Public Safety Canada / Sécurité publique Canada

ARCHIVED - Archiving Content

ARCHIVÉE - Contenu archivé

Archived Content

Information identified as archived is provided for reference, research or recordkeeping purposes. It is not subject to the Government of Canada Web Standards and has not been altered or updated since it was archived. Please contact us to request a format other than those available.

Contenu archivé

L'information dont il est indiqué qu'elle est archivée est fournie à des fins de référence, de recherche ou de tenue de documents. Elle n'est pas assujettie aux normes Web du gouvernement du Canada et elle n'a pas été modifiée ou mise à jour depuis son archivage. Pour obtenir cette information dans un autre format, veuillez communiquer avec nous.

This document is archival in nature and is intended for those who wish to consult archival documents made available from the collection of Public Safety Canada.

Some of these documents are available in only one official language. Translation, to be provided by Public Safety Canada, is available upon request.

Le présent document a une valeur archivistique et fait partie des documents d'archives rendus disponibles par Sécurité publique Canada à ceux qui souhaitent consulter ces documents issus de sa collection.

Certains de ces documents ne sont disponibles que dans une langue officielle. Sécurité publique Canada fournira une traduction sur demande.

Canada

Spatial Analyses of Crime

by Luc Anselin, Jacqueline Cohen, David Cook, Wilpen Gorr, and George Tita

ABSTRACT

The new century brings with it growing interest in crime *places.* This interest spans theory from the perspective of understanding the etiology of crime, and practice from the perspective of developing effective criminal justice interventions to reduce crime. We do not attempt a comprehensive treatment of the substantial body of theoretical and empirical research on place and crime but focus instead on methodological issues in spatial statistical analyses of crime data. Special attention is given to some practical and accessible methods of exploratory data analysis that arguably should be the starting place of any empirical analyses of the relationship of place to crime. Many of the capabilities to support computerized mapping and spatial statistical analyses emerged only recently during the 1990s. The promise of using spatial data and analyses for crime control still remains to be demonstrated and depends on the nature of the relationship between crime and place. If spatial features serve as actuating factors for

Luc Anselin is a Professor in the Department of Agricultural and Consumer Economics of the University of Illinois at Urbana-Champaign and is a member of the National Consortium on Violence Research. Jacqueline Cohen is a Principal Research Scientist at the H. John Heinz III School of Public Policy and Management at Carnegie Mellon University and is a member of the National Consortium on Violence Research. David Cook works in crime analysis for the Greensboro, North Carolina, Police Department. Wilpen Gorr is Professor of Public Policy and Management at the H. John Heinz III School of Public Policy and Management at Carnegie Mellon University. George Tita is Associate Policy Analyst for the Criminal Justice Program at The RAND Corporation and is a member of the National Consortium on Violence Research.

crime, either because of the people who or facilities that are located there, then interventions designed to alter those persons and activities might well affect crime. Alternatively, if the spatial distribution of crime is essentially random, then targeting specific places is not likely to be an effective crime control strategy. Sorting out the place/crime relationship requires analytical methods that are best suited to isolating the impacts of place on crime.

As we near the end of the 20th century, interest in crime *places* continues to grow. The identification of crime hot spots (Sherman, Gartin, and Buerger 1989) was perhaps a watershed in refocusing attention on spatial/locational features of crime. This interest spans theory from the perspective of understanding the etiology of crime, and practice from the perspective of developing effective criminal justice interventions to reduce crime. Theoretical concerns focus on how place might be a factor in crime, either by influencing or shaping the types and levels of criminal behavior by the people who frequent an area, or by attracting to an area people who already share similar criminal inclinations. These theoretical concerns, which are ably addressed in a growing published literature on the criminology of place, are only briefly discussed in this paper.[1] We focus instead on the analytical methods best suited to isolating the impact of place on crime.

Technological advances, primarily in computer capabilities, are fundamental to recent analytical advances in the methods available for analyzing place-based crime data. The advent of computer mapping applications and accompanying geographic information systems (GIS) are crucial to being able to measure and represent the spatial relationships in data. Perhaps the most powerful analytical tools emerging from GIS technologies are (1) flexible spatial aggregation capabilities to facilitate the measurement of place-based crime and (2) simple contiguity matrices for representing neighbor relationships between different areal units. In addition to these analytical advances, computerized police records management systems and computer aided dispatch (CAD) systems of citizen calls to police make it possible to systematically quantify varying levels of criminal activity at different places within a city.

The paper that follows begins with a brief overview of some conceptual links between place and crime. We do not attempt a comprehensive treatment of the substantial body of theoretical and empirical research on this topic. Our intent is merely to provide an illustrative context for the main focus of the paper—spatial statistical analyses of crime data with special emphasis on pragmatic concerns about how these analyses are best implemented. The text guides readers through a variety of methodological concerns relating to the analysis of spatial data and space/time data. Perhaps the most valuable service is to direct analysts to relevant parts of a growing research literature, with many sources published only recently. Thorny issues are raised, not to warn analysts off altogether, but rather to encourage the exercise of due caution in the conduct and interpretation of empirical analyses. Special attention is given to some practical and accessible methods of exploratory data analysis that arguably should be the starting place of any empirical analyses of the relationship of place to crime.

Routine activities that bring together potential offenders and criminal opportunities are especially effective in explaining the role of place in encouraging or inhibiting crime. The resulting crime locales often take the form of facilities—places that people frequent for a specific purpose—that are attractive to offenders or conducive to offending.

Crime and Place

In this section, we briefly review some theoretical and empirical developments in research on crime and place. These trace back to the work of the early social ecologists in France during the middle of the 19th century, through the sociological tradition emerging from the Chicago School in the early 20th century, and finally to the recent revival of this tradition in contemporary ecological studies of crime. The social ecology perspective evolved into more specifically focused, place-based theories of crime, particularly the routine activities theory. Routine activities that bring together potential offenders and criminal opportunities are especially effective in explaining the role of place in encouraging or inhibiting crime. The resulting crime locales often take the form of facilities—places that people frequent for a specific purpose—that are attractive to offenders or conducive to offending. Facilities might provide an abundance of criminal opportunities (e.g., either a target-rich environment for thefts or abandoned or otherwise unguarded properties that could be used for illicit activities like drug dealing). Or they might be the sites of licit behaviors that are associated with increased risk of crime (e.g., heavy alcohol consumption in crowds where disputes can easily turn violent). The relationship between specific types of facilities and observed crime hot spots is an important question, and these chronic crime places are particularly well suited for further empirical investigations of the distinctive criminogenic features associated with place.

Social ecology theories of crime

Early social ecologists

Invariably, research articles that focus on the concentration of crime in distinct types of communities cite the work of the early French social ecologists Guerry ([1833a] 1984, [1833b] 1974) and Quetelet (1833, 1842).[2] As in Durkheim's classic studies of suicide ([1897] 1966) and crime ([1901] 1950) a half-century later, Guerry and Quetelet were interested in explaining differences in community crime levels in terms of the varying social conditions of the resident populations. It is humbling to see the level of analytical sophistication displayed in their early maps of population-based rates of crime, suicide, alcoholism, population age structure, family structure, educational levels, and population diversity in 19th-century French "Departments" (i.e., geopolitical areas analogous to contemporary States or provinces). These historical works are among the earliest examples of a type of empirical social research that falls within the tradition of ecological studies of crime—that is, studies in which the units of analysis are spatially defined population aggregates.

The next flourishing of ecological research on crime was in the early 20th century. More than any other academic body of work, the Chicago School of the early 1920s is responsible for the emergence of ecological studies in sociological research (for example, Park, Burgess, and McKenzie 1925). The Chicago School represents a sociological paradigm that encourages a synthesis of qualitative and quantitative methods. While many view it as atheoretical and primarily empirical, it is difficult to deny its importance in theoretical developments in community studies and criminology.[3] As Abbott (1997, 1152) writes:

> [T]he Chicago School thought—and thinks—that one cannot understand social life without understanding the arrangements of particular social actors in particular social times and places. . . . [N]o social fact makes any sense abstracted from its context in social (and often geographic) space and social time. Social facts are *located facts.* (emphasis in original)

The original data of the Chicago School were records obtained from the Cook County (Illinois) Juvenile Court, Boys' Court and Jail. They included basic demographic measures like age and sex of each offender, along with the offender's home address. The following passage from Bursik and Grasmick (1993, 31) describes the procedure used by Shaw and colleagues to map these data:

> The residential address of each individual . . . was plotted (by hand!) on a base map of the city of Chicago (see Shaw et al. 1929:24) [sic] for a full description of the process) and then copied into outline maps of Chicago by means of a reflector and glass-top table. . . . The rates of delinquency (defined in terms of the number of boys referred to juvenile court) were then computed on the basis of census tracts, the official local community areas of Chicago, and one-square-mile areas of the city, which was their most common operational definition of the neighborhood.

Though not causally related, recent developments of widely accessible computerized mapping and spatial analysis techniques have accompanied the resurgence in popularity of ecological explanations of crime.

Relying only on "visual inspection . . . and rudimentary statistical tests" (Bursik and Grasmick 1993) of the resulting spatial distribution of offenders, Shaw and McKay (1942)[4] emerged with their seminal findings regarding the stability of delinquency over time within certain neighborhoods and the negative relationship between crime and distance from the central business districts. The social disorganization theory of crime was born from these observations.

Other important work on crime and place emerging from the original Chicago School includes Thrasher's (1927) census of urban street gangs. Mapping the locations where gangs formed, Thrasher found "gangland" in the "interstitial" areas of Chicago, and not in areas that could easily be labeled as "commercial" or "residential." Gangs form where "better residential districts recede before the encroachment of business and industry" (p. 23). Understandably, Thrasher did not undertake what was then a formidable task of cataloging all of the features that distinguish "gangland" from nongang areas. With the advent of computers, and perhaps more importantly, the accessibility of computerized census data, this task is much more easily managed today.

The "new" Chicago School

A featured plenary session at the 1996 annual meeting of the American Society of Criminology held in Chicago addressed the question, "Whither the Chicago School?" As an esteemed panel of former Chicago School students and mentors discussed the past, present, and future of Chicago-style ecological studies, it became clear that we are currently in the midst of a Chicago School revival.[5] Over the past two decades, a number of excellent studies have resurrected and advanced the methodological and theoretical traditions of the original Chicago School.[6] Though not causally related, recent developments of widely accessible computerized mapping and spatial analysis techniques have accompanied the resurgence in popularity of ecological explanations of crime. The new GIS capabilities that permit flexible measurements at various levels of spatial aggregation have facilitated many recent analyses of ecological features of crime.

For instance, relying on their ability to map the location of homicides, aggregate these point locations to census tracts, and then examine the distribution of gang homicides controlling for "social disorganization," Curry and Spergel (1988) find crime to be correlated with poverty and a lack of social control, but violence (e.g., homicide) to be correlated with their measure of social disorganization. Tita, Engberg, and Cohen (1999) provide another contemporary ecological study of gangs. They find that the areas where gangs form are low on a variety of measures of informal social control and share features associated with the "underclass." Furthermore, once racial composition is accounted for, their measure of social disorganization is not predictive of gang location. Gangs form in high-crime neighborhoods, but the arrival of gangs in an area does not alter local crime levels. The notable exception is a significant increase in shots fired after gangs form in an area (Tita 1999).

An excellent example of the blending of quantitative spatial measures with qualitative observational studies is Bernard Cohen's (1980) ecological study of street-level prostitution in New York City. Cohen finds that streetwalking spans all levels of income across neighborhoods and census tracts of Manhattan. However, he noticed important similarities in the block faces and street corners frequented by prostitutes and johns. Using hand-drawn maps, Cohen identified "hot spots" of prostitution activity. Relying on participant observation, he recorded and quantified the amount of deviance in the study areas, as well as the age, race, and gender of nearby residents. He extrapolated family structure from census tract data.

Areas with a high incidence of prostitution were notable in their absence of young children and young women. Not surprisingly, households in these areas were much more likely to be made up of single adults and unrelated roommates. Cohen also noted several important crime-enhancing features of the built environment, such as wide streets (to provide inconspicuous traffic flow of johns through the area), the types of business establishments in the area (to attract the "right" clientele), and the spatial proximity of unlit alleys, parks, or lots (to provide locations for sex acts). Although not widely recognized as such, Cohen's (1980) book, *Deviant Street Networks*, may be one of the first empirical studies to document the spatial and temporal intersection of "motivated" offenders and the crime-facilitating properties of place proposed by the routine activities theory (Cohen and Felson 1979).

Bernard Cohen's work underscores the importance of specifying the correct areal unit of analysis in ecological studies. When examining the presence of streetwalkers as a function of various socioeconomic measures aggregated to the level of neighborhoods or census tracts, there were few differences between areas with prostitution and those without. It is only when Cohen examined sub-census tract variation that important differences emerged. Modern GIS capabilities, combined with point data on the locations of individual crimes, make it feasible to routinely obtain measures of crime variables at these nontraditional and smaller levels of aggregation.

Place-based theories of crime

Ecological theories look for explanations of individual actions in general features of the social structure in which an individual is embedded. Place-based theories fall squarely within the theoretical tradition of social ecology, but are more specific about the mechanisms by which structural context is translated into individual action. The dominant theoretical perspectives derive from the routine activities theory (Cohen and Felson 1979) and rational choice theory (Cornish and Clarke 1986). In both cases, the distribution of crime is determined by the intersection in time and space of suitable targets and motivated offenders. This spatial and temporal intersection is determined by the organization of certain types of activities at specific places, ranging from highly structured environments like work and school to less structured environments in the home and leisure places.

