CHAPTER 6

Spatial Regression Models in Criminology: Modeling Social Processes in the Spatial Weights Matrix

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A decade ago, Jacqueline Cohen and George Tita served as guest editors for a special volume of the *Journal of Quantitative Criminology* (Vol 15, #4, 1999) that was dedicated to the study of the diffusion of homicide. In their Editor's Introduction (Cohen and Tita 1999a), they concluded that the results presented in special volume,[1] along with recent work by Morenoff and Sampson (1997), clearly demonstrated that the observed patterns of violence were consistent with patterns one might expect if violence does, in fact, diffuse over space. That is, levels of violence are not randomly distributed; instead, similar rates of violence cluster together in space (i.e., violence exhibits positive spatial autocorrelation.) Furthermore, a growing number of studies began to demonstrate that even after controlling for the ecological features known to be associated with high levels of crime (e.g., poverty, population density, male joblessness, female-headed households, etc), the clustering of high values could not be explained away. These early spatial studies of diffusion helped to establish the existence of an unobserved "neighborhood effect" that seemed to be responsible for spatially concentrated high-crime areas.

Not to diminish the contribution of these studies in advancing our understanding of crime and violence, Cohen and Tita ended their introduction by noting that there was much work to be done.[2] First, in order to understand diffusion, models needed to include a more complete accounting of temporal considerations. Though the spatial analysis of cross-sectional data is helpful in determining whether or not the initial conditions consistent with diffusion are being

[1] The contributors to this special issue included Cork; Mencken and Barnett; Messner, Anselin, Baller, Hawkins, Deane and Tolnay; Cohen and Tita; and Rosenfeld, Bray and Egley.

[2] Cohen and Tita neglect to address the issue of employing the appropriate spatial scale in terms of the spatial unit of analysis. Hipp (2007) and Weisburd et al. (2008) offer excellent treatment of this important topic.

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satisfied, without analyzing change over time one cannot capture the movement of spatial patterns over time. Second, even during the homicide epidemic of the late 1980s and early 1990s, homicide remained a rare event when compared to other types of crimes. In order to fully understand the mechanisms that drive the diffusion of violence, research needed to be conducted on nonlethal violence (as well as other types of crime.) According to the authors, however, the single most daunting challenge facing the researchers was not developing better methods or using better data in order to validate patterns of diffusion; the most important hurdle was to create models that would produce results that could be used to gain a better understanding of the "…mechanisms by which the recent homicide epidemic spread." In other words, Cohen and Tita called upon the research community to create models that would help to unlock the black box of "neighborhood effects" by explicitly modeling the processes that drive the spread of violence.

We hope to achieve several goals in this chapter. Though the term "spatial analysis" can be applied to a broad set of methodologies (e.g., hot spot analysis, journey to crime analysis, exploratory spatial analysis),[3] we wish to focus specifically on the application of spatial regression models to the ecological analysis of crime, which makes use of socio-economic data aggregated or grouped into geographic areas. To do so, however, requires an introductory discussion of the nature of spatial data and the associated exploratory analyses that are now common when using geographically aggregated data. Therefore, we begin with an overview of spatial data, with an emphasis on the key concept of spatial autocorrelation, and provide an overview of exploratory spatial analysis techniques that can assess the presence and level of spatial autocorrelation in spatial data. We then move onto a discussion of spatial regression models developed to address the presence of spatial effects in one's data. Next, we highlight some of the key findings that have emerged from the use of spatial regression in criminology and evaluate whether or not they have helped in the identification of the particular social processes responsible for the clustering and diffusion of crime. Drawing upon our own work (Tita and Greenbaum 2008; Radil et al. 2010; Tita et al. 2009), we hone in on one of the most important, though often overlooked, components of any spatial regression model – the spatial weights matrix or "W." We believe that the mechanisms and processes that drive the diffusion of crime can best be understood by "spatializing" the manner in which information and influence flows across social networks. Therefore, we examine some of the innovative ways that researchers have used to specify "W" in criminology as well as other areas of study. Keeping Cohen and Tita's (1999a, b) argument about unlocking the black box of "neighborhood effects" in mind, we conclude by emphasizing the importance of theoretically- and empirically-grounded specifications of W to this goal.

THE NATURE OF SPATIAL DATA AND SPATIAL DATA ANALYSIS

Criminology, like most social sciences, is an observational science as opposed to an experimental science. This is to say that researchers are not able to experiment with or replicate observed outcomes, which take place at specific locations at specific times. When the structure of the places and spaces in which outcomes occur is thought to affect the processes theorized

[3] For an introductory treatment of these methods and the manner in which they have been used in criminology and criminal justice, see Anselin et al. (2008).

to give rise to the observed outcomes (such as theorized relationships between crime and place – see Morenoff et al. 2001 or Sampson et al. 2002 for recent examples), the location of each outcome is important information for researchers. Spatial data then are those with information about the location of each observation in geographic space.

A fundamental property of spatial data is the overall tendency for observations that are close in geographic space to be more alike than those that are further apart. In geography, this tendency is referred to in "Tobler's First Law of Geography," which states that "everything is related to everything else but near things are more related than distant things" (Tobler 1970: 236). Although more of a general truism than a universal law, Tobler's "law" rightly points out that the clustering of like objects, people, and places on the surface of the earth is the norm, and such organizational patterns are of intrinsic interest to many social scientists (O'Loughlin 2003; Haining 2003). This property is called *spatial dependence* and has important implications for researchers. First, an observation at any given location can provide information about nearby locations and one can therefore make informed estimates about the level of attributes in nearby locations (e.g., spatial interpolation). Second, the tendency of data to vary together across space creates problems for classical inferential statistical models and can undermine the validity of inferences drawn from such models (Anselin 1988).

Another fundamental property of spatial data is the tendency for relationships between variables to vary from place-to-place or across space. This tendency, known as *spatial heterogeneity*, is often due to location-specific effects (Anselin 1988; Fotheringham 1997). Spatial heterogeneity has the important consequence of meaning that a single global relationship for an overall study region may not adequately reflect outcomes in any given location of the study region (Anselin 1988; Fotheringham 1997). Further, variations in local relationships can lead to inconsistent estimates of the effect of variables at global levels, if the relationship between the dependent variable of interest and the independent variables is characterized by a nonlinear function (Fotheringham et al. 2002).[4]

Both of these properties of spatial data have been at the heart of spatial data analysis, which is the development of quantitative analytic techniques that accommodate the nature of spatial data for both descriptive and inferential statistical analysis and modeling (Anselin 1988; Haining 2003; Goodchild 2004). Anselin (1998) has referred to the collection of different methods and techniques for structuring, visualizing, and assessing the presence of the degree of spatial dependence and heterogeneity as exploratory spatial data analysis, or ESDA. For Anselin (1998), the key steps of ESDA involve describing and visualizing the spatial

