, there is a greater net loss of information with more smoothing. The cell size for this evaluation was set by dividing the reference grid into 500 columns, which resulted in an individual cell size of 95 feet-square (Levine, 2004). A fixed search radius was set at 1320 feet, to be consistent with the nearest-neighbor parameters. Normal interpolation was used for this analysis because it develops a continuous estimation over the whole study region and not just the search radius bandwidth. Typically this generates a smoother transition between regions of high density to regions of lower densities.

Kernel density estimation produces a smoothed surface with individual cells representing the interpolated density value for the area covered by that cell. In effect, it produces a finely grained grid lattice within the bounding rectangle with each cell having a unique value. The visual representation of the data is usually through the use of a color ramp with graduated colors and specified cut-points for the different levels of the ramp. Since both the number of gradations and the specification of the cut-points affect the representation of a hot spot area, it is important for the analyst to be transparent in these decisions. For this study, it was decided to use five levels of gradation and to set the cut-points at equal intervals. In effect, this divides the range of the density values into five equal sized groupings, each with 20% of the data range. Hot spots are then defined as the highest valued class, or the densities at or above the 80 percentile. This method is consistent with that recommended by Harries (1999) and Eck et al. (2005). The cells making up the top class (greater than the 80th percentile) were dissolved into a single polygon and used to represent the kernel density hot spot.

Finally, in order to evaluate the neighborhood characteristics of those block groups identified as hot spots, several social organization and land use variables were compared. Using a simple one-way analysis of variance the concentration indices for alcohol outlets (Zhu, Gorman, & Horel, 2004), vacant properties, renter occupied residences, young males (15 years to 25 years of age), families receiving public assistance, and non-residential land use in the hot spot neighborhoods were compared to the non-hotspot neighborhoods. In addition, these block groups were also compared based on the Diversity Index (Mauro, 1995 – the probability that two randomly selected individuals are from different racial or ethnic backgrounds; Brewer & Suchan, 2001) and the median household value for 2003.

It is expected that neighborhoods (block groups) identified as robbery hot spots have a greater concentration of alcohol outlets (Roncek & Maier, 1991; Zhu et al., 2004), vacant housing, renter-occupied housing, young men 15- to 25-years of age, families on public assistance, diversity, and non-residential land use (Sampson & Groves, 1989; Sampson et al., 1997; Smith, Frazee, & Davison, 2000). It is also expected that the median home values are lower in the hot spot neighborhoods (Lynch & Rasmussen, 2001).

RESULTS

VISUAL MAP INSPECTION

All robberies reported to the City of Roanoke Police for the years 2004 through 2007 were geocoded (nominal geo-coding rate of 99%) and mapped for analysis (N=904). Figure 1 shows the distribution of robberies against the Roanoke city backcloth. There are several geographic features

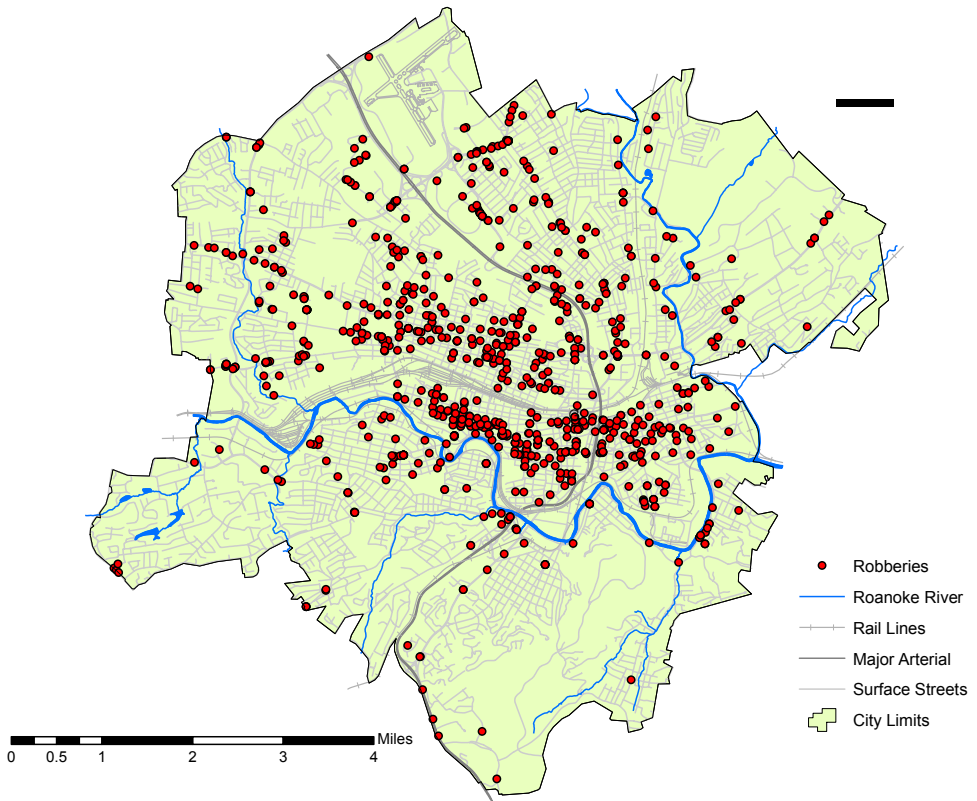


Figure 1. Pin map of robberies 2004-2007

which have an impact on the distribution of crime and criminal behavior in the city. The city is horizontally bifurcated East-West by rail yards and by the Roanoke River (for which the city was named). These two physical features of the geography constrain the distribution of crime such that most of the robberies are near the city center and between the rail lines and the river. Another physical feature is the North-South limited access highway which serves as a partial physical constraint on the crime distribution.

The city is divided into quadrants (NE, SE, SW, and NW) and the center of the quadrants is indicated by the black cross at the center of the map. The downtown business district is immediately to the south of the cross and extends west about three-quarters of a mile. A cursory visual inspection of this “pin map” shows an apparent clustering of robbery in the area to the west of the city center (between the rail yards and the river). There are several other areas of apparent clustering in the northwest quadrant and in the southeast quadrant. The densest appearing area is about a mile and a quarter to the west of the downtown center and south of the tracks. In conducting the visual inspection it was noted that there was an area west of the downtown and slightly northeast (but still south of the rail yard) of the densest clustering of robbery where no robberies occurred; an apparent gap in the pattern. This seemed unusual given the number of robberies surrounding this small area.

