INTENSITY VALUE ANALYSIS AND THE CRIMINOGENIC EFFECTS OF LAND USE FEATURES ON LOCAL CRIME PATTERNS

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Research has shown that crime tends to cluster around certain categories of land uses; for example, assaults group around bars and thefts and vandalism gather in neighborhoods bordering high schools and shopping centers. Environmental criminology explains the criminogenic propensities of these places as the result of increased crime opportunities and activities that attract higher numbers of potential offenders. Current methodologies used to quantify the volume of crime around criminogenic locations, however, lack precision in identification, measurement, and comparison. This article attempts to improve upon previous methodologies by employing a new technique that weighs crime events based on their relative proximity to the land use under study within a constraining buffer. The methodology allows researchers to apply statistical tests and make comparisons across land use, crime types, and jurisdictions. The process is demonstrated with a case study of the clustering of street robberies around subway stations in Philadelphia, PA, USA.

Introduction

The objective of this paper is to present *intensity value analysis*, an enhancement over existing spatial data analysis methods currently used to describe the clustering (or grouping) of crime incidents around land uses and facilities theorized to be criminogenic. These clusters, often referred to as hotspots of crime, are responsible for significantly elevating an area's overall crime rate while also becoming long-term problems for the police and community (Sherman, 1995; Sherman *et al*., 1989). The increased precision of identification, measurement, and comparison of crime clustering available through intensity value analysis may assist criminologists in further understanding opportunity and the ecological backcloth of crime (Brantingham & Brantingham, 1993b) while also allowing for a more effective response by crime control agents.

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This article begins by presenting the theoretical foundation that explains why crime clusters around certain land use and facility types. The article then describes location quotient analysis – a popular existing methodology - and the potential limitations of location quotients for micro-place based studies. After this, the paper explains the process of intensity value analysis. Finally, it demonstrates a real-world application with a case study of street robbery around subway stations in Philadelphia, Pennsylvania, USA.

Land Use and The Clustering Of Crime

As far back as the 19th century, French researchers Guerry and Quetelet noted the non-uniform distribution of crime across regions and associated this with differing ecological and social characteristics (Brantingham & Brantingham, 1991). Later, researchers of the Chicago School of Sociology concluded that characteristics of the urban environment, both socio-economic and physical environmental factors, were responsible for areas or zones of historically high crime rates (Burgess, 1925; Shaw & McKay, 1942; Thrasher, 1927). These early ecological studies examined crime at the macro-level, employing aggregate data to explain crime levels found across regions, cities, and neighborhoods.

More recent studies have shifted the examination from the larger areas to specific places, and from an emphasis on criminality and motivation, to that of the crime event itself (e.g. Eck & Weisburd, 1995). These examinations focus on street corners, land uses, public facilities, or specific business establishments that are frequently found at the center of localized crime clusters. Examinations at this scale explain clustering as resulting from the increased opportunities for criminal acts found at these places. This area of study, known under the umbrella term of *environmental criminology* (Brantingham & Brantingham, 1991) has more direct application to crime prevention, problem-oriented policing, and urban planning than earlier ecological studies that sought to explain criminal motivation, motivation that functioned within a broad spatial framework rather than a place-based approach.

Environmental criminology research has to date been dominated by three interrelated theoretical approaches to explain the location and clustering of crime: rational choice perspective (Clarke & Cornish, 1985; Cornish & Clarke, 1986), routine activities theory (Cohen & Felson, 1979; Eck, 1994), and crime pattern theory (Brantingham & Brantingham, 1993a). Readers of this journal are most likely familiar with these theories so they will not be revisited here; but readers with less familiarity may wish to refer to the citations above and a comprehensive reader such as Wortley and Mazerolle's *Environmental Criminology and Crime Analysis* (2008). Together these three theories state that specific types of land uses and facilities generate crime due to the daily activities associated with them and the number and types of people they attract. The presence of certain land uses is therefore theoretically predictive of crime levels in the neighborhoods surrounding them.

Crime incidents occurring as the result of criminogenic circumstances or activities found at a specific location are not limited to only occurring on the premises of the problem location. This article is concerned with advancing the measurement of crime clustering found not only at a location but also near to land uses and facilities. Both research methodologies and theory concerned only with repeated crime at specific addresses while largely ignoring the situation in the surrounding environment fall under the domain of repeat victimization and are not the specific subject of this paper (for further information on this area see Farrell & Pease, 2001).