[4] We also wish to draw attention to another group of properties directly or indirectly related to how spatial data is represented, organized, and measured by researchers. While not an exhaustive list, border effects, the so-called 'modifiable areal unit problem,' and the challenges of ecological fallacy are three issues commonly encountered by researchers using aggregated spatial data (see Haining 2009). Border effects refer to the fact that the often-arbitrary boundaries of study regions may exclude information that affects outcomes within the study region (see Griffith 1983). The modifiable areal unit problem (MAUP) refers to the fact that the results of statistical analysis, such as correlation and regression, can be sensitive to the geographic zoning system used to group data by area (see Gehlke and Biehl 1934 or Robinson 1950 for classic examples of MAUP, or Openshaw 1996 for a more contemporary review). Ecological fallacy, or the difficulty in inferring individual behavior from aggregate data, is ever present in many social sciences attempting to predict individual behavior from an analysis of geographically aggregated data (see King 1997; O'Loughlin 2003) While well-established in geography, these issues tend to resurface in other disciplines as spatial analysis becomes more prevalent (for an example, see Hipp 2007). For a review of the treatment of some of these issues in the spatial analysis of crime, see Weisburd et al. (2008).

distributions of variables of interest, the identification of atypical locations (so-called "spatial outliers"), uncovering patterns of spatial association (clusters), and assessing any change in the associations between variables across space. While a comprehensive review of ESDA is beyond the scope of this chapter (see Anselin 1998, 1999), we wish to draw attention to the concept of spatial autocorrelation which is commonly present in data aggregated to geographic areal units and is therefore of relevance to criminologists that commonly use such data.

Spatial dependence in spatial data can result in the *spatial autocorrelation* of regression residuals. Spatial autocorrelation occurs when the values of variables sampled at nearby locations are not independent from each other. Spatial autocorrelation may be either *positive* or *negative*. Positive spatial autocorrelation occurs when similar values appear together in space, while negative spatial autocorrelation occurs when dissimilar values appear together. When mapped as part of an ESDA, positively spatially autocorrelated data will appear to cluster together, while a negatively spatially autocorrelated data will result in a pattern in which geographic units of similar values scatter throughout the map (see Fig. 6.1).

The presence of spatial autocorrelation may lead to biased and inconsistent regression model parameter estimates and increase the risk of a type I error (falsely rejecting the null hypothesis). Accordingly, a critical step in model specification when using spatial data is to assess the presence of spatial autocorrelation. And while different methods have been developed to address issues of spatial heterogeneity, such as identifying different spatial regimes (subregions) and modeling each separately (Anselin 1988), spatial dependence must still be addressed within distinct subregions once these have been identified.

A number of statistical methods have been developed to assess spatial autocorrelation in spatial data both globally and locally. As described in the seminal works in geography on spatial autocorrelation by Cliff and Ord (1973, 1981), the basic standard tests for spatial autocorrelation are the join count statistic, suited only for binary data, and more commonly, Moran's I and Geary's C, both suited for continuous data (Cliff and Ord 1973, 1981). Moran's I and Geary's C are global measures of spatial autocorrelation in that they both summarize the total deviation from spatial randomness across a set of spatial data with a single statistic, although they do so in different ways. Moran's I is a cross-product coefficient similar to a Pearson correlation coefficient and ranges from -1 to $+1$. Positive values for Moran's

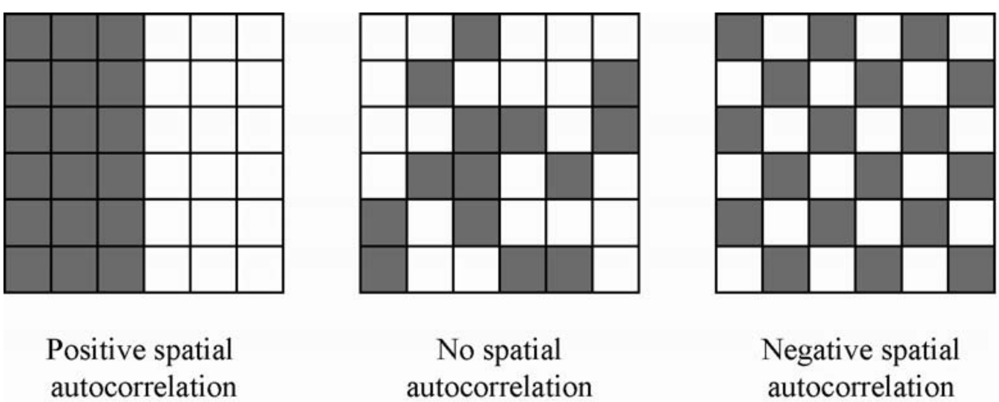

FIGURE 6.1. Spatial data may demonstrate a pattern of positive spatial autocorrelation (*left*), negative spatial autocorrelation (*right*), or a pattern that is not spatially autocorrelated (*center*). Statistical tests, such as Moran's I, should always be used to evaluate the presence of spatial autocorrelation.

I indicate positive spatial autocorrelation and negative values suggest negative spatial autocorrelation. Geary's C coefficient is based on squared deviations, and values of less than one indicate positive spatial autocorrelation, while values larger than one suggest negative spatial autocorrelation. As a counterpart to the global statistics, there are also local statistics that assess spatial autocorrelation at a specific location. These include the Getis and Ord Gi and Gi^* statistics (Getis and Ord 1992; Ord and Getis 1995) and the local Moran's I (Anselin 1995).

SIMULTANEOUS AUTOREGRESSIVE SPATIAL REGRESSION MODELS

While there are a variety of methods to address spatially autocorrelated data in regression models, we focus here on what are commonly referred to as simultaneous autoregressive (SAR) models, the standard workhorse in spatial regression in a variety of social science fields, particularly those that make use of spatially aggregated socioeconomic data (Anselin 2006; Ward and Gleditsch 2008). Spatial regression models, including SAR models, have been, in large part, developed as a response to the recognition that ignoring spatial dependence when it is present creates serious problems. As Anselin (1988) and others have demonstrated, ignoring spatial dependence in spatial data can result in biased and inconsistent estimates for all the coefficients in the model, biased standard errors, or both. Consequently, inferences derived from such models may be significantly flawed. While a thorough treatment of these models is beyond the aims of this chapter, we offer a brief summary of the main variants before moving on to offer some examples of how these models have been used in criminology.

SAR models can take three different basic forms (see Anselin 1988, 2002; Haining 2003). The first SAR model assumes that the autoregressive process occurs only in the dependent or response variable. This is called the "spatial lag" model and it introduces an additional covariate to the standard terms for the independent, or predictor variables and the errors used in an ordinary least squares (OLS) regression (the additional variable is referred to as a "spatial lag" variable which is a weighted average of values for the dependent variable in areas defined as "neighbors"). Drawing on the form of the familiar OLS regression model and following Anselin (1988), the spatial lag model may be presented as

$$Y = \rho W y + X\beta + \varepsilon,$$

where Y is the dependent variable of interest, ρ is the autoregression parameter, W is the spatial weights matrix, X is the independent variable, and ε is the error term.