A field survey of this area of the city shows that it is predominantly made up of wholesale distribution warehouses and some light production (a commercial bakery for example). A cursory

examination of the map in Figure 1 shows that very few robberies occurred in these areas. During the field survey of this area, which lasted about an hour during the middle of a weekday afternoon, there were less than a half dozen people observed on the streets or out of doors. In contrast, the residential area immediately to the west was teeming with people on the sidewalks, in their yards, and on front porches. Clearly, the opportunity surfaces of these two sub-areas vary greatly. This visual examination suggests there may be statistically significant clustering of robberies.

EXPLORATORY SPATIAL DATA ANALYSIS

To test the hypothesis of complete spatial randomness, the data were tested for spatial clustering using several methods. First, the data were aggregated to two different areal units, the 1000 foot-square quadrat surface and the census block groups, and a Moran’s I calculated using *ClusterSeer2™* (Jacquez et al., 2002).

There is a moderately strong, positive spatial autocorrelation for both the quadratic grid surface and for the census block groups. This supports rejection of the hypothesis of complete spatial randomness in both distributions of the robbery data and suggests that robberies do, in fact, cluster in the study region. The spatial clustering for the block groups was slightly stronger than for the 1000-foot grids. This may be, at least in part, due to the substantially lower number of zero-count block groups as compared to the 1000-foot grid. Only three out of the eighty-two (3.66%) block groups had a zero robbery count (and consequently a zero concentration index), whereas 990 of the 1320 (75%) grids had zero counts. Regardless, the difference in the Moran’s statistic was not great (0.048) and both converged in their indication of moderately strong, positive spatial clustering in the lattice data.

Table 1. Spatial Autocorrelation Results – Lattice Data

Method	Moran’s I	E[I]	Normality			Randomization			Monte Carlo*	
			Variance	Z-score	P-value	Variance	Z-score	P-value	Statistic	P-value
Quadrat	0.333	-0.0008	0.0002	23.443	0.0000	0.0002	23.802	0.0000	0.333	0.002
Block Group	0.381	-0.0123	0.0045	5.866	0.0000	0.0041	6.146	0.0000	0.381	0.002

*P-value based on 999 simulations

We next turn to the tests for spatial clustering in the point-pattern data using two methods, the K-order Nearest Neighbor Index and the Ripley’s K test for clustering. The nearest neighbor index was calculated for each year and for the overall robbery distribution and the results are in Table 2.

Table 2. Nearest Neighbor Index

Year	Robberies	NNI	Z-score	P-Value
2004	193	0.541	-12.20	0.0001
2005	228	0.60	-11.34	0.0001
2006	222	0.572	-12.22	0.0001
2007	261	0.592	-12.62	0.0001
Overall	904	0.401	-34.47	0.0001

The nearest neighbor procedure tests for clustering of points against an alternative of a random distribution in the study region. Values less than one indicate spatial clustering among the points and there is an indication of significant clustering for each year individually and for the combined four-year distribution of robberies. In Figure 2 the K-order NNIs are plotted out to 100 neighbors. The plot indicates that the clustering is consistent throughout the distribution. For each year there is a fairly steep increase in the curve to about five nearest neighbors and then the slope gradually flattens out. For the combination of all four years this flattening out occurs at approximately the 20th nearest

