The spatial dependency of crime increase dispersion

Jerry H. Ratcliffe, PhD

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Abstract
A number of analytical techniques (such as the Gini coefficient and the Lorenz curve) can identify unequal distributions in crime frequency among sub-areas within a study region; however, these tools are often aspatial and say nothing about the relationships between spatial units. Using dispersion analysis, a technique that measures the relative dispersion of a crime increase across a region, allows for the identification of particular spatial units that are sufficiently influential to drive up the overall jurisdictional crime rate. In this article, a combination of the order of areal units from a dispersion analysis with a measure of the local level of spatial association is used to develop a tool that can identify clustered areas of *emerging* crime problems. The identification of these second-order spatial processes may be beneficial to police departments and crime prevention practitioners who are interested in the identification of statistically significant clusters of emerging crime hotspots. The process is demonstrated with an example of robbery rates in police sectors of Philadelphia, PA.

Key words
Crime dispersion, spatial association, spatial dependency, robbery, Philadelphia.

Introduction

Identification of concentrations or clusters of greater criminal activity has emerged as a central mechanism precursive to targeting a criminal justice and crime prevention response to crime problems. These clusters of crime are commonly referred to as hotspots – geographic locations "of high crime concentration, relative to the distribution of crime across the whole region of interest" (Chainey and Ratcliffe, 2005, p. 147). Driven by fiscal constraints, increasing demands for managerial professionalism, and a perceived increase in the value of risk and threat management within public safety discourse (Ratcliffe, 2008), policing strategies have emerged that are increasingly place-specific and targeted to areal sub-units within basic police command units. There has been an emergence of an evaluation literature that finds support for *hotspot policing* (Sherman *et al*, 1989; Weisburd *et al*, 1993) as an effective response to high crime problems located within *places* - a rather vague term that is increasingly being used within the environmental criminology domain as indicative of a location or area that is at, or smaller than, the neighborhood level. For example; street-corner drug hotspots were targeted in Oakland, California, in a police operation that reduced crime at the target locations while simultaneously resulting in little significant displacement (Green, 1995); police random attendance at street-corner hotspots was found to have a disruptive effect on crime and disorder in Minneapolis (Sherman and Weisburd, 1995), with further clarification that the optimum crime prevention benefit is attained when police loiter at a hotspot for about 15 minutes at a time (Koper, 1995); and a study in Jersey City (NJ) found not only a reduction in disorder-related emergency calls for service in hotspots targeted for narcotics enforcement, but furthermore there appeared to be a diffusion of benefits to surrounding areas (Weisburd and Green, 1995).

Beyond the policing benefit, there is also a theoretical value in identifying small area crime hotspots. Along with the knowledge that a small number of offenders are responsible for a large proportion amount of crime (Farrington, 1992) and that a small number of victims are victimized a number of times (Ellingworth *et al*, 1995; Farrell and Pease, 1993; Polvi *et al*, 1991; Spelman, 1995), the irregular geographic dispersion of crime is one of the central precepts of the distribution of crime (Trickett *et al*, 1995). The dimensions of detected crime hotspots have changed with improved mechanisms and data quality, such that the *cone of resolution* (Brantingham *et al*, 1976) has moved from the regional to the local, and even to the block and street level. This improvement in vision has enabled environmental criminology theories, such as routine activity theory (Cohen and Felson, 1979; Felson, 1998), the rational choice perspective (Clarke and Felson, 1993; Cornish and Clarke, 1986; Cornish and Clarke, 1987) and crime pattern theory (Brantingham and Brantingham, 1993) to gain traction within the academic sphere. These theoretical constructs articulate a model for the interaction of offenders with criminal opportunities that are distributed in a non-random manner across time and place. Spatial crime research at the microlevel has rewarded researchers with insights into repeat victimization (Ellingworth *et al*, 1995; Farrell and Pease, 1993; Polvi *et al*, 1991; Ratcliffe and McCullagh, 2001; Townsley *et al*, 2000), and more recently, near-repeat victimization (Bowers and Johnson, 2004; Johnson and Bowers, 2004a, 2004b; Ratcliffe and Rengert, 2008; Townsley *et al*, 2003).

The identification of crime hotspots is therefore the starting point for more detailed analyses both theoretically and from a crime prevention perspective, yet delineation of crime hotspots is not yet the subject of a standardized methodology. For example, one research team identified addresses in Minneapolis (MN) where at least three 'more serious predatory offenses' had occurred within a one year period and could be further aggregated into 'hot spots of crime', usually less than one street block in length (Weisburd *et al*, 1993). Other research in the same location laid down a more operational definition of a hotspot for police patrol purposes, including rules regarding the maximum length of a hotspot, spillover to neighboring street blocks, and proximity to other nearby hotspots (Buerger *et al*, 1995).

The use of Geographic Information Systems (GIS) has opened up a plethora of approaches to hotspot identification, techniques such as thematic boundary maps that are organized around administrative boundaries (for example, identifying certain 'hot' census block groups or police beats), or approaches that are unrestrained by local geography and are independent of context beyond the individual crime events. The latter procedures include spatial ellipses (Craglia *et al*, 2000), grid thematic mapping, and continuous surface maps using techniques such as kernel density estimation (Chainey *et al*, 2008: this citation also serves as a useful quantitative evaluation of these techniques). These new approaches free the geographer from artificially constraining hotspot areas to comply with local areal boundaries, boundaries that often mean little to police, offenders or the community; however, they do come with problems of their own. For example, kernel density estimation requires a user to choose a grid cell size and a search bandwidth, spatial ellipses often require a user to determine a minimum points per hotspot as well as the number of clusters to be found *a priori*, and thematic grid mapping approaches again require a grid size selection. Issues of parameter selection plague the most commonly-used approach within the crime mapping community, kernel density estimation. Different parameter choices result in very different visual outputs, and as a result the statistical robustness of some maps has been questioned, especially "when little regard is given to the legend thresholds that are set that help the analyst decide when a cluster of crimes can be defined as a hotspot. This visual definition of a hotspot being very much left to the 'whims and fancies' of the map designer" (Chainey *et al*, 2003, p. 22). Furthermore, little guidance is available for the novice analyst on selection of parameters (Eck *et al*, 2005).

The problems associated with identifying crime hotspots are compounded when the temporal dimension is introduced. Most of the techniques described above are applicable for identifying crime hotspots in snapshots of data – one year of crime, or one month of robbery data, for example. The issues associated with each technique still exist, but now have the additional complication of estimating a suitable way to show a change over time. The problem is illustrated with a simple example. From 2006 to 2007, the US suffered a 7 percent increase in robberies (FBI, 2008). Within this, the state of North Dakota increased by 33 percent. Although this sounds dramatic, the number of robberies increased from 54 in 2006 to 72 in 2007, adding a largely insignificant 18 to the increase. Texas had a far less impressive 4 percent increase in robberies; however this increase added a more substantial 1,464 robberies to the US total in the process. Mapping temporal changes in crime patterns is therefore not simply an issue of rate change, but also of volume.