The second SAR model assumes that the autoregressive process occurs only in the error term. In this case, the usual OLS regression model is complemented by representing the spatial structure in the spatially dependent error term. The error model may be presented as

$$Y = X\beta + \varepsilon, \quad \varepsilon = \lambda W \varepsilon + \mu,$$

where λ is the autoregression parameter, and ε is the error term composed of a spatially autocorrelated component ($W\varepsilon$) and a stochastic component (μ) with the rest as in the spatial lag model. The third SAR model can contain both a spatial lag term for the response variable and a spatial error term, but is not commonly used. Other SAR model possibilities include lagging predictor variables instead of response variables. In this case, another term must also appear in the model for the autoregression parameters (γ) of the spatially lagged predictors (WX). This model takes the form

$$Y = X\beta + WX\lambda + \varepsilon.$$

Combining the response lag and predictor lag terms in a single model is also possible (sometimes referred to as a "mixed" model).

As Anselin (1988) observes, spatial dependence has much to do with notions of relative location between units in potentially different kinds of space and, accordingly, SAR models share a number of common features with network autocorrelation models. Substantively, spatial and network approaches have been used to explore similar questions pertaining to influence and contagion effects, albeit among different units of observations (see Marsden and Friedkin 1993 for examples). In both cases, proximity or connectedness is assumed to facilitate the direct flow of information or influence across units. Individuals or organizations are also more likely to be influenced by the actions, behaviors, or beliefs of others that are proximate on different dimensions, including geographical and social space. Methodologically, the lack of independence among geographical units is identical in its content and construct to the interdependence inherent among the actors in a social network (e.g., Land and Deane 1992).[5]

EXAMPLES FROM CRIMINOLOGY

Much of the spatial analysis of crime can be traced back to the unprecedented increase in youth involved gun violence of the late 1980s' an early 1990s. Scholars and writers in the popular media were quick to start talking in terms of this being a "homicide epidemic." Within the public health framework, an epidemic is simply defined as nonlinear growth of events that typically spread within a subpopulation of susceptible individuals. Using existing data sources (SHR, Chicago Homicide Data, etc.) as well as a set of city-specific microlevel homicide data that were collected in part, or in whole, by the National Consortium on Violence Research (NCOVR)[6] in such cities as Houston, Miami, Pittsburgh, and St. Louis, it was easy for researchers to demonstrate that homicide rates did increase in a nonlinear fashion (e.g., Cohen and Tita 1999b; Rosenfeld et al. 1999; Griffiths and Chavez 2004) at the local level.

Along with these neighborhood-level studies, research at the national level (Blumstein and Rosenfeld 1998; Cork 1999) and the county level (Messner et al. 1999; Baller et al. 2001; Messner and Anselin 2004), have consistently demonstrated two things. First, the subpopulation at greatest risk of homicide victimization during the epidemic was comprised of young urban minority males. Second, homicides exhibit a nonrandom pattern as similar levels of violence cluster in space. Furthermore, the concentration of high violence areas typically occur within disadvantaged urban communities.

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[5] In addition to the advances made by spatially oriented scholars such as Anselin (1988) and Ord (1975), much of the methodological and empirical foundation currently used in spatial analysis was developed by scholars pursuing properties of "network autocorrelation models" (Doreian and Hummon 1976; Doreian 1980).

[6] The National Consortium on Violence Research (NCOVR) at Carnegie Mellon University was supported under Grant SBR 9513040 from the National Science Foundation.

Gangs, Drugs, and Exposure to Violence

As noted above, spurred on by the youth homicide epidemic, there was a considerable increase in the number of published studies that explore the spatial distribution of violent crime, in general, and homicide, in particular. Researchers began to map homicide in an effort to identify susceptible populations, and to determine if the observed patterns of events were at least consistent with spatial diffusion/contagion. From these studies, it was concluded that homicide and violence exhibit strong patterns of spatial concentration.

The presence of positive spatial autocorrelation has been interpreted as evidence of contagion. It is generally accepted that as violence increased during the last epidemic, certain neighborhood-level social processes or "neighborhood effects" were responsible for the geographic spread and ultimately the concentration of violence in disadvantaged areas. This conclusion rests heavily upon two facts. First, even after controlling for the socioeconomic composition of place, patterns of spatial concentration remain. Second, those studies which have examined local spatial patterns of violence over time do find evidence of diffusion (Cohen and Tita's 1999b; Griffiths and Chavez 2004.) Though no definitive answer has emerged as of yet to the question of why violence displays certain spatial patterns, several explanations have been put forth. In general, researchers have focused on the impact of "exposure to violence" (including subcultural explanations) as well as the particular dynamics and structure of violence involving illicit drug markets and/or violent youth gangs.

Viewing exposure as the social process that is responsible for the spatial clustering of violence has its origins in subcultural explanations of violence. Loftin (1986) was the first to argue that the spatial concentration of assaultive violence and its contagious nature was the result of certain subcultural processes. His use of the term "subcultural" refers to a process wherein violence spreads throughout the population as the result of direct social contact. He argues that a small increase in violence can result in an epidemic in two ways. First, an epidemic results when a small increase in assaults sets off a chain reaction of events causing local individuals to enact precautionary/protective measures in hopes of reducing their chances of victimization. At the extreme, individuals take pre-emptive actions (i.e., assault others) to protect against the possibility of being the victim of an assault. As more preemptive assaults occur, even more people take preemptive actions thereby feeding the epidemic.

Secondly, Loftin argues that the very existence of the moral and social networks that link individuals together within their local environment exacerbate the epidemic. "When violence occurs it draws multiple people into the conflict and spreads either the desire to retaliate or the need for preemptive violence through the network, potentially involving ever increasing number of individuals in the fight" (Loftin 1986: 555). Loftin states this process relies upon direct social contact and implicitly suggests that the concentration of violence must be the result of the limited geographic scope of social interactions. However, one could also easily imagine instances where the victims and offenders interact at schools, entertainment districts, or possibly at the types of "staging grounds" where young men battle for respect within the realm of the "code of the streets" (Anderson 1999).

The retaliatory nature of gang violence along with the violence associated with drug markets have also been offered as explanations for spatial patterns of violence. As noted by Tita and Greenbaum (2008), these explanations are basically extensions of the above arguments in that they represent "exposure" to a particular type of violence. That is, rather than exposure to violence leading to a cultural norm that shaped individual behaviors, it was exposure to the structural features of drug markets and urban street gangs that contributed to the escalation and concentration of violence.

Several features of drug markets, especially open-air markets selling crack-cocaine, make them obvious candidates in explaining the diffusion of violence. First, guns quickly became important "tools of the trade" among urban youth dealing crack. As Blumstein (1995) hypothesized and empirically supported by Blumstein and Cork (1996), arming participants in crack markets increases the risks of violence for nonparticipants as well. Faced with increased risks to personal safety, youth outside crack markets increasingly carry guns and use them to settle interpersonal disputes, thereby spreading gun violence more broadly among the youth population. Second, drug markets often involve competition among rivals looking to increase their market share. Therefore, drug related murders are likely to be retaliatory in nature. Though these arguments are certainly plausible, the supporting evidence is mixed. Though Cork (1999) finds that the spatial and temporal patterns of the increase in violence mirror the emergence of crack-cocaine markets in various regions of the nation, studies in Pittsburgh (Cohen and Tita 1999b), and another examining both Chicago and St. Louis (Cohen et al. 1998) find little evidence that drug homicide increased levels of violence or drove local patterns of diffusion.