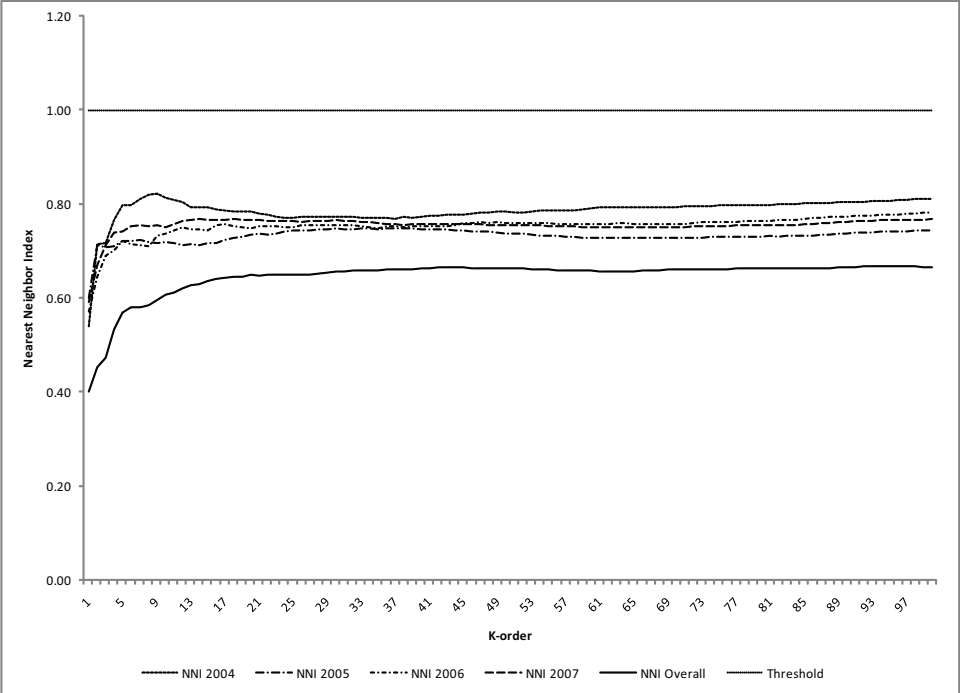


Figure 2. K-order nearest neighbor index

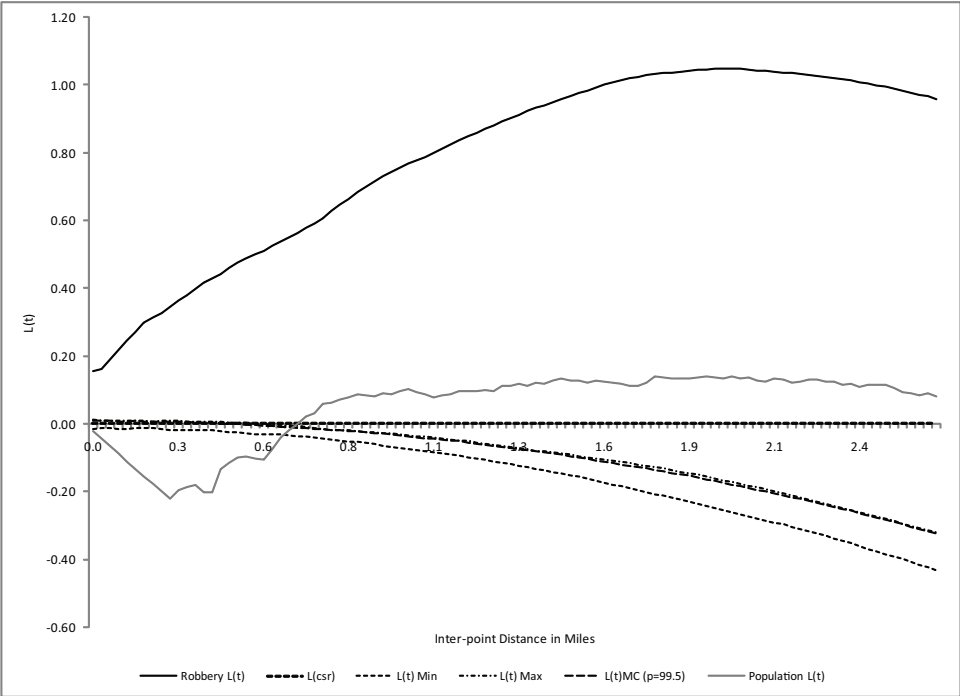


Figure 3. Ripley's K-function robbery with population

neighbor and for the individual years this occurs at about the 10th nearest neighbor. The results of the NNI analysis are confirmed by the plot of the Ripley's K-function (Figure 3).

The Ripley's K-function tests the sample distribution for clustering against a distribution of random points and is compared to a distribution generated with 999 Monte Carlo simulations. In Figure 3, the K-statistic is transformed for linearity ($L(t)$) and plotted over the inter-point distances. In this case it is also compared to the clustering of the population density since crime clusters often simply follow the population cluster pattern. This plot indicates there is clustering throughout the range that exceeds that expected in a spatially random distribution, a Monte Carlo simulation, and that of the population density. The maximum clustering occurs at a 2 mile inter-point distance and then begins to gradually drop off.

We conclude that both the lattice data and the point-pattern data show evidence of significant global spatial clustering. This clustering applies to the entire study region and thus far we have no indication of where the localized clustering, the hot spots, may be occurring. We turn next to the hot spot analysis of the robberies.

HOT SPOT ANALYSIS – LATTICE DATA

We next tested for Local Indicators of Spatial Association (LISA) to examine the specific pattern of the clustering. Using *GeoDa* (Anselin, 2003) LISA maps were generated both for the cumulative dataset and for each individual year. In the LISA analysis, a map is generated that identifies areal units (in this case thousand-foot grid cells) with a high concentration of robberies that are first-order neighbors to other areal units with a high concentration. If the local spatial autocorrelation is significant ($p < .05$) then the cell is categorized as a High-High grid. Similarly, areal units are categorized by LISA as Low-Low (low concentration neighboring a low concentration), Low-High, and High-Low cells. As such, LISA provides for a very coarse hot spot measure by showing where the areal concentration of the crimes is highest, lowest, or non-significant.

The results of this analysis for all four years are mapped in Figure 4. The black blocks are where a grid cell with high robbery concentration is first order neighbor with other grid cells with a high concentration of robberies. The combination of High-High grid squares forms an East-West band in the area south of the rail lines and north of the river. Then, north of the rail lines are two more, smaller, clusters of high robbery concentration. There are also some isolated areas of concentration in the northern part of the city and to the southeast. All the High-High LISA values were significant at the $p < .05$ level indicating significant local spatial autocorrelation. The white areas indicate non-significant LISA values and there were no significant Low-Low areas in the city.

Next we examine the hot spots determined by the LISA analysis of robbery concentration indices for the 82 block groups in the city. The results of this analysis are mapped in Figure 5. The areas of greatest concentration are the block groups at the city center and mostly to the west. There is a block group to the southeast of the city center and the block group immediately to the north which indicate a concentration of robberies. At first this pattern seems slightly different from the map in Figure 4. However, on closer inspection it can be seen that there is one 1000-ft grid in each of these block groups that accounts for the concentration of robberies within the respective block group. This might be considered an example of the spatial ecological fallacy. There is a concentration of robberies in the block group sufficient to designate the whole area as a hot spot. However, these robberies actually concentrate in a relatively small area (0.04 square miles) of each of the relatively larger block groups (0.44 sq. mi. and 0.14 sq. mi. respectively). In other words the actual concentration of robberies occurs in an area one-tenth the size of the larger block group and one-quarter the size of the smaller block group. Yet both larger areal units are designated hot spots.

Unlike the 1000-ft grid analysis, the hot spot analysis of the block groups generates several neighborhoods with significant low concentrations of robberies. These neighborhoods are in the far southwest area and are predominantly middle-class and upper middle-class residential neighborhoods.