Oftentimes, the clustering of crime occurs nearby particular locations, and its causal relationship to the location may not be immediately apparent. For example, a disruptive patron evicted from a bar may wait around the corner to assault his intended victim, or heavily intoxicated customers may fall victim to mugging as they walk to their nearby homes (Roncek & Maier, 1991). Studies of subway systems find few robberies occur inside the stations but rather tend to cluster in nearby blocks; close enough for offenders to have a good selection of riders leaving the area, but far enough away from other passengers and the guardianship of the station (Block & Block, 2000; Block & Davis, 1996). Crime-prone juveniles walking to school frequently take advantage of opportunities they become aware of in the neighborhoods they travel through daily (Roncek & Lobosco, 1983), and drug markets tend to prosper at locations near pawn shops where the cash required for drug purchases can be easily obtained from stolen property (Rengert et al., 2005).

Only through repeated and precise analyses can researchers identify criminogenic facilities and the strength of their influence on crime levels in the surrounding areas. One method, outside of trying to analyze the complexity and breadth of all physical and social relationships associated with a location that may lead to crime, is to identify those businesses or facilities where crime clusters nearby the location. Geographic information systems (GIS) provide the technical opportunity to conduct these types of investigations because a GIS can geocode to a map, with reasonable accuracy, the locations of the places and crime incidents under study. Modern analysis methods such as location quotient analysis and the technique proposed here, intensity value analysis, can then be used to identify which specific facilities promote crime through the identification and size of nearby crime clusters.

"Nearby" is a commonly used term but one with substantial theoretical and methodological implications within the context of the present subject. It implies the importance through causal inference of an identified distance between a criminogenic land use and surrounding crime incidents. Not enough research has presently been accomplished, however, to better quantify how far, even in generalized and aggregate terms, detrimental influences may spread for different land uses and crime types. Location quotient analysis (to be discussed in the next section), a method used in the most recent studies of criminogenic places, can lack an important element of relative proximity in its analytical methodology. It is with the importance of distance in mind that intensity value analysis may be an additional methodology in the toolbox of a crime analyst. More accurate measurement in identifying and comparing crime clustering found at and around theorized criminogenic places is important to both the advancement of crime-place theory and in identifying ways to reduce the negative influence of problem places.

Location Quotients

Place-focused examinations of crime have often required the utilization of innovative research methodologies in the field of criminology. One recently employed method particularly suited to measuring crime clustering around facilities is the location quotient (LQ), a statistical method used in regional studies since the 1940s (Miller et al., 1991) and introduced to criminology by Paul and Patricia Brantingham in the mid-1990s (Brantingham & Brantingham, 1995b). Location quotients compare the characteristics of a sub-area under study to that of the larger, surrounding region. Within regional science, the approach revises sub-area rates such that the new location quotient is centered on the aggregate, region-wide rate. In place-focused criminology, the sub-area is often a circular buffer of some radius drawn around a theorized criminogenic location or facility. The number of reported crime or disorder incidents found within this sub-area is summed and divided by the area of the buffer. The resulting density value is represented as a quotient of the total crime per unit area of the study region, often the surrounding city or regional district. In this way, a location quotient analysis is a two-stage process; calculation of a location-specific crime density followed by comparing that value to the regional rate. Through this process, individual and groups of homogenous land use types (for example, bars or high schools) can be assigned a single LQ value. An LQ value of 2 would indicate the crime density, or clustering, around a particular facility type is twice that of the region, suggesting these facilities and the activities associated with them promote the occurrence of crime. GIS is commonly used to draw the buffers and perform the analysis.

Utilizing location quotient analysis of concentric buffers, Rengert, Ratcliffe, and Chakravorty (2005) found drug markets in Wilmington, Delaware appear to prosper - as evidenced by increased multiyear, localized clustering of arrests - when located within 400 feet of liquor stores, homeless shelters, and check-cashing stores - even while controlling for neighborhood socio-economic factors. Santiago, Galster, and Pettit (2003) used 500- and 2,000-foot buffers around 38 scattered, small unit, public housing sites in Denver, Colorado to argue these complexes had no significant effect on neighborhood crime rates. Location quotient analysis has also been used to measure the effectiveness of police programs directed at crime in small areas or places. For example, Lawton, Taylor, and Luongo (2005) found that placing police officers on 214 drug corners in Philadelphia had little effect on violent crime within 0.1 mile buffer zones; while Newton, Johnson, and Bowers (2004) showed that intense, high-profile policing on a bus route in Liverpool, England reduced theft and assaults incidents within a 200 meter buffer around the bus route.