The merit of mapping changing crime patterns over time may be growing in relevance. Like many Western countries over the last decade and a half, the United States experienced an extended period of crime reduction from a zenith in the mid-1990s. After reaching a peak of 758 violent crimes per 100,000 inhabitants in 1991, the violent crime rate reached a recent low point of 463 per 100,000 in 2004. The pace of reduction appears to have been leveling recently, and in the last couple of years the violent crime rate has shown a disconcerting uptick. Many states and cities across the US have witnessed an increase in crime for the first time in many years and are struggling to cope with both the unwelcome media interest as well as concerns regarding the potential 'gathering storm' of violence; "For a growing number of cities across the United States, violent crime is accelerating at an alarming pace" (PERF, 2006, p. 1). While statewide or citywide increases in crime are always of concern, the geographic realities of crime distribution are such that increases in crime within a particular jurisdiction or administrative region are rarely uniform, and indeed modest jurisdictional increases in recorded crime are often the result of a deterioration in a few sub-areas rather than across large swathes of the territory. Nevertheless, the spatial dynamics of crime distribution are often lost amongst general concern regarding a perceived jurisdiction-wide increase.

Given geographic dispersions of crime are far from uniform, techniques to measure and describe the dispersion or concentration of crime increases may prove beneficial both in terms of articulating the realistic risk of crime to the public, as well as constructing a suitable response. To address this issue, Chilvers (1998, 2001) introduced a measure of crime dispersion that placed aggregate crime increases in greater context with an index of offense dispersion that indicates a global measure of the distribution of crime. Although used to indicate changes within the Australian state of New South Wales (Chilvers, 2002), the idea – and the offense dispersion index - never attracted widespread attention and is generally unused to this day.

This paper aims to revisit the offense dispersion index and demonstrate how this measure of crime dispersion can be used to identify patterns of crime increases. Furthermore, with the addition of spatial measures developed over the last few years by geographers interested in the uneven distribution of event patterns, it is possible to enhance the offense dispersion index with local indicators of spatial association that can delineate clusters of areas that may be more suitable targets of crime prevention and detection activity than traditional measures of high crime regions.

The Offense Dispersion Index

While economists and geographers will be familiar with indices such as the Lorenz curve (Lorenz, 1905) and the Gini coefficient (Glasser, 1962) as measures of inequality within the statistical dispersion of a variable, these measures are applicable to cross-sectional snapshots of crime distribution. Advances in the use of GIS and the allied techniques of Geographic Information Science (GISc) have largely negated the value of these global measures of unequal distribution in favor of localized measures of crime concentration and dispersion, such as exploratory spatial data analysis (ESDA) techniques and localized indicators of spatial association. These mapping approaches often have greater policy relevance and descriptive power. Gini coefficients in particular are vulnerable to Arbia's generalized criticism of indices of geographic concentration that "they do not take into account anything that is truly spatial. In fact any statistical measure of variation of concentration satisfies the condition of *anonymity* with respect to individuals … of being insensitive to any spatial permutation of individual orderings. However this is not a desirable property for a spatial inequality measure" (Arbia, 2001, pp. 272-3, emphasis in original). Non-spatial statisticians would recognize in *anonymity* the more common term *independence*. Irrespective of the many spatial permutations of crime rate within the larger study region, these global measures remain constant. In other words, identical Lorenz curves and Gini coefficients can be achieved with the same distribution of values among geographic units, independent of the actual spatial distribution of values.

In the same vein as the Gini coefficient, Chilvers' (1998, 2001, 2002) dispersion indicator is a relatively simple measure of the dispersion of crime increases that is suited to area-based crime rates disaggregated from a larger region that has seen an increase in crime. Given a study region (R) comprised of numerous internal areas (1…n), the change from one time period (t_0) to a subsequent time period (t_1) is calculated for each area of interest[i]. Once the change is calculated for each area, the areas are ordered from highest to lowest based on this crime change. The highest ranked area is removed from the list and the remaining areas are used to recalculate the crime rate for region R with n-1 areas. Then the next highest ranked area is removed and the region rate for n-2 areas is calculated. The process continually removes the remaining highest ranked area from the ordered list, until only one area remains.

This can be demonstrated in table form using the change in robbery incidents from 2005 to 2006 across police sectors in the City of Philadelphia, PA. Philadelphia is located in the Northeastern corridor of the United States, between New York City and Washington DC. The capital of the United States from 1790 to 1800 it has an area of approximately 150 square miles with a population of about 1.4 million, making it the sixth most populous city in the US. In 2005 (t_0), there were 11,069 robbery incidents reported to the Philadelphia Police Department, while in 2006 (t_1) there were 11,999 reported incidents, an increase of 930 (8.4 percent). This increase was unevenly distributed across 419 police sectors; only 223 (53%) showed increases in robberies. Table 1 shows the impact of removing the top ten police sectors from the citywide calculation of the robbery rate, as explained by the method in the previous paragraph. The citywide measure shows a robbery increase of 8.4 percent, however the largest increase was found in police sector 15K. When this is removed from the citywide calculation, the citywide measure would have been 7.88 percent. When sector 2S is removed, the citywide robbery increase reduces again (to 7.47%), as would be expected.

Beyond a tabular representation, a graph can be constructed indicating the change in crime from t_0 to t_1 as each ordered area is removed from the regional calculation. The solid line in Figure 1 indicates the robbery dispersion level for the city as each sector is removed from the citywide calculation based on the contribution the sector made to the increase. The line shows that on the removal of the 45th of 419 sectors, the city robbery rate would show a reduction in robberies for the city.

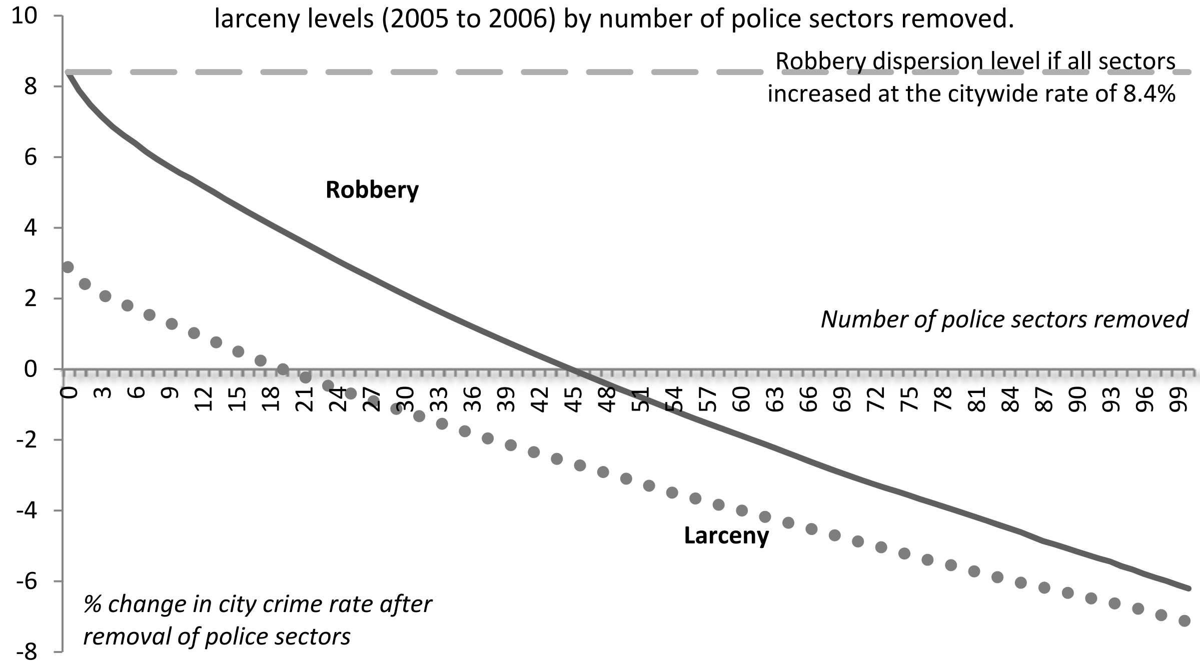
Table 1. Impact of removal of the first ten police sectors on citywide robbery percentage, 2006 to 2007.