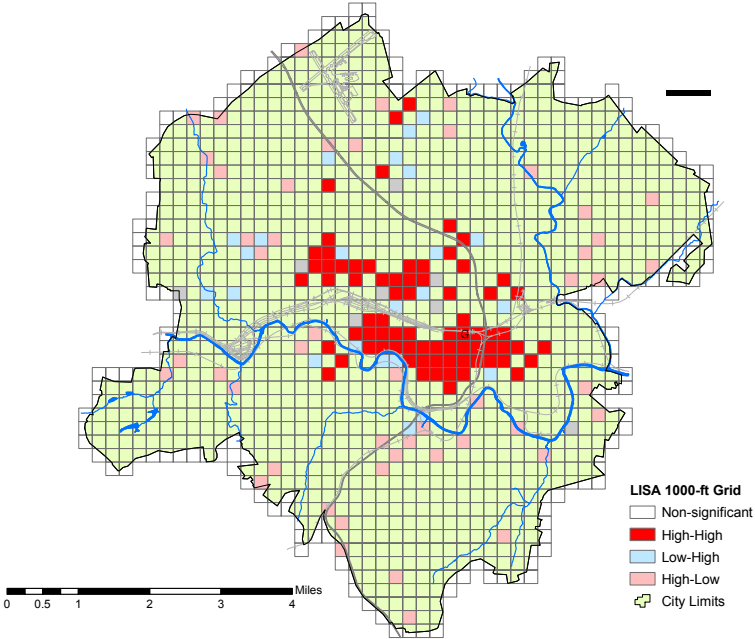


Figure 4. LISA map for 1000-ft grid hot spots

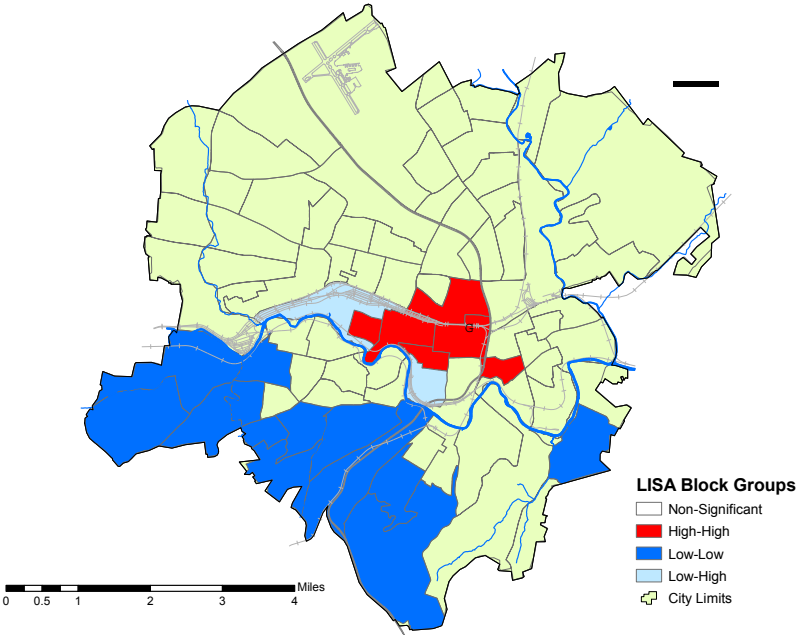


Figure 5. LISA map for block group hot spots

There is also one Low-Low block group in the far southeast area. Interestingly, the quadrat map shows a single High-High concentration in a larger area of low concentrations in the same general area. There is a government housing project at the location of the High-High grid, but it is surrounded by a working class residential neighborhood that makes up most of the block group. This again illustrates the spatial ecological fallacy and the danger of making broad assumptions based on too coarse a level of analysis.

The block groups exhibit much tighter spatial clustering of the hot spots, but in doing so miss the areas in the northwest and out near the airport that are identified by the quadrat analysis. Both approaches do a pretty good job of identifying the major hot spot band extending south and west from the city center. In order to determine the best method for lattice data we examine the hot spot efficiency with the PAI and the RRI (see Table 3).

Table 3. Hot Spot Method Comparison – Lattice Data

Method	Period	Hot Spot N (Robberies)	Area Percent	Hit Rate	Measured PAI	Predictive PAI	RPI
LISA Block Geoup	2004	193	4.03%	27.98%	6.94	-	-
	2005	228	4.47%	16.82%	3.76	6.32	0.912
	2006	222	6.18%	25.23%	4.08	2.92	0.777
	2007	261	7.18%	38.70%	5.39	4.22	1.034
	Overall	904	3.87%	22.79%	5.89	-	-
LISA 1000ft Grid	2004	193	2.51%	30.05%	11.97	-	-
	2005	228	2.67%	31.82%	11.87	8.69	0.726
	2006	222	2.34%	24.77%	10.59	8.27	0.697
	2007	261	3.68%	32.57%	8.85	5.73	0.541
	Overall	904	6.27%	36.17%	5.13	-	-

Examining first the measured PAI, this is an estimate of the accuracy of the existing data comparing the number of robberies in the hot spot (hit rate) to the size of the hot spot (area percent). In general, the greater the PAI ratio the better the hot spot is at capturing a concentration of robberies. For the measured PAI we have five estimates (one for each year and one for the overall) which are directly comparable to one another. It also allows for simple comparison between methods where it appears the Quadrat Grid Method out-performed the Block Group Method. An independent groups *t* test showed that the Block Group Method ($M=5.21$, $sd=1.31$) differed from the Quadrat grid Method ($M=9.68$, $sd=2.84$) in the predicted direction, $t(8)=-3.196$, $p=0.103$, $\eta^2=0.56$. Obviously, these results need to be considered with great caution due to the very limited degrees of freedom. Although the effect size is unusually high (56% of the difference attributed to the hot spot method), this is the least reliable estimate.

The predicted PAI is based upon predicting the subsequent year's robberies with the hot spot established from the base year. In this analysis the hot spots based on the 2004 robberies were used to predict the 2005 robberies and so forth. This resulted in three predicted PAIs for each method (no prediction based on the overall data was possible). Simple qualitative comparison suggests that the Quadrat Grid Method outperformed the Block Group Method in predicting future robberies. An independent groups *t* test showed that the Block Group Method ($M=4.49$, $sd=1.72$) differed from the Quadrat Grid Method ($M=7.56$, $sd=1.60$) in the direction predicted but not significantly so, $t(4)=-2.271$, $p=0.086$ (two tail), $p=0.043$ (one tail), $\eta^2=0.56$. The recapture rate index (RRI) is a slightly different story. Overall, the RRIs for the Block Group Method indicate that it recaptured more of the predicted robberies per unit of area than did the Quadrat Grid Method on a one-to-one comparison. However upon closer inspection we can see that the Block Group Method developed much larger hot spots in terms of the area percentage. In fact, the area occupied by the block group hot spots was

on the order of twice the area of the quadrat grid hot spots. Predicting future occurrence on the basis of large areas is a problem of accuracy over precision. This recalls the issue of the spatial ecological fallacy from above. If we designate the entire city a “hot spot” we would have 100% predictive accuracy but very little precision. The assessment of the efficiency of the hot spot method needs to be a balance between the predictive accuracy and the predictive reliability (precision).