The use of location quotient analysis, while a relatively recent innovation in criminology, holds out the promise of a localized analysis of crime, and does so at a time when interest in the micro-level study of crime is growing. The approach does have some potential limitations, however. First is the way LQ analysis summarizes the spatial pattern, or crime clustering, found within the buffers encircling facilities. In LQ analysis, all crime points are assigned the equal value of one, regardless of their distance from the facility at the buffer's center. Thus, the resulting descriptive value is one of density rather than intensity. Other things being equal, and consistent with Tobler's (1970) first law of geography, it is logical to assume that crime incidents found closer to a theorized criminogenic facility are more likely related to the location than events farther away. Because of this, failing to account for crime proximity limits the overall precision of LQ analysis to a simple ratio of crime count to regional rate. Any two comparably-sized buffers containing the same number of crime points are counted as equal value, regardless of where the points are found in the buffer.

A second issue with LQ analysis concerns the radius (also known as a bandwidth) of the buffer drawn around the facility(s) under study. With the limited research that has been done in this area, there are as yet no guidelines as to suitable distances to use for criminogenic land use studies. Researchers currently must interpret available theory and estimate what distance from a facility criminogenic effects may extend; and choice of radius can likely influence the results of analyses. For example, too-narrow a bandwidth could exclude many crime points that may be related to the criminogenic facility, while an over-expansive buffer may 'wash out' the evidence of a criminogenic effect by increasing the denominator value through inclusion of areas that are not theoretically related to the facility at the center of the buffer.

A further concern lies with the denominator part of the analysis. In place-based LQ analysis where area functions as the chosen denominator, the density of crime points per area unit found within buffers is compared to the density of the entire study area, assuming a uniform distribution. The study area however may include many locales with little or no opportunity for crime, such as airport runways or large, non-developable areas including rivers, reservoirs, other wetlands and mountainous areas. Therefore, including the total area of these features in the analysis (as commonly done in location quotient analysis) skews the data toward higher values and reduces analytical robustness. Attempts to correct this problem can often require the necessity to use masked areas for the denominator (Rengert et al., 2005).

Furthermore, because LQs are ratio values derived from comparisons between crime densities found in buffers with that of a study area, their comparison across different jurisdictions, land uses, or crime types is less meaningful. A LQ value of three for drug arrests around homeless shelters in Wilmington is not directly comparable to the density of arrests for a similar LQ value in Washington DC due to different crime counts. The ratio value may be the same, but the density is not. LQs comparing vehicle thefts and drug arrests around shopping centers in the same city are not comparable for the same reason.

The final issue of concern for LQ analysis is that the method provides no readily available manner in which to verify the statistical strength of the results. The outcome of LQ analysis is a quotient value for individual places or groups of facilities. To the authors' knowledge at present, statistical limitations constrain the ability to test the null hypothesis that crime clustering around certain facilities is significantly different from crime distributions found elsewhere. Thus, location quotients offer a paucity of information to scientific reviewers. Significance testing methods have been suggested in economic area research to provide confidence levels for overall LQ values, but neither of the methods offered are appropriate for comparing facility values to reference sets as in this line of criminological research (see Moineddin & Boyle, 2003).

Intensity Value Analysis (IVA)

Intensity value analysis (IVA) is presented as an enhancement to location quotient analysis because it resolves, or at least substantially minimizes, the problems with LQ analysis described above. Achieving an intensity value involves calculating the intensity of clustering around targeted land uses. Instead of simply counting the number of crime points found within a buffer (as in the first stage of an LQ analysis), intensity value analysis calculates the intensity of crime points into a single, inverse distance-weighted value based on the aggregate proximity of all crime incidents found within the buffer surrounding each facility. In this manner, crime points located farther from the land use feature are assigned lower values, and when summed into a single value for each facility, result in a more precise measurement of spatial patterning than LQ analysis affords.

The intensity measure is calculated thus:

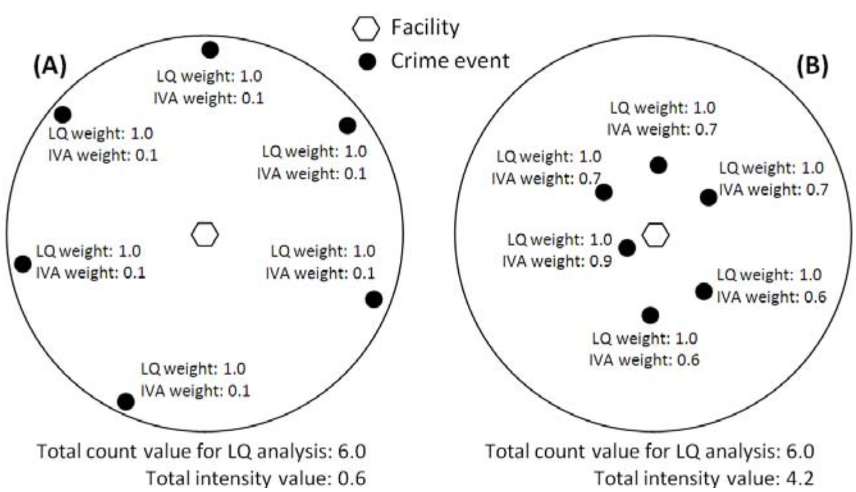
$$\lambda_\tau(r) = \sum_{d_i \le \tau} \left(1 - \frac{d_i}{\tau}\right) \tag{1}$$

