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The Spatial Patterning of County Homicide Rates: An Application of Exploratory Spatial Data Analysis[1]

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The possibility that homicides can spread from one geographic area to another has been entertained for some time by social scientists, yet systematic efforts to demonstrate the existence, or estimate the strength, of such a diffusion process are just beginning. This paper uses exploratory spatial data analysis (ESDA) to examine the distribution of homicides in 78 counties in, or around, the St. Louis metropolitan area for two time periods: a period of relatively stable homicide (1984–1988) and a period of generally increasing homicide (1988–1993). The findings reveal that homicides are distributed nonrandomly, suggestive of positive spatial autocorrelation. Moreover, changes over time in the distribution of homicides suggest the possible diffusion of lethal violence out of one county containing a medium-sized city (Macon County) into two nearby counties (Morgan and Sangamon Counties) located to the west. Although traditional correlates of homicide do not account for its nonrandom spatial distribution across counties, we find some evidence that more affluent areas, or those more rural or agricultural areas, serve as barriers against the diffusion of homicides. The patterns of spatial distribution revealed through ESDA provide an empirical foundation for the specification of multivariate models which can provide formal tests for diffusion processes.

KEY WORDS: spatial patterning; homicide; county homicide rates; exploratory spatial data analysis.

1. INTRODUCTION

Spatial analyses of crime have a long and distinguished history in criminology. Beginning with the pioneering work of Quetelet and Guerry in the 19th century and continuing with the seminal studies of the Chicago school

[1]All color maps, figures, tables, and views indicated in the text can be viewed at http://www.albany.edu/csda/diffusion.html.

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in the beginning of the 20th century, research has demonstrated convincingly that knowledge about the location of criminal incidents can yield powerful insights about the underlying dynamics of crime. As Dennis Roncek (1993, p. 155) has observed recently, "Understanding crime requires understanding where it happens as well as to whom and by whom."

The spatial approach to crime is particularly relevant to the provocative, but as yet largely untested, claim that violence spreads through a diffusion process. The possibility that diffusion might characterize violence has been raised most prominently in the public health and epidemiological literature (cf. Hollinger *et al.*, 1987; Kellerman, 1996). Loftin (1986, p. 550), for example, proposes that assaultive violence can be usefully regarded as "analogous to disease," capable of "contagious transmission."[6] According to this perspective, acts of violence tend to be mutually reinforcing. As information about violent events is transmitted through social networks and other media of communication, the probability of subseqent violence is likely to increase. This kind of transmission process implies a definite spatial patterning of violence because social networks and communication "flows" tend to exhibit a nonrandom geographic distribution.[7]

The present paper examines spatial clustering of homicide for an area comprised of counties of varying population size and urban development surrounding the city of St. Louis. Our analyses are based on the newly developed methodology of exploratory spatial data analysis (ESDA). ESDA is a collection of techniques for the statistical analysis of geographic information. By combining descriptive and traditional graphs in an interactive computing environment, it augments visualization through maps with hypothesis tests for spatial patterns. We apply ESDA to county-level homicide in the St. Louis area to illustrate the utility of this approach for identifying and interpreting the spatial clustering of criminal violence.

2. RATIONALE FOR ESDA

Given the limited knowledge of processes for the spatial distribution of homicide, our methodology is carried out within the exploratory data analysis (EDA) paradigm in general and exploratory spatial data analysis

[6]The possibility of a contagion effect of violence has also been discussed in the literature on Southern lynchings. According to one argument, a lynching in one area results from residents of that area imitating a recent lynching elsewhere (e.g., Ayers, 1984, p. 243). An alternative position, however, describes lynching as a form a "racial terrorism," suggesting the possibility of a deterrent effect in which the likelihood of lynching in one area may actually be *reduced* by mob activity nearby (see, e.g., Tolnay *et al.*, 1996).

[7]As a further illustration, the diffusion of assaultive violence may be driven by displacement. Law enforcement activities designed to reduce drug activity have been shown to stimulate such activity and violence in adjacent areas (Rasmussen *et al.*, 1993).

(ESDA) in particular. EDA consists of a collection of descriptive and graphical statistical tools intended to discover patterns in data and suggest hypotheses by imposing as little prior structure as possible (Tukey, 1977). This then leads to "potentially explicable patterns" (Good, 1983, p. 290), which may become the basis for more formal hypotheses and theoretical constructs. Modern EDA methods emphasize the interaction between human cognition and computation in the form of dynamically linked statistical graphics that allow the user to manipulate directly various views of the data (e.g., Cleveland, 1993; Buja *et al.*, 1996). More specifically, 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 (Anselin, 1994, 1999, 1998; Haining 1990; Bailey and Gatrell, 1995). In the remainder of this section, we first outline the advantages of using an ESDA approach in the current context, followed by a brief discussion of the limitations of traditional methodological approaches.

2.1. Utility of the ESDA Paradigm for the Study of Diffusion

In the study of a diffusion process, a crucial parameter pertains to the location of the initial "shock" to the system (the "innovation") relative to the location of the "adopters" across space and over time. Adopters are either immediate neighbors, members of the so-called mean information field (contagious diffusion), or located in nodes connected to the origin of the innovation in a hierarchical network fashion (hierarchical diffusion) (see Hagerstrand, 1965, 1967; Brown, 1981). In either case, the process of diffusion implies a resulting pattern of values for the variable of interest (homicide rates) that is not spatially random but suggests higher incidences near the location of the origin (following a wave-like pattern over time or a distance-decay profile at any point in time) or near the location of the nodes in the adoption network. In addition, the presence of "barriers" to the diffusion process (either physical or socioeconomic in nature) would also imply a lack of spatial randomness in the form of "regions" of low adoption rates (low homicides) or clear frontiers to the extent of the spread of adoption. Although the nonrandom distribution of homicide is consistent with several competing explanations, a first step in the process of discovering patterns of spatial diffusion is the comparison of observed values to a null hypothesis of spatial randomness. If spatial randomness cannot be rejected, then there is little support for a hypothesis of diffusion. If, on the other hand, spatial randomness is not present, then there may be a diffusion process at work, and any pattern in the location and magnitude of adoption is worthy of further consideration.

ESDA is especially useful to aid in this process, since it has at its core a formal treatment of the notion of spatial autocorrelation, i.e., the phenomenon where locational similarity (observations in spatial proximity) is matched by value similarity (attribute correlation) (for extensive treatments see Cliff and Ord, 1981; Upton and Fingleton, 1985). The particular ESDA techniques used in this paper focus on the detection of *local* patterns of spatial autocorrelation through the implementation of so-called LISA statistics (Anselin, 1995) in a system of dynamically linked graphic windows that visualize the location, magnitude, and pattern in the data, such as box maps, Moran scatterplots, and Moran scatterplot maps (Anselin, 1996; Anselin and Bao, 1997; Anselin and Smirnov, 1998). This allows for the identification of both local clusters reflecting positive or negative spatial autocorrelation as well as spatial outliers (locations of high incidence surrounded by locations of low incidence, and vice versa) that are *significant* in the sense that these patterns are highly unlikely (at the chosen significance level) to have occurred as the outcome of a spatially random process.

The existence of spatial clusters and outliers can be investigated in a comparative static framework, in which one would expect shifts away from the original innovative node (or "seed") in the form of outward moving "fringe" (spread). Constraints on the extent of the outward movement may suggest the existence of barriers to diffusion.