Two important features define gangs that make them especially suitable candidates responsible for diffusion (Decker 1996). First, they are geographically oriented. The turf or "set space" where urban street gangs come together to be a gang is a well defined, subneighborhood area that remains consistent over time (Klein 1995; Moore 1985, 1991; Tita et al. 2005). Second, urban street gangs are linked to other gangs via rivalry networks. As we note below, research has demonstrated (Tita and Greenbaum 2008; Radil et al. 2010; Tita et al. 2009) that it is precisely the geography of gangs and their social networks that present a set of structural properties researchers can exploit to better understand the spatial patterns of gang violence.

Below, we provide a brief review of the extant literature from criminology and public health that have employed spatial regression models. Though not meant to represent an exhaustive review of this burgeoning literature, these studies do represent some of the most widely cited articles in the field. After summarizing the findings and the methods, we make the case for the importance of carefully modeling processes of influence into one's spatial weights matrix (W).

Empirical Studies of Crime Employing Spatial Regression

In what is widely recognized as the first attempt to explicitly model the spatial effects inherent in the production and impact of violence, Morenoff and Sampson (1997) examine the impact of violence on residential change in Chicago. They argue that in addition to reacting to the level of violence in one's own neighborhood, residents also react to the levels of violence around them. Thus, among controlling for the socio-economic measures as well as the trends in terms of residential transition, the authors also include a spatially lagged independent variable in their model to capture the "*spatial diffusion* of homicide" (ibid: 56). Indeed, their findings show that the impact of homicide on population changes will differ in a focal tract depending upon the level of homicide in nearby tracts.

Morenoff et al. (2001) examined the spatial distribution of violence more directly. It is this work that lays out the "exposure" and "diffusion" arguments. They argue that homicide may be spatially clustered because the measures associated with violence (e.g., poverty, population density, etc.) are spatially and temporally clustered, thus exposing residents who live in close proximity to each other to the same set of conditions. Additionally, the social interactions that result in violence are likely to involve "...networks of association that follow geographical vectors" (ibid: 523) along which violence is likely to diffuse. Specifically, they mention the retaliatory nature of gang violence and the fact that homicide is likely to be committed within groups of individuals known to one another. Their final conclusion is that the spatial effects in their models are large in magnitude and that ecological models of crime that focus only on the internal characteristics of the unit of observation (census tract) are likely to suffer from misspecification. Though they find that "space" matters, and that it matters over various spatial regimes (controlling for race of a neighborhood), the precise reason it matters is less clear. As the authors note, they are "...unable to pinpoint the relative contributions of exposure and diffusion" (Ibid: 552).

Rosenfeld et al. (1999) estimated a spatial lag model to determine if the patterns of "gang-motivated" homicides differed compared to nongang youth homicides as well as homicides that involved gang members but lacked any specific gang motivation. Three separate equations are estimated using count data and also including the spatial lag of the count in surrounding census tracts as an explanatory variable. What they find is that controlling for neighborhood characteristics, only the spatial term in only the gang-motivated analysis is statistically significant. The authors see this as evidence of gang-motivated homicides being contagious in nature and that "...the spatial distribution of gang-motivated homicide may reflect intrinsic features of the phenomenon and not simply the presence of facilitating neighborhood characteristics" (Ibid: 512).

Smith et al. (2000) examine diffusion and spatial effects within the context of street robbery. Once again, we see that the amount of street robbery in neighboring areas (census block faces) impacts the level of street robbery on a focal block face. The authors conclude that the spatial effect is consistent with diffusion resulting from the spatial bounds of the "awareness space" (Brantingham and Brantingham 1981) of offenders. Drawing upon the existing "journey to crime" literature, the authors cap awareness space so that only levels of crime in block faces within 1 mile of the focal block face are accounted for in the spatial weights matrix.

Gorman et al. (2001) examine the effects of alcohol outlets on violent crime rates in Camden, New Jersey. Using census block groups at the unit of analysis, Gorman et al. make a methodological argument using a spatial regression model as they identified significant positive spatial autocorrelation in crime rates and offer two spatial models: a spatial error model and a spatial lag model. However, for the lag model, Gorman et al. produce spatial lags of the independent variables rather than of the dependent variable (crime rates). While there is little explanation offered for this modeling choice, the results of the independent variable lag model suggest to the authors that while some explanatory variables in surrounding areas had a significant impact on crime rates in a given unit, the density of alcohol outlets in neighboring areas had no significant impact on crime rates. Gorman et al. find this as evidence that the effects of alcohol outlets on violent crime are highly localized and spatially concentrated and that such effects decay quickly with distance.

Kubrin and Stewart (2006) investigated relationships between neighborhood context and recidivism rates of ex-offenders in Portland, Oregon. Although not expressly interested in spatial diffusion, Kubrin and Stewart attempted to control for spatial autocorrelation in recidivism rates across neighborhoods (measured by census tracts) by including a spatially lagged recidivism variable in their multilevel model. However, due to the limitations of incorporating spatial effects into multilevel models, they were unable to determine if the spatial dependence in the rate of recidivism is evidence of diffusion or due to other effects, such as spillovers.

Hipp et al. (2009) examine patterns of intra- and inter-group crime in an area of Los Angeles, CA that has undergone significant residential transition taking it from majority African-American to majority Latino over the last two decades. Their goal is to understand the impact of this transition on both within-group and across-group violence. To control for spatial effects, they estimate a model that includes spatially lagged predictors. Following the lead of Elffers (2003) and Morenoff (2003), they argue that explicitly modeling the spatial process through the lagged independent variables (median income, change in race/ethnicity, and income inequality between racial/ethnic groups) is theoretically superior to a spatial lag model. They contend that to "estimate a spatial lag model we would need to argue that the level of either intra- or inter-group crime in a neighboring area has a direct 'contagion' effect on crime in a focal area. We do not believe this is the case, especially with respect to inter-group crime events" (Ibid: 41). Instead, they hold that spatial impacts may best be modeled through "...the racial/ethnic composition of adjacent neighborhoods (as these group compositions could affect inter- and intra-group crime rates in the tract of interest), how that racial/ethnic composition has changed, the income level of adjacent neighborhoods (which might create additional stress or protective effects), and economic inequality in adjacent neighborhoods" (Ibid). They employ a weights matrix that captures a distance-decay functions truncated with a 2-mile cutoff. That is, the spatial effect goes to "0" for all census block groups beyond two miles. To summarize, they find that the level of income inequality in surrounding areas has a significant impact on inter-group violence in a focal tract as does the degree to which racial transitioning from African-American to Latino remains ongoing.