where $\lambda_\tau(r)$ is the intensity value for a land use facility r given a bandwidth τ, where $\tau > 0$, and d_i is the distance between the facility and a crime point within the bandwidth. Intensity value analysis seeks out all crime points i within distance τ of the facility and assigns a suitable weight between 1 and 0 to each, such that points closer to the facility will have higher values. The weighting scheme can follow a simple linear design, as shown in Equation 1, such that points located one-half the distance between the facility and the edge of the bandwidth are assigned a value of 0.5, those three-quarters the distance are assigned a value of 0.25, and so on. Other weighting regimes are possible that assign values in non-linear ways. The weighted value for all crime points falling within the chosen bandwidth are summed and assigned to the facility. Points falling outside the bandwidth are ignored. Each facility is thus assigned a single intensity value that describes the aggregate structure of crime points found around it with reference to proximity (distance) rather than density. [2]

There are a number of potential benefits to using intensity values. Intensity value analysis produces a crime clustering value for each studied land use. These values can be used in multiple regression analyses where it may be desirable to expand the research by examining the influence of socio-economic or other factors on the land use, crime clustering phenomena. Intensity value ranges for two different land uses can also be compared via a standard test of the null hypothesis, as we do later in the paper.

A second benefit is that intensity values are more descriptive of crime clustering patterns than LQ analysis because they enhance the density (count-based) simplicity of the buffer measure with a proximity component. Figure 1 demonstrates this enhanced precision in a comparison between IVA and buffer frequency counts (as used by LQs). Note in Figure 1 that both examples are of identically sized buffers with both containing a facility and six crime incidents. In the first example (A), the crime incidents are located at the extreme edge of the

Figure 1
Location Quotient v. Intensity Value Analysis Weighting



Comparisons of count value used in LQ analysis, where each incident within a buffer is counted as having a value of 1.0, to IVA, where incident values are weighted for distance. IVA more precisely summarizes the spatial pattern of the clustering of crime incidents around a facility by including an inverse-distance metric in the calculation.

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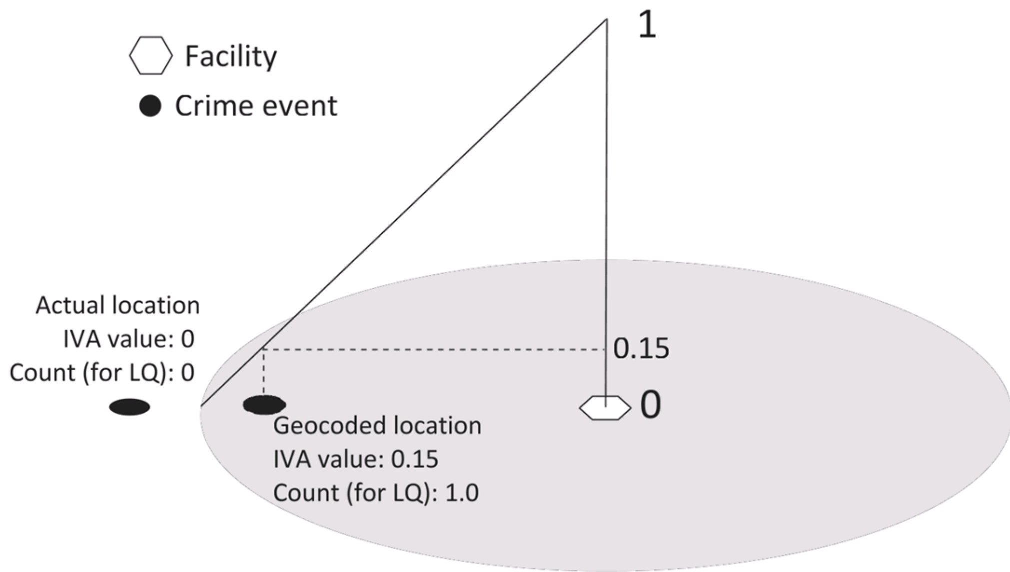
[2] A computer program written by one of the authors (Ratcliffe) was used to run the intensity value analysis in this article. The software is available for download at jratcliffe.net and includes linear, quartic kernel, and exponential weighting schemes (see Ratcliffe, 2007).

buffer, or bandwidth. In the second example (B), the incidents are located much closer to the facility. For each facility in the examples, a LQ buffer frequency count assigns a value of 6, while IVA assigns a value of .6 to the facility where the crime incidents are located at the buffer edges (A) and 4.2 where the crime clusters much closer to the facility at (B). By incorporating a component of distance beyond the binary notation of inside or outside a buffer, IVA scores are a more descriptive and precise measurement of crime clustering around a facility.