Once the locations of clusters and spatial outliers have been identified, a next step in an ESDA is to link these univariate patterns to similar (or opposite) patterns in candidate covariates. This involves the application of a combination of ESDA tools (such as Moran scatterplots and Moran scatterplot maps) with traditional EDA tools, such as histograms, bivariate scatterplots, and box plots. Of particular relevance here is the assessment of the extent to which suggestive patterns of association between homicide and covariates may be attributed to specific subregions in the data (spatial heterogeneity or spatial leverage) rather than to an association that applies uniformly throughout the entire region. This allows for a form of deconstruction of "accepted" empirical relations in terms of their *local* spatial imprint.

2.2. Limitations of Conventional Methods

Our choice of an explicit ESDA approach is strengthened by the fact that conventional methods to assess spatial (and space–time) diffusion, such as map inspection and standard multivariate regression analysis, are potentially flawed and may therefore suggest spurious relationships. While still extremely popular in applied empirical work, the "visual inspection" of maps has long been recognized by cartographers as unreliable in terms of detecting clusters and patterns in the data. Human perception is not sufficiently rigorous to assess "significant" clusters and indeed tends to be biased toward finding patterns, even in spatially random data. It is by now widely accepted that the map as a visualization device cannot be left to unconstrained human interpretation and needs to be augmented with tools to formally assess pattern and structure (for an extensive discussion of modern views on map visualization, see, e.g., Hearnshaw and Unwin, 1994; MacEachren and Kraak, 1997). Furthermore, classic tests for "global" spatial autocorrelation, such as Moran's *I*, while adept at rejecting a null hypothesis of spatial randomness, are ill equipped to identify specific nodes of diffusion and local patterns [for an early discussion of the limitations of global autocorrelation statistics in the investigation of innovation diffusion, see Cliff and Ord (1981, Chap. 3); a recent discussion of local vs. global measures is given by Anselin (1995, 1999)].

Multivariate regression analysis may suggest spurious relationships when the explicit "spatial" nature of the data is not incorporated into the model specification. More precisely, ignoring spatial dependence and/or spatial heterogeneity in the model may lead to false indications of significance, biased parameter estimates, and misleading suggestions of fit (Anselin, 1988; Cressie, 1993). While an explicit spatial econometric approach would remedy this issue, we feel that at this stage there is no sufficiently strong theoretical framework to suggest the precise form of the spatial pattern of diffusion, a necessary element in a full specification of a spatial econometric model. However, ESDA as such is not an end in itself, and it is precisely the application of an organized "search for pattern" that will lead us to a rigorous (though empirical) basis for a model specification that can be used in the next stage of the analysis (a spatial multivariate regression approach). In this paper, we focus on the ESDA aspects and leave the modeling stage for a separate report.

3. DATA AND SCOPE OF THE ANALYSIS

3.1. Counties as Units of Analysis

We examine the spatial clustering of homicide at the county level. There are obviously a wide range of alternative geographic units that could also be used for spatial analysis [e.g., blocks, tracts, cities, MSAs, states; see, e.g., the analyses by Block and Block (1993) and Cohen *et al.* (1998)]. The selection of units of analysis should be guided ideally by knowledge of the phenomenon under investigation, but as noted above, our current theoretical understanding of possible diffusion processes underlying serious violence is primitive at best. We accordingly adopt the position that the wisest strategy is to conduct research using a variety of units of analysis.

Counties offer several distinct advantages for purposes of the present research. First, counties are a common unit of measurement for data collection. The Census Bureau, Bureau of Labor Statistics, and many other federal and state data collection offices tabulate and distribute county-level statistics. Hence, a wide range of social, economic, demographic, and political data is available.

Second, counties, as opposed to cities or MSAs, represent the complete range of social landscapes, from entirely rural to dense metropolitan areas (Nielsen and Alderson, 1997, p. 14). This is important for a couple of reasons. First, it allows us to place urban counties within a larger ecological context and to examine the potential influence of urban homicide on surrounding suburban and rural areas. We are thus able to examine whether increasing rates of homicides in urban centers are followed by corresponding increases in surrounding areas, suggesting a contagion process, or, alternatively, whether homicide tends to "implode" during a period of increasing lethal violence, with homicides concentrated within the urban core while surrounding areas are relatively unaffected. Second, previous research indicates that the social structural determinants of homicide levels differ to some extent in rural areas compared to metropolitan areas (Kposowa and Breault, 1993). The selection of counties as units of analysis enables us to consider whether processes related to the clustering of homicide differ systematically across areas with varying degrees of urban development.

Finally, there is precedent in the literature for using counties as units of analysis in the study of homicide. The injury mortality atlases produced by the Centers for Disease Control and Prevention are based on county-level data. These atlases suggest striking spatial clustering of homicides across counties for the nation at large (U.S. Department of Health and Human Services, 1997). In addition, several recent studies have reported theoretically meaningful results in analyses of the structural covariates of homicide at the county level (De Fronzo and Hannon, 1998; Kposowa and Breault, 1993; Kposowa *et al.*, 1995).

Despite the desirable features of counties, we nevertheless acknowledge important limitations associated with these units. Counties are administrative units, and they might not match the ecological scale at which diffusion processes for homicide operate. Similarly, some counties cover large territories and are comprised of heterogeneous populations. It is conceivable, therefore, that diffusion processes that operate only across relatively small distances, or within relatively homogeneous aggregates, will not be detectable in our analyses. In addition, counties vary considerably in population size; some rural counties have small populations. For these less populated counties, homicide rates may be highly unstable. We consider the issue of variance instability in the course of the analyses.

3.2. The Spatial Area and the Temporal Period

The present research is part of a larger set of studies sponsored by the National Consortium on Violence Research (NCOVR). As part of this effort, selected sites have been chosen for within-city analyses of the spatial and temporal patterning of homicide, including the city of St. Louis. Our county-level research complements the St. Louis city study by examining patterns and trends in homicide in the suburban and rural areas surrounding St. Louis.

Our specific spatial area is the aggregate of counties in the St. Louis Metropolitan Statistical Area (MSA) and additional counties within three layers of adjacency to the MSA (Bureau of the Census, 1988). This selection criterion yields a sufficient number of cases to compute meaningful statistics of spatial clustering. At the same time, the selected geographic area is limited to counties that can be reasonably regarded as within a potential sphere of influence of the St. Louis urban core.

Although St. Louis is the major metropolitan center within the geographic area, five additional counties contain cities of 50,000 residents or more: St. Louis County, MO (Florissant); St. Clair County, IL (East St. Louis); Boone County, MO (Columbia); Sangamon, IL (Springfield); and Macon County, IL (Decatur) [the complete geographic area is depicted in Fig. 1]. St. Louis County and St. Clair County are contiguous to St. Louis and are part of the St. Louis MSA. The other three counties with medium-sized cities are geographically separate from St. Louis and are parts of distinct MSAs.[8] These geographically separated areas can be viewed as "spatial subregimes." In our analyses, we consider the possibility that these counties with urban areas in the subregimes operate as "nodes" through which homicide might diffuse in a hierarchical network fashion.

We have collected annual data for the St. Louis MSA and surrounding counties for the 1979–1995 period. For reasons explained below, the present analyses focus on a subset of those years: 1984–1993.

3.3. Data Sources

The homicide data for this study come from the National Center for Health Statistics (NCHS) mortality files. These data are available on the

[8] In addition to the St. Louis MSA, there are three other MSAs in the region: the Columbia MSA (containing Boone County, MO), the Springfield MSA (containing Sangamon and Menard Counties, IL), and the Decatur MSA (containing Macon County, IL). The county farthest from the city of St. Louis in the spatial area is Texas County, MO, the centroid of which is 132 miles from St. Louis.