In contrast to the small scale studies described above, Baller et al. (2001) focused on national-level patterns of homicide aggregated to counties (see also Messner et al. 1999). Baller and his colleagues examined homicide rates against selected socioeconomic characteristics for continental U.S. counties for four decennial census years (1960, 1970, 1980, and 1990) and concluded that "homicide is strongly clustered in space" in each time period at this scale. Baller et al. also identified the southeastern US as a distinct spatial regime and interpreted a spatial lag model fit as evidence of a diffusion process in this region (the nonsoutheastern regime best fit a spatial error model, which suggested that the spatial autocorrelation in this regime was due to the presence of unmeasured variables). However, the mechanisms for such diffusion are difficult to arrive at for such macrolevel studies and as Baller et al. acknowledge, there is no a priori reason to assume spatial interaction between counties on the topic of homicide and the large amount of spatial aggregation in the data likely contributes to the perceived spatial dependence (2001: 568–569).

With the exception of Kubrin and Stewart (2006), the above studies use SAR spatial models to examine a variety of phenomena, and each time find a spatial story to the issues at hand. In these examples, spatial lag models were the most common choice but spatial error models were also occasionally fielded either as an exploratory technique (Gorman et al. 2001) or as a choice determined by model diagnostics (Baller et al. 2001). When a spatial lag model was used in these examples, the dependent variable was selected for the lag with the exception of Morenoff and Sampson (1997), Gorman et al. (2001) and Hipp et al. (2009), all of whom lagged explanatory variables instead. This overview highlights the increasing consideration of spatial effects in ecological studies of crime at different geographic scales and points to the growing (but not exclusive) use of SAR models to incorporate such effects. However, the formal model of the connection between the geographic units that underpin these and other spatial models receive little attention in some of the examples, and many of the authors use simple measures of unit contiguity or adjacency to formally model the interaction of interest. As an important but often overlooked element of spatial regression model specification we turn our attention to the spatial weight matrix, or W.

THE SPATIAL WEIGHTS MATRIX *W*

Both SAR and network autocorrelation models estimate parameters in the presence of presumably interdependent variables (Anselin 1988; Leenders 2002). This estimation process requires the analyst to define the form and limits of the interdependence and formalize the influence one location (or network node) has on another. In practice, this is accomplished by identifying the connectivity between the units of the study area through a $n \times n$ matrix. The matrix is usually described as a "spatial weight" or "spatial connectivity" matrix and referred to in the SAR models as "W." This W, or matrix of locations, formalizes a priori assumptions about potential interactions between different locations, defining some locations as influential upon a given location and ruling others out.

A simpler way of describing this is that W identifies, in some cases, who is a neighbor and who is not, or with whom an actor interacts. This notion of influence across space is addressed in an empirical sense by criminologists when deciding whether two geographic areal units are contiguous based upon borders or near enough for influence based on distances. However, the construction of W is more than just an empirical choice about neighbors. It is a theoretical decision regarding the processes being discussed and one that has implications for the statistical estimates generated. Whether it is geographical or network space, W is used to represent the dependence among observations in terms of the underlying social or geographic structure that explicitly links actors or geographic units with one another. As Leenders (2002: 26) notes:

> W is supposed to represent the theory a researcher has about the structure of the influence processes in the network. Since any conclusion drawn on the basis of autocorrelation models is conditional upon the specification of W, the scarcity of attention and justification researchers pay to the chosen operationalization of W is striking and alarming. This is especially so, since different specifications of W typically lead to different empirical results.

Following Leender's point, discussions about the nature of W and how different specification choices may affect regression results have indeed been underemphasized in most spatial analytic literature: the relatively few examples to the contrary include Florax and Rey (1995) and Griffith (1996). Despite these noteworthy efforts, Leenders (2002: 44) is correct in his assessment that "the effort devoted by researchers to the appropriate choice of W pales in comparison to the efforts devoted to the development of statistical and mathematical procedures." The net effect of this lack of attention is that theoretical conceptions about the role space plays in producing empirical patterns in a given dataset are often afterthoughts. Hence, the vision of a "spatially integrated social science" (Goodchild et al. 2000) for criminology remains unfulfilled, because when space is included in the analysis of crime or other social processes, it is often added in a default form without consideration of the processes in question.

Such an attention deficit is a cause for concern as the products of the SAR models are quite sensitive to the specification of W. For example, using simulated data, Florax and Rey (1995) conclude that misspecification of W can affect the outcome of spatial dependence tests, such as the commonly used Moran's I test of spatial autocorrelation, and of estimates of variables in spatial regression models. Griffith (1996), also using simulated data, reaches a similar conclusion, stressing that while assuming some connectivity is always more reasonable than assuming no connectivity, both underspecifying (identifying fewer connections between spatial units than really exist) and overspecifying (identifying more connections) W affect both regression estimates and the product of the diagnostic tests (maximum likelihood, or ML, tests) used in spatial econometrics to choose between the lag or error models.

In our review of the models used in the studies outlined above, we find that without exception, each specification of W is based either on simple contiguity, k-nearest neighbors, or the use of distance decay metrics. Although challenging, more careful modeling of spatial processes through the spatial weights matrix is of critical importance to understand the black box of neighborhood effects emphasized by Cohen and Tita (1999a). As previously described, network autocorrelation models involve a similar challenge to spatial models, and the network literature offers useful parallels to the challenge in modeling spatial dependence and interaction. In modeling dependence among nodes, social network analysts often begin with a particular social process in mind and then carefully model that process into the network autocorrelation matrix. For example, edges among nodes may be predicated upon specific social relationships (e.g., friendship, familial, or instrumental ties) or shared membership into formal/informal groups. Alternatively, one can decide that a pair of nodes is connected only when they are similar along some particular dimension such as race, sex, income or "status" (see the discussion of Mears and Bhati (2006) below). These types of important differences can lead to very different specifications of the weights matrix.

Social scientists have employed social network analysis in an effort to explain a number of social processes, most notably the diffusion of innovations, technology, and information among individuals, societies, and organizations (e.g., Coleman et al. 1966; Rogers 1983; Grattet et al. 1998). In defining underlying processes of contagion/social influence, network scientists carefully differentiate between social processes of influence that operate through direct ties or association among actors (referred to as "communication" or "structural cohesion") versus contagion that occurs among individuals who occupy shared positions within a network (referred to as "comparison" or "equivalence"). The decision to choose one process over another – communication versus comparison – is dependent upon one's chosen theory. As Leenders (2002: 26) succinctly states, "Change one's theory, change W."

To highlight the importance of specifying a W that is consistent to with the social process of choice, we draw upon a classic example from the networks literature dealing with the question of why and when certain physicians adopted a new medical innovation (tetracycline). Coleman et al. (1966) posited that peer effects mattered, and demonstrated the importance of structural cohesion or direct social ties in determining who adopted the new drug, and the order in which it was adopted. That is, once a couple of doctors of "higher status" assumed the role of "early adopters," the next wave of adopters was comprised of the initial adopters' friends. Decades later Burt (1987) offered an alternative hypothesis in which he argued that individuals are often most strongly influenced by the actions and behaviors of rivals and competitors and not by their friends. He reanalyzed the data and demonstrated that network position (as measured by "structural equivalence") was the defining predictor of adoption. Burt concluded that friendship, or any form of direct communication, had little to do with the pattern of adoption. Instead, doctors who held similarly high positions of "status" (e.g., subscribed to the multiple medical journals, were younger, made many house calls, kept up on scientific advances) within the medical community adopted earlier than did older doctors, those who spent more time with their patients than keeping up with medical advances, and who subscribed to fewer professional journals. Though neither the line of inquiry (adoption of an innovation/diffusion) nor the methodology (network autocorrelation models) ever changed, the theory employed in the research did.