Figure 2
Treatment of Boundary Events



IVA assigns crime events falling within the bandwidth (grey region) a value between 0 and 1 based upon the inverse-distance weighting scheme (value represented by diagonal line), whereas, LQ analysis assigns all incidents in the buffer the value of 1.0. The impact of geocoding inaccuracy can be reduced substantially with IVA. Here an example misplaced incident is assigned an IVA value of .15, compared with the 1.0 assigned by LQ analysis.

Third, intensity value analysis helps minimize potential problems associated with buffer size selection. Because IVA weighs crime incidents by proximity to the facility and assigns lower values to those located at buffer edges, potential error associated with arbitrary buffer selection is reduced, such as the potential problem associated with selecting an overly-wide buffer and including incidents that are not related to a criminogenic facility. While the points at the extremity of the bandwidth are still selected, their individual contribution to the aggregate score for the facility is relatively small. This results in the suggestion that larger rather than smaller buffer radii could be used for initial crime clustering examinations utilizing intensity value analysis. Recent place-based studies (Rengert et al., 2005; Santiago et al., 2003) find that the crime-enhancing effects of some land uses may extend several city blocks beyond the areas identified in early land use studies (Roncek & Lobosco, 1983; Roncek & Pravatiner, 1989). Clearly, more research is needed in this area; and, as yet, there is no definitive measurement process for identifying the specific distance whereby a criminogenic facility's influence diminishes. As such, while both LQ and IVA employ an arbitrary bandwidth selection, the potential to incorporate significant error within an LQ analysis is substantially greater than with IVA. Points either side of an LQ buffer boundary will jump from a contribution of one to zero in a matter of feet; whereas the inverse distance weighting for points close to the buffer in an intensity value analysis will minimize this threshold effect.

A final advantage of IVA over LQ analysis concerns the way it handles potential inaccuracies in geocoding. For a number of reasons, crime points may not be geocoded with complete precision and accuracy because the crime recording and geocoding process can introduce error to the geolocated point (see Chainey & Ratcliffe, 2005 for an explanation of the various causes of these errors). These errors are often inconsequential for many uses, but in buffer-based analyses, they can be particularly problematic when crime incidents are attributed to occurring within a buffer when in fact they should have been located outside. As stated above, a crime point inaccurately geocoded within a buffer is always assigned a weight of one in LQ analysis, however, IVA would most likely assign a much lower value based upon the inverse-distance weighting scheme that adjusts for the distance to the investigated facility (see Figure 2). This assigned value difference may prove substantial when the summed facility values are used in statistical analyses, thus minimizing some geocoding error impact. As shown in Figure 2, the example facility should have an assigned value of 0, but LQ analysis assigns it a value of 1.0, while IVA assigns the much lower weight of 0.15.

In summary, intensity value analysis replaces the constant model of crime weighting within LQ with an inverse distance weighting for crime points within a user-selected buffer distance. In doing so, the analysis increases the spatiality of the result by adding a proximity component and replacing a density measure (areally-based but non-spatial within the buffer) with an intensity measure (crime events retain their spatial relevance within the buffer). As pointed out by a reviewer of an earlier version of this paper, the LQ is actually a simplified version of the IVA with a constant weight function within the buffer, and a zero measure outside. We do not advocate for a specific weighting function, given that most functions (for example, linear and exponential) will likely produce comparable results for most applications where crime and distance from a facility is a relatively simple relationship. With occasional applications where a buffered distance decay effect may exist (Rossmo, 2000), more complex functions may be suitable. The IVA approach minimizes geocoding error, allows for wider buffer selections that retain spatial relevance near the facility and minimize the influence of arbitrary buffer selection, and is relatively easy to calculate.