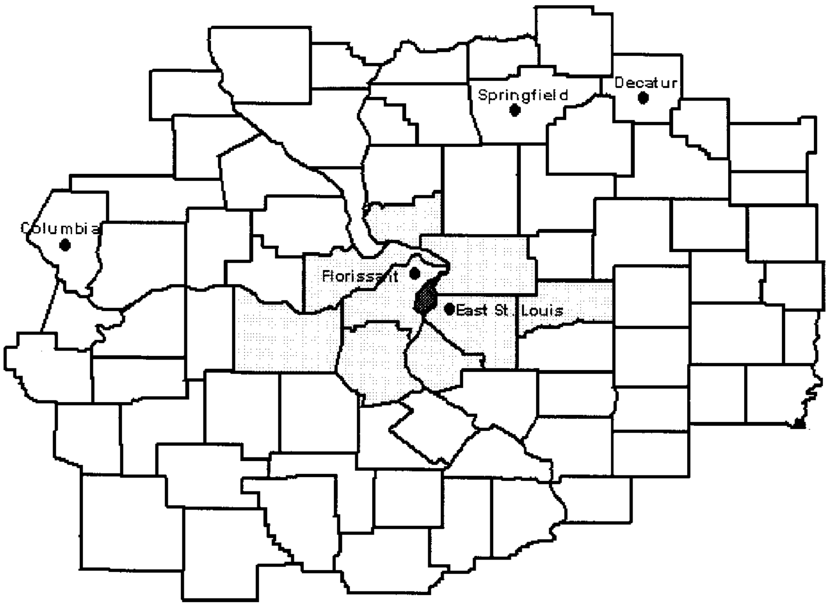

Fig. 1. St. Louis landscape: city of St. Louis (red), remainder of St. Louis MSA (yellow), and other cities with populations larger than 50,000. [Maps with colors can be viewed at htpp://www.albany.edu/csda/diffusion.html].

Centers for Disease Control and Prevention's (CDC) web-page.[9] "Homicides" refer to deaths coded as E960 to E969 using the International Cause of Death (ICD) classification.

In previous research these vital statistics on homicide from the NCHS have been compared with the criminal homicide data provided by the Federal Bureau of Investigation (FBI) (Riedel, 1999; Rokaw *et al.*, 1990). In general, the NCHS recording system catches more homicides than that of the FBI. Because the FBI is dependent on reports from police agencies, and because not all police agencies make reports to the FBI, national NCHS figures are typically higher than those of the FBI (Riedel, 1999).

The homicide data used here are aggregated by decedents' county of residence and expressed as a rate per 100,000 resident population. This is the procedure recommended by the CDC on the grounds that it is difficult to estimate the size of the population at risk accurately when data are aggregated by county of occurrence (U.S. Department of Health and Human Services, no date, p. 5). We follow the precedent of CDC in the present

[9]We used the CDC's WONDER system to obtain the homicide data.

research to illustrate ESDA, although we caution that the selection of place of residence versus place of occurrence may affect interpretations about spatial patterning and possible diffusion processes.[10]

To select possible covariates of homicide, we began with the seminal work of Land *et al.* (1990) and used decennial census data to construct county measures of the structural covariates identified in their work. Measures for the following variables were drawn from the U.S. Counties 1996 cd-rom: population, population density, percentage black, percentage of families below poverty, percentage of the civilian labor force that is unemployed, median family income, Gini index of family inequality, percentage of the population aged 15–29, percentage of males aged 15 and over who are divorced, and the percentage of family households with own children present with a spouse absent. This source combines information from the 1980 and 1990 Census summary tape files (STF1 and STF3).

Following Land *et al.* (1990), we performed principal components analysis to simplify the covariate space. The results yielded two components: a population structure component reflecting population size and population density, and a resource deprivation/affluence component, based on measures of percentage black, percentage of families below poverty, median family income, Gini index of family income inequality, and the percentage of family households with own children present with a spouse absent. Two composite indexes were constructed based on the loadings from these analyses.

We also consider some additional variables (described along with the results) to interpret the observed spatial clustering of homicide. The sources for these variables are the U.S. Counties 1996 and the Regional Economic Information Systems (REIS) cd-roms.

4. APPLICATION OF ESDA TO THE ST. LOUIS REGION

4.1. Preliminary Concerns: Temporal Aggregation

Although we previously justified our selection of a spatial region around the St. Louis metropolitan area and noted the broader time period

[10]In preliminary explorations, we have aggregated NCHS homicide data by both decendents' county of occurrence and residence for 1980 in the St. Louis spatial region. There is substantial overlap: 80% of all homicides in 1980 occurred in the decendent's county of residence. Further, we compared our NCHS county of residence data to the FBI's SHR data, aggregated by county of occurrence, for the St. Louis sample for the years 1979 to 1994. As expected, the NCHS counts are consistently higher than the SHR homicide counts. The two series nevertheless trend very similarly [see Fig. 3 of Riedel (1998) for the same national comparison over time]. In subsequent analyses, we plan to examine in greater detail the consequences of using place of occurrence vs. place of residence in the analysis of spatial patterning of homicide.

under consideration (i.e., 1979–1995), we have not yet identified the specific time intervals to be used in our analysis of county-level homicide rates. At one extreme, we could use the finest temporal resolution possible—annual rates for each of the 17 years between 1979 and 1995. At the other extreme, we could use the crudest temporal aggregation by lumping homicides across all years into a single homicide rate for the 17-year period.

Aggregating homicides for the entire 17-year period has a number of distinct advantages, the most notable of which are that it provides the greatest degree of stability in the county-level homicide rates and it summarizes the phenomenon, homicide, in the most parsimonious manner. This approach, however, is tenable only if the causal processes in the time series are in an *equilibrium state*. That is, homicide and its causal factors must be in a *stable* relationship throughout the time series. This does not imply that the time series of homicide rates is *stationary*, i.e., not trending up or down, but rather that the relationship between homicide and its antecedents is constant. In the language of regression analysis, the same values for the regression coefficients must hold throughout the time series (Coleman 1968, p. 444).

We assess the assumption of temporal equilibrium in two ways. First, we examine trending in the homicide rate time series. Figure 2 plots annual homicide rates aggregated over the entire St. Louis-area sample of counties. In general, three temporal regimes emerge: (1) a period of decreasing homicide rates (1979–1984), (2) a period of relative stability (1984–1988), and (3) a period of increasing homicide rates (1988–1993).

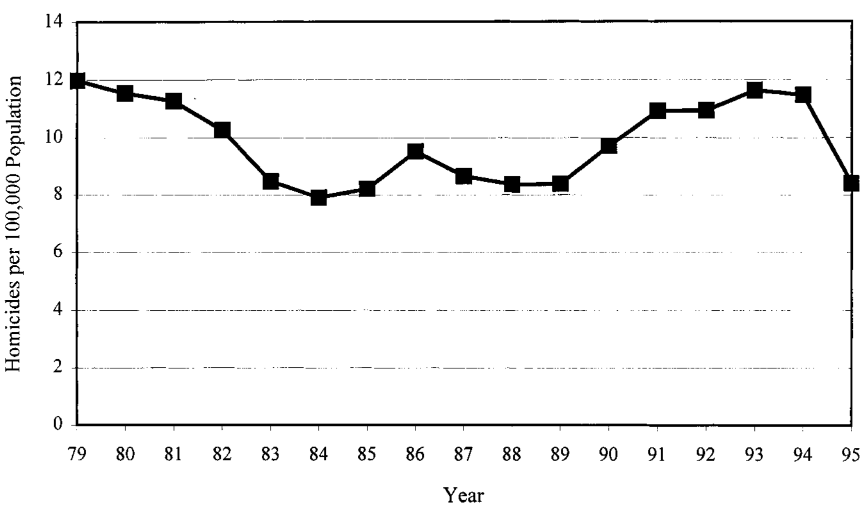

Fig. 2. Annual homicide rates: St. Louis sample.