Number of sectors removed	Police sector	Citywide change after removal of sector (%)	Citywide robberies 2005 (t_0)	Citywide robberies 2006 (t_1)
Citywide	8.402	11069	11999	
1	15K	7.883	10985	11851
2	2S	7.477	10953	11772
3	25L	7.147	10844	11619
4	2K	6.855	10809	11550
5	15H	6.612	10708	11416
6	15G	6.392	10576	11252
7	25N	6.146	10543	11191
8	15P	5.932	10519	11143
9	24H	5.737	10476	11077
10	15M	5.548	10437	11016

The significance of this in terms of crime clustering can be demonstrated by comparison to the top dashed line in Figure 1, a line that shows the projected robbery dispersion had each police sector individually increased from 2005 to 2006 by the citywide rate of 8.402 percent. In effect, this top (dashed) line indicates a null hypothesis level showing the dispersion graph if all areas had behaved in a uniform manner. By comparing the dashed line with the solid line for the actual dispersion of robbery, the significance of just a few sectors in driving up the city rate becomes apparent.

Beyond these graphical and tabular indications of dispersion, Chilvers (1998) suggested an Offence Dispersion Index (ODI) as a global indication of the dispersion factor. The ODI is the proportion of areas that must be removed from the region-wide calculation before an increase in crime is transformed to a decrease, or at least a no-change steady state. For example, in Philadelphia it was necessary to remove 45 police sectors before the city posted a crime reduction. Given these 45 sectors were removed from a total of 419, the increase in robberies in Philadelphia from 2005 to 2006 has an ODI of 0.11. As a comparison, recorded larceny incidents for the city over the same period have an ODI of just 0.0048. ODI values close to zero suggest a low

Figure 1. Dispersion of percentage change in Philadelphia (PA) robbery and larceny levels (2005 to 2006) by number of police sectors removed.



crime increase dispersion factor, while ODI values closer to a value of one suggest that crime increases are associated with a problem across many areas. This can be seen in the dispersion levels in Figure 1. The robbery dispersion level has a steeper slope than larcenies (shown for comparison purposes as grey dots). Given that larcenies only increased citywide by 2.89 percent, the number of sectors that contributed to the overall city increase is much lower as we would expect (the city rate becomes negative on the removal of the 20th police sector). What is informative, however, is the slope angle of the two offense types. The shallower angle of the larceny line suggests that larceny increases have less clustering than robberies increases.

A further simple measure that can be added to Chilvers' index is a Non-Contributory Dispersion Index (NCDI), a ratio using areas in the region that did not contribute to the crime increase but themselves still showed crime increases[ii]. With our robbery example, a total of 223 sectors showed robbery increases of which we know that the top 45 contributed to the citywide increase in robbery. The NCDI value for robberies of 0.42 is based on the 178 sectors that posted increases, as a ratio of the total number of sectors (419).

The NCDI helps to indicate the dispersion of areas that are also areas of concern for policy-makers and is an indication of the angle of the dispersion line (such as in Figure 1) once the line descends below the reduction threshold. These areas do not contribute to the increase in crime across the region (as the top 45 in our example do); the increases in the non-contributory areas are offset by decreases in other areas of the region. However, it is worth including a measure of these areas from a crime control policy perspective because it is useful for strategic planning operations to understand the spread of areas posting a crime increase. A large NCDI value closer to unity will indicate a spreading problem that may be an emerging issue for much of a region whereas a low NCDI, especially in conjunction with a low ODI value, may suggest that measures targeted to a few problem areas may be a more effective use of resources.

Taken at face value, the ODI (alongside the NCDI introduced here) is vulnerable to the same criticism of aspatiality leveled towards indices of geographical concentration of failing to incorporate a sense of spatial sensitivity (Arbia, 2001). However, the output from the process does provide an ordered list of regions based on their contribution to the collective increase in a variable (with crime as the variable of interest in this paper), and this ordered list can be combined with spatial tools to better appreciate any localized variation in spatial patterns, as will be demonstrated in the next section.

Incorporating spatial association measures

The issue with aspatial measures of inequality in variables (such as the Gini coefficient and Lorenz curve), that the output is only indicative of broad trends and is not informative regarding spatial clusters of areas of concern, is equally applicable to the dispersion measure. Thus the dispersion index, as introduced by Chilvers, is simply an additional measure that provides a global indication of the uneven distribution of crime increases, a measure that could be obtained by a number of different indices. The aspatial nature of the index might have some slight academic interest and might be used as a comparison across different crime types or locations (as done in this paper with larcenies and robberies, for example) but the measure as it stands lack practical policy value. Greater crime reduction relevance could be obtained by combining the output from the dispersion analysis with some indication of spatiality of the areas that contribute to the overall crime increase.

For example, from an operational perspective of police commanders seeking to allocate resources to combat crime problems, it is not necessarily easy to simply increase resources to a particular sector. If the 45 police sectors that contributed to the 8.4 percent increase in robberies across Philadelphia were contiguous, the policing and crime prevention implications would be significantly different than if the 45 sectors were spread across the city. City-wide response units are common and are sent to a particular region of a city perceived to have an emerging problem. These types of units are therefore sent to a neighborhood consisting of numerous sectors and often more than one district. Addressing a single conterminous crime problem would allow police to concentrate resources, deploy saturation patrols, and better employ criminal intelligence to examine the underlying neighborhood conditions that correlated with the increase in crime. It is also possible that more concerted effort may result in a diffusion of benefits, whereby the positive outcome in a targeted area is transmitted to neighboring sites (Clarke and Weisburd, 1994; Green, 1995; Ratcliffe, 2002; Weisburd and Green, 1995; Weisburd *et al*, 2006). These tactics would be harder to employ if the 45 sectors were spread across the city. Therefore the implication of the spatial arrangement of the 45 sectors is a matter of significant policy relevance.