Enhancing the Comparative Value of IVA

An additional possibility with intensity value analysis is to make a comparison of the initial values to additional sets of location data. A second location set could consist of a random sample of points or street intersections from across the study area which could be used to compare a suspected criminogenic facility with a null hypothesis scenario (to establish a base standard) or another facility type, such as used when comparing the density of assaults around bars to the density of assaults around private clubs and restaurants. The intensity values for the comparison group (standard or facility type) would be calculated utilizing the same crime type(s) and buffer radius as used in the initial analysis. This results in two groups of intensity values that can be plotted into a histogram where differences in crime clustering can be identified visually. If the researcher wishes, statistical tests can also be applied (with some caveats). For example, if the buffers for both types of location do not overlap, a t-test of the null hypothesis may be applied to the two groups of values to verify whether or not they significantly differ in the clustering of crime incidents. In the example that follows, we use a random selection of street corners not associated with a criminogenic facility in question, and this approach appears to work well. It is equally possible to use intensity value analysis to compare the crime intensity around, for example, bars with the crime intensity around banks with ATM facilities.

Case Study: Street Robberies and Subway Stations

A number of researchers have noted a crime correlation with rapid transit stations. Block and Davis (1996) found that street robberies concentrate within one and a half blocks of Chicago's elevated train system stations, while Block and Block (2000) found similar patterns around subway stations in the Bronx. It is argued that these stations play the role of crime generators (Brantingham & Brantingham, 1995a) in that they attract many passengers who may be preoccupied, intoxicated, or unfamiliar with the area, providing a large selection of easy targets for offenders. Studies of street robbers show they are selective of their victims, preferring those who exhibit inattentiveness and cues that they are likely to possess cash and will not resist during the assault (Wright & Decker, 1997).

Researchers, however, note that it is not in the subway or on the train platforms where most crimes occur, but rather on the immediate surrounding streets or parking lots (Block & Davis, 1996; La Vigne, 1996). The concentration of other passengers, station workers, and transit police within the confines of stations helps prevent offenses, leaving the solitary passenger walking to or away from the station after work, shopping, or a night of entertainment as the easier target. Street robberies near transit stops are also found to occur at higher frequencies during late night hours due to the lack of guardianship (Block & Davis, 1996).

The 22 stations of the Broad Street subway line in Philadelphia, Pennsylvania are the focus of this study. Although other subway lines are located in Philadelphia, only this line was selected because the Broad Street line, which travels north and south and bisects the city at its mid-center, travels through neighborhoods of varying socio-demographic, income, and crime levels. Additionally, the assumptions of statistical independence necessary for a t-test analysis could not be met with the other subway lines because several stations were too closely situated resulting in overlapping buffers with the radius length selected for this examination (see below).

The data for this study consisted of all reported street robberies recorded by the Philadelphia Police Department in 2002 and 2003 (n = 12,814). Locations for each robbery were provided by the police department in the form of X, Y coordinates. The State Plane Coordinate System, Pennsylvania South 3702 (feet) was used for this analysis (although any projected coordinate system is acceptable for IVA analysis). Subway station locations were provided by the Philadelphia Police Department and were also in X, Y coordinate form. A bandwidth of 728 feet was used in this study, which is twice the distance of the mean street segment length (364 feet) in Philadelphia, equivalent to the approximate distance of two street blocks.

For comparison, 500 random street corners were selected from all intersecting streets within the city of Philadelphia (n = 21,152) using the random selection process of SPSS[3]. To minimize edge effects, a problem affecting analytical robustness due to the potential for bandwidth extending outside the study area where no crime is recorded (Chainey & Ratcliffe, 2005), a 364 foot buffer was drawn in from the city limits using GIS. The random 500 street corners were then selected from all intersections in the city falling outside this guard area and

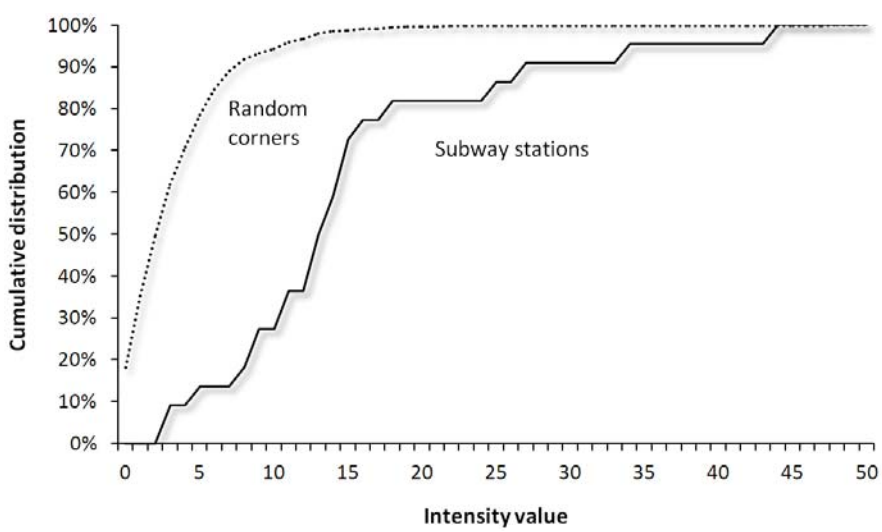
[3] The number of street corners was rounded up from 377 recommended by a sample size calculator to ensure a minimum confidence level of 95% and confidence interval of 5%.