Routine activities

The routine activities theory was first introduced in Cohen and Felson (1979), later refined in Felson (1986, 1994), and extended to crime pattern theory in Brantingham and Brantingham (1993). Place is central to this perspective, serving as the locus where *motivated offenders* come together with *desirable targets* in the absence of *crime suppressors* (who include guardians, intimate handlers [Felson 1986], and place managers [Eck 1994]). This convergence of crime opportunities in space and time is facilitated by various situational features, of both the physical and social variety, that provide a context or setting that is more or less conducive to crime (Clarke 1992).

Place can facilitate (or inhibit) crime in two ways. First, the physical or built features of a place can decrease the social control capacities of various crime suppressors. Such concerns motivate interest in the design of "defensible space" (Jeffrey 1971; Newman 1972). For example, Newman's study of public housing suggests that highrise housing increases population density, but because residents live vertically, they are physically removed from monitoring activities in public spaces, especially those at street level.[7] These conditions leave this type of housing with relatively few place managers who will monitor and control public behavior and seriously limit the levels of informal social control exercised over all forms of disruptive behavior from minor incivilities to more serious illicit activities. Roncek and Francik (1981) find elevated crime levels in and near public housing even after including controls for the composition of the resident population on a variety of attributes. This provides support for a criminogenic role of the facility itself that is independent of the types of people who are found there.

Second, aside from physical features, crime at places is apparently influenced by the routine activities that occur there. Crime is not distributed evenly or randomly over space. Instead, higher levels of crime plague places with some types of facilities and not others. In some cases, crimes seem to be elevated by a target-rich environment—for example, thefts of 24-hour convenience stores, auto thefts from large parking lots, or robberies of shoppers in heavily frequented commercial areas (e.g., Engstad 1975; Duffala 1976; Brantingham and Brantingham 1982). In others, certain activities such as alcohol consumption seem to contribute to increased levels of violence (Roncek and Bell 1981; Roncek and Pravatiner 1989; Roncek and Maier 1991; Homel and Clark 1995; Block and Block 1995). Still other places seem to be prone to higher levels of crime because of the types of people they attract and repel. Places with abandoned buildings or rundown housing with absentee owners are attractive to illicit drug dealers who are looking for places where they can establish stable marketing locations without fear of owner or neighbor complaints (Eck 1994).

Crime hot spots

The concentration of crime in identifiable places was noted in Brantingham and Brantingham (1982). These crime hot spots are prime exemplars of the potential value of place in the analysis of crime. Sherman, Gartin, and Buerger (1989) published one of the first studies to quantify what many qualitative studies had suggested—namely, that crime in a city is highly concentrated in relatively few small areas. The study found that 3.3 percent of street addresses and intersections in Minneapolis generated 50.4 percent of all dispatched police calls for service. Similar patterns emerged in other cities (Pierce, Spaar, and Briggs 1988; Sherman 1992; and Weisburd and Green 1994). While often motivated by pragmatic concerns about what interventions are likely to be effective in reducing crime, results like these also serve to sharply focus crime theory on developing satisfactory accounts of these apparently strong relationships between crime and place.

Crime studies that examine the spatial distribution of crime clearly demonstrate that certain land uses and population characteristics are associated with crime hot spots. Roncek and Maier (1991) found a positive relationship between levels of crime and the number of taverns and lounges located in city blocks in Cleveland. The influence of taverns on crime was compounded when the taverns were located in areas with more anonymity and lower guardianship. Five of the top ten hot spots identified in Sherman, Gartin, and Buerger (1989) included bars. Cohen, Gorr, and Olligschlaeger (1993) found that drug hot spots tended to be in areas with nuisance bars, rundown commercial establishments, or areas with poverty and low family cohesion as measured by female-headed households.

Skogan and Maxfield (1981) reported that environmental conditions such as abandoned buildings, public incivilities such as fights and other minor assaults, disorderly youths, broken windows or other forms of vandalism, public drug use or drinking, prostitution, loitering, noise, litter, and obscene behavior increase community fear of crime. "Broken windows" and other public signs of disorder may also contribute to actual increases in more serious crime as visible signs of urban disorder signal that a community has lost its ability to exercise social control, further encouraging and perpetuating crime (Wilson and Kelling 1982; Greenberg, Rohe, and Williams 1985). Likewise, vigorous law enforcement strategies directed against various forms of public disorder and nuisance violations may actually inhibit more serious crimes by establishing visible signs of a vigilant and self-protective community (Boydstrun 1975; Wilson and Boland 1978; Pate et al. 1985; Sherman 1986; Sampson and Cohen 1988; Kelling and Coles 1996). This suggests that crime hot spots may arise first as concentrations of "soft" crimes that later harden to more serious crimes.

Whether or not hot spots contribute to crime in a causal way depends on whether or not the elevated levels of crime observed at hot spots are systematic (regular and predictable) and not just random occurrences. If hot spots are random and can occur anywhere, then crime in these locations does not depend on distinctive features found in the observed hot spots; and crime reduction efforts that target these features are likely to fail. Thus, careful identification of hot spots and methodologically sound analyses to establish whether they have meaningful links to crime are crucial.

Spatial Data Analysis Tools

The spatial concentration of crime in hot spots leads naturally to their representation on crime maps. Maps of crime incidents permit rapid identification of the geographic location of crime hot spots, but by themselves they contribute little to understanding why crime is concentrated in certain locations. A crucial aspect of pattern recognition techniques such as hot spot analysis is the determination of the extent to which patterns on the map reflect "true" clusters or outliers or whether they are spurious. As is well known, simple visual interpretation of the map is inadequate in this respect because the human mind is conditioned to find meaning and identify patterns and clusters, even when the data represented may be purely random. The use of sound cartographic principles alone does not ensure that a proper interpretation is obtained (Rheingans and Landreth 1995; Gahegan and O'Brien 1997; MacEachren and Kraak 1997). What is needed is a careful structuring of the visualization strategy while supplementing the visual aspects with quantitative information (Cleveland 1993).

Hot spot representation

A crime hot spot is a location, or small area within an identifiable boundary, with a concentration of criminal incidents. These chronic crime places where crime is concentrated at high rates over extended periods of time may be analogous to the small percentage of chronic offenders who are responsible for a large percentage of crime.[8] To date, little is known about the actual life cycle of crime hot spots. Sherman (1995) and Spelman (1995) were first to invoke many features of offender criminal careers to describe careers of hot spots in terms of processes like initiation, growth, crime-type hardening or escalation in crime seriousness, persistence, decline, displacement, and termination. Their research also broke new ground by beginning to empirically explore the merits of this characterization, looking for evidence of sustained offending over time in some locations.

Minimally, crime hot spots share the key features of a boundary and criminal events within that boundary (e.g., 911 calls, offense reports). Perhaps the easiest means of identifying hot spots is to partition a jurisdiction into a fixed set of boundaries (e.g., square grid cells, census block groups, or some other boundary set) and to develop a set of rules (a "rule base") using threshold values. Sherman and Weisburd (1995) objectively defined hot spots in terms of location, time interval, crime types, and number of events.

Suppose that the boundaries are square grid cells of a fixed size and origin. Then a rule for hot spot *initiation* at any grid cell might be the following: If the cell were not a hot spot in the previous time period but the number of crimes of a designated type now exceeds a specified threshold value, then the cell becomes a hot spot during the current period. A rule base will incorporate life cycle states, time intervals, threshold crime counts, and changes in crime counts. Gorr, Olligschlaeger, and Szczypula (1998) are designing such a rule base to empirically explore the numbers, durations, branching probabilities, crime mixes, and concentrations of hot spots.

The choice of boundaries—fixed or ad hoc—is of particular interest in representing hot spots. Fixed boundaries (e.g., census tracts, police precincts, or uniform grid cells) have the advantage of giving rise to the space/time series data commonly used for crime reporting and spatial modeling. Their disadvantage is that hot spots may cross the fixed boundaries or vary in size. One example of ad hoc clustering of observed crime point data are the ellipses created in STAC (Spatial and Temporal Analysis of Crime) software (Block 1994). Such boundaries have the advantage of yielding sizes and shapes tuned specifically to individual hot spots. They, however, do not yield a consistent collection of space and time series data on crimes and enforcement activities. As modelers, we prefer fixed boundaries.

Hot spots are, by definition, small in area. Using visual inspection of pin maps and threshold counts for "hard" and "soft" crimes, Sherman and Weisburd

(1995) identified hot spots in Minneapolis, Minnesota, of no more than one linear block of a street—an area in which a police officer can easily see and be seen. Hot times were between 7:00 p.m. and 3:00 a.m. For drug markets in Jersey City, New Jersey, hot spots were defined by intersections and the four connected street blocks, and hot times were from noon to midnight (Weisburd and Green 1994). This scale may be too small for most practical purposes. For example, hot spots may move short distances over short time periods (e.g., displacement to nearby locations in response to enforcement activities). Hot spot areas of a few blocks in size or even larger may better accommodate such sporadic short-term moves within what is essentially the same activity space.

The presence of variations in the estimated effects of models arising from differences in the areal units that are selected for analysis is known as the modifiable areal unit problem (MAUP) in geography (Holt et al. 1996). Widely varying parameter estimates can result from reaggregating data by areal units of different sizes. For example, Gehlke and Biehl (1934) found that correlation coefficients tended to increase with the level of aggregation of census tracts. Fotheringham and Wong (1991) found that changes in the parameter estimates of multiple linear regression models were complex and unpredictable when changing the scale at which data were collected and aggregated. Though important in theory, MAUP is likely to be of less concern in analyses of hot spots, because size is often dictated by the need to represent crime hot spots for enforcement purposes, and this function constrains the range of relevant sizes.

Hot spot modeling and analysis

Understanding the relationship between place and crime requires knowledge of the dynamics of hot spot development over space and time, with special attention to the ways that a location's facilities and utilization contribute to criminal behavior. This sort of knowledge can be derived from combining theory with exploratory and confirmatory empirical research. Several kinds of spatial models and analyses are appropriate for hot spots. Preliminary to actual causal models, these include descriptive models and predictive models.

Descriptive models

The life cycle of hot spots includes various stages of development, the duration of time spent in each stage, and branching probabilities of transitions between the stages. A better understanding of hot spots requires space and time data of crime and its covariates for a sample of cities. Those data should include a consistent rule base for classifying fixed areas into non-hot spots and hot spots at different stages of development. Then analysts will have a better basis for distinguishing random stochastic phenomena, such as regression to the mean (some hot spots fade on their own accord), from systematic hardening of soft-crime hot spots to more serious crimes.

Predictive models

After description, the next step in understanding hot spots is building successful predictive models. For example, the "broken windows" hypothesis posits that a variety of soft crimes (e.g., vandalism and public order disturbances) serve as leading indicators of serious crimes like assault and robbery. Leading indicator models require multivariate data that include the dependent variable (e.g., number of robberies per month) along with precursor leading indicator variables that are lagged one or more time periods (e.g., number of gang- or drug-related 911 calls from prior months). Lags may also be over space, such as a simple total or weighted average of 911 calls at contiguous (nearby) locations in prior months.[9]

The Vector Autoregression (VAR) model is a common time series model for estimating and testing leading indicators. Researchers have used VAR models extensively for applied modeling and forecasting since the work of Sims (1980). These are simple multivariate models in which a variable is explained by its own past values and past values of all other variables (leading indicators) in the system (Holden 1995). The Bayesian Vector Autoregression (BVAR) model is a restricted form of VAR.

Introduced by Litterman (1980, 1986), BVAR relies on Bayes' estimates of priors to overcome collinearity and degrees of freedom problems that typically arise in applications of vector autoregressive models. Doan, Litterman, and Sims (1984) introduced the so-called Minnesota priors for BVAR. LeSage and Pan (1995) introduced spatial contiguity to further specify the priors in regional studies. BVAR models have been successful in time series analysis and forecasting models for regional data, especially in exploratory analyses of the appropriate time- and space-lagged model specifications (LeSage 1989, 1990; LeSage and Pan 1995).

Granger and Newbold (1977, 224–226) introduced rules and tests for a weak form of causality testing based on VAR and relative to the limited information set of variables used. Now known as "Granger causality," Factor A "Granger causes" B if Lag A is a significant predictor of B, but Lag B is not a significant predictor of A. Enders (1995, 315) presents a standard F-test to determine Granger causality.

Exploratory spatial data analysis

Recently, the set of methods for structuring the visualization of spatial data has been referred to as *exploratory spatial data* analysis, or ESDA. As defined by Anselin (1994, 1998, 1999a), ESDA is a collection of techniques to describe and visualize spatial distributions; identify atypical locations or spatial outliers; discover patterns of spatial association, clusters, or hot spots; and suggest spatial regimes or other forms of spatial heterogeneity (changing structure or changing association across space). As such, ESDA forms a subset of exploratory data analysis or EDA (Tukey 1977), but with an explicit focus on the distinguishing characteristics of geographical data (Anselin 1989). In this section, we outline how principles from ESDA are relevant in the analysis of spatial patterns in crime. Specifically, we start by reviewing the concept of spatial autocorrelation and how it can be applied to both point data (e.g., location of burglaries) and areal data (e.g., number of homicides or homicide rate per census tract). We next outline some recently developed approaches that focus on "local" indicators of spatial association (or LISA) and discuss how these may be used to detect hot spots and spatial outliers. Finally, we review the integration of these techniques in an interactive computing environment.

The interest in quantification of patterns in maps has led to a large number of spatial statistics and other map summaries, reviewed in the classic treatments of spatial autocorrelation by Cliff and Ord (1973, 1981). Similarly, detection of clusters and outliers in maps is a major concern in epidemiology and medical statistics, and a large body of literature is devoted to the topic (e.g., as reviewed in Marshall 1991). Formally, the presence or absence of pattern is indicated by the concept of *spatial autocorrelation*, or the co-incidence of similarity in value with similarity in location. In other words, when high values in a place tend to be associated with high values at nearby locations, or low values with low values for the neighbors, positive spatial autocorrelation or *spatial clustering* is said to occur. In contrast, when high values at a location are surrounded by nearby low values, or vice versa, negative spatial autocorrelation is present in the form of *spatial outliers*. The point of reference in the analysis of spatial autocorrelation is spatial randomness, or the lack of any structure. For example, under spatial randomness, the particular arrangement of crimes on a given map would be just as likely as any other arrangement, and any grouping of high or low values in a particular area would be totally spurious.