Therefore, from a research perspective, variation in event patterns is often the starting point for analysis rather than a descriptive endpoint in itself (Boots and Okabe, 2007). The various *global* measures of complete spatial randomness (examples include the nearest neighbor index and Moran's I coefficient of spatial autocorrelation) retain certain well-known limitations, including; the assumption of spatial stationarity in the underlying processes that drive the evident pattern; the potential to be influenced by edge effects; and vulnerability to the modifiable areal unit problem (MAUP) (Openshaw, 1984; Unwin, 1996). The response from the quantitative geographic community has been the development of *exploratory spatial data analysis* (ESDA) and *local* statistics that are able to explain more about an individual datum point or area in relation to the spatial dependency of the location with neighboring places (Chainey and Ratcliffe, 2005). These local statistics have become more useful as the availability of spatially-referenced data has allowed for more analysis on a finer spatial resolution resulting in the capacity to explore large data sets in which numerous regimes of spatial association may be operating (Anselin, 1996). For example, the Geographically Weighted Regression technique (Fotheringham *et al*, 2002) is able to model and quantify significant non-static variation across independent variables within study areas. A further tool that can enhance the policy relevance of the output from a dispersion analysis is the use of Local Indicators of Spatial Association (LISA) (Anselin, 1995; Getis and Ord, 1992; Ord and Getis, 1995). Probably the most well-known of these statistics are the family of G_i and G_i^* statistics (Getis and Ord, 1992, 1996; Ord and Getis, 2001; Zhang and Murayama, 2000) and the *local Moran's I* (Anselin, 1995), the latter being used extensively in the explanation of the spatial characteristics of homicide (Mencken and Barnett, 1999; Messner and Anselin, 2004; Messner *et al*, 1999). The application of the local Moran's I can be demonstrated by returning to the example of the 2005-to-2006 increase in robberies across Philadelphia police sectors.

The robbery distribution for 2006 is shown in Figure 2. From a visual inspection there are apparent clusters, with the highest robbery levels recorded in the north and inner northeast, and in the southwest of the city. The evidence of clustering is supported by the calculation of a Moran's I coefficient (0.54), an indication of spatial autocorrelation.

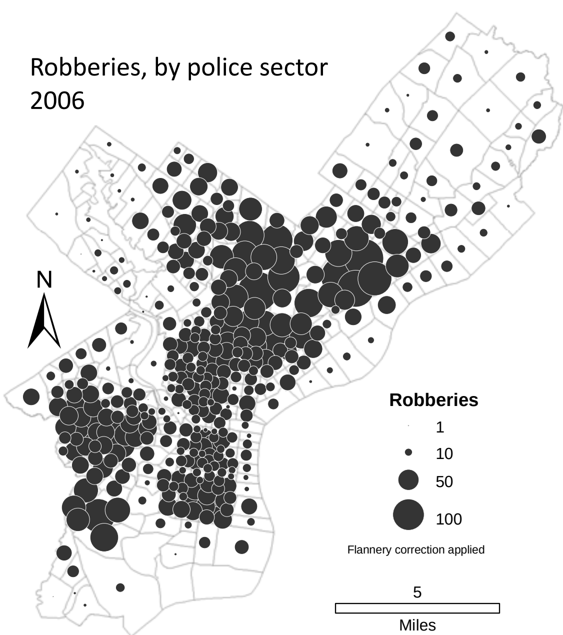


Figure 2. 2006 robbery totals by police sector, Philadelphia, PA.

Spatial autocorrelation can be defined in the following manner. Consider χ_i to be the count of robberies in each of *n* police sectors as separate observations of *X* such that each χ_i is drawn from the same population (Philadelphia robberies). If every pair of χ_i is uncorrelated then the robbery data lack spatial autocorrelation; however, if the data are not pairwise uncorrelated then the data indicate spatial autocorrelation (Cliff and Ord, 1969). The Moran's I test computes an index (range 0-1) of the clustering of like values by indicating a product-moment correlation coefficient suggesting pairwise correlation among neighboring values. A key parameter in such a calculation is the determination of *neighbor*. Various options exist, and this paper takes a standard approach of determining neighborliness based on a spatial weights matrix whereby two areal units are determined to be neighbors if their boundaries touch at any point. In the language of spatial analysis, these areas are determined to be neighbors based on a first order, queen contiguity matrix; the use of the term *queen* stemming from the ability of that chess piece to move towards squares that only touch at one point, rather than a *rook* contiguity matrix approach where areal units must share a length of common boundary (Chainey and Ratcliffe, 2005).

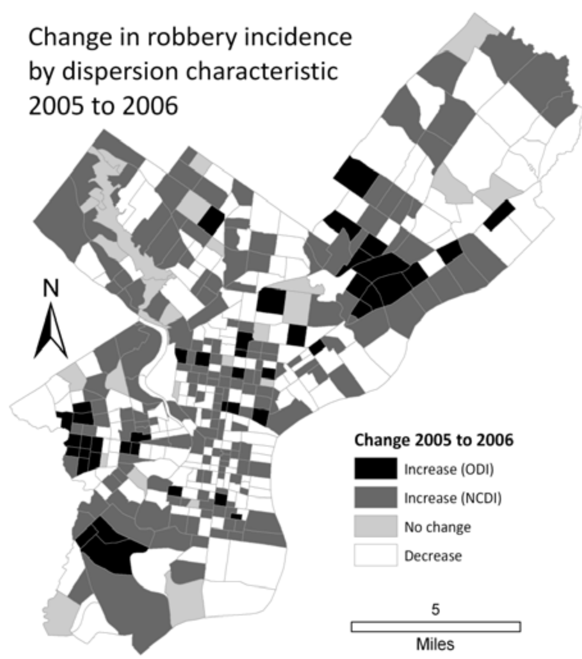


Figure 3. ODI, ONCI, no change, and crime decrease police sectors for Philadelphia robberies, 2005 to 2006.

Based on the single order, queen contiguity weights matrix and a two-tailed significance test, the Moran's I value for 2006 Philadelphia robberies is 0.54, demonstrating significant clustering of similar values (significant to $p<=0.001$). The global Moran's I value lends strong statistical support to the visual impression that high robbery count sectors are often located close to other sectors with high values, and vice versa. ODI sectors and NCDI sectors are shown in Figure 3 along with areas that did not have a change in the number of robberies from 2005 to 2006, and with areas where crime decreased over that period. With an ODI value of 0.11 (NCDI = 0.425) it can be seen by comparing Figure 2 and Figure 3 that the 45 sectors that have to be removed before the robbery rate would have shown a decrease - labeled 'Increase (ODI)' - are in some of the high crime areas; however, they are not necessarily closely correlated with the highest crime areas (by volume). If the ranking of the police sector by increase in crime exactly matched the crime volume in the sector we would expect a correlation of -1 (a perfect negative correlation); however, the ranking of the sector removed with the crime frequency for 2006 has a correlation of -0.327. High crime areas are *not necessarily high increase areas* with emerging problems.

Localized spatial association

Spatial autocorrelation, namely a relationship between the values of a variable at one location and the values at neighboring sites, has often been perceived as a problem that confounds traditional statistical tests (Cliff and Ord, 1969). The lack of independence between variables measured in contiguous areal units inhibits the standard assumptions of many parametric tests (Chainey and Ratcliffe, 2005). Attempts have been made since the 1950s (for examples of classic works in this area, see Cliff and Ord, 1969; Moran, 1950) to develop statistics to measure the degree of second-order spatial autocorrelation in spatially referenced datasets where variables are measured within discreet but adjoining areal units, and second-order spatial tests now exist for point patterns (Getis and Franklin, 1987). A significant development in the field arrived with the evolution of sufficient computing power to employ computationally intensive sampling tests that allowed researchers to develop null hypotheses based on Monte Carlo simulations and avoid the assumption of a normally-distributed population (Besag and Diggle, 1977; Fisher and Langford, 1995; Fotheringham and Brunsdon, 2004; Hope, 1968).