Hot spot analyses based on areal units are not particularly precise though. Due to the necessary aggregation of crimes to the areal unit, there is a net loss of information about the actual location of robbery incidents. In order to address this issue, we next evaluated the robberies with several point-pattern based hot spot methods.

HOT SPOT ANALYSIS – POINT-PATTERN DATA

Three different point-pattern methods as implemented by *CrimeStat III* were compared. The first was the Spatial and Temporal Analysis of Crime (STAC) algorithm which produces hot spots in the form of ellipses and convex hulls. The second method was Nearest Neighbor Hierarchical clustering (NNH) which also produces output in the form of ellipses and convex hulls. Finally, we evaluated the interpolation method of Kernel Density Estimation (KDE) which produces a smoothed surface (similar to a raster) within a bounding rectangle placed over the study region. The intensity variable in each cell represents the smoothed absolute density estimation of robberies in that cell. The results of that evaluation appear in Table 4.

Table 4. Hot Spot Method Comparison – Point-Pattern Data

Method	Period	Hot Spot N (Robberies)	Area Percent	Hit Rate	Measured PAI	Predictive PAI
STAC	Ellipses	2004	37	1.53%	19.17%	12.53
		2005	70	2.97%	30.70%	10.34
		2006	60	1.78%	27.03%	15.18
		2007	68	3.68%	26.05%	7.08
		Overall	264	3.31%	29.20%	8.82
	Convex Hulls	2004	62	2.39%	32.12%	13.44
		2005	105	4.24%	46.05%	10.86
		2006	86	1.80%	38.74%	21.52
		2007	111	5.77%	42.53%	7.37
		Overall	408	5.55%	45.13%	8.13
NNH	Ellipses	2004	31	0.63%	16.06%	25.49
		2005	38	0.64%	16.67%	26.04
		2006	57	1.59%	25.68%	16.15
		2007	51	1.46%	19.54%	13.38
		Overall	248	2.64%	27.43%	10.39
	Convex Hulls	2004	48	0.57%	24.87%	43.63
		2005	53	0.63%	23.24%	36.90
		2006	86	1.28%	38.74%	30.26
		2007	79	1.10%	30.27%	27.52
		Overall	397	3.21%	43.92%	13.68
Kernel Density Estimation		2004	22	0.46%	11.40%	24.78
		2005	32	0.56%	14.56%	25.97
		2006	22	0.88%	9.91%	11.26
		2007	65	2.51%	24.90%	9.92
		Overall	52	0.27%	5.75%	21.30

The measured PAI was calculated for each year individually and for the whole four-year period. This produced a standardized score for each of the five different methods of hot spot generation and allows for the direct comparison of those methods. The measured PAI is an optimization of the ratio between the number of incidents in the hot spot to the area covered by the hot spot. A simple one-way analysis of variance was conducted on the measured PAI scores with the hot spot method as the factoring variable. The results indicate that there were significant differences between the hot spotting methods, $F(4,20)=5.397$, $p=0.004$, $\eta^2=0.519$. Post hoc comparisons were performed using least significant differences (LSD, a generous procedure) and the Scheffé test (a more conservative approach). Descriptive statistics for the methods are reported in Table 5.

Table 5. Descriptive Statistics for Hot Spot Methods – Measured PAI

Method		Mean	SD
STAC	Ellipses	10.79	3.17
	Convex Hulls	12.26	5.70
NNH	Ellipses	18.29	7.12
	Convex Hulls	30.40	11.24
	KDE	18.64	7.57
	Total	18.08	9.80

NNH Convex Hulls appears to be the superior technique based on the means of the measured PAI. On the post hoc comparisons with the LSD procedure the NNH Convex Hulls was significantly better than the other four methods (STAC Ellipses, $p=0.0005$; STAC CH, $p=0.001$; NNH Ellipses, $p=0.018$; and KDE, $p=0.021$). However, with the more conservative Scheffé procedure, NNH Convex Hulls were only significantly better than two of the other approaches (STAC Ellipses, $p=0.011$; STAC CH, $p=0.02$; NNH Ellipses, $p=0.20$; and KDE, $p=0.224$). It is also interesting to note that even though the NNH Convex Hull method is superior for each individual year's hot spot generation, KDE seems to perform much better when there are multiple years (time periods) on which to base the density estimation. The difference is in basing the KDE hot spot surface on 904 data points as opposed to less than a third of that number of incidents for any individual year.

Table 6. Descriptive Statistics for Hot Spot Methods – Predictive PAI

Method		Mean	SD
STAC	Ellipses	8.40	2.17
	Convex Hulls	6.23	0.189
NNH	Ellipses	11.25	5.58
	Convex Hulls	14.20	8.81
	KDE	10.69	3.47
	Total	10.15	5.07

Predictive PAIs were calculated for each year based on the prediction for the subsequent year. This resulted in three predictive PAIs for each method with a total of fifteen predictive PAIs. The means and standard deviations are reported in Table 6. However, there were no significant differences between the predictive PAIs ($F(4, 10)=1.086$, $p=0.414$). In a qualitative comparison of the means, the NNH Convex Hulls again seems to be the best performer for prospective hot spot analysis. However, with this small sample size this raw difference was not found to be significant.

In evaluating the consistency (reliability) of the prediction method, we computed RRI for each period for which a prediction could be made for each hot spotting method. There were no significant differences found in analyzing the means of the RRI for the different methods. It is interesting, however, that the STAC Ellipses method seems to do better than the others in this regard (mean

RRI=0.681). Also, the method with the least reliable performance was the NNH Convex Hulls (mean RRI=0.365). Based on these results we decided to do a more comprehensive analysis of hot spot methods and their predictive ability.

In order to accomplish this we evaluated each of the five methods (STAC Ellipses, STAC Convex Hulls, NNH Ellipses, NNH Convex Hulls, and KDE) using one-year, two-year and three-year prediction bases. We also varied the incident inclusion parameters for the STAC and NNH methods for the two-year base predictions, testing it at a minimum of 7, 10, and 15 incidents to make up a hot spot. The two-year period was selected because the number of robberies in the base was about halfway between the total four-year base ($N=904$) and the smaller numbers for individual years. We also used prospective time periods of a 1-year prediction and a two-year prediction and compared the RRIs between these two predictions. The results of this analysis are in Table 7.

