Remote Sensing and Spatial Statistics as Tools in Crime Analysis

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This chapter explores the feasibility and utility of using aerial photography or remotely sensed satellite imagery to identify geographic or "place" features that may be associated with criminal activity. It assesses whether or not variables derived from satellite images can provide surrogate relationships between land use and crime. A review of the remote sensing literature suggests two basic approaches to the use of remotely sensed images in law enforcement: (1) tactical; and (2) analytical. The tactical approach uses the imagery as a background to the maps and other spatial information that an officer on the beat might have as he or she is investigating a crime or emergency situation. The analytical approach uses the remotely sensed images to create

new variables that may serve as proxies for the risk of crime in particular locations. In this study we employ the analytical approach to the use of remotely sensed images, classifying images according to the presence or absence of vegetation within a pixel, as well as the classification of specific urban attributes, such as parking lots. We also employ spatial statistics to quantify the relationship between features of the images and crime events on the ground, and these analyses may be particularly useful as input to policy decisions about policing within the community.

INTRODUCTION

The concept of place is essential to crime pattern theory because the characteristics of place influence the likelihood of a crime. Most crimes are not random events, nor are they randomly distributed in terms of where they occur (Rossmo, 1995). Some areas are more prone to criminal activity than are others (Coomb et. al., 1994; Roncek & Maier, 1991). This spatial variability is a result of the spatially non-random distribution of people who will be motivated to perpetrate a crime, and the spatially non-random distribution of factors (the opportunities) that increase the odds that a person or property will be victimized (Hakim & Rengert, 1981). Motivation tends to be person-specific, whereas opportunity tends to relate more specifically to the characteristics of place (Eck & Weisburd, 1995). These place-specific characteristics may be institutional (such as the amount of police activity oriented toward preventing crime or arresting criminals) and/or they may be more environmental (such as the presence of a large parking lot full of automobiles).

Crime literature has abundant references relating crime patterns to specific geographic features. For example, opportunities for some crimes, such as burglary and robberies, may be particularly enhanced by the existence of commercial areas and parking lots (Canter, 1997; Hill, 2003). Brantingham and Brantingham (1994) reported crack houses induce crimes (dealing in illegal drugs) that have a multiplier effect in the neighborhoods in which they are located, raising the burglary and theft volumes in their vicinity as customers raise the money to buy the drugs. The recognition of the concept of place in crime theory allows a new dimension to implementing crime prevention. Mapping crime locations and associating crime activities to mapped urban features offers the potential to enhance an understanding of the non-random nature of crime locations and to improve crime prevention measures.

Crime event maps provide only a portion of the context of place. Context is provided more meaningfully through the use of remotely sensed images (aerial photographs and satellite images), which are then combined with the crime event maps in a geographic information system (GIS). Hirschfield and others (1995), in their study of GIS analyses of spatially-referenced crimes, report that the use of maps as backdrops to plots of spatially referenced crime events led to a dramatic increase in the number of visual clues presented to investigators and thus facilitated the interpretation of the pattern and location of crime incidents. As Hirschfield and Bowers (1997) and Olligsclaeger (2003) observed, crime pattern maps alone do not allow an investigator to analyze in depth the relationships between levels of crime and the social and physical environment. In addition to maps, information is also needed about the types of social and physical environment which characterize areas of high crime. A potential solution to these crime-pattern map limitations is to use the powerful tools of remote sensing (RS) and aerial photography.

An extensive set of RS tools and techniques have been developed and are widely used by numerous disciplines to capture the characteristics of the physical environment (Jensen & Cowen, 1999). These same tools offer the potential to enhance the understanding of the relationships of crime to the physical environment and improve the understanding of place and geographic perspective in crime analysis. Aerial photo and remote sensing imagery can be a good source of data to provide the information on physical environment for law enforcement agencies.

Our interest in this research is to identify aspects of the natural and built environment that may be conducive to crime or may impose barriers to crime and thus will influence the opportunities for crime, and thereby will provide an independent determinant of the local crime rate. More specifically, we are interested in discovering whether remotely sensed images can provide information about this relative risk of crime that might not otherwise be available to crime analysts.

The objectives in this study are two-fold: (1) to use remotely sensed images to create new variables that may help to identify geographic locations that have a lower or higher relationship to crime; and then (2) to quantify the spatial mix of propensity and opportunity by bringing both sets of variables into a geographic information system for spatial statistical analysis. We do this with data for Carlsbad, California--a suburban community in San Diego County.

BACKGROUND

Our spatial approach to crime analysis generally follows the human ecological paradigm of behavior (Poston & Frisbie, 1998)--that where you live influences your life chances and social contacts, which in turn influence a wide range of behavioral patterns, including criminal activity. The crime rate is determined by the combined effects of motivation, opportunity, and the distance between the geographic areas in which criminals reside and those in which opportunities for crime exist. For certain classes of crime, the local crime rate will be a function of the geographic concentration of people who fit the descriptive profile of those persons with a greater propensity to commit crime, and the geographic concentration of opportunities for crime.

A review of the remote sensing literature suggests two basic approaches to the use of remotely sensed images in law enforcement: (1) tactical; and (2) analytical. The tactical approach uses the imagery as a background to the maps and other spatial information that an officer on the beat might have as he or she is investigating a crime or emergency situation. Imagery could be used in tactical operations such as deploying law enforcement resources at the scene of an on-going crime event (e.g., bank robbery or hostage event). A tactical approach example using aerial photography and remote sensing in crime analysis was reported by Messina and May (2003) in a case of carjacking in Overland Park, Kansas. With the aid of aerial photo, the prosecution was able to help recreate the scene and provide the parties involved with a better visualization of the area. Tactical applications might also include crime event assessment, visibility analysis, situational awareness, ingress/egress control, and related uses.