Point pattern analysis

The formal assessment of the presence and extent of spatial autocorrelation depends on the type of data under consideration. The simplest situation is when only the location of a given phenomenon is known (for example, the street addresses where burglaries occurred). In this situation, the primary interest lies in assessing whether these locations, abstracted as points on a map, are seemingly randomly scattered across space, or instead, show systematic patterns in the form of clusters (more points are systematically closer together than they would be in a purely random case) or dispersion (more points are systematically further away from each other than under randomness). Point pattern analysis is concerned with detecting when "significant" deviations from spatial randomness occur.[10]

Quadrat count method. The construction of tests for point patterns may be approached in a number of different ways. A popular technique that is easily carried out in a GIS environment is the quadrat count method, in which a square grid is overlaid on the points. The number of points in each grid cell is counted and compared with "expected" number under spatial randomness by means of a chi-squared test of goodness-of-fit. While intuitive and readily implemented, this approach suffers from a number of conceptual problems, such as arbitrariness in the choice of the grid cell size and the possibility of correlation between counts in nearby cells (spatial autocorrelation).

Kernel estimation. A natural extension of the quadrat approach is kernel estimation, in which a smooth estimate of the intensity of the point process is derived by means of a moving window over the data. In other words, the number of points within the moving window (sometimes transformed to improve interpretation and visualization) is taken as an indicator of the intensity of the event at that location (e.g., how many burglaries per square mile). Rather than the points themselves, this intensity measure can be visualized in a map and assessed for systematic deviations from randomness. A particular implementation of this technique consists of drawing many overlapping circles of variable sizes and assessing the extent to which "clusters" may be present. For example, this is implemented in the "geographical analysis machine" of Openshaw and associates (Openshaw et al. 1987, 1988; for a recent review, see Openshaw and Alvanides 1999).[11]

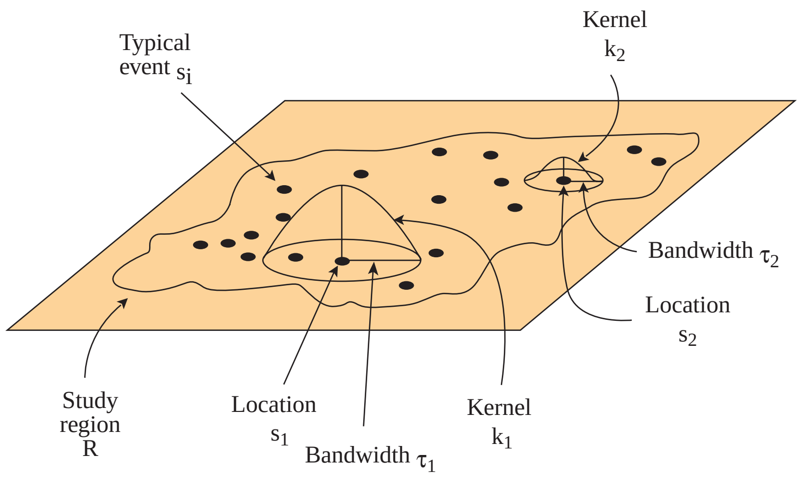
Kernel estimation or kernel smoothing is one method for examining large-scale global trends in point data. The goal of kernel estimation is to estimate how event levels vary continuously across a study area based on an observed point pattern for a sample of points (Bailey and Gatrell 1995; Williamson et al. 1998). Kernel estimation creates a smooth map of values using spatial data. The smoothed map appears like a spatially based histogram, with the level at each location along the map reflecting the point pattern intensity for the surrounding area.

In kernel estimation, a moving three-dimensional function (k_1) of a given radius or “bandwidth” visits every cell of a fine grid that has been overlaid on the study region or area. As the kernel visits each cell, distances are measured from the center of the grid cell (s_1) to each observation (s_i) falling within the bandwidth (τ_1). Each distance contributes to the intensity level of that grid cell, with greater weight given to observations lying closer to the center of the cell (see exhibit 1).

The choice of an appropriate bandwidth is crucial when applying kernel estimation to point data, and can prove a significant weakness if selected arbitrarily (see Silverman 1986). Bandwidth is crucial because it determines the amount of smoothing applied to a point pattern. In general, a large bandwidth will result in a large amount of smoothing, producing a fluid map with low intensity levels. A smaller bandwidth results in less smoothing, producing a spiky map with local variations in intensity levels. Ideally, bandwidth should represent the actual distance between the points in the distribution. However, there is no steadfast rule for determining bandwidth.[12]

Kernel estimation has been applied across a number of different fields, particularly epidemiology. In epidemiological applications, a distribution of discrete points, each of which represents the incidence of disease among the population, is transformed into a continuous smoothed surface map indicating disease risk (see Sabel 1998).[13] By transforming spatial point patterns of criminal incidents

Exhibit 1. Kernel estimation



Source: Adapted from Bailey and Gatrell (1995).

into a smooth image, kernel estimation can be equally effective in visualizing areas of criminal activity and risk.

Kernel estimation offers several practical benefits in the spatial analysis of crime. The first benefit is accessibility. Kernel estimation allows analysts to visually simplify and examine complex point patterns of criminal incidents. The greater accessibility of point data on crime incidents can easily result in data overload (Block 1998). Displaying even modest amounts of point data on a map can quickly become confusing and uninformative. Kernel estimation does not diminish the import of point-based spatial data. Instead, a smooth image captures and displays hot spots and potential hot spots as areas of high density. These areas of high density can then be verified by examining the level of statistical significance of estimated hot areas to determine the likelihood of observing levels this high if incidents are in fact distributed randomly over space and time.

Kernel estimation also allows greater flexibility in defining the borders of hot spots and in analyzing hot spot areas. Hot spot areas are often influenced by natural boundaries that break up population areas, such as gullies and highways. These boundaries make the areas irregular in shape. In addition, concentrations of crime often flow across police beats and jurisdictions rather than being confined to predefined administrative boundaries. Therefore, whenever the distribution of crime is not uniform, the contours that define hot spot areas are unlikely to be the well-behaved circles or ellipses required in some crime-clustering methods (e.g., STAC method in Block 1998). Kernel estimation allows for flexible boundaries and the display of the intensity of criminal incidents across an entire region.

Finally, kernel estimation can be important in analyzing incident patterns over time. Density images can be compared for consecutive or corresponding time periods (e.g., the same month or year-to-date comparisons in successive years). These provide a context for interpreting short-term changes in relation to long-term trends and seasonal patterns. Kernel smoothed maps also reveal the larger spatial context of changes over time.

Distance statistics

Other point pattern techniques are based on the distance between the points, either between each point and its nearest neighbor (nearest neighbor statistics) or between all the points (second order statistics). The underlying rationale is that when events are clustered in space, small interpoint distances should be more prevalent than under spatial randomness. A large number of nearest neighbor statistics have been suggested in the literature.[14] Their properties are either derived or approximated analytically, or, more interestingly, based on a computational approach. The latter consists of simulating the location of the same number of points as in the dataset (e.g., the total number of burglaries in a given year) by randomly assigning locations, thus mimicking the null hypothesis of spatial randomness. For each of the simulated patterns, the value of the statistic (or statistics) can be computed, thus yielding a reference distribution to which the statistic for the observed pattern can be compared. This provides an intuitive and highly visual way to assess the degree of nonrandomness in a point pattern. For example, this can be applied to the empirical cumulative distribution function for the nearest neighbor distances for each point, or to all the distances between points.[15]

Nearest neighbor statistics have been extended to test for clusters in space and time. For example, the Knox statistic (Knox 1964) consists of counting how many pairs of events are closer in space and time than would be the case under randomness.[16] Although initially developed to detect clusters of disease incidence, the application of these methods to criminal activity is straightforward.

The techniques discussed so far address so-called "general" levels of clustering (or, global spatial autocorrelation) in the sense of assessing the extent to which spatial randomness can be rejected. In many instances, it is interesting to locate "where" the clusters may be present. For example, one may be interested in finding out if the clusters center around particular locations of crime-inducing facilities, such as liquor stores or 24-hour convenience stores. Such tests are referred to as "focused" tests (Besag and Newell 1991) and relate the number of points in a cell (or counts of events) to the distance from a "putative source." Again, the general principle underlying these tests is that deviations from spatial randomness would yield a higher frequency of points close to the putative source.[17]

A fundamental concept in the analysis of spatial autocorrelation for areal data is the spatial weights matrix. The spatial weights matrix is used to formalize a notion of locational similarity and is central to every test statistic.

Estimation of spatial point processes

Tests for point patterns or clusters of events are implemented in a number of software packages, several of which are readily available commercially or as freeware/shareware. Most of these can also easily be integrated in a GIS environment. For example, nearest neighbor statistics and the K function are included in the S+SpatialStats add-on to the S-Plus statistical package (MathSoft 1996), which can be integrated with the ArcView GIS through the S+ArcView link (Bao et al. forthcoming).[18] Infomap (Bailey and Gatrell 1995) contains a number of quadrat count methods, as well as nearest neighbor and second order statistics, together with a set of basic mapping functions. A wide range of cluster and scan statistics are also included in Stat! (BioMedware 1994), which, although developed with health events in mind, can be readily applied to crime statistics. A specific focus on pattern detection in the locations of crime incidents is implemented in the CrimeStat package. This software tool, which was developed with the support of the National Institute of Justice, can be linked to a variety of commercial GIS software and spatial data formats (Levine 1999).

Areal analysis

So far, the discussion of spatial autocorrelation has dealt with situations where the data come in the form of points, and their location is the primary focus of interest. An equally important setting is that in which the data are collected for areal units or "regions," such as homicide counts or rates by county or census tract.[19] A large number of spatial autocorrelation tests have been developed to assess the extent to which the spatial arrangement of values on a map shows deviations from a null hypothesis of spatial randomness, as reviewed in Cliff and Ord (1973, 1981), Upton and Fingleton (1985), and Griffith (1987), among others.

A fundamental concept in the analysis of spatial autocorrelation for areal data is the spatial weights matrix. This is a square matrix of dimension equal to the number of observations, with each row and column corresponding to an observation. Typically, an element w_{ij} of the weights matrix W is non-zero if locations i and j are neighbors, and zero otherwise (by convention, the diagonal elements w_{ii} equal zero). A wide range of criteria may be used to define neighbors, such as binary contiguity (common boundary) or distance bands (locations within a given distance of each other), or even general "social" distance.[20] The spatial weights matrix is used to formalize a notion of locational similarity and is central to every test statistic. In practice, spatial weights are typically derived from the boundary files or coordinate data in a geographic information system (see Can 1996).

Viewed from a more technical standpoint, almost every test for "global" spatial autocorrelation can be expressed as a special case of a general cross-product or "gamma" statistic (Hubert 1985, 1987; Hubert, Golledge, and Costanzo 1981). This statistic consists of a sum of cross-products between two sets of terms, one related to the similarity in value between two observations, the other to their similarity in location, or, $\Gamma=\Sigma_i\Sigma_j a_{ij}.w_{ij}$. In this expression, the a_{ij} term corresponds to value similarity, such as a cross product, $x_i.x_j$, or a squared difference

$(x_i-x_j)^2$, while the w_{ij} are elements in a spatial weights matrix. Inference for this general class of statistics is based on permutation. Specifically, a reference distribution is constructed that simulates spatial randomness by arbitrarily rearranging the values observed in a given map over the available locations and recomputing the statistic for each of these random arrangements.

Classic statistics

Classic test statistics for spatial autocorrelation are the join count statistic, Moran's I and Geary's c (Cliff and Ord 1973). The join count statistic is appropriate when the data are binary, for example, the presence (coded B for black) or absence (coded W for white) of arson fires by city block. The number of times neighboring spatial units also have B in common is called a BB join count.[21] The tests are based on the extent to which the observed number of BB joins (or, WW, BW) is compatible with a null hypothesis of spatial randomness. Similarly, when the data are variables measured on a continuous scale (such as crime rates or counts of homicides), Moran's I and Geary's c statistics measure the deviation from spatial randomness. Moran's I is a cross-product coefficient similar to a Pearson correlation coefficient and scaled to be less than one in absolute value. Positive values for Moran's I indicate positive spatial autocorrelation (clustering), while negative values suggest spatial outliers.[22] In contrast to Moran's I, Geary's c coefficient is based on squared deviations. Values of Geary's c less than one indicate positive spatial autocorrelation, while values larger than one suggest negative spatial autocorrelation.[23] Adjustments to Moran's I to account for the variance instability in rates have been suggested in the epidemiological literature, for example, the Ipop statistic of Oden (1995). Extensions of Moran's I to a multivariate setting are outlined in Wartenberg (1985).

Moran scatterplot

When variables are used in standardized form (that is, their mean is zero and standard deviation one), the degree of spatial autocorrelation in a dataset can be readily visualized by means of a special scatterplot, termed Moran scatterplot in Anselin (1995, 1996). The Moran scatterplot is centered on the mean and shows the value of a variable (z) on the horizontal axis against its spatial lag (Wz, or $\Sigma_j w_{ij} z_j$; i.e., a weighted average of the neighboring values) on the vertical axis. The four quadrants in the scatterplot correspond to locations where high values are surrounded by high values in the upper right (an above mean z with an above mean Wz), or low values are surrounded by low values in the lower left, both indicating positive spatial autocorrelation. The two other quadrants correspond with negative spatial autocorrelation, or high values surrounded by low values (high z, low Wz) and low values surrounded by high values (low z, high Wz). The slope of the linear regression line through the Moran scatterplot is Moran's I coefficient. Moreover, a map showing the locations that correspond to the four quadrants provides a summary view of the overall patterns in the data. Hence, this device provides an intuitive means to visualize the degree of spatial autocorrelation, not only in a traditional cross-sectional setting, but also across variables and over time (Anselin 1998). Recent illustrative examples of the application of these concepts in homicide studies can be found in Sampson, Morenoff, and Earls (1999) and Cohen and Tita (1999).