While a problem for traditional aspatial analyses, spatial autocorrelation can be used to extract additional value from spatially-referenced data sets, enhancing our understanding of the underlying spatial patterns. While the Gini coefficient, Lorenz curve, location quotient (discussed later in this article), and dispersion index are, on the surface, aspatial and in some cases vulnerable to first-order spatial effects (region-wide trend), the addition of a localized measure of spatial association can introduce an outcome that is statistically valid, but also spatially relevant. This has the capacity to add significant value for both theoretical development and certainly for policy formation within the criminal justice system. Within the Philadelphia example, local indicators of spatial association can be used to identify statistically significant clusters of police sectors based not on the volume of crime in a sector, but rather on the order of sectors based on the change in crime from one year to a subsequent year. Though the ranking and the crime level have a negative correlation, the local patterns of association are better described as *hotspots of emerging crime problems* rather than hotspots of crime.

Local Moran's I is a statistic that can be used to measure the extent of similarity or dissimilarity in a crime variable across neighboring spatial units (Mencken and Barnett, 1999; Messner and Anselin, 2004). Given the widespread realization of spatial instabilities across different areas of a study region, the local variant of the global Moran's I is a useful indicator of the spatial instabilities of a variable within regions (Cohen and Tita, 1999). Frequency change in robberies across Philadelphia police sectors from 2005 to 2006 shows significant clustering (Moran's I =

0.2152, $p<0.05$), but while the global Moran I statistic can test for an overall tendency towards spatial autocorrelation in the attribute values across a study region, it is the ability of the local test to identify sub-regions of over-concentration of high or low values that appeals as an enhancement to the dispersion measure. In Figure 3, police sectors are classified according to their ODI, NCDI or other measure, but the output from a dispersion analysis also retains the order of the sector ranked by its contribution to the increase in crime across the city. It is therefore possible to detect statistically significant sub-regions where problem sectors that increased in crime substantially from one year to the next are clustered, either by rank or by the change in robbery frequency.

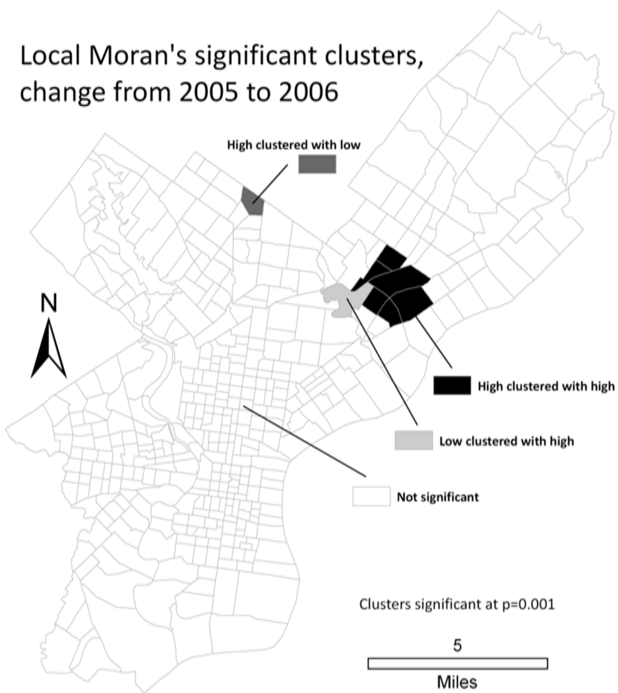


Figure 4. Significant spatial clusters in robbery frequency change from 2005 to 2006 by police sector, at p=0.001 with 999 simulations.

Given that the variable under examination is the change from t_0 to t_1, the local Moran's I test would look to identify areas where a high value is surrounded by other high values. This is done in Figure 4 with a map showing the significant robbery increase local Moran's I sectors based on their similarity to surrounding sectors, calculated using a significance level of $p<=0.001$ and first order queen contiguity to determine localized spatial neighborliness. Figure 4 provides decision-makers with knowledge unavailable through the Gini, Lorenz, location quotient, or even the ODI value from a dispersion analysis. It demonstrates significant clusters of locations that contributed significantly to the increase in robberies. In this way, the output from the dispersion analysis is given spatial meaning allowing an ODI value of 0.11 to develop into real policy significance in terms of policing and crime prevention. While Figure 2 would rightly lead one to conclude that many areas of the city are plagued by robbery, Figure 4 suggests that one particular area has shown a significant change from 2005 and represents a part of the city with a significant *emerging* problem in 2006.

The limitation of location quotients

A reviewer of a previous iteration of this paper commented that the location quotient (LQ) would serve a similar function and would be easier to compute. This comment is worth examining for two reasons. First, it serves to address the accuracy of this claim, and second, it demonstrates the broader limitation of analytical methods that are aspatial (in Arbia's (2001) terminology).

The LQ has a relatively long history as a tool to indicate economic inequality in regional data and has long been used by regional scientists (Brantingham and Brantingham, 1995). LQs are calculated as ratio of the local measure of a variable relative to a reference measure, usually the region-wide rate of the variable in question. For example, the LQ for each Philadelphia police sector for 2006 robberies would be the number of robberies in the sector as a ratio of the expected number of robberies in the sector if all robberies were distributed equally among the 419 sectors. LQs have recently been used in the first stages of a multi-stage analysis of the criminogenic environment around street-corner drug markets (McCord and Ratcliffe, 2007), but are more widely applied to economic variables such as industrial clusters (Feser *et al*, 2005) and the transportation equipment industry (Carroll *et al*, 2008).

Like the dispersion index, the LQ is not inherently spatial because it does not reflect relationships between spatial neighbors (Carroll *et al*, 2008). Furthermore, while having value as an exploratory tool (for an example, see McCord and Ratcliffe, 2007), the LQ is also susceptible to first-order spatial effects, whereby the effects "relate to variation in the mean value of the process in space, a global or large-scale trend" (Feser *et al*, 2005, p. 402). Because the LQ reports a localized rate relative to a global rate, rather than a localized count contribution (as the dispersion value demonstrated in this paper), the LQ is vulnerable to the influence of police sectors with initially small robbery counts that post increases at t_1, increases that are relatively substantial as a rate denominated on the value a t_0, but are however still small in terms of actual frequency. Returning to an example used in the introduction to this paper, this would mean that in the analysis of US robberies from 2006 to 2007, North Dakota, with a 33 percent increase in crimes would have a larger LQ than Texas, even though the latter added 1,446 more robberies to the US total.

Furthermore, both dispersion and LQ analyses are likely to demonstrate some measure of second-order spatial processes. These second-order processes relate to the internal variance between neighbors (Getis and Franklin, 1987). It is possible that measuring the internal variance of dispersion (or LQ) values could be additionally beneficial to understanding the crime distribution; however, caution is necessary - the variable in question differs. The outcome from an LQ is a measure of the ratio change in the police sector relative to the overall city change, whereas the dispersion measure (as used in this paper) is an indication of the absolute contribution of a police sector to the overall city change. These measures are not the same.

This can be demonstrated with the Philadelphia robbery change from 2005 to 2006 example. Calculation of the LQ for each police sector, after controlling for negative values, results in LQs that range from zero to 2.42. Irrespective that the selection of a suitable cutoff for a high crime area using LQs is largely arbitrary, employing the methodology used by Carroll *et al* (2008) where the cutoff is an LQ of greater than one results in the selection of 191 police sectors. The dispersion analysis showed that many of these sectors did not contribute significantly to the increase in robbery across the city, and the notion that the output from a dispersion analysis is effectively the same as the LQ is not supported.