The analytical approach uses the remotely sensed images to create new variables that may serve as proxies for the risk of crime in particular locations. In these applications the images are used to add data to the analysis of crime in an attempt to better understand the spatial distribution of crime within a community. In this study we employ the analytical approach to the use of remotely sensed images, classifying images according to the presence or absence of vegetation within a pixel, as well as the classification of specific urban attributes, such as parking lots.

Opportunities for some crimes, such as burglary and car theft, may be particularly enhanced by the existence of commercial areas and parking lots, and we propose to measure these characteristics with parcel maps and with satellite images from which we can determine parking lots and places with substantially reduced vegetation. Especially in southern California, vegetation will be denser in less densely settled areas, and will be less dense in commercial and multiple-family dwelling areas. Since the latter two categories of land use represent higher-than-average opportunities for several crimes, the vegetation index from a satellite image should provide a good surrogate measure of such risks.

STUDY AREA

A subset of the City of Carlsbad in the County of San Diego was selected for study. This subset, bounded on the west by the Pacific Ocean, on the north and south by the Buena Vista and Aqua Hedionda Lagoons and on the east by the El Camino Real highway, provided the desired diversity of land use categories. The study area includes 7,369 parcels. Figure 1 shows the spatial extent of the City of Carlsbad with an outline defining the area selected for image analysis.

[Figure 1 about here]

DATA AND METHODS

Dependent Variable—Spatial Pattern of Crime Events

Crime events recorded for the period from June 1995 through December1998 were used in this study. This period was selected to assure that the data represented recent trends in both criminal activity and land use patterns within the study area. Several of the FBI Part I crimes, especially robbery, aggravated assault, and the four property crimes of burglary, larceny-theft, motor vehicle theft, and arson, were the focus of this analysis. Analysis of these crimes has the advantages that (a) they are serious enough so that under-reporting should not be a major methodological issue (Coombs et al., 1994); and (b) community concern about them means that local police departments and elected officials have an interest in new analyses that might offer insights into lowering the risk of such crimes occurring. The database includes both arrests and reported crimes, but our focus in this analysis is on the location of reported crimes--where did the police go when notified of a crime? As shown in Table 1, there are data on 10,256 crime events within the categories listed above during the period under investigation for the geographic area within the study site. These crime events represent the dependent variables in our analysis.

[Table 1 about here]

Figure 2 shows the spatial distribution of Part I crime events geocoded by street address within the study area for the period of December 1995 through June1998. The map shows that the geocoded crime events are not uniformly distributed throughout the study area. It is important to note that geocoding generally assigns street addresses proportionally along street centerlines based upon street address numeric values and can result in lateral displacement when house addresses are not uniformly spaced along a street. Another potential limitation of the address geocoding process is that addresses are located along a street centerline and then offset to the left or right a uniform distance to place the crime location within a parcel. The off-set distance used in the crime database of this study was 45 feet.

[Figure 2 about here]

There are more crime events in the urbanized western portion of the map and in multifamily residential areas in the northeastern corner of the map. The south central and southeastern portions of the study area are predominantly single-family, residential areas and show a both a lower density of events and more uniform distribution. There are also small clusters of crime events at the intersections of major thoroughfares. The spatial patterning of these crime events represents the dependent variable of interest in our analysis.

Independent Variables—Propensity and Opportunity for Crime

The data for the independent variables used in this study come from three different sources: (1) census data at the block group level and parcel map data used as a layer within the GIS; and (2) the classification of a satellite image. The sections below describe each source of data.

Census Data

From the 1990 census this source we derived variables that are related to the propensity to crime, often used to profile an area for crime risk. These demographic and housing characteristics include the percent black, percent Hispanic, percent of the population aged 15-24, percent unemployed, percent with only a high school education or less, the percent that had been living in the same house five years prior to the census, the percent of the population that was not proficient in English, the percent of the population that was at or below the poverty level, the percent of homes that were occupied by renters, the percent of homes that were small (less than three bedrooms), and the percent of households that were one-person. Data were aggregated at the block-group level, which was the smallest geographic unit of analysis available for these variables.

Several variables from the census were also used to measure opportunities for crime. These included data on the percent of households that are multiple- family dwellings, percent of housing units that are vacant, and the percent of housing units that were apartments.

Remotely Sensed Images

The ability to relate map features to some dependent variable (in this case, crime) is sometimes called spatial proximity analysis (O'Sullivan & Unwin, 2003). We have approached the application of information from remotely sensed images to crime analysis from two slightly different directions: (1) a generalized scheme of pixel classification designed to reduce the image to understandable patterns or spectral signatures that can then be tested for their association with hot/cold spots for specific types of crime; and (2) the "heads up" digitizing of specific environmental features that may relate to crime, such as the existence of alley-ways, parking lots, open spaces, proximity to freeway ramps, vacant lots, house setbacks, which may either raise or lower the opportunity for crime at a particular location.

A merged 10 m SPOT PAN and 20 3-band SPOT XS image of the study area taken in 1995 was generated by RGB to IHS transformation of a three-band SPOT XS image and using SPOT PAN instead of Intensity band in order to take advantage of the fine spatial resolution of PAN and the high radiometric resolution of XS. The merged SPOT PAN and XS image was classified for vegetation/non-vegetation in ERDAS Imagine software using an unsupervised classification scheme. First an ISODATA (Iterative Self-Organizing Data Analysis Technique) clustering method was performed on the entire study area to create ten different spectrally homogeneous classes (Jensen, 1996). These ten classes were then reduced to two categories (vegetation and non-vegetation) by visually examining the ten spectral classes in the screen. In this application, vegetation mainly indicates the areas covered by trees, brushes and grasses while the non-vegetation includes various buildings, roads, cleared lands, and water. Several spectral classes generated by the classification might have mixed pixels or boundary pixels that can not be identified as being either vegetation or non-vegetation, thus producing an error term. The aid of 1m resolution scanned color aerial photos was used for these classes to identify the majority of classes in these pixels. For each class, the pixels belonging to it were displayed and geolinked to those in the 1m scanned color image. If the majority of pixels in the scanned image could be seen visually to be vegetation, then that class was assigned to vegetation.