MOVING BEYOND SIMPLE CONTIGUITY/DISTANCE BASED SPECIFICATIONS OF W

Recently, in order to better capture specific processes or patterns of influence, criminologists have begun to explore alternative specifications of the weights matrix that move beyond simple contiguity or distance. Mears and Bhati (2006) build off the long-standing finding that resource deprivation is positively associated with local levels of violence by asking whether the level of resource deprivation in other counties could influence violence in a focal neighborhood. In addition to controlling for the level of disadvantage in surrounding communities, the authors also construct weights matrices based upon the level of "social similarity" between places. The authors smartly point out that what happens in focal neighborhood might only influence events in other neighborhoods if there is a mixing of the population between the two places. Though the research does not actually have network data linking the friendships and communication across place, they reason on the bases of "homophily" (Blau and Blau 1982; McPherson et al. 2001) that social interactions are more likely among "similar" individuals. Using various measures of resource deprivation to construct alternative measures of W, controlling for both resource deprivation in surrounding neighborhoods (as well as controlling for spatial lags of homicide, the dependent variable), they find that geographic as well as "social proximity" to resource deprivation was associated with higher homicide rates. Furthermore, social proximity, or nearness in terms of social similarity, had a much stronger impact than did geographic proximity alone. An interesting finding from their research is that while these results held for both instrumental and expressive types of homicides, no effect was found with regard to gang-related homicides. For that insight into this finding, we turn to a recent set of studies looking specifically at gang violence.

In an effort to better understand the spatial distribution of violence involving gang members, Tita and Greenbaum (2008) and Tita et al. (2009) also examine spatially proximate effects of violence as well as violence in socially proximate communities. This body of research lays out a very clear hypothesis regarding how gang violence in an area might influence gang violence in other areas. By exploiting the spatial nature of gangs (they hang out in specific areas, known as "set space" (Tita et al. 2005)), and the social dynamics of gangs (they are linked to other gangs through a network of rivalries), they hypothesize that the violence in a focal area will have a stronger impact on violence in areas that are linked through the sociospatial dimensions of the gang rivalry network than will spatial contiguity alone. In fact, the studies in Los Angeles, CA (Tita et al. 2009) and in Pittsburgh, PA (Tita and Greenbaum 2008) both demonstrate support for this hypothesis. That is, the purely geographic nature of "diffusion" was muted when one controlled for whether or not proximate (or nonproximate) areas (block groups) were linked by containing the set space of rival gangs. The authors of both studies are careful to point out that they constructed their weights matrices with a specific process in mind – the transmission of violence through a gang rivalry network – and caution that had they been interested in looking at other types of violence (e.g., drug violence, domestic violence), their particular "social similarity matrix" would have been inappropriate.

SUMMARY

The use of spatial regression has clearly advanced our understanding of crime patterns at both the local (neighborhood) and county level. We include Table 6.1 as a summary of both the traditional and the more creative research examining spatial effects. Summarizing the table, we know that whether for recidivism, homicide, gang violence, or robbery, there is evidence for spatial dependence and possible spatial interaction processes at work. We also know that addressing the spatial autocorrelation present in most aggregated crime data offers more reliable modeling estimates and that attempting to understand the substantive sources of spatial dependence in the social processes of crime leads is a critical step in model specification. However, as Table 6.1 demonstrates, our thinking and operationalization of the spatial processes has, until recently, remained at the level of only accounting for connections between units in the simplest of geographic terms. Complex theoretical stories about the mechanisms of diffusion between places can quickly become lost in a spatial weight matrix that uses the simplest conceptions of geography (simple measures of adjacency/contiguity, or distance such as Rook/queen's contiguity, linear distance decay functions, or k-nearest neighbor) to specify the nature of interaction, including scope, direction, and intensity. As there remains no statistical method capable of estimating the "best fit" of a spatial weight matrix to one's data (Leenders 2002: 38), embodying theory into the specification of W is the only sensible recourse available.

A recent article by Sampson and Sharkey (2008) examined intra-urban movement patterns of 4,000 families in Chicago between 1994 and 2002. The take-away point of this research is that there is great disparity in the types of places that people move to, and that where people move can be explained by controlling for race and economic. While there is evidence that poor whites or poor Latinos will move into nonpoor neighborhoods that may contain sizable white populations, the mobility of blacks along all levels of income is restricted among existing predominately black neighborhoods. Nonpoor blacks rarely move into other nonpoor areas comprised of nonblacks, and while some poor blacks may move into nonpoor black communities, the vast majority of moves for poor African-Americans are into other poor black neighborhoods. We highlight this research because it provides the richness of data to truly understand the sociospatial nature of influence. From these findings, it seems evident that incidents of violence in poor black neighborhoods are far more likely to diffuse into other poor black neighborhoods than in surrounding, nonblack (poor or otherwise) neighborhoods. In this regard, it confirms the assumptions of Mears and Bhati (2006) regarding the connectivity among places based on social similarity, but the level of detail in this study far exceeds the use of resource deprivation as a proxy for social interaction.

We think that Sampson (2008) said it best noting that "The advent of GIS modeling and new data sources on social interactions and networks of spatial connection are revealing the profound spatial ordering of a bewildering array of urban phenomenon." If we want to tackle the question posed by Cohen and Tita (1999a) that motivated this chapter, researchers need to exploit these types of data sets to truly understand the processes by which violence diffuses across space.

TABLE 6.1. Summary of empirical studies using spatial regression in the study of crime

Author	Topic	Model type	Estimation	Specification of *W*	Conclusions
Morenoff and Sampson (1997)	Effects of violence on residential change; contagious nature of residential change	Spatially lagged dependent variable (Wy) using residential change along with spatially lagged independent variables (Wx) using homicide rate	2-stage least squares using the spatial lag of "residential change potential" (Wy) and the "homicide potential" (Wx) explanatory variables in the second-stage of estimation	Distance decay, weighted by distance from centroid	Impact of homicide on population changes will differ in a focal tract depending upon the level of homicide in nearby tracts
Morenoff et al. (2001)	Spatial distribution of homicide crime	Spatially lagged dependent variable (Wy)	Maximum-likelihood estimation using a two stage approach – Step one estimates a log-homicide rates while the second step includes a spatial lag of the estimated rate	Rook's case geographic contiguity (shared border lengths)	Spatial dependence in levels of violence persists controlling for community disadvantage as well as "collective efficacy"
Rosenfeld et al. (1999)	Spatial distribution of gang-motivated, gang-affiliated and nongang youth homicide	Spatially lagged dependent count variables (Wy)	Maximum-likelihood estimation of count models	Inverse distance across all space	Gang-motivated homicide shows greater spatial dependence, suggesting contagious nature of these types of events