Discussion

This article has revisited the dispersion analysis and index from Chilvers (1998, 2001, 2002) and argued that, while the ODI does inform practitioners about the relative distribution of crime increases, the addition of spatial analysis techniques that are able to examine second-order spatial associations adds value to the identification of crime-increase clusters across jurisdictions. On its own, the dispersion index is a minor addition to techniques that can measure the unequal spread of crime across multiple areal units – a point that is largely accepted as a truism in the academic world; however, the addition of a spatial association component does bring out supplemental features of the dispersion analysis that are not available through other means. That being said, the combination of dispersion and local Moran's I still represents a starting point for analysis rather than an end in itself. The approach used in this paper does not provide a groundbreaking new methodology but does provide analysts of crime with a different way to examine crime event distribution over time and, for some, a new way to conceptualize changing temporal patterns. Effective crime reduction through strategies such as problem-oriented policing requires greater analysis than the identification of emerging crime hotspots alone (Braga and Weisburd, 2006; Goldstein, 1979, 2003; Scott, 2000; Tilley, 2003). This paper therefore discusses an adjunct to crime analysis, a technique that can enhance spatio-temporal studies of crime, but only in anticipation of more detailed interrogation of the emerging crime hotspots identified.

Beyond more in-depth academic and policy relevant strategic thinking, there may be value in the identification of emerging hotspots from a front-line policing perspective. While there has been a capacity to identify high crime areas for many years, the dispersion analysis approach provides a more robust method to quantify emerging areas of criminality and a modicum of predictive capability for new areas of concern. Through combination of the dispersion analysis output with new techniques from GISc, it is now possible to identify sub-regions where emerging crime problems are clustered. Police tactics grounded in Compstat (Firman, 2003; Mazerolle *et al*, 2007; Walsh, 2001; Weisburd *et al*, 2003; Weisburd *et al*, 2006) and Broken Windows (Kelling, 1999; Sousa and Kelling, 2006; Wilson and Kelling, 1982) may lack sophistication, but they do emphasize the importance of attention to *emerging* crime problems while at the same time being cognizant of long-term crime issues. The ability to better identify emerging crime threats from one time period to another may be of benefit to practitioners of these approaches to policing.

There may also be value in examining ODI and NDCI values together. Small ODI values indicate a low crime increase dispersion factor, while values greater than 0.2 suggest that the crime increase in the overall region was dispersed across a large area (in other words, 20 percent of the sub-regions actively contributed to the crime increase). With higher ODI values, the crime increase is widespread and indicative of a systemic problem in the region. However, even with smaller ODI values (suggestive of pockets of problems rather than a region-wide issue), if these are accompanied by relatively large NCDI scores, this suggests a generalized crime increase that is not contained within problem pockets. So even when the numbers of areas that formally contributed to a crime increase are low (perhaps with ODI values of less than 0.1), accompanying NCDI values that are relatively high should caution analysts that modest crime increases are not localized. Of course, interpretation of ODI and NCDI values should be approached cautiously, given that these numbers are relative to the crime problem at hand, the level of increase, and the number of internal spatial units within the city or study region. Future research may be able to expand our knowledge of appropriate interpretive levels for ODI and NCDI.

The combined approach advocated in this article is applicable across numerous scales, both spatial and temporal. While rates were used in Chilvers' original work, frequency counts can be employed as demonstrated here. Use of frequency counts negates the need to consider percentage changes in small-area studies where some police sectors may have a zero count in the first temporal period. This approach is also grounded in the realities of crime control. The removal of an area from a dispersion analysis does not mean that the area would have to stop all crime. Policy makers would no doubt be unwilling to entertain crime prevention ideas and decisions for resource priorities based on the suggestion that all crime in some areas be prevented. Removal (in an analytical sense) is simply a way of exploring a scenario whereby the crime in the area is reprojected to have remained constant from t_0 to t_1. This is a more realistic proposition to many police officers and politicians.

The approach demonstrated here remains as vulnerable to the modifiable areal unit problem (MAUP) (Bailey and Gatrell, 1995; Openshaw, 1984; Unwin, 1996) as many other studies. In other words, the outcome has the potential to change if different zonal boundaries are the subject of analysis, or alternatively if different scales of aggregation are employed. Within the constraints of working with established administrative boundaries, this problem is not resolved; however, the use of LISA tools such as the local Moran's I can help to identify sub-regions of greater spatial homogeneity in variables. The statistically significant local Moran's I cluster in Figure 4 (high clustered with high) suggests an area where the underlying conditions that favor a robbery increase extend beyond the constraints of an individual police sector and are a feature of a larger area, possibly based on conditions of socio-economics or urban structure. Even without addressing the deeper problems of the MAUP, this analysis provides a tool that will help researchers who are constrained to work within the framework of administrative regions dictated by needs that are not necessarily rooted in criminal behavior. From a research perspective, this technique helps identify regions for further study.

Like many interesting ideas that find their way into published work and then disappear without a trace, the dispersion analysis has languished in obscurity for a number of years. Perhaps a reappearance on its own does not deserve merit; however, the introduction here of a method to extend the value of the ODI by examining second-order spatial characteristics of the order of areas derived from the global methodology may help to both re-evaluate dispersion analysis and use the combination of dispersion with a local measure of spatial autocorrelation to provide decision-makers in the criminal justice system with a statistically-robust tool to identify emerging crime and disorder problems.

References

Anselin, L. (1995) Local Indicators of Spatial Association - LISA. *Geographical Analysis, 27*(2): 93-115.

Anselin, L. (1996) The Moran scatterplot as an ESDA tool to assess local instability in spatial association. In: M. Fischer, H. J. Scholten and D. Unwin (eds.) *Spatial Analytical Perspectives on GIS.* London: Taylor and Francis, pp. 111-125.

Arbia, G. (2001) The role of spatial effects in the empirical analysis of regional concentration. *Geographical Systems, 3*(3): 271-281.

Bailey, T. C., and Gatrell, A. C. (1995) *Interactive Spatial Data Analysis* (Second ed.). London: Longman.

Besag, J., and Diggle, P. J. (1977) Simple Monte Carlo tests for spatial pattern. *Applied Statistics, 26*(3): 327-333.

Boots, B., and Okabe, A. (2007) Local statistical spatial analysis: Inventory and prospect. *International Journal of Geographical Information Science, 21*(4): 355-375.

Bowers, K. J., and Johnson, S. D. (2004) Who commits near repeats? A test of the boost explanation. *Western Criminology Review, 5*(3): 12-24.

Braga, A. A., and Weisburd, D. (2006) Problem-oriented policing: the disconnect between principles and practice. In: D. Weisburd and A. A. Braga (eds.), *Police Innovation: Contrasting Perspectives*. New York: Cambridge University Press, pp. 133-152.

Brantingham, P., and Brantingham, P. (1995) Location quotients and crime hotspots in the city. In: C. Block, M. Dabdoub and S. Fregly (eds.), *Crime analysis through computer mapping.* Washington DC: Police Executive Research Forum, pp. 129-149.