For the 1-year prediction base the NNH methods performed the best (mean predictive PAI=12.73, $sd=6.79$) and STAC methods the least well (mean predictive PAI=7.32, $sd=1.82$), with the KDE approach in between (mean predictive PAI=10.69, $sd=3.47$). A simple one-way ANOVA was not significant ($F(2,12)=1.968$, $p=0.182$). However, when examining the predictive precision (RRI), a different pattern emerges with the STAC methods exhibiting the greatest reliability (mean 1-year RRI=0.56, $sd=0.205$) and the NNH methods the least (mean 1-year RRI=0.43, $sd=0.165$). This pattern repeats with the 2-year predictions with the NNH methods showing the best predictive accuracy (mean predictive PAI=10.54, $sd=3.44$) and the weakest predictive reliability (mean 2-year RRI=0.33, $sd=0.098$). Again, the STAC methods had the weakest predictive accuracy at two years, but the best predictive precision and the KDE methods were in between. The 2-year predictions were not tested for significant differences because of the small number of predictions ($n=10$).

The predicted hot spots based on two years of accumulated incidents showed an overall improvement in the predictive accuracy of the KDE method (mean 2-year predicted PAI=9.615, $sd=0.856$), especially in comparison to the STAC method (mean 2-year predicted PAI=6.273, $sd=1.035$). Although the difference between all three methods was tested for significance, the results must be considered with great caution ($F(2,23)=10.198$, $p=0.001$, $\eta^2=0.470$). No post-hoc analysis was performed, but it is likely that the important difference is between the KDE and NNH methods (mean 2-year predicted PAI=9.297, $sd=2.264$) compared to the STAC method. Qualitatively, both the KDE and NNH methods outperformed the STAC method.

When we consider the predictive reliability (1-year RRI, 2-year prediction base) the same story emerges as before. The STAC method (mean 1-year RRI=0.625, $sd=0.102$) is more reliable in its recapture rate for predictions compared to the KDE (mean 1-year RRI=0.521, $sd=0.201$) and NNH (mean 1-year RRI=0.474, $sd=0.139$) methods. This difference was significant, with the same caveats as above with an $F(2,23)=4.351$, $p=0.025$, and $\eta^2=0.274$. The 2-year predicted RRI was evaluated qualitatively and the STAC method (mean 2-year RRI=0.727, $sd=0.110$) clearly did better than either the KDE method (RRI=0.502) or the NNH method (mean 2-year RRI=0.510, $sd=0.077$). So, while the KDE and NNH methods have better predictive accuracy from a two-year base, the STAC method's predictions, while slightly less accurate, are more consistent.

The final hot spot comparison evaluated the predictive accuracy of the three methods from a three-year base used to predict one year prospectively. In this case the evaluation of the method is based entirely on a qualitative assessment of the derived predictive accuracy indices and the recapture rate indices. The overall best PAI was for the KDE method (10.79) and it also had an RRI (0.608) that is indicative of good consistency. The NNH method was the next best performer with respect to accuracy, but had the lowest RRI scores. The STAC method, once again, showed the weakest predictive accuracy but was consistent in the predictions it did make. It seems that the advantage of the KDE method is dependent on an adequate history from which to base its kernel estimations.

Table 7. Hot Spot Prediction Analysis

Method		Prediction Base	Incidents for Inclusion	Robberies in Base	Percent of Area	Base Hit Rate	Measured PAI	1-year AI	2-year PAI	1-year RRI	2-year RRI
Single Year Prediction Base											
STAC	Ellipse	2004	7	193	1.53%	19.17%	12.53	10.89	8.24	0.869	0.658
	Convex Hull				2.39%	32.12%	13.44	6.27	7.16	0.467	0.533
	Ellipse	2005	7	228	2.97%	30.70%	10.34	7.43	6.97	0.719	0.674
	Convex Hull				4.24%	46.05%	10.86	6.02	6.42	0.554	0.591
	Ellipse	2006	7	222	1.78%	27.03%	15.18	6.89	-	0.454	-
	Convex Hull				1.80%	38.74%	21.52	6.39	-	0.297	-
NNH	Ellipse	2004	7	193	0.63%	16.06%	25.49	17.40	11.44	0.683	0.449
	Convex Hull				0.57%	24.87%	43.63	23.85	15.02	0.547	0.344
	Ellipse	2005	7	228	0.64%	16.67%	26.04	9.85	7.78	0.378	0.299
	Convex Hull				0.63%	23.24%	36.90	12.16	7.91	0.330	0.214
	Ellipse	2006	7	222	1.59%	25.68%	16.15	6.51	-	0.403	-
	Convex Hull				1.28%	38.74%	30.26	6.59	-	0.218	-
KDE		2004	-	193	0.46%	11.40%	24.78	13.83	6.85	0.558	0.276
		2005	-	228	0.56%	14.56%	25.97	11.26	10.26	0.434	0.395
		2006	-	222	0.88%	9.91%	11.26	6.97	-	0.619	-
STAC	Ellipse	'04+'05	7	421	3.15%	31.59%	10.03	8.01	7.30	0.799	0.728
	Convex Hull				4.57%	47.27%	10.34	6.51	6.04	0.630	0.584
STAC	Ellipse	'04+'05	10	421	2.20%	22.33%	10.15	6.35	7.84	0.626	0.772
	Convex Hull				3.50%	36.58%	10.45	6.05	6.35	0.579	0.608
STAC	Ellipse	'04+'05	15	421	2.18%	22.09%	10.13	6.61	8.26	0.653	0.815
	Convex Hull				3.92%	28.74%	7.33	5.17	6.26	0.705	0.854
NNH	Ellipse	'04+'05	7	421	2.42%	30.88%	12.76	10.24	6.97	0.803	0.546
	Convex Hull				2.14%	47.51%	22.20	12.00	8.77	0.541	0.395
NNH	Ellipse	'04+'05	10	421	1.15%	19.00%	16.52	9.79	10.33	0.593	0.625
	Convex Hull				1.26%	30.40%	24.13	11.44	11.56	0.474	0.479
NNH	Ellipse	'04+'05	15	421	0.52%	11.64%	22.38	11.26	11.79	0.503	0.527
	Convex Hull				0.73%	19.71%	27.01	12.34	13.12	0.457	0.486
KDE		'04+'05	-	421	0.45%	10.69%	23.75	9.01	11.92	0.379	0.502
STAC	Ellipse	'05+'06	7	450	3.36%	32.44%	9.66	6.05	-	0.626	-
	Convex Hull				4.37%	48.89%	11.19	5.00	-	0.447	-
STAC	Ellipse	'05+'06	10	450	2.49%	27.33%	10.98	8.00	-	0.729	-
	Convex Hull				3.32%	42.89%	12.92	6.69	-	0.518	-
STAC	Ellipse	'05+'06	15	450	2.56%	22.67%	8.85	6.14	-	0.694	-
	Convex Hull				3.75%	35.56%	9.48	4.70	-	0.496	-
NNH	Ellipse	'05+'06	7	450	2.18%	31.56%	14.48	5.98	-	0.413	-
	Convex Hull				2.03%	48.22%	23.75	6.98	-	0.294	-
NNH	Ellipse	'05+'06	10	450	1.36%	21.56%	15.85	6.76	-	0.426	-
	Convex Hull				1.50%	33.78%	22.52	6.64	-	0.295	-
NNH	Ellipse	'05+'06	15	450	0.90%	16.22%	18.02	9.37	-	0.520	-
	Convex Hull				1.05%	25.11%	23.92	8.76	-	0.366	-
KDE		'05+'06	-	450	0.75%	11.56%	15.41	10.22	-	0.663	-
STAC	Ellipse	'04+'05+'06	15	643	2.75%	27.99%	10.18	7.11	-	0.698	-
	Convex Hull				5.19%	42.46%	8.18	5.24	-	0.641	-
NNH	Ellipse	'04+'05+'06	15	643	1.53%	21.77%	14.23	7.01	-	0.493	-
	Convex Hull				1.80%	34.37%	19.09	9.15	-	0.479	-
KDE		'04+'05+'06	-	643	0.71%	12.60%	17.74	10.79	-	0.608	-