A 300-meter grid was then draped over the classified imagery to create a set of data for spatial data analysis. The 300-meter size was chosen as a size large enough to ensure that there was a statistically adequate number of crime events within each cell, yet small enough to produce a sufficient number of cells (n = 285) for the statistical analysis. The classified image thus produced a variable representing the proportion of pixels within each grid cell that were classified as non-vegetated. As can be seen in Table 2, the average proportion of non-vegetation was 0.52, with a median of 0.50, a standard deviation of 0.18, and very little skewness to the distribution. These data are shown graphically in Figure 3.

[Table 2 about here]

[Figure 3 about here]

From the aerial image we were also able to digitize the plots of land that were used for open, off-street parking. From the resulting polygons we calculated the percentage of the total area of each grid cell that was devoted to parking. These variables are also summarized in Table 2.

Spatial Data Analysis

The same 300 meter grid was then intersected with the crime data (the set of dependent variables--see Table 2), and all other independent variables. Organizing data in this way permits modeling with later regression techniques to test hypotheses about the environmental influence on the density of crime events. Given the potential inaccuracies in the geocoding of crime events, such an aggregation perhaps reflects a reasonable approximation of the environmental influence on criminal activity. Using ArcView we laid 300 meter grids over the study area, and then added the number of crimes in each grid. The dependent variable is thus the number of crime events occurring in each grid cell, and the independent variables are the proportions or rates of each variable occurring in each grid cell. These variables are summarized in Table 2. The census variables for each grid were aggregated from the block-group level using the weighted linear method. The weights were decided by the area percentages of blocks falling in each grid. This simple interpolation did not consider the spatial relationship between blocks and may over- or under-estimate values in some grids. However, these over- or under-estimated values should be small. The creation of the grid means that the dependent variable (number of crimes in each grid) is equivalent to a rate, since each number is implicitly normalized by an area of equivalent size.

The analysis proceeds in three steps: (1) an analysis of the spatial clustering of crimes using Gi* statistics (Getis & Ord, 1992)--are there some places within the study site where crime is much more likely to occur than others? (2) a traditional regression analysis in which spatial location is not taken into account--how much of the variability in crime can be explained by the predictor variables that attempt to measure the propensity and opportunity for crime; and (3) a spatially filtered regression analysis in which we quantify the importance of spatial clustering as a predictor of the incidence of crime.

The data set includes a fairly large number of independent variables grouped under the broad headings of propensity and opportunity. Since each of the variables listed under these headings has a high likelihood of being correlated with the others, we decided to reduce the number of variables by means of a principal components factor analysis. Using a varimax rotation with 25 iterations, the number of variables under "propensity" was reduced to three components, using combinations of the variables shown in Table 2. The combination of these three components explained 80 percent of the total variation in the eleven independent

Table 3 shows the rotated factor loadings for each variable within each of the three statistically significant components. The factor coefficient scores for each variable were then used as weights to produce a weighted sum score for each component, thus creating a set of new, combined variables which were then used in the remainder of the analysis. Thus, the initial eleven variables measuring propensity to crime have been reduced to three variables.

[Table 3 about here]

Using the same technique of factor analysis, we reduced five of the six variables that measured "opportunity" into two components, as shown in Table 4. The five variables reduced to two components which together explained 66 percent of the variation in the constituent variables. The first component consisted of the variables "percent of area devoted to parking" and "percent of area in commercial property." We called this component "Commercial." The second component included the variables "percent of housing units that are apartments," “percent of housing units that are vacant," and "percent of area in multiple family dwellings." We called this component "Residential." These results are consistent with our more qualitative analysis of the data described above, in which commercial parcels and residential parcels seemed clearly to differ in the risk of crime events.

[Table 4 about here]

Several new spatial statistics permit increased quantitative sophistication of Crime Pattern Analysis (CPA)--a variation on Point Pattern Analysis (PPA)--which has long been an informal staple of efficient community policing (Openshaw et al., 1993). The Illinois Criminal Justice Information Authority has developed a program called STAC (Spatial and Temporal Analysis of Crime) to help detect clusters or "hot spots" of crime (Illinois Criminal Justice Information Authority, 1998).

Using raster grid data, we then introduce the spatial component at the local level. The local spatial statistic utilized is the $G^*_i(d)$ statistic (Getis & Ord, 1992; Ord & Getis, 1995), which measures the clustering of similar values around a given point at a specified distance from that point, relative to the point pattern in the entire geographic surface. There are two uses to which we shall put the $G^*_i(d)$ statistic. First, it has the ability to locate "hot spots" where low or high values are clustered. These spatial clusters may then be investigated further (either qualitatively or quantitatively) to discover the sources of the clustering. The second use of the $G^*_i(d)$ statistic is as a spatial filter to extract the spatially autocorrelated portion of each of the variables in the regression variable, and then to reintroduce the spatial variable into the regression equation as a separate factor (Getis, 1995).