Distance-based statistics

An alternative perspective on spatial autocorrelation for data available at discrete locations (points, areas) is to consider these as sampling points for an underlying continuous surface in a geostatistical approach. For example, crime statistics by police station would be used to estimate a continuous crime surface for the whole city. The primary interest in this paradigm lies in spatial interpolation, or kriging. The measure of spatial autocorrelation is taken to be a function of the squared difference between the values for each pair of observations compared with the distance that separates them. Formally, this is carried out in a variogram (or, more precisely, a semi-variogram).[24] One visualization of the variogram consists of a scatterplot of the squared differences organized by distance band, possibly with a box plot for each distance band—a variogram cloud plot or variogram box plot (see Cressie 1993; Haslett et al. 1991). Another visualization focuses on each distance lag separately, in a spatially lagged scatterplot (Cressie 1984). The mean or median in the variogram cloud plot for each distance band suggests an overall pattern for the change in spatial autocorrelation with distance, and a focus on outliers indicates pairs of observations that may unduly influence this central tendency (see also Majure and Cressie 1997; Anselin 1998, 1999a).

Modern computational implementations of exploratory data analysis are based on the paradigm of dynamically linked windows, in which the user interacts with different "views" of the data on a computer screen.

Local indicators of spatial association—LISA statistics

The measures of spatial autocorrelation reviewed so far are general, or global, in the sense that the overall pattern in the data is summarized in a single statistic. Paralleling the focused tests of point pattern analysis, *local* indicators of spatial association (LISA) provide a measure of the extent to which the arrangement of values around a specific location deviates from spatial randomness. Closely related to the focused tests, the G_i and G_i* statistics of Getis and Ord (1992; Ord and Getis 1995) measure the extent to which the concentration of high or low values within a given distance band around a location deviates from spatial randomness. These statistics are designed to find clusters of high or low values. They can be applied to each location in turn or to using increasing distance bands away from a given location. A general framework for LISA is outlined in Anselin (1995), where local forms are derived for several global statistics, such as the local Moran and local Geary statistics.[25] The local Moran is closely related to the Moran scatterplot and indicates the presence of local clusters or local spatial outliers. LISA statistics lend themselves well to visualization by means of a GIS, for example, in symbol maps that show the locations with significant local statistics. In addition, when combined with a Moran scatterplot, the locations with significant local Moran can be classified in terms of the type of association they represent.

Estimation of spatial autocorrelation

Routines to test for spatial autocorrelation are found in a wide range of special purpose as well as commercial software. An extensive listing is given on the AI–GEOSTAT's Web site (http://curie.ei.jrc.it:80/software). Other recent reviews can be found in Legendre (1993) and Levine (1996). Most of these software implementations are specialized and contain one or a few statistic(s). Comprehensive treatments are the S+SpatialStats add-on for the S-Plus statistical system (MathSoft 1996) and the SpaceStat™ package (Anselin 1992). The latter is the only system to date that contains both global and local spatial statistics. It is integrated with the ArcView GIS by means of an extension, which, among other things, allows for the visualization of Moran scatterplot maps and locations with significant LISA.[26]

Modern computational implementations of exploratory data analysis are based on the paradigm of dynamically linked windows, in which the user interacts with different "views" of the data on a computer screen. The views typically consist of standard statistical graphics such as histograms, box plots, and scatterplots, but increasingly include a map as well. The dynamic linking consists of allowing an analyst who uses a pointing device (mouse) to establish connections between data points in different graphs, highlight (brush) subsets of the data and rotate, cut through, and project high dimensional data (for a recent review, see Buja, Cook, and Swayne 1996). Geographical data can easily be included in this framework when viewed as x, y points in a standard scatterplot. A more extensive framework that also includes choropleth maps was originally proposed in the Spider software of Haslett, Unwin, and associates (Haslett, Wills, and Unwin 1990; Haslett et al. 1991; Unwin 1996; Unwin et al. 1996).

Recent efforts in this regard also incorporate explicitly spatial statistics, such as a variogram cloud or box plot, Moran scatterplot, and LISA maps in a spatial association visualizer (Anselin 1998).

A practical example of a link between a GIS and various exploratory data analysis tools is represented by the work of Symanzik and colleagues (1998, 1999). Here, a form of software integration is obtained between the ArcView GIS and the XGobi (Buja, Cook, and Swayne 1996) and XploRe (Härdle, Klinke, and Turlach 1995) EDA software packages. This link is based on point data and allows for the brushing of a variogram cloud plot. Each of the exploration tools can be used in isolation or linked with the other. As long as the data are represented by points, powerful visualization can be obtained, including space-time dynamics and complex multivariate linkages.[27] For example, this method can be used to track the location and frequency of a given type of crime across space as well as over time and to suggest potentially useful correlates. A similar approach is taken in the implementation of dynamically linked windows in the DynESDA extension for ArcView (Anselin and Smirnov 1998). Here, a view in ArcView is augmented with a series of statistical graphs, including histograms, boxplots, scatterplots, and Moran scatterplots that are all dynamically linked. Using brushing and linking techniques, both multivariate as well as spatial association between a number of variables can be assessed and visualized. A recent application of this technique to the study of the spatial diffusion of homicides is given by Messner and colleagues (1999).

Until recently, the role of space (and space-time) was not explicitly acknowledged in the methodology used in these studies, but it is central in a number of respects. Spatial concentration will tend to result in spatial autocorrelation, which runs counter to the usual assumption of independence in regression analysis. In addition, strong spatial variation in criminal activity suggests the need for an explicit spatial perspective and the consideration of spatial heterogeneity (spatial structural change).

Spatial Modeling

The techniques of exploratory analysis reviewed in the previous section are extremely useful in assessing the existence and location of nonrandom local patterns in spatial data. However, they are also limited by the lack of mechanisms to "explain" the observed patterns. EDA and ESDA are exploratory by nature. They "suggest" potential associations between variables and elicit hypotheses, but the formal testing of these hypotheses is left for confirmatory

As is now increasingly recognized, in this instance specialized methods of spatial regression analysis (spatial econometrics) must be used to avoid potentially biased results and faulty inference due to the presence of so-called **spatial effects**, *consisting of* **spatial dependence** *and* **spatial heterogeneity.**

analysis, typically carried out by means of multivariate regression modeling (Anselin and Getis 1992).

In the specific context of criminal justice, regression analysis plays a crucial role in the attempts to explain the causes of criminal activity (e.g., Land, McCall, and Cohen 1990; Kposowa and Breault 1993; DeFronzo and Hannon 1998). Until recently, the role of space (and space-time) was not explicitly acknowledged in the methodology used in these studies, but it is central in a number of respects. For example, it is well known that urban crimes such as theft and burglary, as well as most categories of violent crimes, are likely to be spatially concentrated in low-income urban areas that have relatively high proportions of unemployed persons and racial minorities. This spatial concentration will tend to result in spatial autocorrelation, which runs counter to the usual assumption of independence in regression analysis. In addition, law enforcement efforts (Chambliss 1994) and gang activity (Cohen et al. 1998) vary spatially, strongly suggesting the need for an explicit spatial perspective (Roncek 1993) and the consideration of spatial heterogeneity (spatial structural change). A spatial perspective is further motivated by the findings of large-scale spatial differences for various crimes (for example, urban, suburban, and rural as reported in the Federal Bureau of Investigation's Uniform Crime Reports as well as the Bureau of Justice Statistics' semiannual National Crime Victimization Survey). This in turn has prompted a search for spatial mechanisms such as proximity and diffusion to explain these phenomena (Tolnay, Deane, and Beck 1996; Morenoff and Sampson 1997; Sampson, Morenoff, and Earls 1999).

The challenge of spatial effects

In most of these studies, the regression analysis employs data for cross-sectional units, such as census tracts or counties. As is now increasingly recognized, in this instance specialized methods of spatial regression analysis (spatial econometrics) must be used to avoid potentially biased results and faulty inference (Anselin 1988; Anselin and Bera 1998). This is due to the presence of *spatial effects*, consisting of *spatial dependence* and *spatial heterogeneity,* which violate the basic assumptions underlying classical regression analysis. Statisticians have long been aware of the problems associated with analyzing spatial (geographical) data, but spatial statistical techniques did not disseminate into the empirical practice of the mainstream social sciences until recently (for a review, see Anselin 1999b).[28]

The motivation for the explicit incorporation of spatial effects in regression models that explain criminal activity is twofold. On the one hand, crime and enforcement data are readily geocoded, but the spatial scale of observation does not necessarily match the spatial scale of the process under study. For example, the occurrence of certain types of crimes, say dealing in illicit drugs, may be explained by socioeconomic variables and land use data collected at the block level. However, if the illicit drug trading zone for a given group covers multiple blocks, the data for several units of observation will be correlated. Similarly, if the unmodeled variables such as "social capital" or "sense of community" spill over across multiple units of observation, a spatial correlation of these "errors" will result. Hence, the concern with accounting for the presence of spatial autocorrelation in a regression model is driven by the fact that the analysis is based on *spatial data* for which the unit of observation is largely arbitrary (such as administrative units). The methodology focuses on making sure that the estimates and inference from the regression analysis (whether for spatial or a-spatial models) are correct in the presence of spatial autocorrelation.

The two different motivations for consideration of spatial effects in regression models lead to methods to handle spatial dependence as a **nuisance** *(data problems) versus* **substantive** *spatial dependence (theory driven). Formally, this results in techniques to model spatial dependence in the error terms of the regression model or to transform the variables in the model to eliminate spatial correlation (spatial filtering), versus methods to explicitly add a spatial interaction variable as one of the regressors in the model.*

On the other hand, much recent theoretical work in urban sociology, economics, and criminology has emphasized concepts related to the "interaction" of agents, such as copycatting, social norms, neighborhood effects, diffusion, and other peer group effects. These theories focus on questions of how individual interactions can lead to emergent collective behavior and aggregate patterns (e.g., Brock and Durlauf 1995; Akerlof 1997; Durlauf 1994; Borjas 1995; Glaeser, Sacerdote, and Scheinkman 1996). Here, the need for an explicit *spatial model* is driven by theoretical concerns and the interest lies in a correct specification of the form and range of interaction and the estimation of its strength.

Spatial statistical techniques

The two different motivations for consideration of spatial effects in regression models lead to methods to handle spatial dependence as a *nuisance* (data problems) versus *substantive* spatial dependence (theory driven) (Anselin 1989). Formally, this results in techniques to model spatial dependence in the error terms of the regression model or to transform the variables in the model to eliminate spatial correlation (spatial filtering), versus methods to explicitly add a spatial interaction variable as one of the regressors in the model. Common to all methodological approaches is the need to rigorously express the notion of "neighbor effects," which is based on the concept of a spatial weights matrix, discussed previously. A spatially explicit variable takes the form of a "spatial lag" or spatially lagged dependent variable, which consists of a weighted average of the neighboring values. More precisely, the spatial lag of a dependent variable at location i, y_i, would be $\Sigma_j w_{ij}y_j$, where the weighted sum is over those "neighbors" j that have a nonzero value for element w_{ij} in the weights matrix (or, in general, the weight is w_{ij}). For practical purposes, the elements of the spatial weights matrix are often row-standardized, which facilitates interpretation and comparison across models (for technical details, see Anselin 1988, forthcoming; Anselin and Bera 1998).

A typical specification of a linear regression equation that expresses substantive spatial interaction (or spatial autocorrelation) is the *mixed regressive, spatial autoregressive model,* or *spatial lag* model. This includes, in addition to the usual set of regressors (say, x_i, the regressive part), a spatially lagged dependent variable $\Sigma_j w_{ij}y_j$, (the spatial autoregressive part), with a spatial autoregressive coefficient ρ.[29] The inclusion of a spatial lag term is similar to a temporal autoregressive term in time series analysis, although there are several important differences that require a specialized methodology for estimation and testing.[30]

The interpretation of the spatial lag model is best illustrated with a simple example. Say we were interested in explaining the crime rate by the usual socioeconomic variables as well as by a police intervention measure, and assume that the data are collected at the census-tract level. The spatial lag would capture the average crime rate for neighboring tracts. This measure of "potential" crime is one way to formalize the spatial interaction in the model. Therefore, the significance and value of the autoregressive coefficient have a direct interpretation as an indication of the strength of the spatial interaction. In our example, the estimate for ρ would suggest to what extent the crime rate in each census tract is "explained" by the average of the neighbors.