(continued)

Table 6.1. (continued)

Author	Topic	Model type	Estimation	Specification of W	Conclusions
Smith et al. (2000)	Spatial effects of street robbery	Spatial lagged dependent variable (Wy)	Generalized negative binomial regression	K-nearest neighbor variant: sample of 20 face blocks within 1 mile radius of focal block; sample limited to only two directions (either n/s or e/w from focal block)	Street robbery in neighboring areas (census block faces) impacts the level of street robbery on a focal block face
Baller et al. (2001)	County level spatial patterns of homicide	Spatial regimes; spatial error and spatially lagged dependent variable (Wy; We)	Maximum-likelihood: Robust Lagrange Multiplier tests	K-nearest neighbor (all counties connected to exactly 10 nearest (by centroid distance) neighboring counties)	South US region shows evidence of homicide diffusion; spatial dependence in nonSouth likely due to unobserved variables
Gorman et al. (2001)	Effects of alcohol outlets on violent crime rates	Spatial error and spatially lagged independent variables (Wx, We)	Maximum likelihood	Queen's case geographic contiguity (shared border lengths and/or border points)	The density of alcohol outlets in neighboring areas had no significant impact on crime rates in focal units.

(continued)

TABLE 6.1. (continued)

Author	Topic	Model type	Estimation	Specification of *W*	Conclusions
Mears and Bhati (2006)	Spatial distribution of homicide, by type	Spatially lagged dependent variable (Wy); socially lagged dependent variable; Social and spatially weighted independent variables (Wx).	Negative binomial using natural log of homicide counts	Geographic space is measured using queen's case contiguity; Social space is measured by comparing measures of social similarity (including resource deprivation) between each pair of communities. The similarity matrix decays exponentially as dissimilarity increases.	With the exception of gang homicide, social similarity among geographic units is more strongly related to homicide than is geographic adjacency.
Kubrin and Stewart (2006)	Effects of neighborhood context on recidivism rates	Multilevel model (included a spatial lag variable) (Wy)	HLM with the inclusion of a spatially lagged measure of recidivism rates.	Queen's case geographic contiguity	Spatial dependence in recidivism; unable to assess evidence for diffusion

(continued)

TABLE 6.1. (continued)

Author	Topic	Model type	Estimation	Specification of *W*	Conclusions
Tita and Greenbaum 2008; Tita et al. 2009	Spatial distribution of gang violence	Spatially lagged dependent variable (Wy); socially lagged dependent variable	"Anselin-alternative method" using the "violence potential" as an instrumental variable in 2-stage estimation	Geographic space is measured using queen's case contiguity; Social space is constructed using the location of gangs in space, and the rivalry network that links them socially	Spatial dependence is best modeled by considering the socio-spatial distribution of gang rivalries, which extend beyond contiguous neighbors.
Hipp et al. (2009)	Intra-group and inter-group Violence	Spatially lagged independent variables (Wx)	Negative binomial with spatially lagged X's	Distance decay, 2 mile maximum	Clear evidence of income inequality and racial transition in surrounding tracts impacting inter-group violence in focal tract

REFERENCES

Anderson E (1999) Code of the street: decency, violence, and the moral life of the inner city. W. W. Norton & Company, New York

Anselin L (1988) Spatial econometrics: methods and models. Kluwer, Boston

Anselin L (2002) Under the hood: issues in the specification and interpretation of spatial regression models. Agric Econ 27(3):247–267

Anselin L (1995) Local indicators of spatial association – LISA. Geogr Anal 27(1):93–115

Anselin L (1998) Exploratory spatial data analysis in a geocomputational environment. In: Longley P, Brooks S, McDonnell R, Macmillan B (eds) Geocomputation, a primer. Wiley, New York

Anselin L (1999) Interactive techniques and exploratory spatial data analysis. In: Longley P, Goodchild M, Maguire D, Rhind D (eds) Geographical information systems. Wiley, New York

Anselin L (2006) Spatial econometrics. In: Mills TC, Patterson K (eds) Palgrave handbook of econometrics: volume 1, econometric theory. Palgrave Macmillan, Basingstoke, pp 901–941

Anselin L, Griffiths E, Tita G (2008) Crime mapping and hot spot analysis. In: Wortley R, Mazerolle L (eds) Environmental criminology and crime analysis Willan Publishing, UK, pp 97–116

Baller R, Anselin L, Messner S, Deane G, Hawkins D (2001) Structural covariates of U.S. county homicide rates: incorporating spatial effects. Criminology 39(3):561–590

Blau J, Blau P (1982) Cost of inequality: metropolitan structure and violent crime journal. Am Sociol Rev 47(1): 114–129

Blumstein Ad (1995) Youth violence, guns, and the illicit-drug industry. J Crim Law Criminol 86:10–36

Blumstein A, Cork D (1996) Linking gun availability to youth gun violence. Law Contemp Probl 59(1):5–24

Blumstein A, Rosenfeld R (1998) Explaining recent trends in us homicide rates. J Crim Law Criminol 88:1175–1216

Brantingham PJ, Brantingham PL (1981) Environmental criminology. Sage Publications, Beverly Hills

Burt R (1987) Social contagion and innovation: cohesion versus structural equivalence. Am J Sociol 92:1287–1335

Cliff AD, Ord JK (1973) Spatial autocorrelation. Pion, London

Cliff AD, Ord JK (1981) Spatial processes, models, and applications. Pion, London

Cohen J, Tita G (1999a) Editors' introduction. J Quant Criminol 15(4):373–378

Cohen J, Tita G (1999b) Diffusion in homicide: exploring a general method for detecting spatial diffusion processes. J Quant Criminol 15(4):451–493

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

Coleman J, Katz E, Menzel H (1966) Medical innovation: a diffusion study. Bobbs-Merrill, New York

Cork D (1999) Examining space–time interaction in city-level homicide data: crack markets and the diffusion of guns among youth. J Quant Criminol 15(4):379–406

Decker S (1996) Collective and normative features of gang violence. Justice Q 13:243–264

Doreian P (1980) Linear models with spatially distributed data: spatial disturbances or spatial effects? Sociol Methods Res 9:29–60

Doreian P, Hummon N (1976) Modeling social processes. Elsevier, New York

Elffers H (2003) Analyzing neighbourhood influence in criminology. J Neth Soc Stat Oper Res 57(3):347–367

Florax R, Rey S (1995) The impacts of misspecified spatial interaction in linear regression models. In: Anselin L, Florax R (eds) New directions in spatial econometrics. Springer, Berlin, pp 111–135

Fotheringham AS (1997) Trends in quantitative methods i: stressing the local. Prog Hum Geogr 21:88–96

Fotheringham AS, Charlton M, Brundson S (2002) Geographically weighted regression: the analysis of spatially varying relationships. Wiley, New York

Gehlke C, Biehl K (1934) Certain effects of grouping upon the size of the correlation coefficient in census tract material. J Am Stat Assoc 29:169–170

Getis A, Ord JK (1992) The analysis of spatial association by use of distance statistics. Geogr Anal 24:189–206