RESULTS

Crime Event Distribution

Of the 7,369 parcels within the study area, only 1589 (21.6 percent) experienced a crime incident. Only 764 (10.3 percent) experienced more than one crime event. The five parcels with the highest crime events are located in the top central portion (major commercial land use) of the study area and account for over 3,100 crime events representing nearly one third (31.2 percent) of all crimes in the study. Of the twelve parcels having histories of greater than 50 crime events, a review of land use and aerial photographs revealed that nine parcels (75 percent) were associated with a shopping center land use and associated businesses. Of the remaining three parcels, two were associated with schools and one with a multi-family residence. Examination of the aerial photography associated with these twelve high-crime incident parcels revealed several common geographic features that may be associated with increased crime activity. It is suspected that no single attribute is a dominant cause of increased crime activity by itself, but in combination with other elements, the net result is to make an individual parcel attractive as a location for perpetrating a criminal act. Eight of the nine shopping center parcels are associated with rapid freeway access. The single parcel without immediate freeway access possessed the lowest repeat crime incidence of the nine parcels. It is believed that this attribute contributes to concern about rapid ingress/egress by potential perpetrators. All shopping center parcels were adjacent to a major thoroughfare and had commercial parking lots serving multi-businesses.

It is believed that these attributes contribute to concerns about access and an ability to observe potential business targets or pedestrian victims. Parking lots appear to allow perpetrator presence and observation without raising suspicion. With multiple businesses serviced by a single parking lot, the presence of strangers (others business establishment customers) is common place and would not raise concern. All shopping center parcels with high crime rates have at least on parcel border consisting of a “dead” zone in which visibility and pedestrian access or both are limited. Those community shopping center parcels with the more than one parcel border bounded by a “dead” zone have higher crime rates than community shopping centers with a single “dead” zone borders.

Two of the twelve parcels having repeat-crime histories greater than 50 events are schools. It is suspected that the single greatest attribute associated with criminal activity on school parcels is not the physical environment of the school, but rather the concentration of individuals present in one place on a recurring basis. Review of the data base's crime event records show that the majority of incidents occur on weekdays when schools are in session. Peak event times during school days correspond to the mid-day lunch hour and the end of the school day. The ability to recognize the location of schools from aerial or remotely sensed images may suffice as a surrogate indicator of increased crime at the school parcel and in immediately surrounding parcels within a temporally short walk time of the school.

One of the twelve parcels having a crime event history greater than 50 events was a multi-residence parcel. This parcel shared similar characteristics in terms of legitimized public space (proximity to a communal parking lot and a public park), barriers limiting visibility and restricted pedestrian thoroughfare ("dead" zone) and proximity to a major thoroughfare as higher crime rate parcels. However, this single land use observation precludes drawing any conclusions, although the similarities are intriguing.

Statistical Analysis Results

Geographic information systems have been increasingly applied to crime statistics to map "hot spots"--places where crimes tend to cluster spatially (Johnson, 2000). The analysis showed that burglaries and assaults were most closely related to the proportion of land in each grid cell that was classified as non-vegetated, and a qualitative sense of clustering can be gleaned from examining that figure. However, the statistical analysis of clustering, using the G* statistic as discussed above, produced the results in Figure 4, which plots the grid cells in which the number of burglaries is clustered to a statistically significant degree (at the .05 level of statistical significance). These cells represent the burglary “hot spots” in Carlsbad.

[Figure 4 about here]

Regress analysis was used to test if independent variables can explain this spatial patterning of crime in Carlsbad. The independent variables are reduced to three indices of propensity after the principal component factor analysis to commit crime (based on demographic descriptors—“immigrant poor,” “poor, young, and Hispanic,” and “mobile and black”) and three indices of the opportunity to commit crime (based on census data, parcel data, and imagery data—“commercial,” “residential,” and percent non-vegetated). These predictor variables were regressed on each type of crime. Table 5 summarizes the results in terms of the adjusted R^2 and the statistically significant predictor variables.

[Table 5 about here]

The data in Table 5 show that the opportunity factor of being commercial was the single most important predictor of crime in the Carlsbad. This variable emerged as the most important statistically significant predictor of each type of crime under analysis in this study. Robbery was also influenced by the factor of Poor-Young-Hispanic, and the opportunity factor of residential areas that were disproportionately multiple family dwellings and vacant dwellings. Assault was influenced by the factor of Poor-Young-Hispanic, and also by the opportunity factor of the index of non-vegetation, meaning that areas that were less vegetated were more likely to be associated with assaults. Larceny and auto theft were influenced only by the commercial factor.

The results for burglary showed the highest level of prediction by our assembled set of variables, and the detailed results of the regression model for burglary are shown in Table 6. As is true with each type of crime, the identification of a grid cell as being commercial was the single most important predictor of where burglaries were occurring, but the socio-demographic profile associated with the immigrant-poor was also a significant predictor, as was the percent of the grid cell that was classified as being non-vegetated. The image classification appears to be a surrogate for the areas that are more densely built-out and that are proximate to the commercial areas. On its own, the index of non-vegetation is able to explain 22 percent of the variation in crime in Carlsbad. In combination with the other variables, it explained nearly half (48 percent) of the spatial variability in crime in Carlsbad.

[Table 6 about here]

The regression model for the prediction of burglaries, as shown in Table 5, was tested for autocorrelation in the residuals. If a statistically significant level of autocorrelation were present, it would indicate that a correction would be necessary in the regression results and thus the spatial filtering process described above would have been appropriate. The possibility of autocorrelation was heightened, of course, by the fact that the census data were collected at the block group level, but we applied those data to a smaller areal unit of the 300 meter grid cell. Thus, contiguous grid cells might have identical values for census-derived variables. However, the residuals were not spatially autocorrelated, indicating that the spatial component of the relationship is included within the data themselves. Therefore, no additional adjustment was necessary. As a result, we can proceed directly to an assessment of the usefulness of the regression results. Could we predict the burglary hot spots in Carlsbad based solely on the combination of census data and the data derived from the remotely sensed images?