There are two potential pitfalls in this interpretation. First, the spatial lag does not "explain" anything (similar to a time lag in time series), but instead is a proxy for the simultaneity in the whole system. This is best seen in a formal way, but for the sake of simplicity can be thought of as a *spatial multiplier.* After transforming the model to reduced form, so only "exogenous" variables remain on the right-hand side of the equation, it follows that the value of y at each location (e.g., the crime rate) depends not only on the explanatory variables for that location (the x_i), but also on these variables at all other locations, suitably adjusted to reflect the effect of distance decay. In our example, the presence of a spatial multiplier implies that a change in police intervention at one location (census tract) not only affects the crime rate at that location, but at all other locations in the system as well (suitably decayed), hence the notion of a multiplier.[31]

The second problem is due to the use of aggregate entities, such as census tracts or counties, as observational units. The interpretation of the autoregressive term as an indication of "interaction" between units can easily lead to an "ecological fallacy." This follows from the fact that these units are not social agents themselves, but only aggregates (averages) of individual behavioral units. Drawing inferences for individual behavior from relations observed at the aggregate level can only be carried out under a strict set of assumptions (essentially imposing extreme homogeneity), which is clearly unwarranted in the current context (for an extensive discussion, see King 1997).[32] An alternative interpretation is that the spatial lag model allows for *filtering out* the potentially confounding effect of spatial autocorrelation in the variable under consideration. The main motivation for this is to obtain the proper inference on the coefficients of the other covariates in the model (the β). For example, spatial autocorrelation of the lag variety may result from a mismatch between the spatial extent of the criminal activity and the census tract as the spatial unit of observation.[33]

From an estimation point of view, the problem with this model is that the spatial lag term contains the dependent variables for neighboring observations, which in turn contain the spatial lag for their neighbors, and so on, leading to simultaneity (the spatial multiplier effect mentioned previously). This simultaneity results in a nonzero correlation between the spatial lag and the error term, which violates a standard regression assumption. Consequently, ordinary least squares (OLS) estimation will yield inconsistent (and biased) estimates, and inference based on this method will be flawed. Instead of OLS, specialized estimation methods must be employed that properly account for the spatial simultaneity in the model. These methods are either based on the maximum likelihood (ML) principle, or on the application of instrumental variable (IV) estimation in a spatial two-stage, least-squares approach.[34]

In contrast to the lag model, there are a number of ways to incorporate the spatial autocorrelation into the structure of the regression model error term. The most commonly used models are based on spatial processes, such as a spatial autoregressive (SAR) or spatial moving average (SMA) process, in parallel to the time series convention.[35] The particular form for the process yields a nondiagonal covariance structure for the errors, with the value and sign of the off-diagonal elements corresponding to the "spatial correlation" (that is, the correlation between the error terms at two different locations).

An interesting aspect of this correlation structure is the range of interaction that is implied. For a SAR process, every error term is correlated with every other error term, but the magnitude of the correlation follows a distance decay effect. In other words, the implied interaction is global, as in the spatial multiplier of the spatial lag model. In contrast, the SMA process yields local interaction, where only first and second order neighbors have a nonzero correlation. Since this pertains to the error terms in a model, or the "ignored" or "unmeasurable" effects, the two specifications also have different policy implications. For example, if there were an unmeasurable "neighborhood" effect in our model of crime, the SAR specification would imply that change in this effect in one location affects all the locations in the system, whereas in an SMA specification this change would only affect the immediate neighbors. However, more precisely, these measurement errors only pertain to the precision of the estimates, and "on average" their impact is zero on the predicted crime, in contrast to the spatial multiplier in the lag model, in which shocks pertaining to the regressor (X) are transmitted throughout the system.

In space, the error variances are also heteroskedastic, which is not the case in the time domain (see Anselin and Bera 1998). The heteroskedasticity is induced by the spatial process and will complicate specification testing (i.e., distinguishing "true" heteroskedasticity from that induced by a spatial process). This is an important distinction between the spatial error processes and their covariance structure and the time series counterpart.

An alternative approach to handling spatial processes is to specify the magnitude of the spatial error covariance as a function of the distance that separates pairs of observations.[36] This "direct representation" approach is inspired by geostatistical modeling and lends itself well to spatial forecasting (or interpolation). In contrast to the spatial process models, there is no induced heteroskedasticity. However, for the direct representation approach to yield a valid covariance (e.g., to avoid negative variances), a number of restrictive assumptions must be satisfied (see e.g., Cressie 1993; Anselin forthcoming).

The estimation of spatial error models falls under the generic category of regression models with nonspherical error variance. Technically, a form of generalized least squares will be applied, although in contrast to the time domain, there is no simple two-step estimation procedure. Instead, an explicit maximum likelihood approach or generalized moment technique must be followed.[37] In these methods, the coefficient of the spatial model is considered a "nuisance" parameter in the sense that it improves the precision of the estimates for the regressors (β), but in and of itself is of little interest.

Compared with spatial dependence, spatial effects in the form of spatial heterogeneity can be handled in a fairly straightforward way with standard econometric models. The resulting heteroskedasticity, varying coefficients, or structural instability is only distinct in the sense that the specification of the heterogeneity is in terms of *spatial* or regional differences (e.g., different crime rates in central city versus suburb). However, because spatial heterogeneity often occurs jointly with spatial dependence (or the two are observationally equivalent), explicit consideration of the latter is required in empirical applications. Examples of techniques that address spatial heterogeneity are spatial analysis of variance (Sokal et al. 1993), spatially varying coefficients as some form of hierarchical linear modeling in the spatial expansion method (Jones and Casetti 1992; Casetti 1997), locally different regression coefficients in the spatial adaptive filter (Foster and Gorr 1986; Gorr and Olligschlaeger 1994), geographically weighted regression (Brunsdon, Fotheringham, and Charlton 1996; McMillen and McDonald 1997), and the correction for spatial outliers by means of Bayesian techniques (LeSage 1997, 1999).

When observations are available for a cross-section at different points in time, in the form of panel data, it becomes possible to model complex combinations of spatial heterogeneity and spatial dependence.[38] For example, different model coefficients can be specified for different subregions and/or different time periods; the spatial autoregressive coefficients can be allowed to vary over time, etc. The types of methods appropriate for addressing such models consist of seemingly unrelated regressions, error components, and Bayesian approaches, in conjunction with a spatial lag or spatial error dependence. Overviews of the methodological issues are given in Anselin (1988, ch. 10; 1990b, 1999b) and LeSage (1995).

In practice, the most important aspect of spatial modeling may well be specification testing. In fact, even if discovering spatial interaction of some form is not of primary interest, ignoring spatial lag or spatial error dependence when it is present creates serious model misspecification. Of the two spatial effects, ignoring lag dependence is the more serious offense, since, as an omitted variable problem, it results in biased and inconsistent estimates for all the coefficients in the model; and the inference derived from these estimates is flawed. When spatial error dependence is ignored, the resulting OLS estimator remains unbiased, although it is no longer most efficient. Moreover, the estimates for the OLS coefficient standard errors will be biased, and, consequently, t-tests and measures of fit will be misleading.

Spatial model estimation

Tests for the presence of potential spatial effects are complicated by a number of factors. First, as mentioned earlier, spatial processes yield heteroskedastic errors, so that it will be difficult to distinguish true heteroskedasticity from that induced by the spatial processes. The reverse is true as well, so that tests against spatial dependence will be sensitive to the presence of heteroskedasticity and may point to the wrong alternative. Second, the spatial lag and spatial error specifications are highly related, so that tests against one form of dependence will also have power against the other form, again complicating the specification search. Third, all tests for spatial effects are based on large sample properties (asymptotics) and their performance in small data sets may be suspect.

If spatial features serve as actuating factors for crime, either because of the people or facilities that are located there, then interventions designed to alter those persons and activities might well affect crime. Alternatively, if the spatial distribution of crime is essentially random, then targeting specific places is not likely to be an effective crime control strategy.

Despite these problems, however, there are a number of practical guidelines that can be followed in empirical applications. The most straightforward testing approach is to use Lagrange Multiplier tests that are based on the residuals of an OLS regression. Separate tests are available for a spatial lag and a spatial error alternative, and a simple rule of thumb exists to guide the researcher in the proper direction (the most significant test suggests the proper alternative).[39] Other tests with high power are based on the application of Moran's I to regression residuals, which is a valid misspecification test against a wide range of alternatives and applicable in various econometric specifications (Anselin and Kelejian 1997; Kelejian and Robinson 1998, 1999; Kelejian and Prucha 1999b; Pinkse 1999).

Spatial econometric methods are not routinely incorporated in commercial software packages. Hence, several authors have developed "tricks" to carry out estimation and specification testing using macro or script facilities in statistical computing software. Examples are routines in Limdep, Gauss, Shazam, and S-Plus in Anselin and Hudak (1992), and maximum likelihood estimation in SAS (Griffith 1993), Matlab (Pace and Barry 1998), or R (Bivand 1999). Estimation of spatial error models is included in the S+SpatialStats add-on to the S-Plus software

(MathSoft 1996), but the only comprehensive suite of routines to handle both specification testing and estimation is contained in SpaceStat (Anselin 1992).

Conclusion

As we near the end of the 20th century, spatial analyses of crime remain poised at the early stages of development. Many of the capabilities to support computerized mapping and spatial statistical analyses emerged only recently during the 1990s. The promise of using spatial data and analyses for crime control still remains to be demonstrated, and its usefulness depends on the nature of the relationship between crime and place. If spatial features serve as actuating factors for crime, either because of the people or facilities that are located there, then interventions designed to alter those persons and activities might well affect crime. Alternatively, if the spatial distribution of crime is essentially random, then targeting specific places is not likely to be an effective crime control strategy.

Research aimed at sorting out the nature of the relationship between place and crime is crucial and becoming increasingly feasible as spatial data capabilities proliferate. One of the first priorities is research on the nature of crime hot spots, especially the typical life course (or crime "career") of areas with high concentrations of crime, to determine whether the unusually high levels persist for any length of time. While spatial analyses remain a promising tool, the very early stage of research on the relationship between crime and place is reason for a degree of caution. Considerably more research is needed before we look to location as a primary target for crime control efforts. Both basic social science research and well-designed applied research on specific police interventions will be of value.

Notes

1. An overview of the literature, including the theoretical underpinnings of the crime-place relationship and empirically based results, is available in Eck and Weisburd (1995). See also Weisburd (1997).

2. See, for example, Sampson (1986) and Eck and Weisburd (1995).

3. See Ritzer (1988) for a critique of the Chicago School.

4. See the 1969 University of Chicago Press edition with new chapters of updated data.

5. The panel consisted of James Short, Robert Sampson, Robert Bursik, Ruth Horowitz, Karen Heimer, and Ross Matsueda.

6. For examples of empirical and theoretical treatments of social disorganization and social control theories, see Bursik (1986, 1988), Bursik and Grasmick (1993), Sampson (1986, 1995), Sampson and Groves (1989), Abbott (1997), and Wikstrom (1998).

7. To those physical dimensions, we would add the general disenfranchisement of residents from having a stake in maintaining both the physical and social environment of this special type of housing.

8. Wolfgang and colleagues highlighted the impact of chronic offenders within birth cohorts of boys in Philadelphia (Wolfgang, Figlio, and Sellin 1972; Wolfgang, Thornberry, and Figlio 1987; Tracy, Wolfgang, and Figlio 1990). Similarly, skewed distributions of offending, in which a small number of offenders are responsible for a disproportionately large share of crimes, have been repeatedly confirmed both in official criminal records (Blumstein and Cohen 1979; Shannon 1988; Haapanen 1990), and in self-reports by offenders (Petersilia, Greenwood, and Lavin 1977; Peterson and Braiker 1981; Chaiken and Chaiken 1982, 1985; English 1990; Miranne and Geerken 1991; Horney and Marshall 1991). Such distributions are quite common for a wide array of behaviors (Greenberg 1991).

9. See discussion of spatial lags in the subsection titled "Areal analysis."

10. Highly readable introductions to point pattern analysis are given in Boots and Getis (1988), Upton and Fingleton (1985), and Bailey and Gatrell (1995). More advanced materials are contained in Cliff and Ord (1973), Ripley (1981), Diggle (1983), and Cressie (1993), among others.

11. Similar ideas, but with a more formal probabilistic basis, underlie the cluster tests of Besag and Newell (1991), Turnbull et al. (1990), and Kulldorff's scan statistic (Kulldorff and Nagarwalla 1995; Nagarwalla 1996; Hjalmars et al. 1996). The principle of using a spatial window to compute smoothed rates from a GIS consisting of the addresses of the occurrence of an event is also discussed in Rushton and Lolonis (1996).

12. There are several "rules of thumb" for determining bandwidth. For a discussion of these rules of thumb, see Bailey and Gatrell (1995) and Williamson et al. (1998).

13. Surface maps arise naturally for representing geographical variations in risk. They also can be derived for other attributes thought to be associated with an outcome. For example, results from a sample of point estimates of crime offending risk by age and birth cohort of offenders could be transformed to a smoothed surface of risk over all ages and cohorts.

14. For example, Cressie (1993, 604) lists no less than 17 nearest neighbor statistics. See also Ord (1990) for an extensive review.

15. This is the familiar K-function outlined in Ripley (1976); see also Bailey and Gatrell (1995, ch. 3).

16. For an extension and generalization, see Ederer, Myers, and Mantel (1964), Mantel (1967), and Bailey and Gatrell (1995, ch. 4).

17. See also Diggle (1991), Lawson (1993), Diggle and Rowlingson (1994), Waller et al. (1995), and Waller (1996) for reviews of the methodology.

18. A more comprehensive set of S-based software for point pattern analysis is contained in the Splancs (spatial point pattern analysis code in s-plus) routines of Rowlingson and Diggle (1993); see also Venables and Ripley (1998).

19. In Cressie's (1993) taxonomy of spatial data statistics, these types of data are referred to as lattice data.

20. For an extensive discussion of spatial weights, see Cliff and Ord (1981), Upton and Fingleton (1985), and Anselin (1988).

21. Formally, a BB join count statistic is $(^1/_2)\ \Sigma_i\Sigma_j\ w_{ij}x_i.x_j$, where w_{ij} are the elements of a binary spatial weights matrix (i.e., one for neighbors, zero for others) and x_i, x_j take on 1 for B, 0 for W. Similarly, WW joint counts are $(^1/_2)\ \Sigma_i\Sigma_j\ w_{ij}(1–x_i)(1–x_j)$. See Cliff and Ord (1973, 1981) and Upton and Fingleton (1985) for extensive treatments.