Despite the evidence of distinct temporal regimes for the entire St. Louis region, it is possible that St. Louis (City) is dominating the aggregate rates for the region. To assess this possibility, we calculate the time series for St. Louis City and remaining counties separately. These are shown in Fig. 3.

Figure 3a is the time series for St. Louis City. It is nearly identical to the aggregate time series in Fig. 2, again revealing three temporal regimes.

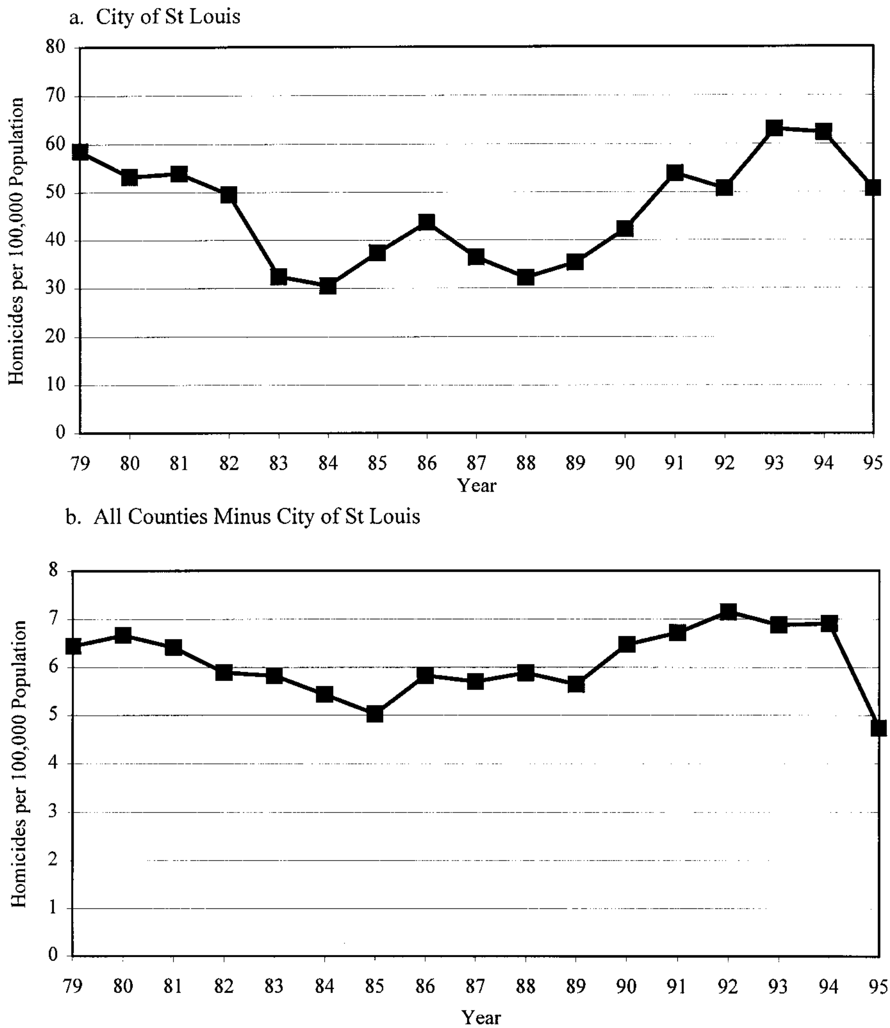

Fig. 3. Annual homicide rates in St. Louis region.

Figure 3b is the time series for the remaining counties in the St. Louis spatial region. It too is indicative of three temporal regimes, although the effect of the decline in 1995 is more severe than in St. Louis City. Interestingly, the temporal regimes outside of St. Louis City appear to lag behind city regimes by a year or two—this would be expected if homicide trends *diffused* out of the city.

The second manner through which we investigate an assumption of temporal equilibrium is by examination of annual global Moran's *I* statistics.[11] Moran's *I* is the most widely known measure of spatial clustering (Cliff and Ord, 1973; Cressie, 1993; Haining, 1990; Upton and Fingelton, 1985). It is a summary, or global, indication of spatial autocorrelation.

The distinguishing characteristic of measures for spatial autocorrelation is that the spatial arrangement of the observations is taken into account explicitly. This is done through the use of the spatial weights matrix, the elements of which are nonzero for pairs of observations that are assumed to correlate ("neighbors") and zero for others. By convention, the diagonal elements are set to zero (no unit is a neighbor to itself). The definition of "neighbor" depends on the context and the purpose of the analysis, and an almost-infinite number of possibilities can be considered (for an extensive discussion see Cliff and Ord, 1980; Upton and Fingelton, 1985; Haining, 1990). In our analysis, the focus is on diffusion and hence we use the general notion of contiguity to define neighbors. This is operationalized by taking either counties with a common boundary as neighbors (first order contiguity) or counties whose centroids (geographical center of gravity) are within a given distance of each other (distance-based contiguity). Since our primary purpose is to establish whether or not spatial randomness is present and how spatial diffusion may be reflected in the pattern of homicides, the choice of a simple contiguity definition is appropriate (other studies may consider metrics such as social distance for example). When implementing a distance-based contiguity, we are implicitly assuming a lack of directional bias in the diffusion process. Also, in order to make sure that every county is connected with at least one other county, we chose the max–min nearest neighbor distance as the cutoff criterion. For the counties in our sample, this distance is 31.7 mi, which ensures that no "islands" are present in the sample.

Table I reports the annual global Moran's *I* statistics for the St. Louis sample, 1979–1995. Table IA reports coefficients based on annual homicide rates; Table IB reports coefficients for selected temporal averages. Moran's *I* has an expected value of $-[1/(n-1)]$. Note that this expectation

[11]All computations of spatial statistics were done with SpaceStat Version 1.90 and the DynESDA extension for ArcView.

Table I. Global Moran's I Statistics: Homicide Rates (Empirical Pseudo-Significance Based on 999 Random Permutations)[a]

Year	I statistic
A. Annual homicide rate	
1979	0.100*
1980	0.070
1981	0.017
1982	0.149*
1983	0.167*
1984	0.030
1985	0.028
1986	0.119*
1987	0.066
1988	0.094
1989	0.113*
1990	0.035
1991	0.082
1992	0.041
1993	0.024
1994	0.087
1995	0.080
B. Average homicide rates	
1979–1995	0.134*
1988–1993	0.141*
1984–1988	0.125*
1979–1984	0.118*

[a] Years in Panel B represent the full period (1979–1995), the period of increasing homicide rates (1988–1993), the period of stable homicide rates (1984–1988), and the period of decreasing homicide rates (1979–1984).
*$p \leq 0.05$ (two-tailed tests).

approaches zero, the expectation for an ordinary correlation coefficient, as the number of areal units becomes large. Values of I that exceed $-[1/(n-1)]$ indicate positive spatial autocorrelation in which values of x_i tend to be similar to neighboring values; values of I below the expectation indicate negative spatial autocorrelation. The statistical evidence in this table again casts doubt on an assumption of temporal equilibrium as the annual spatial dependence of counties is highly unstable. The I values range between 0.17 and 0.02 and they are erratic throughout the study period. In addition, tests of statistical significance reject evidence of spatial association in 12 of the 17 years.