The answer is shown graphically in Figure 5, where it can be seen that the hot spots predicted by the regression model, calculated using the G* statistic, are centered on the same hot spots generated by the crime data alone. The predicted values are not quite so tightly focused geographically as are the actual data, but nonetheless the data suggest that the combination of census and remotely sensed data may, on their own, be powerful predictors of where burglaries are occurring in a community, largely because they help to identify those places in which the apparent opportunities for burglaries exist.

[Figure 5 about here]

It should be noted that our model does not include a feedback mechanism and so it is not able directly to capture the dynamic nature of crime as outlined by Freeman and his associates (1996), in which it is hypothesized that high crime areas beget additional crime because the probability of arrest declines as the number of criminals increases, thereby increasing the motivation to engage in criminal behavior. However, to the extent that those neighborhoods in which crime does exist are identified by the variables we have included in the model, then the feedback should be incorporated indirectly into the standardized beta coefficients of the neighborhood variables.

SUMMARY AND CONCLUSIONS

This chapter illustrates that crime locations are not spatially random and that place characteristics influence the decision to commit a crime. The study also suggests that certain land use activities are more attractive to criminal activity than are others, including commercial areas and residential areas dominated by apartments. Additional location factors such as proximity to freeway on/off ramps, location adjacent to a major thoroughfare, the presence of parking lots that serve multiple businesses, and the presence of visibility and pedestrian-thoroughfare barriers also contribute to making some shopping center locations more attractive to the commission of crime than parcels lacking these attributes.

The study also suggests that many of the location factors which make certain land parcels attractive to committing a crime can be observed and mapped from aerial photographs and high-resolution remotely sensed imagery. Aerial photography and remotely sensed imagery having spatial resolutions sufficient to detect and identify features with spatial dimensions less than one meter are necessary to identify the surrogate crime variables identified in the study. Color imagery was superior to panchromatic imagery in the detection and identification process. These approaches to the use of remotely sensed images will tend to be community-specific and require detailed interpretation of the images.

It is demonstrated that the classification of a satellite image into an index of non-vegetation facilitated the prediction of where burglaries occurred in the study site, and increased the prediction of geographic hot spots of burglary. The prediction of these hot spots did not reveal any startling new information to the local police department when this information was presented to them, but it did quantify their otherwise *ad hoc* impressions of where criminal activity was concentrated within their community. This process of quantification can be important as a policy tool to direct attention to the exact policing needs in the community.

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Figure 1 Map showing the location of the City of Carlsbad and the study area located in the northwest portion of the city