22. Moran's $I = (N/S_0)\ \Sigma_i\Sigma_j w_{ij}z_iz_j / \Sigma_i\ z_i^2$, where the z_i are variables in deviations from the mean, w_{ij} are elements of a possibly row-standardized spatial weights matrix and S_0 is a scaling factor equal to the sum of all the elements in the weights matrix. For details, see Cliff and Ord (1973, 1981), and Upton and Fingleton (1985).

23. Geary's $c = (N\text{-}1)/2S_0\ [\Sigma_i\Sigma_j\ w_{ij}(x_i–x_j)^2 / \Sigma_i\ z_i^2]$, where the x_i are the original variables and z_i deviations from the mean; the other notation is as in footnote 22. For details, see Cliff and Ord (1973, 1981), and Upton and Fingleton (1985).

24. For a formal treatment, see Cressie (1993). A more introductory overview is offered in Isaaks and Srivastava (1989).

25. LISA are different from regional measures of spatial autocorrelation, which are global statistics applied to a subset of the data, as in Munasinghe and Morris (1996).

26. S+SpatialStats also contains a set of functions to carry out geostatistical analysis. Specialized routines for geostatistics and kriging can be found in Deutsch and Journel (1992) and Pannatier (1996).

27. For further details, see also Cook et al. (1996, 1997).

28. An extensive review of the statistical perspective is given in Cressie (1993).

29. In matrix notation, with y as an N by 1 vector of observations on the dependent variable, X as an N by K matrix of observations on the explanatory variables with regression coefficient vector β, Wy as a vector of spatially lagged dependent variables with spatial autoregressive coefficient ρ, and ε as a vector of random (independent,

identically distributed, or i.i.d) errors, the model can be expressed as $y = \rho Wy + X\beta + \varepsilon$. An extensive discussion of technical issues can be found in Anselin (1988, 1999b) and Anselin and Bera (1998).

30. See Anselin and Bera (1998) for an extensive discussion of the differences between dependence in spatial models and in time series models.

31. Formally, the reduced form is $y = (I–\rho W)^{-1}X\beta + (I–\rho W)^{-1}\varepsilon$, where W is the N by N spatial weights matrix and I is an identity matrix (see Anselin 1988).

32. The ecological fallacy problem is known in spatial analysis as the "modifiable areal unit problem," which in essence means that different results will be found when the size and arrangement of the spatial units of observation changes. The classic reference is Openshaw (1979).

33. For a more extensive discussion of the idea behind spatial filtering, see Getis (1995). Also note the difference between this concept of filtering and the spatial adaptive filter model of Foster and Gorr (1986), which offers an approach to deal with spatial heterogeneity.

34. The original ML estimator is due to Ord (1975) (see also Anselin 1988 and Cressie 1993 for technical details). IV estimation is outlined in Anselin (1988, 1990a), Land and Deane (1992), and Kelejian and Robinson (1993), among others.

35. In matrix notation, a spatial autoregressive error process (SAR) can be expressed as $\varepsilon = \lambda W\varepsilon + u$, whereas a spatial moving average process (SMA) is $\varepsilon = \lambda Wu + u$ (with ε as the regression error terms, λ as the spatial parameter, W as the weights matrix, and u as a vector of i.i.d. errors).

36. This type of model is commonly used in real estate analysis, originally in Dubin (1988). See also Olmo (1995) and Basu and Thibodeau (1998) for some recent examples.

37. Reviews of the relevant issues can be found in Ord (1975), Anselin (1988), and Kelejian and Prucha (1997, 1998, 1999a).

38. The panel data setting is different from true space-time dynamics, for example, as the basis of space-time forecasting.

39. Reviews are given in Anselin and Florax (1995), Anselin et al. (1996), and Anselin (forthcoming).

References

Abbott, Andrew. 1997. Of time and space: The contemporary relevance of the Chicago School. *Social Forces* 75:1149–1182.

Akerlof, George A. 1997. Social distance and social decision. *Econometrica* 65:1005–1027.

Anselin, Luc. Forthcoming. Rao's score test in spatial econometrics. *Journal of Statistical Planning and Inference.*

———. 1999a. Interactive techniques and exploratory spatial data analysis. In *Geographical information systems.* 2d ed. Edited by P. Longley, M. Goodchild, D. Maguire, and D. Rhind. New York: John Wiley & Sons.

———. 1999b. Spatial econometrics. In *Companion in theoretical econometrics,* edited by B. Baltagi. Oxford: Basil Blackwell.

———. 1998. Exploratory spatial data analysis in a geocomputational environment. In *Geocomputation, a primer,* edited by P. Longley, S. Brooks, R. McDonnell, and B. Macmillan. New York: John Wiley & Sons.

———. 1996. The Moran scatterplot as an ESDA tool to assess local instability in spatial association. In *Spatial analytical perspectives on GIS,* edited by M. Fischer, H. Scholten, and D. Unwin. London: Taylor and Francis.

———. 1995. Local indicators of spatial association—LISA. *Geographical Analysis* 27:93–115.

———. 1994. Exploratory spatial data analysis and geographic information systems. In *New tools for spatial analysis,* edited by M. Painho. Luxembourg: Eurostat.

———. 1992. SpaceStat™, a software package for the analysis of spatial data. Santa Barbara: University of California, Santa Barbara, National Center for Geographic Information and Analysis. Retrieved 30 April 2000 from the World Wide Web: http://www.spacestat.com.

———. 1990a. Some robust approaches to testing and estimation in spatial econometrics. *Regional Science and Urban Economics* 20:141–163.

———. 1990b. Spatial dependence and spatial structural instability in applied regression analysis. *Journal of Regional Science* 30:185–207.

———. 1989. What is special about spatial data. Technical Report 89–4. Santa Barbara: University of California, Santa Barbara, National Center for Geographic Information and Analysis. [Contained on CD–ROM. Fundamental research in geographic information and analysis. Santa Barbara: National Center for Geographic Information and Analysis.]

———. 1988. *Spatial econometrics: Methods and models.* Boston: Kluwer Academic Publishers.

Anselin, Luc, and Anil Bera. 1998. Spatial dependence in linear regression models with an introduction to spatial econometrics. In *Handbook of applied economic statistics,* edited by Amman Ullah and David E.A. Giles. New York: Marcel Dekker.

Anselin, L., A. Bera, R. Florax, and M. Yoon. 1996. Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics* 26:77–104.

Anselin, Luc, and Raymond Florax. 1995. Small sample properties of tests for spatial dependence in regression models: Some further results. In *New directions in spatial econometrics,* edited by L. Anselin and R. Florax. Berlin: Springer-Verlag.

Anselin, Luc, and Arthur Getis. 1992. Spatial statistical analysis and geographic information systems. *Annals of Regional Science* 26:19–33.

Anselin, Luc, and Sheri Hudak. 1992. Spatial econometrics in practice, a review of software options. *Regional Science and Urban Economics* 22:509–536.

Anselin, Luc, and Harry H. Kelejian. 1997. Testing for spatial autocorrelation in the presence of endogenous regressors. *International Regional Science Review* 20:153–182.

Anselin, L., and O. Smirnov. 1998. The *DynESDA extension for ArcView.* Retrieved 30 April 2000 from the World Wide Web: http://www.spacestat.com/downloads.htm.

Bailey, Trevor C., and Anthony Gatrell. 1995. *Interactive spatial data analysis.* Harlow, England: Longman Scientific & Technical.

Bao, S., L. Anselin, D. Martin, and D. Stralberg. Forthcoming. Seamless integration of spatial statistics and GIS: the S-Plus for ArcView and the S+Grassland Links. *Journal of Geographical Systems.*

Basu, Sabyasachi, and Thomas G. Thibodeau. 1998. Analysis of spatial autocorrelation in housing prices. *Journal of Real Estate Finance and Economics* 17:61–85.

Besag, J., and J. Newell. 1991. The detection of clusters in rare diseases. *Journal of the Royal Statistical Society* A 154:143–155.

BioMedware.1994. *Stat! Statistical software for the clustering of health events.* Ann Arbor, Michigan: BioMedware.

Bivand, Roger. Forthcoming. Implementing functions for spatial statistical analysis using the R language. *Journal of Geographical Systems.*

Block, Carolyn R. 1998. The GeoArchive: Information foundation for community policing. In *Crime mapping and crime prevention,* edited by D. Weisburd and T. McEwen. Monsey, New York: Criminal Justice Press.

———. 1994. *STAC hot spot areas: A statistical tool for law enforcement decisions.* Chicago: Illinois Criminal Justice and Information Authority. Retrieved 30 April 2000 from the World Wide Web: http://www.icjia.state.il.us/public/pdf/stac/Hotspot.pdf.

Block, Richard, and Carolyn Block. 1995. Space, place, and crime: Hot-spot areas and hot places of liquor-related crime. In *Crime and place,* edited by J.E. Eck and D. Weisburd. Vol. 4 of *Crime prevention studies.* Monsey, New York: Criminal Justice Press.

Blumstein, Alfred, and Jacqueline Cohen. 1979. Estimation of individual crime rates from arrest records. *Journal of Criminal Law and Criminology* 70:561–585.

Boots, Barry, and Arthur Getis. 1988. *Point pattern analysis.* Newbury Park, California: Sage Publications.

Borjas, George. 1995. Ethnicity, neighborhoods, and human-capital externalities. *American Economic Review* 85:365–390.

Boydstrun, J.E. 1975. *San Diego field interrogation: Final report.* Washington, D.C.: Police Foundation.

Brantingham, P.L., and P.J. Brantingham. 1993. Environment, routine, and situation: Toward a pattern theory of crime. In *Routine activity and rational choice: Advances in criminological theory,* edited by Ronald V. Clarke and Marcus Felson. Vol. 5. New Brunswick, New Jersey: Transaction Publishers.

———. 1982. Mobility, notoriety, and crime: A study of crime patterns in urban nodal points. *Journal of Environmental Systems* 11:89–99.

Brock, William A., and Steven N. Durlauf. 1995. Discrete choice with social interactions. I: Theory. Working paper no. W5291. National Bureau of Economic Research, Cambridge, Massachusetts.

Brunsdon, C., A. Fotheringham, and M. Charlton. 1996. Geographically weighted regression: A method for exploring spatial nonstationarity. *Geographical Analysis* 28:281–298.

Buja, A., D. Cook, and D.F. Swayne. 1996. Interactive high-dimensional data visualization. *Journal of Computational and Graphical Statistics* 5:78–99.

Bursik, Robert J. 1988. Social disorganization and theories of crime and delinquency: Problems and prospects. *Criminology* 26:519–551.

———. 1986. Ecological stability and the dynamics of delinquency. In *Communities and crime,* edited by A.J. Reiss, Jr., and M. Tonry. Vol. 8 of *Crime and justice: A review of research.* Chicago: University of Chicago Press.

Bursik, Robert J., and Harold G. Grasmick. 1993. *Neighborhoods and crime: The dimensions of effective community control.* New York: Lexington Books.

Can, A. 1996. Weight matrices and spatial autocorrelation statistics using a topological vector data model. *International Journal of Geographical Information Systems* 10:1009–1017.

Casetti, Emilio. 1997. The expansion method, mathematical modeling, and spatial econometrics. *International Regional Science Review* 20:9–33.

Chaiken, Jan M., and Marcia Chaiken. 1985. Identifying high-rate serious offenders. Draft report. Santa Monica, California: RAND.

———. 1982. *Varieties of criminal behavior.* Santa Monica, California: RAND.

Chambliss, W.J. 1994. Policing the ghetto underclass: The politics of law and law enforcement. *Social Problems* 41 (May): 177–194.

Clarke, Ronald V., ed. 1992. *Situational crime prevention: Successful case studies.* Albany, New York: Harrow & Heston.

Cleveland, W.S. 1993. *Visualizing data.* Summit, New Jersey: Hobart Press.

Cliff, A.D., and J.K. Ord. 1981. *Spatial processes, models, and applications.* London: Pion.

———. 1973. *Spatial autocorrelation.* London: Pion.

Cohen, Bernard. 1980. *Deviant street networks.* Lexington, Massachusetts: Lexington Books.

Cohen, Jacqueline, Wilpen Gorr, and Andreas Olligschlaeger. 1993. Modeling street-level illicit drug markets. Working paper 93–64, The H. John Heinz III School of Public Policy and Management, Carnegie Mellon University, Pittsburgh.

Cohen, J., D. Cork, J. Engberg, and G. Tita. 1998. The role of drug markets and gangs in local homicide rates. *Homicide Studies* 2:241–262.

Cohen, J., and G. Tita. 1999. Spatial diffusion in homicide: An exploratory analysis. *Journal of Quantitative Criminology* 15 (4): 451–493.

Cohen, Lawrence E., and Marcus Felson. 1979. Social change and crime rate trends: A routine activity approach. *American Sociological Review* 44:588–605.

Cook, D., J. Majure, J. Symanzik, and N. Cressie. 1996. Dynamic graphics in a GIS: Exploring and analyzing multivariate spatial data using linked software. *Computational Statistics* 11:467–480.

Cook, D., J. Symanzik, J. Majure, and N. Cressie. 1997. Dynamic graphics in a GIS: More examples using linked software. *Computers and Geosciences* 23:371–385.

Cornish, L.E., and R.V. Clarke. 1986. *The reasoning criminal: Rational choice perspectives on offending.* New York: Springer-Verlag.

Cressie, N. 1984. Towards resistant geostatistics. In *Geostatistics for natural resources characterization,* Part I, edited by G. Verly, M. Davic, A.G. Journel, and A. Marechal. Dordrecht, The Netherlands: D. Reidel.

Cressie, Noel A.C. 1993. *Statistics for spatial data.* New York: John Wiley & Sons.

Curry, David, and Irving Spergel. 1988. Gang homicide, delinquency, and community. *Criminology* 26:381–405.

DeFronzo, J., and L. Hannon. 1998. Welfare assistance levels and homicide rates. *Homicide Studies* 1:31–45.