The information revealed in the figures and in Table I challenges the notion of temporal equilibrium over the entire study period. Alternatively, we could move to the other extreme and rely on annual rates. The principal advantage of this approach lies in its maximization of temporal detail. The annual instability evidenced in Table IA (probably reflecting instability in rates for counties with small populations), however, cautions against the spatial analysis of annual homicide rates. This instability could be overcome by aggregating or averaging over several years, such as 3-year periods or 3-year moving averages. Alternatively, one could employ the temporal regimes revealed in the figures. We choose to examine temporal regimes because (1) the regimes represent substantively interesting periods of homicide decline, stationarity, and increase; and (2) this choice satisfies Occam's Razor, that is, it is more parsimonious than 3-year aggregations or moving averages. To simplify the application of ESDA, our subsequent analyses in this paper concentrate on two of the periods, i.e., the periods of *stability*, 1984–1988, and *increase*, 1988–1993.[12] Note that significant spatial autocorrelation is observed in each of the three periods, as well as for the entire period (see Table IB).

4.2. Describing the Distribution of Homicide Rates

The first graphic evidence of the basic geographic distribution of homicide rates, in and around the St. Louis MSA, is presented in Linked View (Fig. 4). For both the *stable* (1984–1988) and the *increasing* (1988–1993) homicide periods the Linked View presents two types of information: (1) box maps which show the location (quartile) of every county within the overall distribution of homicide rates for the period and (2) box plots which show graphically the variation of homicide rates (based on the interquartile range) during the period. In both the maps and the plots "outlier" counties are also identified (yellow). Outliers are those counties with homicide rates for the respective period that fall significantly above the upper boundary of the interquartile range.[13]

[12]The years 1984 and 1988 constitute rather clear turning points. However, it is difficult to determine whether these years are best regarded as the end of one regime or the beginning of another. Rather than make an arbitrary decision to locate the year in one or the other regime, we allow the regimes to overlap for these years. This procedure should introduce a conservative bias in the search for changes in spatial patterns over time.

[13]A box map is a quartile map in which the outliers are highlighted. The box map and the box plot are dynamically linked in the sense that when observations are highlighted (clicked with a mouse on the screen) in one view, the corresponding observations in the other views are highlighted as well. A box map is a simple device to detect "special" observations in an ESDA approach (Anselin, 1999). To be considered an "outlier" a county's homicide rate must fall above the upper boundary of the interquartile range by an amount that is at least one and one-half times the value of the interquartile range.

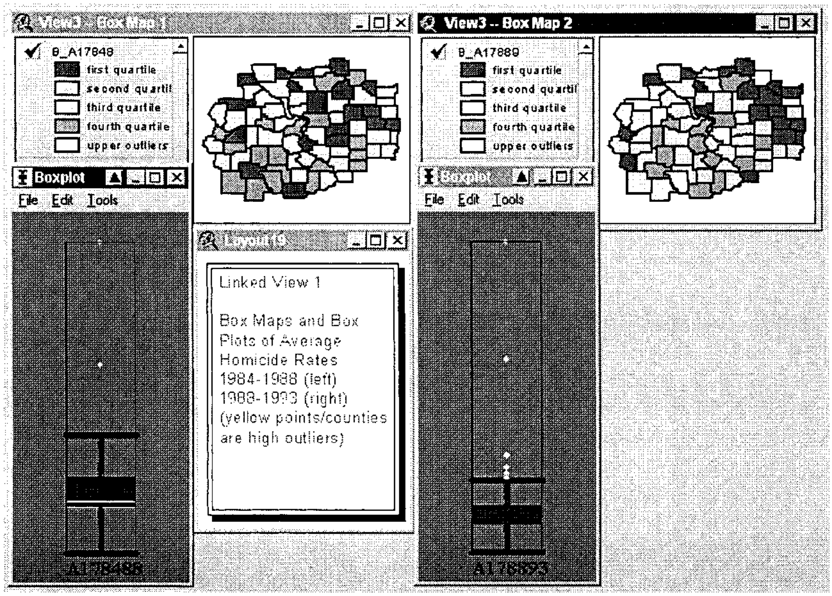

Fig. 4. Box maps and box plots of average homicide rates, 1984–1988 (left) and 1988–1993 (right) (yellow points/counties are high outliers).

Visual inspection of the box map for the period of stable homicide rates reveals that the counties tend to fall into two general regimes, defined by a diagonal line running from the upper left of the region to the lower right. Those counties falling below the diagonal show generally higher homicide rates (third and fourth quartiles), while those counties above the diagonal are characterized by lower homicide rates (first and second quartiles). Between 1984 and 1988, only two areas had homicide rates so extremely high that they can be considered outliers—St. Louis City and St. Clair County, IL. These basic patterns in the geographic distribution of homicide might be viewed as evidence of a spatial clustering of homicide rates; however, as demonstrated below, that conclusion would be premature.

The geographic distribution of homicide appears to have shifted between the periods of stable and those of increasing homicide. The "southwest vs. northeast" division deteriorates somewhat over time, with more "high homicide" counties becoming evident in the northeast quadrant. Indeed, an especially salient characteristic of the box map for the latter (increasing) period is the emergence of four additional outliers—Reynolds County, MO; Bond County, IL; Macon County, IL; and Cumberland County, IL. However, the substantive importance of these four new outliers should be interpreted cautiously. First, their homicide rates are far more modest than those for the two outliers that appear in both box maps (St. Louis City and St. Clair County, IL). Second, there is some evidence to suggest that three of the new outliers (all except Macon County, IL) may have achieved that status because of variance instability.[14]

As might be expected, the variation in homicide rates grew larger during the period of increasing homicide. However, inspection of the box plots for both periods reveals that this was due entirely to the influence of the four new outliers that emerged during the later period. In fact, when the outliers in both plots are excluded from consideration, we find that the variance in homicide rates actually shrank as overall homicide rates in the region increased—an unexpected outcome. The "compression" of homicide rates among the nonoutlier counties produced a considerably smaller interquartile range in 1988–1993 than was observed in 1984–1988. To some extent, this compression may be partially responsible for the emergence of new outliers, as the threshold for "outlier status" grew more modest.

The box maps and box plots are useful for describing the general characteristics of the distribution of homicide throughout the 78-county area under study and for revealing specific areas with exceptionally high levels of homicide. However, they are limited in their ability to identify any significant spatial clustering of homicide rates (high or low). For that purpose we turn to a consideration of a global statistic for spatial autocorrelation (Moran's *I*), its local counterpart (Local Moran), and its decomposition into four types of spatial association (Moran scatterplot and Moran scatterplot map).[15]

4.3. The Spatial Autocorrelation of Homicide

Critical to assessing the presence or degree of spatial clustering, but missing from the evidence presented in Linked View 1, is a systematic consideration of homicide levels in neighboring counties. That is, the classification for each county in the box maps, by quartiles, is based only on the level of homicide in that county and its location in the overall distribution of homicide for all counties combined. In contrast, measures of spatial autocorrelation explicitly take into account the spatial arrangement of the

[14]For these three counties, the large increases in homicide rates are based on relatively small changes in the count of homicides between periods: Cumberland County, IL (counts of 1 and 7 and rates of 1.85 and 10.86), Bond County, IL (counts of 2 and 9 and rates of 2.58 and 9.92), and Reynolds County, MO (counts of 2 and 5 and rates of 5.86 and 12.58). In contrast, the increase in homicide rates for Macon County (from 6.04 to 9.05) reflects a substantial jump in homicide counts (from 37 to 64).