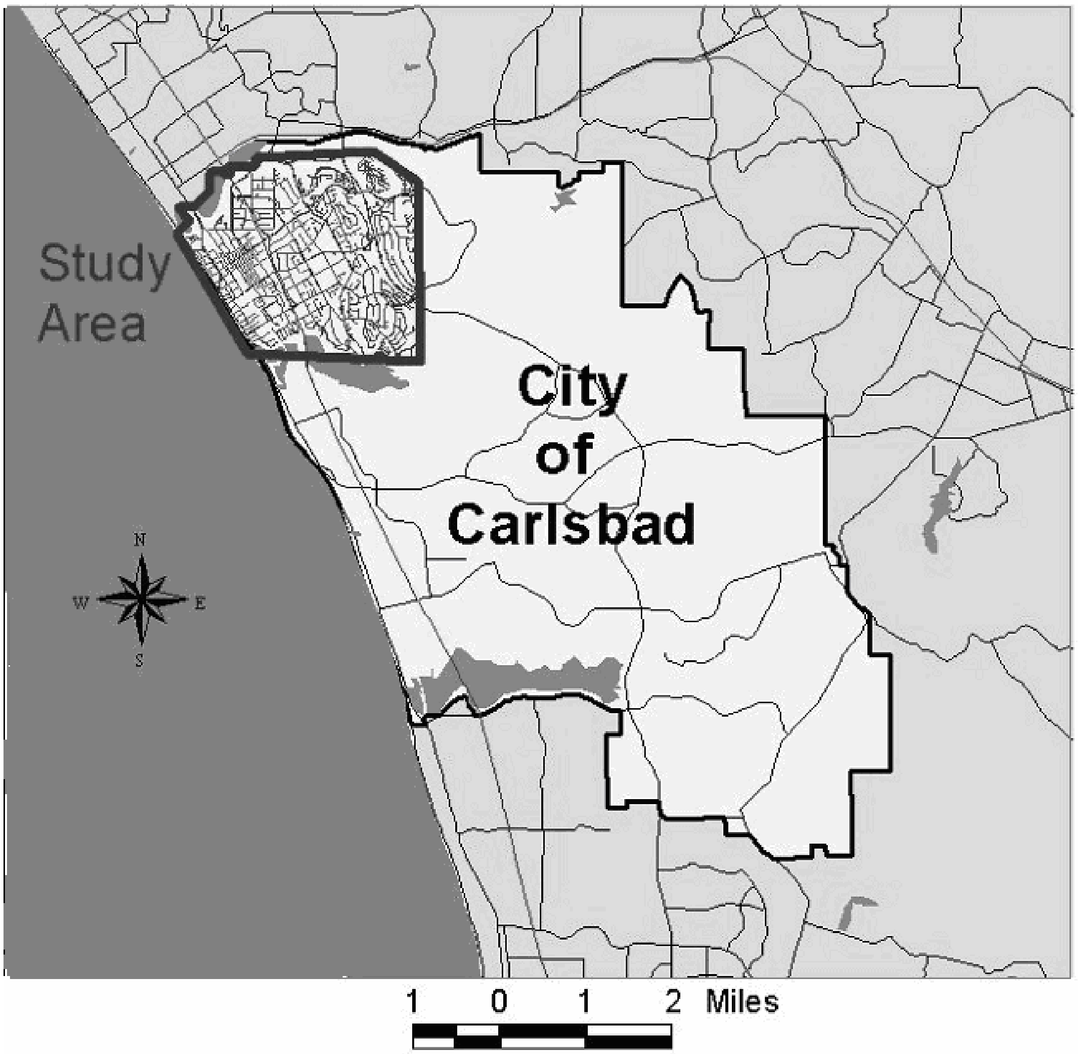

Figure 2 Distribution of Part I crime events by geocoded street address

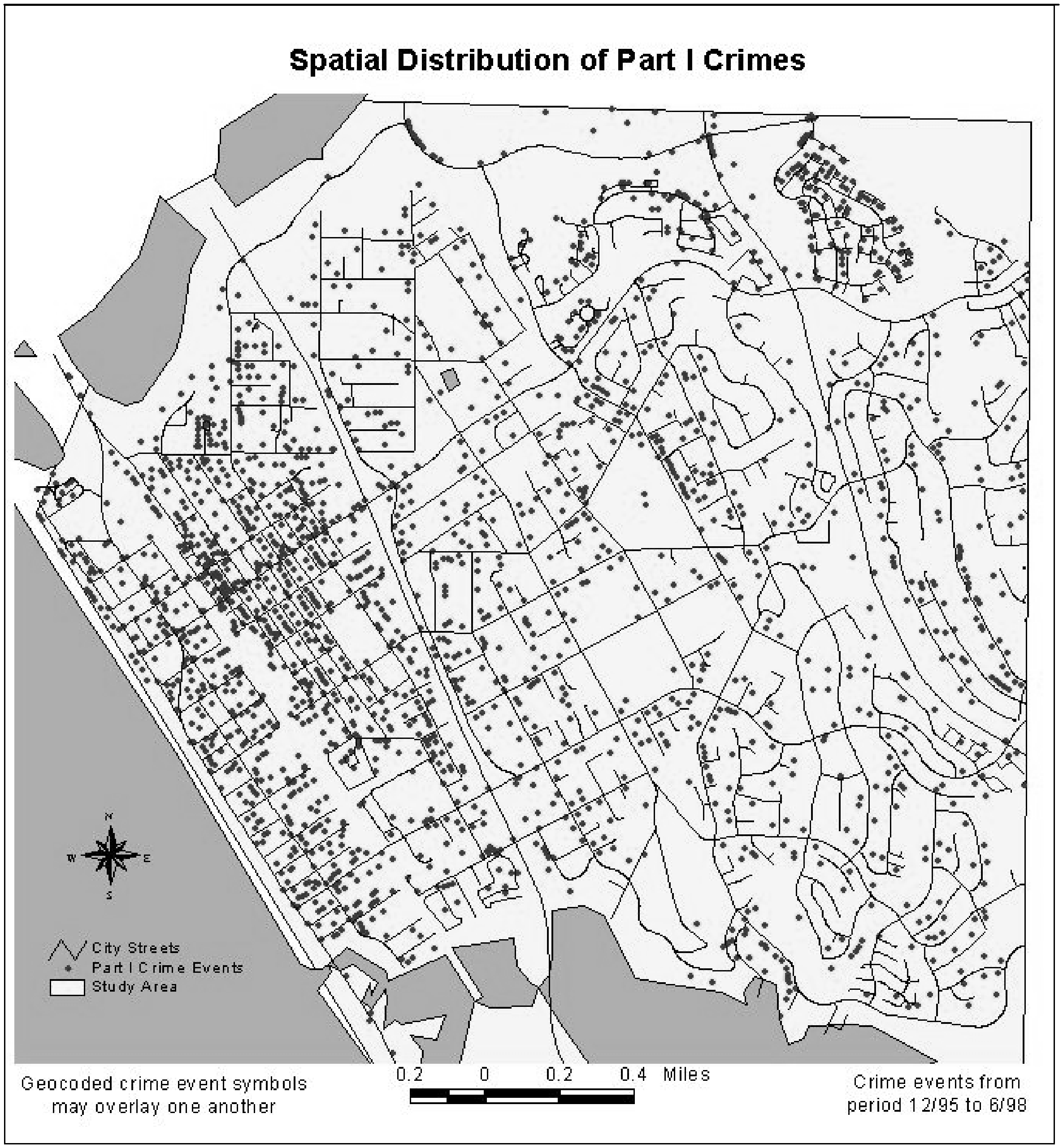

Figure 3 Percent Non-Vegetation by Grid Cell in Study Area