Deutsch, C.V., and A.G. Journel. 1992. *GSLIB geostatistical software library and user's guide.* New York: Oxford University Press.

Diggle, Peter. 1991. A point process modeling approach to raised incidence of a rare phenomenon in the vicinity of a pre-specified point. *Journal of the Royal Statistical Society* A 153:349–362.

———. 1983. *Statistical analysis of spatial point patterns.* London: Academic Press.

Diggle, P., and B.S. Rowlingson. 1994. A conditional approach to point process modeling of elevated risk. *Journal of the Royal Statistical Society* A 157:433–440.

Doan, T., R.B. Litterman, and C. Sims. 1984. Forecasting and conditional projections using realistic prior distributions. *Econometric Reviews* 3:1–100.

Dubin, Robin. 1988. Estimation of regression coefficients in the presence of spatially autocorrelated error terms. *Review of Economics and Statistics* 70:466–474.

Duffala, D.C. 1976. Convenience stores, armed robbery, and physical environmental features. *American Behavioral Scientist* 20:227–246.

Durkheim, Emile. [1897] 1966. *Suicide.* Translated by John A. Spaulding and George Simpson. New York: Free Press.

———. [1901] 1950. *The rules of the sociological method.* Translated by S.A Solovay and J.H. Mueller. Glencoe, Illinois: Free Press.

Durlauf, Steven N. 1994. Spillovers, stratification, and inequality. *European Economic Review* 38:836–845.

Eck, John E. 1994. Drug markets and drug places: A case control study of the spatial structure of illicit drug dealing. Ph.D. diss., University of Maryland.

Eck, John E., and David Weisburd. 1995. Crime places in crime theory. In *Crime and place,* edited by J.E. Eck and D. Weisburd. Vol. 4 of *Crime prevention studies.* Monsey, New York: Criminal Justice Press.

Ederer, F., H.M. Myers, and N. Mantel. 1964. A statistical problem in space and time: Do leukemia cases come in clusters? *Biometrics* 20:626–638.

Enders, Walter. 1995. *Applied econometric time series.* New York: John Wiley & Sons.

English, Kim. 1990. Measuring crime rates in Colorado: 1988–89. Paper presented at the Annual Meeting of the American Society of Criminology, November, Baltimore.

Engstad, P.A. 1975. Environmental opportunities and the ecology of crime. In *Crime in Canadian society,* edited by R.A. Silverman and J.J. Teevan. Toronto: Butterworths.

Felson, Marcus. 1994. *Crime and everyday life: Impact and implications for society.* Thousand Oaks, California: Pine Forge Press.

———. 1986. Linking criminal choices, routine activities, informal crime control, and criminal outcomes. In *The reasoning criminal: Rational choice perspectives on offending,* edited by D. Cornish and R.V. Clarke. New York: Springer-Verlag.

Foster, S., and W. Gorr. 1986. An adaptive filter for estimating spatially-varying parameters: Application to modeling police hours spent in response to calls for service. *Management Science* 32:878–889.

Fotheringham, A.S., and D.W.S. Wong. 1991. The modifiable areal unit problem in multivariate statistical analysis. *Environment and Planning* A 32:1025–1044.

Gahegan, Mark, and David O’Brien. 1997. A strategy and architecture for the visualization of complex geographical datasets. *International Journal of Pattern Recognition and Artificial Intelligence* 11:239–261.

Gehlke, C., and Biehl, K. 1934. Certain effects of grouping upon the size of the correlation coefficient in census tract material. *Journal of the American Statistical Association* 29:169–170.

Getis, A. 1995. Spatial filtering in a regression framework: Examples using data on urban crime, regional inequality, and government expenditures. In *New directions in spatial econometrics,* edited by L. Anselin and R. Florax. Berlin: Springer-Verlag.

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

Glaeser, E., B. Sacerdote, and J. Scheinkman. 1996. Crime and social interactions. *Quarterly Journal of Economics* 111:507–548.

Gorr, W., and A. Olligschlaeger. 1994. Weighted spatial adaptive filtering: Monte Carlo studies and application to illicit drug market modeling. *Geographical Analysis* 26:67–87.

Gorr, Wilpen L., Andreas M. Olligschlaeger, and Janusz Szczypula. 1998. Crime hot spot forecasting: Modeling and comparative evaluation. Paper prepared under NIJ grant no. 98–IJ–CX–K005, U.S. Department of Justice, National Institute of Justice, Washington, D.C.

Granger, C.W.J., and Paul Newbold. 1977. *Forecasting economic time series.* New York: Academic Press.

Greenberg, David F. 1991. Modeling criminal careers. *Criminology* 29:17–46.

Greenberg, S., W. Rohe, and J. Williams. 1985. *Informal citizen action and crime prevention at the neighborhood level: Synthesis and assessment of the research.* Executive Summary, NCJ 97977. Washington, D.C.: U.S. Department of Justice, National Institute of Justice.

Griffith, Daniel. 1993. *Spatial regression analysis on the PC: Spatial statistics using SAS.* Washington, D.C.: Association of American Geographers.

———. 1987. *Spatial autocorrelation, a primer.* Washington, D.C.: Association of American Geographers.

Guerry, A. [1833a] 1984. Note. In *Research on the propensity for crime at different ages,* by A. Quetelet. Translated by Sawyer F. Sylvester. Cincinnati: Anderson Publishing Company.

———. [1833b] 1974. *Essai sur la Statistique Morale de la France.* New York: Clearwater.

Haapanen, Rudy A. 1990. *Selective incapacitation and the serious offender.* New York: Springer-Verlag.

Härdle, W., S. Klinke, and B.A. Turlach. 1995. *XploRe: An interactive statistical computing environment.* Berlin: Springer-Verlag.

Haslett, J., R. Bradley, P. Craig, A. Unwin, and G. Wills. 1991. Dynamic graphics for exploring spatial data with applications to global and local anomalies. *American Statistician* 45:234–242.

Haslett, J., G. Wills, and A. Unwin. 1990. Spider, an interactive statistical tool for the analysis of spatially distributed data. *International Journal of Geographical Information Systems* 4:285–296.

Hjalmars, Ulf, Martin Kulldorff, Goran Gustafsson, and Neville Nagarwalla. 1996. Childhood leukaemia in Sweden: Using GIS and a spatial scan statistic for cluster detection. *Statistics in Medicine* 15:707–715.

Holden, Ken. 1995. Vector autoregression modelling and forecasting. *Journal of Forecasting* 14:159–166.

Holt, D., D.G. Steel, M. Tranmer, and N. Wrigley. 1996. Aggregation and ecological effects in geographically based data. *Geographical Analysis* 28:224–262.

Homel, R., and J. Clark. 1995. The prediction and prevention of violence in pubs and clubs. In *Crime prevention studies,* edited by R.V. Clarke. Vol. 3. Monsey, New York: Criminal Justice Press.

Horney, Julie, and Ineke H. Marshall. 1991. Measuring lambda through self reports. *Criminology* 29:471–496.

Hubert, Lawrence. 1987. *Assignment methods in combinatorial data analysis.* New York: Marcel Dekker.

———. 1985. Combinatorial data analysis: Association and partial association. *Psychometrika* 50:449–467.

Hubert, L.J., R. Golledge, and M. Costanzo. 1981. Generalized procedures for evaluating spatial autocorrelation. *Geographical Analysis* 13:224–233.

Isaaks, E.H., and R.M. Srivastava. 1989. *An introduction to applied geostatistics.* Oxford: Oxford University Press.

Jeffrey, C.R. 1971. *Crime prevention through environmental design.* Beverly Hills: Sage Publications.

Jones, J.P., and E. Casetti. 1992. *Applications of the expansion method.* London: Routledge.

Kelejian, Harry H., and Ingmar Prucha. 1999a. A generalized moments estimator for the autoregressive parameter in a spatial model. *International Economic Review* 40 (2): 509–533.

———. 1999b. On the asymptotic distribution of the Moran I Test statistic with applications. Working paper, Department of Economics, University of Maryland, College Park.

———. 1998. A generalized two stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances. *Journal of Real Estate Finance and Economics* 17:99–121.

———. 1997. Estimation of spatial regression models with autoregressive errors by two stage least squares procedures: A serious problem. *International Regional Science Review* 20:103–111.

Kelejian, Harry H., and Dennis P. Robinson. 1999. The influence of spatially correlated heteroskedasticity on tests for spatial correlation. In *Advances in spatial econometrics,* edited by L. Anselin and R. Florax. Heidelberg: Springer-Verlag.

———. 1998. A suggested test for spatial autocorrelation and/or heteroskedasticity and corresponding Monte Carlo results. *Regional Science and Urban Economics* 28:389–417.

———. 1993. A suggested method of estimation for spatial interdependent models with autocorrelated errors, and an application to a county expenditure model. *Papers in Regional Science* 72:297–312.

Kelling, G.L., and C.M. Coles. 1996. *Fixing broken windows: Restoring order and reducing crime in our communities.* New York: Free Press.

King, Gary. 1997. *A solution to the ecological inference problem.* Princeton, New Jersey: Princeton University Press.

Knox, E.G. 1964. The detection of space-time interactions. *Applied Statistics* 13:25–29.

Kposowa, A., and K.D. Breault. 1993. Reassessing the structural covariates for U.S. homicide rates: A county level study. *Sociological Forces* 26:27–46.

Kulldorff, Martin, and Neville Nagarwalla. 1995. Spatial disease clusters: Detection and inference. *Statistics in Medicine* 14:799–810.

Land, K., and G. Deane. 1992. On the large-sample estimation of regression models with spatial- or network-effects terms: A two stage least squares approach. In *Sociological methodology,* edited by P. Marsden. San Francisco: Jossey-Bass.

Land, K., P. McCall, and L. Cohen. 1990. Structural covariates of homicide rates: Are there invariances across time and social space? *American Journal of Sociology* 95:922–963.

Lawson, A.B. 1993. On the analysis of mortality events associated with a prespecified fixed point. *Journal of the Royal Statistical Society* A 156:363–377.

Legendre, Pierre. 1993. Spatial autocorrelation: Trouble or new paradigm? *Ecology* 74:1659–1673.

LeSage, James. 1999. A family of geographically weighted regression models. In *Advances in spatial econometrics,* edited by L. Anselin and R. Florax. Heidelberg: Springer-Verlag.

———. 1997. Bayesian estimation of spatial autoregressive models. *International Regional Science Review* 20:113–129.

———. 1995. A multiprocess mixture model to estimate space-time dimensions of weekly pricing of certificates of deposit. In *New directions in spatial econometrics,* edited by L. Anselin and R. Florax. Berlin: Springer-Verlag.

———. 1990. Forecasting turning points in metropolitan employment growth rates using Bayesian techniques. *Journal of Regional Science* 30:533–548.

———. 1989. Incorporating regional wage relations in local forecasting models with a Bayesian prior. *International Journal of Forecasting* 5:37–47.

LeSage, J.P., and Z. Pan. 1995. Using spatial contiguity as Bayesian prior information in regional forecasting models. *International Regional Science Review* 18:33–53.

Levine, N. 1999. *CrimeStat: A spatial statistics program for the analysis of crime incident locations.* Washington, D.C.: U.S. Department of Justice, National Institute of Justice.

———. 1996. Spatial statistics and GIS: Software tools to quantify spatial patterns. *Journal of the American Planning Association* 62:381–391.

Litterman, R.B. 1986. Forecasting with Bayesian vector autoregressions—Five years of experience. *Journal of Business & Economic Statistics* 4:25–38.

———. 1980. Techniques for forecasting with vector autoregressions. Ph.D. diss., University of Minnesota.

MacEachren, A.M., and M.-J. Kraak. 1997. Exploratory cartographic visualization: Advancing the agenda. *Computers and Geosciences* 23:335–343.

Majure, J., and N. Cressie. 1997. Dynamic graphics for exploring spatial dependence in multivariate spatial data. *Geographical Systems* 4:131–158.

Mantel, N. 1967. The detection of disease clustering and a generalised regression approach. *Cancer Research* 27:209–220.

Marshall, Roger J. 1991. A review of methods for the statistical analysis of spatial patterns of disease. *Journal of the Royal Statistical Society* A 154:421–441.

MathSoft. 1996. *S+SpatialStats.* Seattle: MathSoft.

McMillen, Daniel, and John F. McDonald. 1997. A nonparametric analysis of employment density in a polycentric city. *Journal of Regional Science* 37:591–612.

Messner, S., L. Anselin, R. Baller, D. Hawkins, G. Deane, and S. Tolnay. 1999. The spatial patterning of county homicide rates: An application of exploratory spatial data analysis. *Journal of Quantitative Criminology* 15 (4): 423–450.

Miranne, Alfred C., and Michael Geerken. 1991. The New Orleans inmate survey: A test of Greenwood's predictive scale. *Criminology* 29:497–518.

Morenoff, J., and R.J. Sampson. 1997. Violent crime and the spatial dynamics of neighborhood transition: Chicago 1970–1990. *Social Forces* 76:31–64.

Munasinghe, R., and R. Morris. 1996. Localization of disease clusters using regional measures of spatial autocorrelation. *Statistics in Medicine* 15:893–905.

Nagarwalla, Neville. 1996. A scan statistic with a variable window. *Statistics in Medicine* 15:845–850.

Newman, Oscar. 1972. *Defensible space.* New York: Macmillan.

Oden, N. 1995. Adjusting Moran's I for population density. *Statistics in Medicine* 12:1915–1929.

Olmo, J.C. 1995. Spatial estimation of housing prices and locational rents. *Urban Studies* 32:1331–1344.

Openshaw, Stan. 1979. A million or so correlation coefficients: Three experiments on the modifiable areal unit problem. In *Statistical methods in the spatial sciences,* edited by N. Wrigley. London: Pion.