within city limits. Because the analysis method used a linear inverse-distance weighting method that assigned lower values to crime points located at extreme distances, the approach of excluding all intersections with 364 feet of the city boundary rather than the 728 feet corresponding with the bandwidth reduced the influence of edge effects while not significantly reducing the area of the city available for comparative study. This method resulted in 320 (1.5%) of the total 21,152 street corners in the city being excluded from the random corner analysis. The X, Y coordinates of the 500 random corner points were obtained from the GIS software and retained for the analysis.[4]

Results

Intensity value analysis was performed for each group, resulting in individual street robbery intensity values for each of the 500 random street corners and 22 subway stations. The mean intensity value for the 500 random street corners was 3.1 ($SD = 3.9$) and the mean value for subway stations was 14.7 ($SD = 9.7$). These results indicated considerably greater clustering of street robberies around the subway stations. It should be pointed out that we are dealing here with all of the subway stations available, and thus a population and not a sample; however, as Fotheringham and Brunsdon (2004) point out, statistical tests can permit a researcher to make inference regarding a process, and process inference is a potentially valuable, if rarely employed, use of statistical tests. With a one-sample t-test (used due to differences in sample/population sizes), it was determined that the difference in intensity values was statistically significant ($p < .001$, $t = 5.618$, $df = 21$).

Figure 3
Cumulative Distribution of Intensity Values of Street Robberies

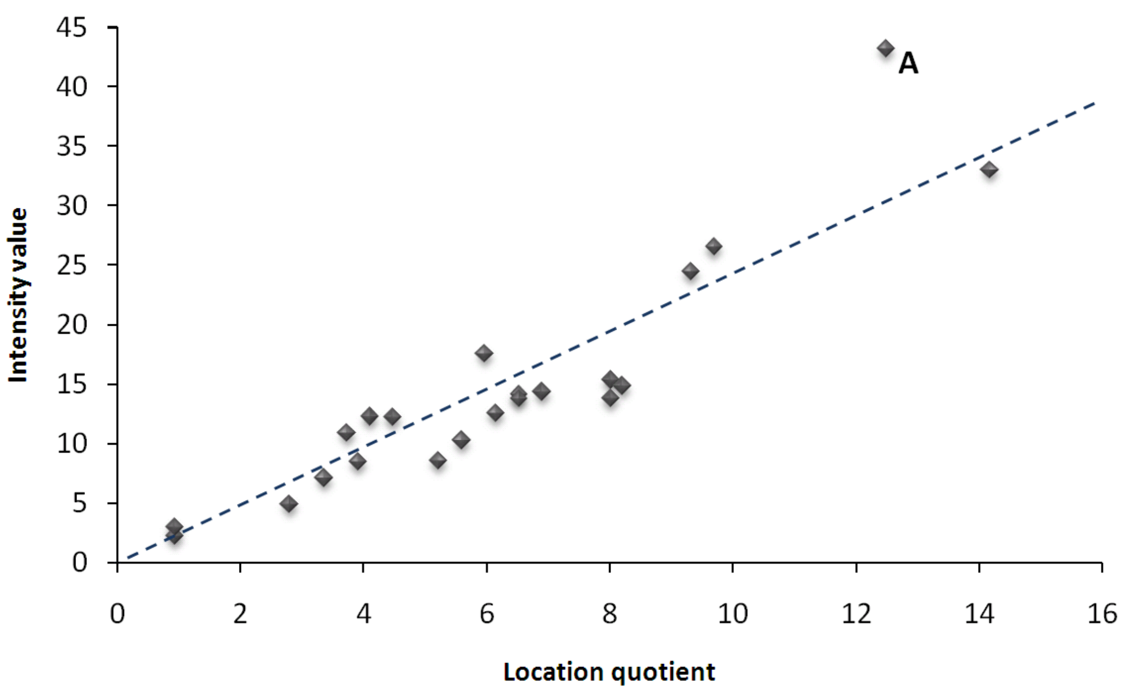


[4]To avoid violating statistical rules of independence, a systematic process was used to ensure selected random street corners were not so close to others that they overlapped within the chosen bandwidth distance (728 ft). This was accomplished by first drawing a 728-foot buffer around each selected random corner in the GIS and inspecting for overlaps. Those that overlapped were systematically removed based upon a rotating system: on overlapping buffers, the one that was further north on the map was first removed, followed by one that overlapped further south, until overlaps were no longer observed. Approximately 775 selected random street corners were necessary to develop the final 500 without overlapping buffers.