[15]An extensive discussion of the graphical devices and terminology used in ESDA is given by Anselin (1995, 1996, 1999).

values. A global measure of spatial autocorrelation, such as the Moran's I statistics reported in Table I, provides an indication of the extent to which the spatial pattern of the whole data set (hence, "global") is compatible with a null hypothesis of randomness. Local indicators of spatial association [or LISA; an acronym coined by Anselin (1995)] assess a null hypothesis of spatial randomness by comparing the values in each specific location with values in neighboring locations.[16] Several LISA statistics can be considered, but a local version of Moran's I is particularly useful in that it allows for the decomposition of the pattern of spatial association into four categories, corresponding with four quadrants in the Moran scatterplot (Anselin, 1996). Two of these categories, imply positive spatial association, namely, when an above-average value in a location is surounded by neighbors whose values are above average (high–high) or when a below-average value is surrounded by neighbors with below average values (low–low). In contrast, negative spatial association is implied when a high (above average) value is surrounded by low neighbors, and vice versa. Both of these instances are labeled spatial outliers when the matching LISA statistics are significant. Each of the quadrants matches a different color in the so-called Moran scatterplot map, a map that shows both the locations with significant LISA statistics (i.e., a rejection of the null hypothesis of spatial randomness) and the category of spatial association.

The classification into four categories of spatial association is illustrated by the Moran scatterplots in Linked View 2 (Fig. 5). The horizontal axis is expressed in standard deviation units for the homicide rate. The vertical axis represents the standardized spatial weighted average (average of the neighbors) for the homicide rates. The slope of the linear regression smoother through the scatterplot is the Moran's I coefficient, as shown by Anselin (1996). This allows for an easy interpretation of changes in global spatial association (the slope) as well as a focus on local spatial association (the quadrant). A county's location among these four quadrants determines whether it is classified as "high–high," "low–low," "high–low," or "low–low" in the Moran scatterplot map. The local Moran's I statistic is used to determine whether the location of the county in the scatterplot map is statistically significant, that is, whether the autocorrelation is greater than would be expected by chance.[17] The scatterplots presented in Linked View 2 (Fig. 5) also report the Global Moran's I statistic described above as a measure of spatial autocorrelation among all counties in the analysis.

[16]The local Moran is defined as $I_i = (z_i/m_2)\sum_j w_{ij}z_j$, with, $m_2 = \sum_i z_i^2$; observations z_i and z_j are in mean-deviation form, and the summation over j is such that only neighboring values are included.

[17]As implemented in the SpaceStat software, the significance of the Local Moran statistic is determined by generating a reference distribution using 999 random permutations.

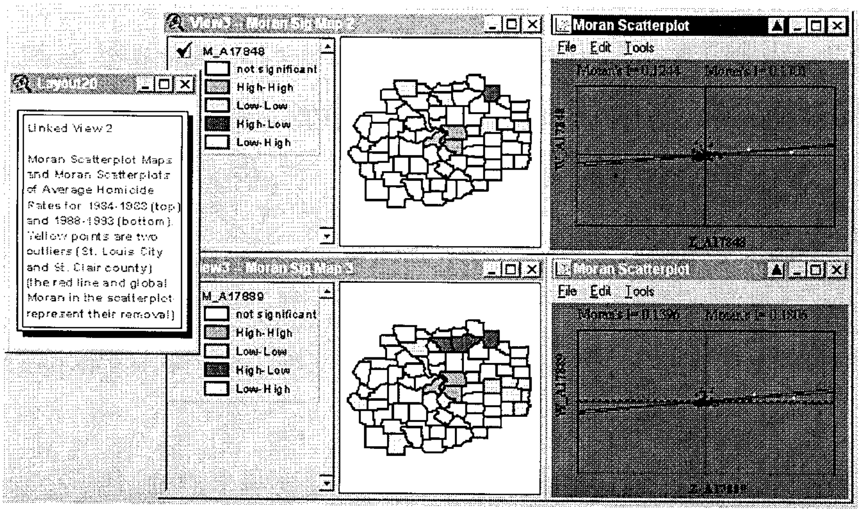

Fig. 5. Moran scatterplot maps and Moran scatterplots of average homicide rates for 1984–1988 (top) and 1988–1993 (bottom). Yellow points are two outliers (St. Louis City and St. Clair County). The red line and global Moran in the scatterplot represent their removal.

Beginning with the Moran scatterplot map for the period of stable homicide, we find evidence of spatial grouping. A cluster of counties with high homicide rates, as well as neighbors with high homicide rates, is apparent in the area around St. Louis City. This "urban core" of high homicide is also implicated in the three surrounding counties with low homicide rates, but high-homicide neighbors. These are suburban residential counties near the city of St. Louis. In addition, two clusters of low-homicide counties, surrounded by other counties with low homicide rates, can be seen in the northern and eastern fringes of the region. Consistent with a possible diffusion process, a distinct "hot spot" appears in the data centered around the St. Louis urban core, while "cool spots" are also detected in areas geographically removed from St. Louis.[18]

Turning to the subsequent period during which homicide rates increased throughout the region, the same general profile of spatial clustering appears in the Moran scatterplot map. However, one notable difference emerges during the later period—involving Morgan and Sangamon

[18]The research on "hot spots" typically involves ecological areas much smaller in scale than counties, such as city blocks or "places" (Roncek and Maier, 1991; Sherman *et al.*, 1989). For linguistic convenience, we use the terms "hot spots" and "cool spots" to refer to county clusters corresponding to the high–high and low–low quadrants of the Moran scatterplot, but we do not imply that the processes underlying spatial clustering are analogous for ecological units at different levels of aggregation.

Counties in the upper tier of the region. During the earlier period, Macon County, IL, had a high homicide rate and was surrounded by counties with low homicide rates. Its neighbor to the west, Sangamon County, did not have a statistically significant local Moran's *I*. In turn, Sangamon County's neighbor, Morgan County, was part of a cluster of counties with low homicide rates, with neighbors that shared that status. By the later time period, however, both Sangamon and Morgan Counties made the transition to "high-homicide" counties, surrounded by "low-homicide" counties. In conjunction with Macon County, they now formed a string of counties, suggesting the possible east-to-west diffusion of homicide out of Macon County, as homicide in general increased throughout the region.

A final piece of evidence about the spatial clustering of homicide can be gleaned from the Moran scatterplots. The Global Moran's *I* for both time periods, 0.1244 and 0.1396, respectively, are significant at the 0.05 level and suggest positive clustering such that counties with high homicide rates tend to have neighbors that also have high rates or, conversely, counties with low homicide rates "cluster together" with other low-homicide counties. Furthermore, the scatterplots show that this overall clustering is not due simply to the disproportionate influence of the two, neighboring, counties with the highest homicide rates in the region—St. Louis City and St. Clair County. In fact, the degree of spatial clustering *increases* when those two counties are omitted from the analysis, to 0.1701 and 0.1806 for the earlier and later time periods, respectively.

4.4. Searching for Covariates

In our previous discussion of the rationale for using ESDA, we acknowledged the importance of linking univariate patterns in the spatial distribution of homicide to global and/or local patterns of association with covariates. We turn now to this objective.

Our initial selection of covariates of homicide follows the lead of Land *et al.* (1990). In their highly influential study, they report that reasonably invariant relationships with homicide rates can be observed for samples of cities, metropolitan areas, and states once multicollinearity is reduced through the construction of principal component indexes. The ESDA described in this section reports results for the most powerful predictor of homicide in Land *et al.*'s model—the resource deprivation/affluence component (RDAC). We examine spatial patterns and bivariate relationships with RDAC for the *stable* (1984–1988) and *increasing* (1988–1993) temporal homicide regimes.