Brantingham, P. J., Dyreson, D. A., and Brantingham, P. L. (1976) Crime seen through a cone of resolution. *American Behavioral Scientist, 20*(2): 261-273.

Brantingham, P. L., and Brantingham, P. J. (1993) Environment, routine, and situation: Toward a pattern theory of crime. In: R. V. Clarke and M. Felson (eds.), *Routine Activity and Rational Choice* (Vol. 5). New Brunswick: Transaction publishers, pp. 259-294.

Buerger, M. E., Cohn, E. G., and Petrosino, A. J. (1995) Defining the "hot spots of crime": Operationalizing theoretical concepts for field research. In: J. E. Eck and D. Weisburd (eds.), *Crime and Place* (Volume 4). Monsey, NY: Criminal Justice Press, pp. 237-257.

Carroll, M. C., Reid, N., and Smith, B. W. (2008) Location quotients versus spatial autocorrelation in identifying potential cluster regions. *Annals of Regional Science, 42*(2): 449-463.

Chainey, S., and Ratcliffe, J. H. (2005) *GIS and Crime Mapping*. London: John Wiley and Sons.

Chainey, S., Reid, S., and Stuart, N. (2003) When is a hotspot a hotspot? A procedure for creating statistically robust hotspot maps of crime. In: D. B. Kidner, G. Higgs and S. D. White (eds.), *Socio-Economic Applications of Geographic Information Science.* London: Taylor and Francis, pp. 21-36.

Chainey, S., Tompson, L., and Uhlig, S. (2008) The utility of hotspot mapping for predicting spatial patterns of crime. *Security Journal, 21*(1-2): 4-28.

Chilvers, M. (1998) Measuring crime dispersion. *Contemporary Issues in Crime and Justice (NSW Bureau of Crime Statistics and Research),* No. 39, 12 pages.

Chilvers, M. (2001) Measuring crime dispersion. *International Journal of Police Science and Management, 3*(4): 350-363.

Chilvers, M. (2002) Crime increases in perspective: The regional dispersion of crime in NSW, 2001. *Contemporary Issues in Crime and Justice (NSW Bureau of Crime Statistics and Research)* No. 67, 8 pages.

Clarke, R. V., and Felson, M. (1993) Introduction: Criminology, routine activity, and rational choice. In: R. V. Clarke and M. Felson (eds.), *Routine Activity and Rational Choice* (Volume 5), New Brunswick: Transaction publishers, pp. 259-294.

Clarke, R. V., and Weisburd, D. (1994) Diffusion of crime control benefits. In: R. V. Clarke (ed.), *Crime Prevention Studies* (Volume 2), Monsey, NY: Criminal Justice Press, pp. 165-183.

Cliff, A. D., and Ord, J. K. (1969) The problem of spatial autocorrelation. In: A. J. Scott (ed.), *London Papers in Regional Science.* London: Pion, pp. 25-55.

Cohen, J., and Tita, G. (1999) Diffusion in homicide: Exploring a general method for detecting spatial diffusion processes. *Journal of Quantitative Criminology, 15*(4): 451-493.

Cohen, L. E., and Felson, M. (1979) Social change and crime rate trends: A routine activity approach. *American Sociological Review, 44:* 588-608.

Cornish, D., and Clarke, R. (1986) *The Reasoning Criminal: Rational Choice Perspectives on Offending*. New York: Springer-Verlag.

Cornish, D. B., and Clarke, R. V. (1987) Understanding crime displacement: An application of rational choice theory. *Criminology, 25*(4): 933-947.

Craglia, M., Haining, R., and Wiles, P. (2000) A comparative evaluation of approaches to urban crime pattern analysis. *Urban Studies, 37*(4): 711-729.

Eck, J. E., Chainey, S., Cameron, J. G., Leitner, M., and Wilson, R. E. (2005) *Mapping Crime: Understanding Hot Spots* (Special Report) Washington DC: National Institute of Justice.

Ellingworth, D., Farrell, G., and Pease, K. (1995) A victim is a victim is a victim? *British Journal of Criminology, 35*(3): 360-365.

Farrell, G., and Pease, K. (1993) Once bitten, twice bitten: Repeat victimisation and its implications for crime prevention. *Police Research Group: Crime Prevention Unit Series, Paper 46*, 32 pages.

Farrington, D. P. (1992) Criminal career research in the United Kingdom. *British Journal of Criminology, 32*(4): 521-536.

FBI. (2008) Crime in the United States, Uniform Crime Reports. 2007.

Felson, M. (1998) *Crime and everyday life: Impact and implications for society* (Second ed.) Thousand Oaks, California: Pine Forge Press.

Feser, E., Sweeney, S., and Renski, H. (2005) A descriptive analysis of discrete US industrial complexes. *Journal of Regional Science, 45*(2): 398-419.

Firman, J. R. (2003) Deconstructing CompStat to clarify its intent. *Criminology and Public Policy, 2*(3): 457-460.

Fisher, P. F., and Langford, M. (1995) Modelling the errors in areal interpolation between zonal systems by Monte Carlo simulation. *Environment and Planning A, 27:* 211-244.

Fotheringham, A. S., Brunsdon, C., and Charlton, M. (2002) *Geographically Weighted Regression*. Chichester (UK): John Wiley.

Fotheringham, S. A., and Brunsdon, C. (2004) Some thoughts on inference in the analysis of spatial data. *International Journal of Geographical Information Science, 18*(5): 447-457.

Getis, A., and Franklin, J. (1987) Second-order neighborhood analysis of mapped point patterns. *Ecology, 68*(3): 473-477.

Getis, A., and Ord, J. K. (1992) The analysis of spatial association by use of distance statistics. *Geographical Analysis, 24*(3): 189-206.

Getis, A., and Ord, J. K. (1996) Local spatial statistics: an overview. In: P. Longley and M. Batty (eds.), *Spatial Analysis: Modelling in a GIS environment* (First ed.) London: GeoInformation International.

Glasser, G. J. (1962) Variance formulas for the mean difference and coefficient of concentration. *Journal of the American Statistical Association, 57*(299): 648-654.

Goldstein, H. (1979) Improving policing: A problem-oriented approach. *Crime and Delinquency, 25*(2): 236-258.

Goldstein, H. (2003) On further developing problem-oriented policing: The most critical need, the major impediments, and a proposal. In: J. Knutsson (ed.), *Problem-Oriented Policing: From Innovation to Mainstream,* Monsey, NJ: Criminal Justice Press, pp. 13-47.

Green, L. (1995) Cleaning up drug hot spots in Oakland, California: The displacement and diffusion effects. *Justice Quarterly, 12*(4): 737-754.

Hope, A. C. A. (1968) A simplified Monte Carlo significance test procedure. *Journal of the Royal Statistical Society, Series B, 30*: 583-598.

Johnson, S. D., and Bowers, K. J. (2004a) The burglary as clue to the future: The beginnings of prospective hot-spotting. *European Journal of Criminology, 1*(2): 237–255.

Johnson, S. D., and Bowers, K. J. (2004b) The stability of space-time clusters of burglary. *British Journal of Criminology, 44*(1): 55-65.

Kelling, G. L. (1999) *"Broken Windows" and Police Discretion* (Research Report No. NCJ 178259) Washington DC: NIJ.