Figure 4 Burglary Hot Spots in the Study Area using G* statistic

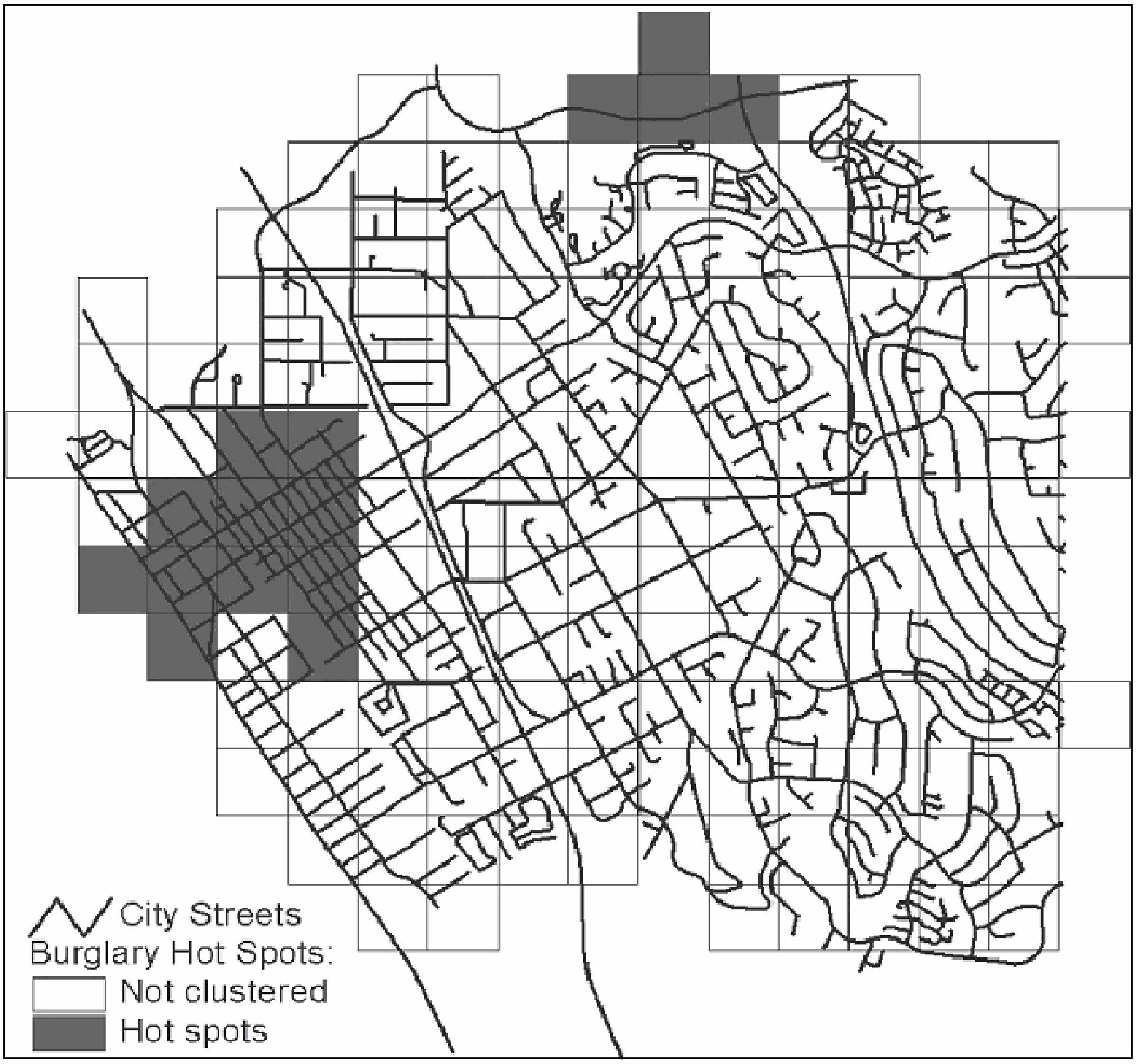

Figure 5 Burglary Hot Spots in Carlsbad Predicted by the Combination of the Factors "Commercial," "Immigrant-Poor," and "Percent non-vegetated"