The top two panels in Linked View 3 (Fig. 6) display the Moran scatterplot map for RDAC (measured in 1985) and the Moran scatterplot map

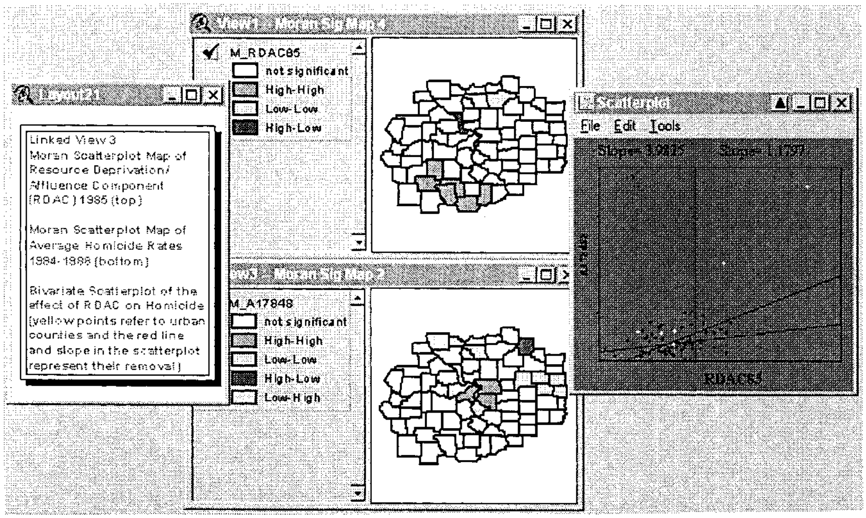

Fig. 6. Moran scatterplot map of resource deprivation/affluence component (RDAC), 1985 (top). Moran scatterplot map of average homicide rates, 1984–1988 (bottom). Bivariate scatterplot of the effect of RDAC on homicide. Yellow points refer to urban counties and the red line and slope in the scatterplot represent their removal.

for the averaged homicide rates for the stable 1984–1988 period. The bottom panel presents the bivariate scatterplot of homicide on RDAC. Linked View 4 (Fig. 7) replicates the maps and scatterplot for the period of increasing homicide (1988–1993) with RDAC measured in 1990.

Beginning with the stable period (Linked View 3; Fig. 6), one observation is immediately evident in the two maps: there is little relationship between RDAC and homicide in the local Moran statistic. In other words, local dependencies in homicide are spatially distinct from local dependencies in RDAC. Resource deprivation is clustered among counties located in the southwest quadrant (located in the Ozark mountain subregion) of our spatial region in both periods, while homicide clusters are consistently situated north of this quadrant.

Turning to the scatterplot, the blue line represents the slope of the relationship when all counties are considered. The slope suggests a moderately strong positive relationship between RDAC and homicide rates, a finding which is consistent with past research using other units of analysis. However, the scatterplot also suggests that selected counties may be exerting strong leverage on the observed relationship. The dynamic linking capabilities of ESDA allows us to highlight and identify the two outliers on the scatterplot—St. Louis City and St. Clair County (which contains East St.

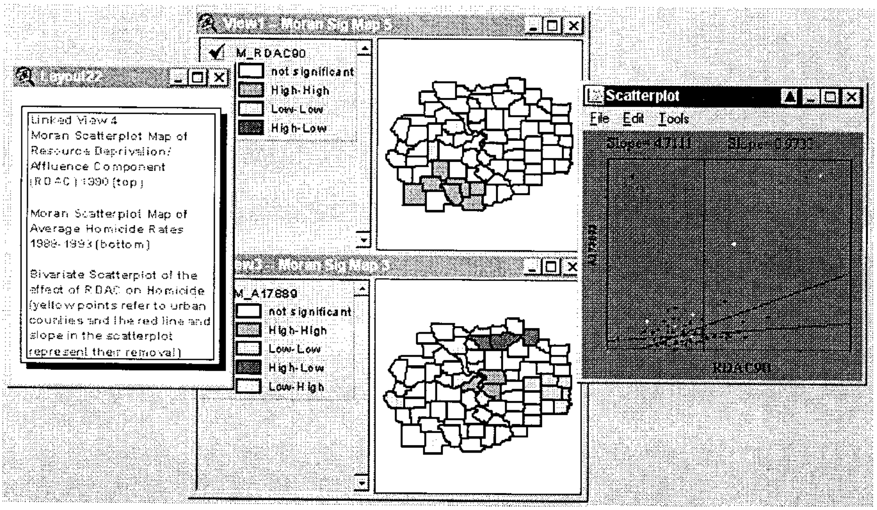

Fig. 7. Moran scatterplot map of resource deprivation/affluence component (RDAC), 1990 (top). Moran scatterplot map of average homicide rates, 1988–1993 (bottom). Bivariate scatterplot of the effect of RDAC on homicide. Yellow points refer to urban counties and the red line and slope in the scatterplot represent their removal.

Louis). These initial observations suggest that the relationship between homicide and RDAC might differ appreciably for urban and nonurban counties. Once again using the dynamic linking capabilities of ESDA, we can select the five counties containing cities with populations of 50,000 or more (Boone, Macon, Sangamon, St. Clair, and St. Louis Counties), along with St. Louis City. These cases are depicted in yellow in the scatterplot. The red line in the scatterplot represents the slope of the relationship between homicide rates and RDAC when these highlighted cases (the urban areas) are removed. The results reveal a very flat slope, indicating that the overall assocation between RDAC and homicide rates is due almost entirely to the influence of the urban areas. Analogous results are obtained in the analysis of the period of increasing homicide (Linked View 4; Fig. 7).

Our investigation of other significant predictors in the Land *et al.* (1990) baseline model yields nearly identical results to those obtained from the bivariate regression and spatial covariation of homicide with these predictors. Moreover, multivariate analyses (not shown) confirm these conclusions: the statistically significant effects of covariates of homicide in county-level analyses are entirely attributable to influential cases represented by urban centers. This raises the question as to whether there are alternative covariates of homicide in non-urban counties, or if the level of homicide (rates) is so low (and perhaps unstable) outside of urban areas that it is random with respect to county-level covariates. Further analyses reported below point toward alternative indicators that are significantly related to homicide rates in rural counties.

4.5. Barriers to Diffusion

Thus far, we have focused on evidence of the diffusion of homicides to surrounding areas, and possible covariates. It is also instructive to explore reasons for the apparent failure of homicide to "spread" to geographically proximate areas. Are there features of counties that effectively serve as barriers to diffusion? To address this question, we have searched for variables that distinguish "barrier" counties in the spatial area, i.e., those counties that are proximate to the two apparent "hot spots"—the Macon/Sangamon/Morgan area in the Northeastern segment and the St. Louis urban core.

There are no cities in the barrier counties for the Macon/Sangamon/Morgan cluster, which suggests that aspects of rural social structure might distinguish these counties from others. To search for relevant variables, we have examined correlations between homicide rates and a wide variety of social and economic variables for the nonurban counties in the sample (the six counties that contain cities were excluded). Interestingly, rural homicide is strongly correlated (r approximately = –0.30) with a measure of agricultural activity or ruralness: cash earned from the sale of crops. This correlation is stronger than those involving the predictors from the model of Land *et al.* (1990). In addition, the variable for cash earned from crops exhibits a statistically significant negative effect on homicide rates for the sample of nonurban counties in a multiple regression with the controls for the variables in Land *et al.*'s model.