DISCUSSION

This study evaluated the problem of street robberies in Roanoke, Virginia using a method of convergent hot spot analysis for all the robberies reported to the police from 2004 to 2007. There were a total of 904 robberies that occurred in this period. A second purpose of this study was to evaluate the different hot spot methods using a recently developed method for analyzing the predictive accuracy of hot spot methods (Chainey et al., 2008a; Levine, 2008). Through this convergent analysis it was hoped that the robbery problem in Roanoke could be localized and potential solutions identified.

Figure 6 shows a composite of all the hot spot methods based on the full four year period. The lattice data methods (quadrat 1000-ft grid and block group) are beneath the point-pattern hot spots. Two of the point-pattern hot spot methods (STAC ellipses and convex hulls and NNH ellipses and convex hulls) combine the convex hulls (black polygon) and hot spot ellipses (gray area). All the methods tend to converge on the same areas of the city indicating good overall agreement among the different methods. There are some smaller hot spot areas exhibited by different methods that do not conform to the larger convergence, but these are infrequent. In particular, the 1000-ft grid method generated a few isolated hot grids in the southeast, southwest, and northwest quadrants of the city. The NNH ellipse and convex hull method also generated a hot spot in the southeast that did not converge with any other hot spots.

This convergent hot spot analysis of robbery in Roanoke identified several problem areas. Some of these areas were crime generators, while others were crime attractors. As such, they necessarily require a different response by the police and the community. The effectiveness of hot spot policing is well documented in the literature. Braga (2005) completed a comprehensive review of randomized controlled trials of police actions focusing on identified hot spots and concluded that such action helped prevent crime and disorder in the targeted neighborhoods. For the crime attractor locations, an increase in both guardianship (formal and informal) and better place management by merchants and business people would assist focused policing efforts. For crime generating neighborhoods it will take a more strategic approach involving not only the police, but social service agencies, housing authorities, code enforcement offices, and localized community action groups to make a major impact on crime and disorder generally, and robbery in particular.

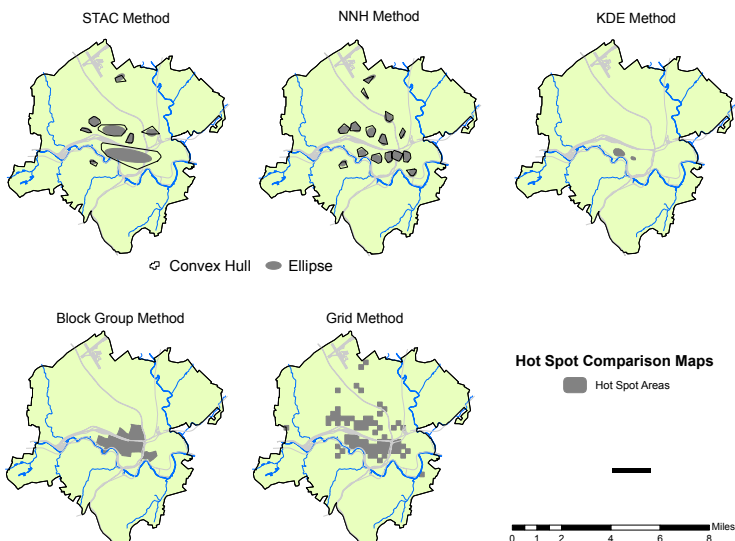


Figure 6. Comparison maps for hot spots methods

HOT SPOT METHODS ANALYSIS

An important purpose of this research was to evaluate several different hot spot methods to address a specific crime problem. Chainey et al., (2008a) made a very important contribution to the evaluation of hot spot methods with their development of the predictive accuracy index (PAI). In their research they came down unequivocally in favor of the kernel density estimation approach to hot spot analysis. Although this was true in their application of hot spot methods, several authors responded with criticisms about their strong conclusion in favor of the KDE method (Pezzuchi, 2008; Levine, 2008). However, despite their criticisms of some of the methodology used by Chainey and his colleagues, both Pezzuchi (2008) and Levine (2008) lauded the authors for their creative development of the PAI. In this study we've tried to address some of the criticisms of Chainey et al.'s original methods evaluation by including more contemporary nearest neighbor techniques, varying some of the hot spot parameters, and including Levine's recapture rate index (RRI). In his response to Chainey et al., Levine (2008) evaluated several different crime types as did Chainey et al. in the original study. We did not do that, instead choosing to concentrate our effort on an identified crime problem, robbery.