Goodchild MF (2004) GIScience, geography, form, and process Ann Assoc Am Geogr 94(4):709–714

Goodchild MF, Anselin L, Appelbaum R Harthorn B (2000) Toward spatially integrated social science. Int Reg Sci Rev 23:139–159

Gorman DM, Speer PW, Gruenewald PJ, Labouvie EW (2001) Spatial dynamics of alcohol availability, neighborhood structure and violent crime. J Stud Alcohol 62(5):628–636

Grattet R, Jenness V, Curry T (1998) The homogenization and differentiation of 'hate crime' law in the U.S., 1978–1995: an analysis of innovation and diffusion in the criminalization of bigotry. Am Sociol Rev 63:286–307

Griffith DA (1983) The boundary value problem in spatial statistical analysis. J Reg Sci 23:377–378

Griffith DA (1996) Some guidelines for specifying the geographic weights matrix contained in the spatial statistical models. In: Arlinghaus SL (ed) Practical handbook of spatial statistics. CRC Press, Boca Raton, pp 65–82
Griffiths E, Chavez JM (2004) Communities, street guns, and homicide trajectories in Chicago, 1980–1995: merging methods for examining homicide trends across space and time. Criminology 42(4):941–978
Haining R (2003) Spatial data analysis: theory and practice. Cambridge University Press, Cambridge
Haining R (2009) The special nature of spatial data. In: Fotheringham S, Rogerson PA (eds) The sage handbook of spatial analysis. Sage, Thousand Oaks, CA
Hipp JR (2007) Block, tract, and levels of aggregation: neighborhood structure and crime and disorder as a case in point. Am Sociol Rev 72:659–680
Hipp J, Tita G, Boggess L (2009) Inter- and intra-group interactions: the case of everyday violent crime as an expression of group conflict or social disorganization. Criminology 47(2):521–564
King G (1997) A solution to the ecological inference problem: reconstructing individual behavior from aggregate data. Princeton University Press, Princeton
Klein M (1995) The American street gang: its nature, prevalence and control. Oxford University Press, New York
Kubrin CE, Stewart EA (2006) Predicting who reoffends: the neglected role of neighborhood context in recidivism studies. Criminology 44:165–197
Land KC, Deane G (1992) On the large-sample estimation of regression models with spatial or network effects terms: a two-stage least-squares approach. In: Marsden P (ed) Sociological methodology 1992 Basil Blackwell, Oxford, pp 221–248
Leenders R (2002) Modeling social influence through network autocorrelation: constructing the weight matrix. Soc Networks 24:21–47
Loftin C (1986) Assultive violence as a contagious process. Bull N Y Acad Med 62:550–555
Marsden PV, Friedkin NE (1993) Network studies of social influence. Sociol Methods Res 22:125–149
McPherson M, Smith-Lovin L, Cook J (2001) Birds of a feather: homophily in social networks. Ann Rev Sociol 27:415–44
Mears D, Bhati A (2006) No community is an island: the effects of resource deprivation on urban violence in spatially and socially proximate communities. Criminology 44(3):509–548
Mencken FC, Barnett C (1999) Murder, nonnegligent manslaughter, and spatial autocorrelation in mid-south counties. J Quant Criminol 15(4):407–422
Messner SF, Anselin L (2004) Spatial analyses of homicide with areal data. In: Goodchild MF, Janelle DG (eds) Spatially integrated social science. Oxford University Press, Oxford, pp 127–144
Messner SF, Anselin L, Baller RD, Hawkins DF, Deane G, Tolnay SE (1999) The spatial patterning of county homicide rates: an application of exploratory spatial data analysis. J Quant Criminol 15(4):423–450
Moore J (1985) Isolation and stigmatization in the development of an underclass: the case of Chicano gangs in east Los Angeles. Soc Probl 33:1–12
Moore J (1991) Going down to the barrio: homeboys and homegirls in change. Temple University Press, Philadelphia
Morenoff J, Sampson RJ (1997) Violent crime and the spatial dynamics of neighborhood transition: Chicago, 1970–1990. Soc Forces 76(1):31–64
Morenoff J, Sampson RJ, Raudenbush S (2001) Neighborhood inequality, collective efficacy, and the spatial dynamics of urban violence. Criminology 39:517–560
Morenoff J. (2003) Neighborhood mechanisms and the spatial dynamics of birth weight. Am J Sociol 108:976–1017
O'Loughlin J (2003) Spatial analysis in political geography. In: Agnew JA, Mitchell K, Tuathail GÓ (eds) A companion to political geography. Blackwell Pub, Malden, MA, pp 30–46
Openshaw S (1996) Developing GIS-relevant zone-based spatial analysis methods. In: Longley P, Batty M (eds) Spatial analysis: modeling in a GIS environment. Wiley, New York, pp 55–73
Ord JK (1975) Estimation methods for models of spatial interaction. J Am Stat Assoc 70:120–126
Ord JK, Getis A (1995) Local spatial autocorrelation statistics: distributional issues and an application. Geogr Anal 27:286–306
Radil S, Flint C, Tita G (2010) Spatializing social networks: geographies of gang rivalry, territoriality, and violence in Los Angeles. Ann Assoc Am Geogr 99(2) Forthcoming
Robinson W (1950) Ecological correlation and the behavior of individuals. Am Sociol Rev 15:351–357
Rogers E (1983) Diffusion of innovations. Free Press, New York
Rosenfeld R, Bray TM, Egley A (1999) Facilitating violence: a comparison of gang-motivated, gang-affiliated, and nongang youth homicides. J Quant Criminol, 15(4):494–516
Sampson R (2008) "After school" Chicago: space and the city. Urban Geogr 29(2):127–137
Sampson R, Sharkey P (2008) Neighborhood selection and the social reproduction of concentrated racial inequality. Demography 45(1):1–29

Sampson R, Morenoff J, Gannon-Rowley T (2002) Assessing neighborhood effects: Social processes and new directions in research. Annu Rev Sociol 28:443–478

Smith WR, Frazee SG, Davison EL (2000) Furthering the integration of routine activity and social disorganization theories: small units of analysis and the study of street robbery as a diffusion process. Criminology 38:489–523

Tita G, Radil S, Flint C (2009) Modeling the spatial distribution of crime through contiguity, social influence, and status. In 2009 Crime and Place Conference, Manassas, VA, April 22, 2009

Tita G, Cohen J, Engberg J (2005) An ecological study of the location of gang 'set space'. Soc Probl 52:272–299

Tita G, Greenbaum R (2008) Crime, neighborhoods and units of analysis: putting space in its Place. In: Weisburd D, Bernasco W, Bruinsma GJN (eds) Putting crime in its place: units of analysis in spatial crime research. Springer, New York, pp 145–170

Tobler WR (1970) A computer movie simulating urban growth in the detroit region. Econ Geogr 46:234–240

Ward MD, Gleditsch K (2008) Spatial regression models. Sage, Thousand Oaks, CA

Weisburd D, Bernasco W, Bruinsma GJN (eds) (2008) Putting crime in its place: units of analysis in spatial crime research. Springer, New York