To further understand how the crime values differed, the robbery intensity values for the 22 subway stations and 500 random street corners were placed into a cumulative distribution chart for visual comparison (Figure 3). As shown, approximately 18% of the random 500 street corners had zero intensity values indicating no street robberies occurred within two blocks (728 feet) of the corners. By comparison, none of the subway stations had zero intensity values. Additionally, the chart shows that the robbery intensity values for the street corners were considerably skewed with a few high crime corners, while subway stations show a more even distribution of crime around the stations.

The intensity values and their corresponding location quotients for the 22 stations are also displayed in Figure 4 as a scatter plot. As shown, while intensity values are generally correlated with their corresponding LQ values, the intensity values are not limited to numerator increments of whole numbers because they account for both density and proximity, while location quotients are density (count per area) values alone. This can be seen in Figure 4 as the points vary around the mean ratio of intensity value to location quotient score, as indicated by the dashed line. Stations that are located above the dashed line indicate that the subway station in question is likely to have a greater clustering of crime events close to the station compared to stations below the line. Thus, we can define the danger of street robbery within two blocks distance of Philadelphia's subway stations in more precise terms: high risk levels found at and immediately adjacent to some subway stations, and more diffused risk found in surrounding neighborhoods at other stations.

Figure 4
Subway Station Intensity and Location Quotient Values



The variation is caused by the introduction of a proximity measure in the intensity value. The dashed line indicates the mean ratio between location quotient and intensity value. Subway stations above the line (and one in particular at A) are likely to have crime events that are nearer to the station than subway stations identified below the line.

It is beyond the scope of this paper to speculate on what may be advancing the clustering of robberies more immediately around some subway stations in Philadelphia. Further analysis of the environment and social activities at each station and surrounding neighborhood is needed. It is, however, clear from the intensity value analysis that street robberies cluster around Broad Street subway stations in Philadelphia, much more than found around random street corners from across the city. Additionally, intensity value analysis identified subway stations where robbery clustering is closer to the transit facility itself, either in the station or immediately adjacent to it, than the mean expected level (see the station marked as 'A' in Figure 4). This information, unavailable in a location quotient analysis alone, is useful to crime practitioners and police concerned with public transportation safety, and anyone whose research is aimed at identifying characteristics and activities of transit facilities associated with varying crime levels.

Conclusion

Ecological theories of crime have become more place-focused in recent decades, allowing criminologists to add alternative explanations to the genesis of crime and why it tends to cluster across the urban landscape. These theories and associated studies should be of great importance to those who seek to prevent and control crime. When crime clustering is accurately measured, evaluated, and interpreted using contemporary place-based theory, police departments and local governmental agencies have the potential to become more effective in their use of regulatory and criminal enforcement efforts aimed at high crime places.

Place-based theory is helping researchers understand how the many daily routines and activities associated with specific venues can promote crime, both at and around the locations. Counting crimes at locations alone is not enough to evaluate fully the criminogenic nature of a facility or its influence on the surrounding community. Many incidents may move onto nearby sidewalks or streets, or the facility may promote crime in the immediate region due to its activities or the increased number of potential offenders it may draw to an area. Intensity value analysis (IVA) is therefore only a starting point; however, it offers several enhancements over location quotient analysis. For example, IVA adds precision to the spatial descriptions of crime clustering, while also allowing the use of significance tests of the null hypothesis. This proposed method also offers researchers the ability to use a more realistic base rate when comparing crime clustered around criminogenic facilities with overall study areas. It also provides outcome measurements that can be compared across land uses, crime types, and jurisdictions.

The present study of subway stations using intensity value analysis revealed a concentration of street robberies around these facilities. This finding concurs with theory proposing the crime-attracting properties of these land uses. The result revealed through the scatter plot, and confirmed via the t-test, is that it is not just a few stops with high rates of robbery, but rather all subway stops along the Broad Street line that are associated with clusters of street robberies. The use of random street intersections was an applicable comparison because subway stop entrances in Philadelphia are frequently located at or nearby street intersections. Thus, we present evidence that it is the presence of subway stations themselves, and not street intersections in general, that attract street robberies. Of course, not all subway stations are alike. For example, the analysis showed that crime clusters much closer to a number of stations.

This ability to more precisely measure and evaluate crime clustering may prove helpful in further development of place-focused criminology and crime prevention. For example, comparisons made through intensity value analysis between different types of businesses that provide alcoholic beverages, bus stops and subway stations, convenience stores and supermarkets, public and private high schools, and so forth, may help identify latent behaviors or activities that increase opportunity or otherwise promote crime.

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