When asked our conclusions about the best hot spot method to employ, we can answer with a resounding, "It depends." The study of crime is complicated by the fact that it is the result of multiple causal vectors and it is a rare event (in the broad array of daily human activity). As a behavioral phenomenon it tends to resist reductionistic thinking and it is unlikely that a single method works best for all situations. That is certainly what we found in this analysis.

The lattice data approaches, for which we eschewed the simple count intensity approach in favor of using concentration indices and density measures, tended to have the lowest PAIs. But the RRIs indicated that the larger areal units had some predictive advantage in their precision. This suggests that if the purpose of the hot spot analysis is strategic in nature, this may be the preferred method. Since the method covers neighborhood areas, it can be used in community action planning without the risk of jeopardizing the confidentiality of individual victims or victim locations. The use of lattice data approaches tends to better identify persistent problem areas. As such it is probably better to build these hot spot maps on a longer time period (several years for example) to represent a historical problem area. By the same token, solutions built from these analyses need to be strategic in nature incorporating the neighborhood, community action groups, multiple government agencies, and novel policing efforts such as CCTV-patrol (Brown, 1995). While the police can serve a leadership role in this comprehensive strategy, it should not be left to the police to handle the problem alone.

With shorter time periods, it seemed that the NNH convex hulls consistently scored the highest PAIs. However, this may have been at the sacrifice of some precision as the RRIs tended to be lower for this method. With longer prediction bases (2-year and 3-year) the KDE method tended to produce the highest PAIs and the corresponding RRIs remained pretty good, indicating a balance of accuracy and precision. These two methods tended to trade places as to the best method, although both consistently outperformed the STAC methods. However, the STAC methods (which typically involved larger hot spots in area coverage) tended to produce the best RRIs. Perhaps the STAC method could be employed along with the thematic mapping methods for a more strategic plan of action, and the NNH and KDE methods used for tactical planning and immediate action.

It was noted that in predicting a nearer-term future from a limited time period (one year predicting the next year) the NNH methods tended to excel. However, as a longer time period was used for the prediction base, the KDE methods became stronger. This calls attention to the need to focus on the prediction base in making a decision about prospective hot spot methods. Similarly, extending the predicted period out to two years in the future, there was a general decline in both the PAIs and RRIs. Since the underlying crime phenomenon is both spatially and temporally lagged, the further into the future you try to predict there is a corresponding loss of accuracy and precision. We also, noted variations in the PAIs based on the alteration of some of the hot spot parameters, calling attention

yet again to the importance making an informed choice about parameter selection. In practice, most analysts tend to decide on their parameters through an empirical trial-and-error procedure. However, in the past, the final decision was often made on a T-LAR judgment call (that looks about right). With Chainey et al.'s (2008a) introduction of the PAI, Levine's RRI, the analyst now has a useful metric to make the choice about the best hot spot method.

CONCLUSIONS

We found the PAI and RRI to be very useful in the evaluation of a convergent hot spot analysis of robbery. It pointed to the fact that there is no one best method for all situations and that the method chosen must conform to the context of the problem being analyzed. However, unlike in the past when a new analyst had to rely on the advice and guidance of a more experienced analyst (if available), or commit to a lengthy trial-and-error adjustment, the PAI and RRI give a more scientifically based method for making the judgment call. Using this metric speeds up the process of hot spot analysis and gives the analyst a means by which to conduct on-going quality control of their hot spot methods. It is quick and easy to calculate, and should probably become a routine part of the analyst's tool box. It also lends itself to automation and may become a regular output parameter in the future.

There are several limitations to the present study that must be taken into consideration. First of all, like any study based on official crime statistics, this study was conducted on an analog of the true robbery situation in Roanoke. We have some evidence of this in the proportion of offenses coded "suspected criminal activity involved." These were cases where the victim was suspected of being involved in criminal activity at the time of the offense. It is assumed that someone who gets robbed in the course of some other criminal endeavor may be reticent to report the crime to the police. We have no way of knowing the actual incidence of un-reported robbery. This analysis, then, can only be generalized to robbery officially reported to the police. It must also be kept in mind that this study was restricted to one crime type, and both Chainey et al. (2008a) and Levine (2008) found variations in the efficiency of different methods based on crime types.

The parameters set for the different hot spot methods were originally developed through a combination of theoretical and empirical means. However, we know that even small variations in both the number of incidents included and the search bandwidth could produce very different hot spot surfaces and consequently different PAI and RRI estimates. Even for this dataset the conclusions about the best hot spot method could change based on this metric. We also used an arbitrary time period of one year on which to base our prospective analysis. We expanded that to two- and three-year prediction bases and noted changes in both the PAIs and RRIs calculated.

We are uncertain what the optimal prediction base should be and would encourage further research to begin to define this parameter. The necessary limitations of the available data restricted us to an abbreviated prediction base of only three years. In that light, we cannot be confident in the stability of the predictions and would encourage future research to use longer time periods to help define an optimal prediction base period.

Finally, the testing for differences in the PAIs and RRIs was conducted under the assumption that these phenomena are normally distributed. The results of those analyses should be considered with great caution due to the very small sample sizes used in the analysis.

Future research in the efficiency of hot spotting methods should explore the broader range of parameter setting by crime type and size of study region. In this study, we evaluated a fairly narrow range of options in the development of our hot spots. While this information triangulated nicely and provided some useful guidance, there is a much that can be learned from a multi-site, multi-method, evaluation of different crime types. In addition, a more comprehensive study can explore the efficiency of different computational algorithms (e.g. – for kernel density interpolation) and different edge correction factors.

The use of convergent hot spot methods is a solution to this type of analysis that can give the analyst much greater confidence in their product. The introduction of the PAI and RRI as an efficiency metric means that the working analyst no longer needs to read tea leaves to determine the best combination of methods and parameters for analyzing crime in their community. As each method confirms the findings of the other, the analyst can be more assured that they are looking at a real crime phenomenon based on the mapped data and not a statistical fluke. Through improved evaluation of hot spot methods the analyst is more confidently able to present their analytic product to command and operational staff. The PAI and RRI show great promise in the evaluation and comparison of different methods and we would encourage others to pursue this line of inquiry and evaluation.

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