Koper, C. S. (1995) Just enough police presence: Reducing crime and disorderly behavior by optimizing patrol time in crime hot spots. *Justice Quarterly, 12*(4): 649-672.

Lorenz, M. O. (1905) Methods of measuring the concentration of wealth. *Publications of the American Statistical Association, 9*(70): 209-219.

Mazerolle, L., Rombouts, S., and McBroom, J. (2007) The impact of COMPSTAT on reported crime in Queensland. *Policing: An International Journal of Police Strategies and Management, 30*(2): 237-256.

McCord, E., and Ratcliffe, J. H. (2007) A micro-spatial analysis of the demographic and criminogenic environment of drug markets in Philadelphia. *Australian and New Zealand Journal of Criminology, 40*(1): 43-63.

Mencken, F. C., and Barnett, C. (1999) Murder, nonnegligent manslaughter and spatial autocorrelation in mid-South counties. *Journal of Quantitative Criminology, 15*(4): 407-422.

Messner, S. F., and Anselin, L. (2004) Spatial analyses of homicide with areal data. In: M. F. Goodchild and D. G. Janelle (eds.), *Spatially Integrated Social Science.* New York, NY: Oxford University Press, pp. 127-144.

Messner, S. F., Anselin, L., Baller, R. D., Hawkins, D. F., Deane, G., and Tolnay, S. E. (1999) The spatial patterning of county homicide rates: An application of Exploratory Spatial Data Analysis. *Journal of Quantitative Criminology, 15*(4): 423-450.

Moran, P. A. P. (1950) Notes on continuous stochastic phenomena. *Biometrika, 37*: 17-23.

Openshaw, S. (1984) The modifiable areal unit problem. *Concepts and Techniques in Modern Geography, No. 38,* 41 pages.

Ord, J. K., and Getis, A. (1995) Local Spatial Autocorrelation Statistics: Distributional issues and an application. *Geographical Analysis, 27*(4): 286-306.

Ord, J. K., and Getis, A. (2001) Testing for local spatial autocorrelation in the presence of global autocorrelation. *Journal of Regional Science, 41*(3): 411-432.

PERF. (2006) *A Gathering Storm - Violent Crime in America*. Washington DC: Police Executive Research Forum.

Polvi, N., Looman, T., Humphries, C., and Pease, K. (1991) The time course of repeat burglary victimization. *British Journal of Criminology, 31*(4): 411-414.

Ratcliffe, J. H. (2002) Burglary reduction and the myth of displacement. *Trends and Issues in Crime and Criminal Justice, No. 232*, 6 pages.

Ratcliffe, J. H. (2008) *Intelligence-Led Policing*. Cullompton, Devon: Willan Publishing.

Ratcliffe, J. H., and McCullagh, M. J. (2001) Crime, repeat victimisation and GIS. In: K. Bowers and A. Hirschfield (eds.), *Mapping and Analysing Crime Data*. London: Taylor and Francis, pp. 61-92.

Ratcliffe, J. H., and Rengert, G. F. (2008) Near repeat patterns in Philadelphia shootings. *Security Journal, 21*(1-2): 58-76.

Scott, M. S. (2000) *Problem-Oriented Policing: Reflections on the First 20 Years*. Washington DC: COPS Office.

Sherman, L. W., Gartin, P., and Buerger, M. E. (1989) Hot Spots of predatory crime: Routine activities and the criminology of place. *Criminology, 27*(1): 27-55.

Sherman, L. W., and Weisburd, D. (1995) General deterrent effects of police patrol in crime "hot spots": A randomized, controlled trial. *Justice Quarterly, 12*(4): 625-648.

Sousa, W. H., and Kelling, G. L. (2006) Of "broken windows," criminology, and criminal justice. In: D. Weisburd and A. A. Braga (eds.), *Police Innovation: Contrasting*

Perspectives. New York: Cambridge University Press, pp. 77-97.

Spelman, W. (1995) Once bitten, then what - cross-sectional and time-course explanations of repeat victimization. *British Journal of Criminology, 35*(3): 366-383.

Tilley, N. (2003) Community policing, problem-oriented policing and intelligence-led policing. In: T. Newburn (ed.), *Handbook of Policing*. Cullompton, Devon: Willan Publishing, pp. 311-339.

Townsley, M., Homel, R., and Chaseling, J. (2000) Repeat burglary victimisation: Spatial and temporal patterns. *Australian and New Zealand Journal of Criminology, 33*(1): 37-63.

Townsley, M., Homel, R., and Chaseling, J. (2003) Infectious burglaries: A test of the near repeat hypothesis. *British Journal of Criminology, 43*(3): 61-633.

Trickett, A., Ellingworth, D., Hope, T., and Pease, K. (1995) Crime victimization in the eighties - changes in area and regional inequality. *British Journal of Criminology, 35*(3): 343-359.

Unwin, D. J. (1996) GIS, spatial analysis and spatial statistics. *Progress in Human Geography, 20*(4): 540-551.

Walsh, W. F. (2001) Compstat: an analysis of an emerging police managerial paradigm. *Policing: An International Journal of Police Strategies and Management, 24*(3): 347-362.

Weisburd, D., and Green, L. (1995) Measuring immediate spatial displacement: methodological issues and problems. In: J. E. Eck and D. Weisburd (eds.), *Crime and Place* (Volume 4). Monsey, NY: Criminal Justice Press, pp. 349-361.

Weisburd, D., and Green, L. (1995) Policing drug hot spots: The Jersey City drug market analysis experiment. *Justice Quarterly, 12*(4): 711-735.

Weisburd, D., Maher, L., Sherman, L., Buerger, M., Cohn, E., and Petrisino, A. (1993) Contrasting crime general and crime specific theory: The case of hot spots of crime. In: F. Alder and W. S. Laufer (eds.), *New directions in criminological theory* (Volume 4). London: Transaction publishers, pp. 45-70.

Weisburd, D., Mastrofski, S. D., McNally, A. M., Greenspan, R., and Willis, J. J. (2003) Reforming to preserve: CompStat and strategic problem solving in American policing. *Criminology and Public Policy, 2*(3): 421-456.

Weisburd, D., Mastrofski, S. D., Willis, J. J., and Greenspan, R. (2006) Changing everything so that everything can remain the same: Compstat and American policing. In: D. Weisburd and A. A. Braga (eds.), *Police Innovation: Contrasting Perspectives*. New York: Cambridge University Press, pp. 284-301.

Weisburd, D., Wyckoff, L. A., Ready, J., Eck, J., Hinkle, J. C., and Gajewski, F. (2006) Does crime just move around the corner? A controlled study of spatial diffusion and diffusion of crime control benefits. *Criminology, 44*(3): 549-591.

Wilson, J. Q., and Kelling, G. L. (1982) Broken Windows: The police and neighborhood safety. *The Atlantic Monthly,* March*:* pp. 29-38.

Zhang, C., and Murayama, Y. (2000) Testing local spatial autocorrelation using k-order neighbours. *International Journal of Geographical Information Science, 14*(7): 681-692.

[i] Chilvers (1998) explains how this can be done for a population-corrected rate, but frequency counts are used in this paper for simplicity and demonstration purposes.

[ii] A stand-alone software program that calculates the ODI and NCDI is available as a free download from the author's website at www.jratcliffe.net.