Openshaw, S., and S. Alvanides. 1999. Applying geocomputation to the analysis of spatial distributions. In *Geographical Information Systems.* 2d ed. Edited by P. Longley, M. Goodchild, D. Maguire, and D. Rhind. New York: John Wiley & Sons.

Openshaw, S., M. Charlton, C. Wymer, and A. Craft. 1987. A Mark 1 geographical analysis machine for the automated analysis of point datasets. *International Journal of Geographical Information Systems* 1:335–358.

Openshaw, S., A. Craft, M. Charlton, and J. Birch. 1988. Investigation of leukemia clusters by use of a geographical analysis machine. *Lancet* 1:272–273.

Ord, J. Keith. 1990. Statistical methods for point pattern data. In *Spatial statistics: Past, present, and future,* edited by D. Griffith. Ann Arbor: ImaGE.

———. 1975. Estimation methods for models of spatial interaction. *Journal of the American Statistical Association* 70:120–126.

Ord, J.K., and A. Getis. 1995. Local spatial autocorrelation statistics: Distributional issues and an application. *Geographical Analysis* 27:286–306.

Pace, R.K., and R. Barry. 1998. *Spatial Statistics Toolbox 1.0.* Baton Rouge: Louisiana State University, Real Estate Institute.

Pannatier, Yvan. 1996. *Variowin, software for spatial data analysis in 2D.* Heidelberg: Springer-Verlag.

Park, R.E., E.W. Burgess, and R.D. McKenzie, eds. 1925. *The city.* Chicago: University of Chicago Press.

Pate, A., W.G. Skogan, M.A. Wycoff, and L.W. Sherman. 1985. *Reducing the signs of crime: Executive summary.* Washington, D.C.: Police Foundation.

Petersilia, Joan, Peter W. Greenwood, and M. Lavin. 1977. *Criminal careers of habitual offenders.* Santa Monica, California: RAND.

Peterson, Mark A., and Harriet B. Braiker. 1981. *Doing crime: A survey of California prison inmates.* Cambridge, Massachusetts: Oelgeschlager, Gunn, and Hain.

Pierce, G., S.A. Spaar, and L. Briggs IV. 1988. The character of police work: Strategic and tactical implications. M.S. thesis, Northeastern University, Center for Applied Social Research.

Pinkse, Joris. 1999. Moran-flavored test with nuisance parameters. In *Advances in spatial econometrics,* edited by L. Anselin and R. Florax. Heidelberg: Springer-Verlag.

Quetelet, Adolphe J. [1833] 1984. *Research on the propensity for crime at different ages.* Translated by Sawyer F. Sylvester. Cincinnati: Anderson Publishing Company.

———. [1842] 1969. *A treatise on man and the development of his faculties. A facsim. reproduction of the English translation of 1842.* Gainesville, Florida: Scholar's Facsimiles and Reprints.

Rheingans, P., and C. Landreth. 1995. Perceptual principles for effective visualizations. In *Perceptual issues in visualization,* edited by G. Grinstein and H. Levkovitz. Berlin: Springer- Verlag.

Ripley, Brian. 1981. *Spatial statistics.* New York: John Wiley & Sons.

———. 1976. The second order analysis of stationary point processes. *Journal of Applied Probability* 13:255–266.

Ritzer, George. 1988. *Contemporary sociological theory.* New York: Alfred A. Knopf.

Roncek, D. 1993. Mapping crime: An inescapable but valuable task for intracommunity analysis. In *Questions and answers in lethal and non-lethal violence: Proceedings of the second annual workshop of the Homicide Research Working Group,* edited Carolyn Block and Richard L. Block. NCJ 147480. Washington, D.C.: U.S. Department of Justice, National Institute of Justice.

Roncek, Dennis W., and R. Bell. 1981. Bars, blocks, and crime. *Journal of Environmental Systems* 11:35–47.

Roncek, Dennis W., and J.M.A. Francik. 1981. Housing projects and crime: Testing the proximity hypothesis. *Social Problems* 29:151–166.

Roncek, Dennis W., and P.A. Maier. 1991. Bars, blocks, and crimes revisited: Linking the theory of routine activities to the empiricism of hot spots. *Criminology* 29:725–755.

Roncek, Dennis W., and M.A. Pravatiner. 1989. Additional evidence that taverns enhance nearby crime. *Sociology and Social Research* 73:185–188.

Rowlingson, B.S., and P.J. Diggle. 1993. Splancs: Spatial point pattern analysis code in S-Plus. *Computers and Geosciences* 19:627–655.

Rushton, Gerard, and Panos Lolonis. 1996. Exploratory spatial analysis of birth defect rates in an urban population. *Statistics in Medicine* 15:717–726.

Sabel, Clive. 1998. Peaks and troughs: Space-time cluster detection in rare diseases. Working paper presented at the Environmental Systems Research Institute International User Conference, 27–31 July. Retrieved 30 March 2000 from the World Wide Web: http://www.esri.com/library/userconf/proc98/PROCEED.HTM.

Sampson, Robert J. 1995. The community. In *Crime,* edited by James Q. Wilson and Joan Petersilia. San Francisco: ICS Press.

———. 1986. Crime in cities: The effects of formal and informal social control. In *Communities and crime,* edited by A.J. Reiss, Jr., and M. Tonry. Vol. 8 of *Crime and justice: A review of research.* Chicago: University of Chicago Press.

Sampson, Robert J., and Jacqueline Cohen. 1988. Deterrent effects of the police on crime: A replication and theoretical extension. *Law & Society Review* 22:165–189.

Sampson, Robert J., and W. Byron Groves. 1989. Community structure and crime: Testing social-disorganization theory. *American Journal of Sociology* 94:774–802.

Sampson, Robert J., Jeffrey Morenoff, and Felton Earls. 1999. Beyond social capital: Neighborhood mechanism and structural sources of collective efficacy for children. *American Sociological Review* 64:633–660.

Shannon, Lyle W. 1988. *Criminal career continuity.* New York: Human Sciences Press.

Shaw, Clifford R., and Henry D. McKay. 1942. *Juvenile delinquency and urban areas: A study of rates of delinquents in relation to differential characteristics of local communities in American cities.* Chicago: University of Chicago Press.

Shaw, Clifford R., Frederick M. Zorbaugh, Henry D. McKay, and Leonard S. Cottrell. 1929. *Delinquency areas.* Chicago: University of Chicago Press.

Sherman, Lawrence W. 1995. Hot spots of crime and criminal careers of places. In *Crime and place,* edited by J.E. Eck and D. Weisburd. Vol. 4 of *Crime prevention studies.* Monsey, New York: Criminal Justice Press.

———. 1992. Attacking crime: Police and crime control. In *Modern policing,* edited by M. Tonry and N. Morris. Vol. 15 of *Crime and justice: A review of research.* Chicago: University of Chicago Press.

———. 1986. Policing communities: What works? In *Communities and crime,* edited by A.J. Reiss, Jr., and M. Tonry. Vol. 8 of *Crime and justice: A review of research.* Chicago: University of Chicago Press.

Sherman, L.W., P.R. Gartin, and M.E. Buerger. 1989. Hot spots of predatory crime: Routine activities and the criminology of place. *Criminology* 27:27–55.

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

Silverman, B.W. 1986. *Density estimation for statistics and data analysis.* London: Chapman & Hall.

Sims, C.A. 1980. Macroeconomics and reality. *Econometrica* 48:1–48.

Skogan, W.G., and M.G. Maxfield. 1981. *Coping with crime: Individual and neighborhood reactions.* Beverly Hills: Sage Publications.

Sokal, R., N. Oden, B. Thomson, and J. Kim. 1993. Testing for regional differences in means: Distinguishing inherent from spurious spatial autocorrelation by restricted randomization. *Geographical Analysis* 25:199–210.

Spelman, William. 1995. Criminal careers of public places. In *Crime and place,* edited by J.E. Eck and D. Weisburd. Vol. 4 of *Crime and prevention studies.* Monsey, New York: Criminal Justice Press.

Symanzik J., S. Klinke, S. Schmelzer, D. Cook, and N. Lewin. 1998. The ArcView/XGobi/XploRe environment: Technical details and applications for spatial data analysis. ASA Proceedings of the Section on Statistical Graphics. Alexandria, Virginia: American Statistical Association.

Symanzik J., T. Kötter, S. Schmelzer, S. Klinke, D. Cooke, D. Swayne. Forthcoming. Spatial data analysis in the dynamically linked ArcView/XGobi/XploRe environment. *Computing Science and Statistics.*

Thrasher, Frederick. 1927. *The gang.* Chicago: University of Chicago Press.

Tita, George E. 1999. An ecological study of urban street gangs and their impact on crime. Ph.D. diss., The H. John Heinz III School of Public Policy and Management, Carnegie Mellon University, Pittsburgh.

Tita, George E., John Engberg, and Jacqueline Cohen. 1999. An ecological study of violent gangs: The social organization of set space. Working paper, National Consortium on Violence Research, Carnegie Mellon University, Pittsburgh.

Tolnay, S.E., G. Deane, and E.M. Beck. 1996. Vicarious violence: Spatial effects on Southern lynchings, 1890–1919. *American Journal of Sociology* 102:788–815.

Tracy, Paul E., Marvin E. Wolfgang, and Robert M. Figlio. 1990. *Delinquency careers in two birth cohorts.* New York: Plenum Press.

Tukey, John W. 1977. *Exploratory data analysis.* Reading, Massachusetts: Addison-Wesley.

Turnbull, B.W., E.J. Iwano, W.S. Burnett, H.L. Howe, and L.C. Clarke. 1990. Monitoring for clusters of disease: Application to leukemia incidence in upstate New York. *American Journal of Epidemiology* 132:S136–S143.

Unwin, A. 1996. Exploratory spatial analysis and local statistics. *Computational Statistics* 11:387–400.

Unwin, A., G. Hawkins, H. Hofman, and B. Siegl. 1996. Interactive graphics for data sets with missing values—MANET. *Journal of Computational and Graphical Statistics* 5:113–122.

Upton, Graham, and Bernard Fingleton. 1985. *Spatial data analysis by example.* New York: John Wiley & Sons.

Venables, W., and B. Ripley. 1998. *Modern applied statistics with S-Plus.* 2d ed. New York: Springer-Verlag.

Waller, Lance. 1996. Statistical power and design of focused clustering studies. *Statistics in Medicine* 15:765–782.

Waller, Lance, Bruce Turnbull, Goran Gustafsson, Ulf Hjalmars, and Bertil Andersson. 1995. Detection and assessment of clusters of disease: An application to nuclear power plant facilities and childhood leukaemia in Sweden. *Statistics in Medicine* 14:3–16.

Wartenberg, D. 1985. Multivariate spatial autocorrelation: A method for exploratory geographical analysis. *Geographical Analysis* 17:263–283.

Weisburd, David. 1997. *Reorienting crime prevention research and policy: From the causes of criminality to the context of crime.* Research Report, NCJ 165041. Washington, D.C.: U.S. Department of Justice, National Institute of Justice.

Weisburd, D.L., and L. Green. 1994. Defining the street level drug market. In *Drugs and crime: Evaluating public policy initiatives,* edited by D.L. MacKenzie and C.D. Uchida. Beverly Hills: Sage Publications.

Wikstrom, Per-Olaf. 1998. Communities and crime. In *Handbook of crime and punishment,* edited by Michael Tonry. New York: Oxford University Press.

Williamson, Doug, Sara McLafferty, Victor Goldsmith, John Mollenkopf, and Phil McGuire. 1998. Smoothing crime incident data: New methods for determining the bandwidth in Kernel estimation. Working paper presented at the Environmental Systems Research Institute International User Conference, 27–31 July. Retrieved 30 March 2000 from the World Wide Web: http://www.esri.com/library/userconf/proc98/PROCEED.HTM.

Wilson, J.Q., and B. Boland. 1978. The effect of the police on crime. *Law & Society Review* 12:367–390.

Wilson, J.Q., and G.L. Kelling. 1982. Broken windows: The police and neighborhood safety. *Atlantic Monthly* 249:29–38.

Wolfgang, Marvin E., Robert M. Figlio, and Thorsten Sellin. 1972. *Delinquency in a birth cohort.* Chicago: University of Chicago Press.

Wolfgang, Marvin E., Terence P. Thornberry, and Robert M. Figlio. 1987. *From boy to man, from delinquency to crime.* Chicago: University of Chicago Press.

Spatial analysis can be employed in both an exploratory and well as a more confirmatory manner with the primary purpose of identifying how certain community or ecological factors (such as population characteristics or the built environment) influence the spatial patterns of crime. Two topics of particular interest include examining for evidence of the diffusion of crime and in evaluating the effectiveness of geographically targeted crime reduction strategies. Crime mapping can also be used to visualize and analyze the movement or target selection patterns of criminals. Mapping software allows Crime Mapping and Spatial Analysis - ITC Mapping and Spatial Analysis By Mostafa Ahmadi (CASE STUDY) OF MAP CALCULATION WITH BUFFER OF MAIN STREETS IN (B) ...Authors: Mostafa AhmadiAffiliation: Indian Institutes of TechnologyAbout: Spatial analysisDocuments. Spatial Analysis of Crime Report DatasetsDocuments. Probabilistic and spatial liquefaction analysis using CPT data: a case study for Alameda County siteDocuments.Â Spatial eigenvector filtering for spatiotemporal crime mapping and spatial crime analysisDocuments. Spatial Microsimulation and Crime AnalysisDocuments. Spatial Statistics in Crime AnalysisDocuments. GIS Based Spatial and Temporal Analysis of Crimes, a Case Study ...Documents. Spatial Analyses of Crime. Chapter (PDF Available) Â· January 2000 with 677 Reads. In book: Measurement and Analysis of Crime and Justice. Criminal Justice 2000, Volume 4, Publisher: US Department of Justice, Office of Justice Programs, National Institute of Justice, Editors: D Duffe, pp.213-262. Cite this publication.