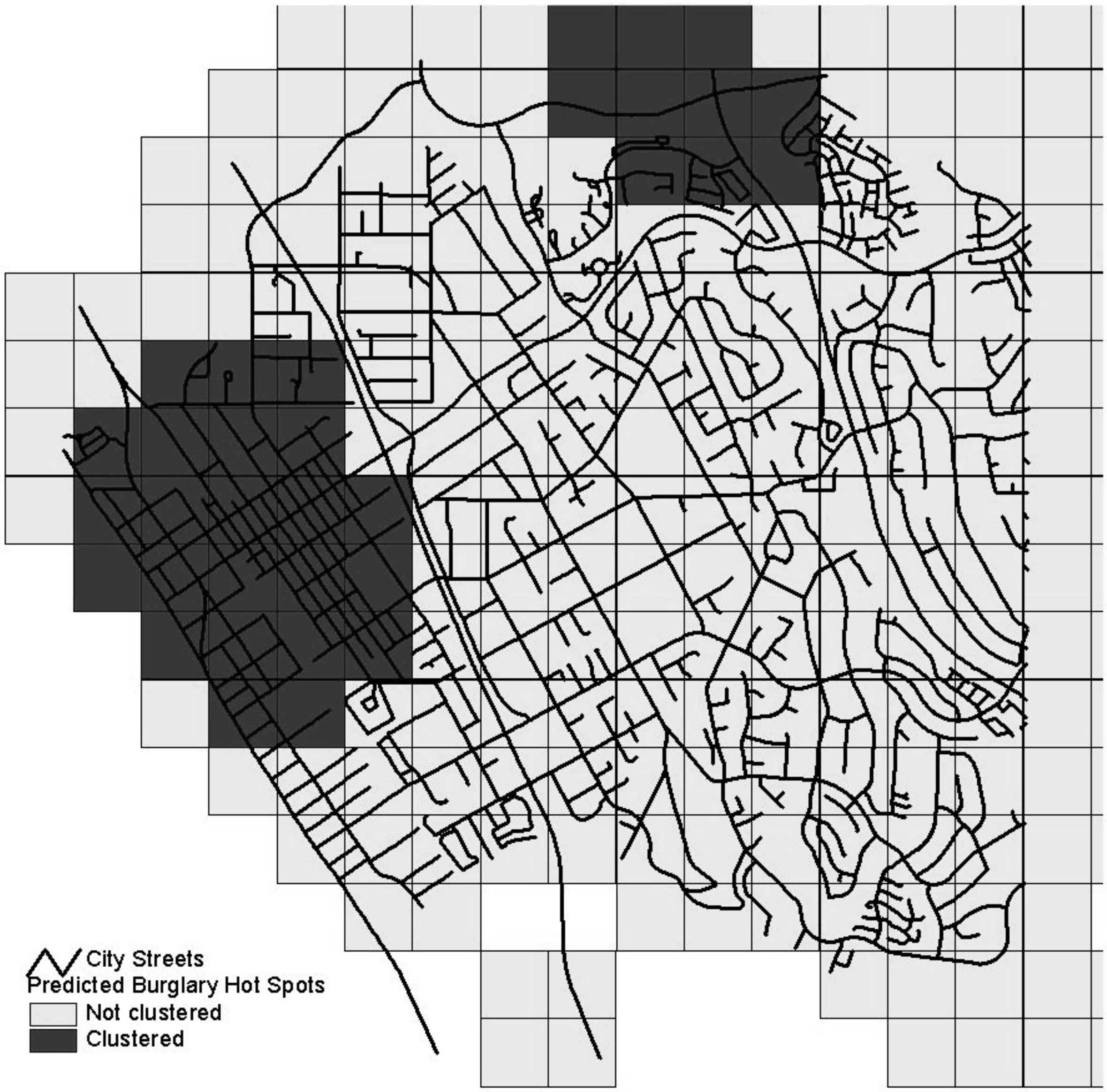

Table 1 Crime categories and counts in Carlsbad, California, for the period from December 1995 through June 1998

Part I Crime Category	**Count**	**Percent**
Arson	30	0.3%
Assault	1,717	16.7%
Burglary	1,861	18.1%
Larceny (Theft)	5,574	54.3%
Robbery	285	2.8%
Vehicle Theft	789	7.7%
	10,256	100.0%

Table 2 Summary Measures Used in Data Analysis, Based on 300m Grid Cell for Study Site

Type of variable	**Variable name**	**Short name**	**Mean**	**Median**	**Standard Deviation**
Dependent	All Part I crimes	ALLCRIM	41.58	11.5	95.43
	Robbery	ROBBREY	1.13	0.00	3.75
	Assault	ASSAULT	4.92	1.00	9.94
	Burglary	BURGLRY	6.55	3.00	9.57
	Larceny	LARCENY	24.42	6.00	69.30
	Auto Theft	AUTOTHFT	4.32	1.00	12.77
	Arson	ARSON	0.11	0.00	0.42
Independent - Propensity	Percent at or below poverty level	PCTPOVTY	6.94	4.61	5.89
	Percent unemployed	PCTUNEMP	5.40	4.26	8.57
	Percent high school or less	PCTHS	31.55	28.10	10.37
	Percent in same house 5 years ago	PCTNOMIG	32.91	34.23	15.43
	Percent not proficient in English	PCTNOENG	17.86	16.58	13.91
	Percent aged 15-24	PCT1524	13.76	13.55	4.77
	Percent Hispanic	PCTHISP	14.98	10.02	13.28
	Percent Black	PCTBLCK	1.62	1.29	1.10
	Percent housing units that are small (less than 3 bedroom)	PCTSMHS	17.12	15.45	13.84
	Percent housing units that are renter-occupied	PCTRENT	36.39	36.73	19.36
	Percent households that are one-person	PCT1PHH	21.97	19.05	9.54
Independent - Opportunity	Proportion of are classified as non-vegetation	NONVEG	0.52	0.50	0.18
	Percent of area used for parking	PCTPARKG	3.04	0.00	8.17
	Percent of area used for commercial	PCTCOMM	6.35	0.00	19.45
	Percent of area used for multiple- family dwellings	PCTMULTI	9.82	0.00	22.88
	Percent of housing units that are apartments	PCTAPTB	29.76	31.05	21.07
	Percent of housing units that are vacant	PCTVACNT	7.53	6.53	7.20

Table 3 Rotated Component Matrix Reducing the Number of Independent "Propensity" Variables

Original Variable:	Component 1 Immigrant Poor	Component 2 Poor, Young, Hispanic	Component 3 Mobile and Black
PCT1PHH	.933	.022	-.057
PCTSMHS	.884	.355	.163
PCTRENT	.757	.401	.410
PCTHS	.710	.496	-.133
PCTNOENG	.703	.517	.185
PCTPOVTY	.505	.767	.113
PCTUNEMP	.097	.736	-.106
PCTHISP	.549	.697	.071
PCT1524	.404	.612	.471
PCTBLCK	-.132	.197	.893
PCTNOMIG	-.258	.361	-.719

(Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization; Rotation converged in 7 iterations)

Table 4 Rotated Component Matrix Reducing the Number of Independent "Opportunity" Variables

Original variable:	Component 1 Commercial	Component 2 Residential
PCTPARKG	.916	.007
PCTCOMM	.909	.007
PCTAPTB	.252	.798
PCTVACNT	-.120	.775
PCTMULTI	.387	.425

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 3 iterations.

Table 5 Predicting Crimes in Carlsbad

Type of Crime	R	R^2	Statistically significant predictor variables (in order of size of standardized beta coefficient)
Burglary	0.700	0.486	Commercial, Immigrant Poor, Non-vegetation index
Robbery	0.610	0.356	Commercial, Poor-Young-Hispanic, Residential
Larceny	0.599	0.346	Commercial
Assault	0.562	0.303	Commercial, Non-vegetation index, Poor-Young-Hispanic
Auto Theft	0.484	0.225	Commercial
ALL PART I	0.642	0.400	Commercial

Table 6 Which Factors Best Predict Where Burglaries Occur in Carlsbad?

Variable	Beta	T	Significance
Commercial *(opportunity=pct commercial+pct parking)*	0.486	7.850	0.000
Immigrant Poor *(propensity=pct no english+pct high school or less+pct renters+pct small house+pct 1 person hh)*	0.250	2.334	0.021
Percent non-vegetated	0.168	2.388	0.018
R = .704; Adjusted R^2 = .483			
Dependent variable = Number of burglaries in grid cell			

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