Linked View 5 (Fig. 8) contains a Moran scatterplot map of homicide rates for the increasing period and a histogram representing the variable cash from crops (both were averaged for the years 1988 to 1993). By dynamically linking these views we are able to highlight the counties surrounding Macon, Sangamon, and Morgan counties and see instantaneously where they fall on the cash from crops measure. As shown in Linked View 5 (Fig. 8), the barrier counties tend to fall at the upper end of the cash from crops distribution. It appears that highly agricultural or rural counties act as barriers to the diffusion of violence. In contrast, these barrier counties fall directly in the middle of the distribution for RDAC (not shown). These results, in combination with the earlier analyses of the conventional structural covariates of homicide, suggest that the predictors of rural and urban homicide may be different.

Shifting attention to the St. Louis urban core, it sees likely that the apparent barrier counties (the three "low–high" counties near St. Louis in

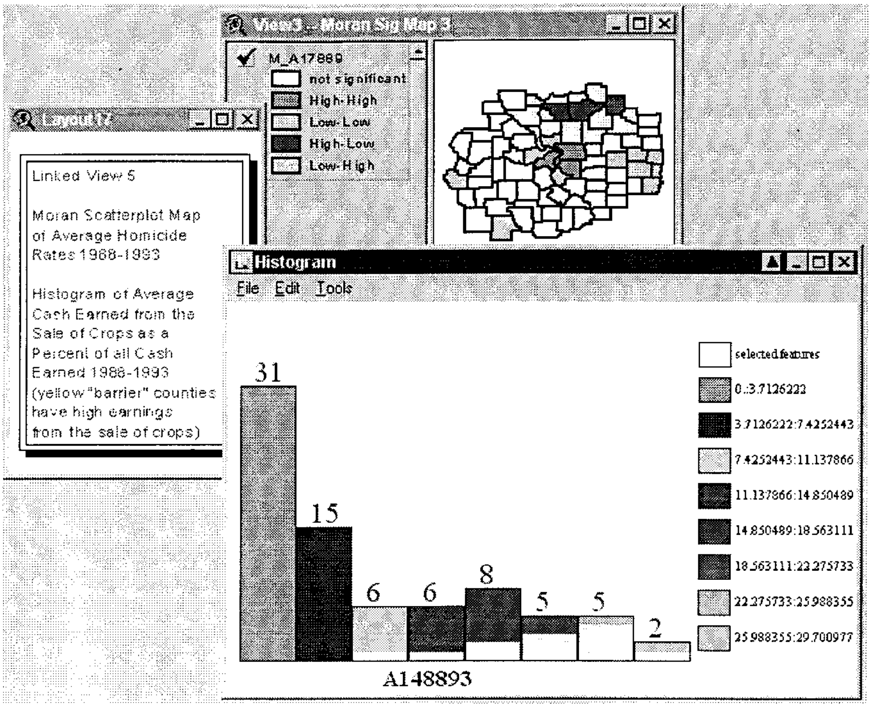

Fig. 8. Moran scatterplot map of the average homicide rate, 1988–1993. Histogram of average cash earned from the sale of crops as a percentage of all cash earned, 1988–1993. Yellow "barrier" counties have high earnings from the sale of crops.

Linked View 2; Fig. 5) are primarily affluent suburbs. This hypothesis is confirmed when a Moran scatterplot map of homicide rates in the increasing period is linked with the Histogram for the RDAC (Linked View 6; Fig. 9). The results are striking. The counties along the western fringe of the St. Louis MSA are among the most affluent (least disadvantaged) in the area. At the urban core, affluent suburbs appear to act as barriers to the diffusion of violence. Given the economic well-being of these western MSA counties, we suggest that if diffusion from St. Louis were to occur in the future, it would most likely occur in the eastern part of the St. Louis MSA.

5. CONCLUSION

Our application of ESDA to county-level homicides in the St. Louis area leads to several substantively important conclusions. First, the hypothesis of spatial randomness is clearly rejected. Statistically significant spatial

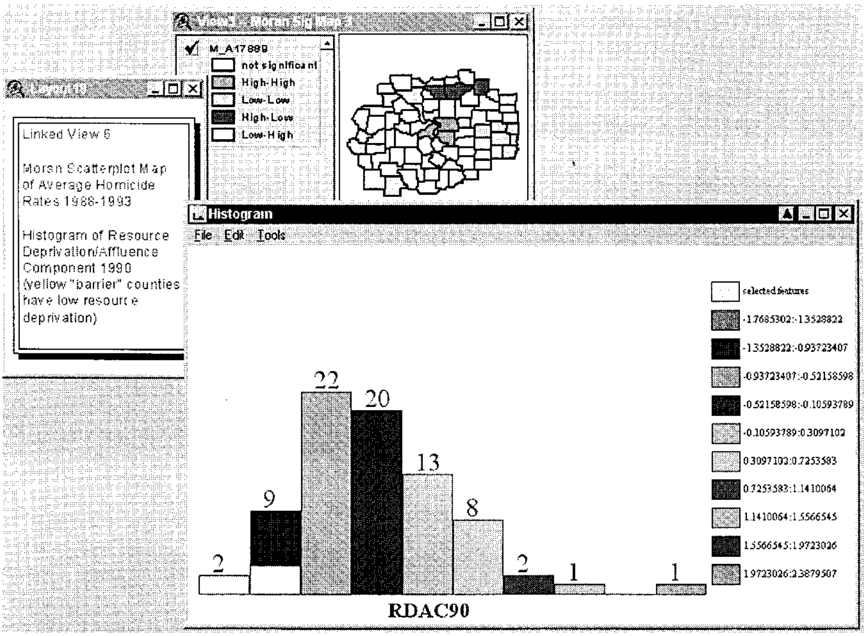

Fig. 9. Moran scatterplot map of average homicide rates, 1988–1993. Histogram of resource deprivation/affluence component, 1990. Yellow "barrier" counties have low resource deprivation.

clusters are observed in both periods under investigation, one of stable homicide rates and one of increasing homicide rates for the region as a whole. These results provide justification for further consideration of local patterns of spatial autocorrelation.

Second, some of the observed local patterns of autocorrelation are suggestive of possible diffusion processes. The comparative static analyses reveal clustering—"hot spots" and "cold spots"—that would be expected as a result of a contagious diffusion process in the past. In both periods, high homicide rate counties are clustered around the St. Louis urban core, while clusters of low homicide rates appear in territories removed from this core. The dynamic comparison across the two periods also provides evidence consistent with a diffusion process. A new high homicide rate cluster appears in the second period, suggesting the possible spread of homicide from Macon County to two counties to the west. This pattern is suggestive of a hierarchical diffusion process wherein smaller urban centers (Decatur and Springfield) serve as "nodes" for the spread of homicide from major metropolitan centers. We have regarded St. Louis as the urban core of the spatial area, but the Decatur/Springfield spatial subregime could conceivably operate as a node connected to another nearby major metropolitan area—Chicago. Our analyses cannot determine which of these processes is at work, but they both warrant further inquiry.

Third, our analyses reveal that the covariates of homicide rates that have emerged in previous research based on other units of analysis and geographic areas do not offer a satisfactory explanation of the clustering of homicide in the St. Louis region. The spatial distributions for these covariates do not mirror those for homicide rates in any systematic way. In addition, the explanatory power of these conventional covariates for the region at large is due almost entirely to the effects among the urban counties. These results are consistent with previous county-level studies indicating that the determinants of homicide vary in some important respects across different kinds of ecological units (cf. Kposowa and Breault, 1993; Kposowa *et al.*, 1995).

Finally, our analyses point to possible barriers to the diffusion of homicide. Those counties surrounding the Macon County "hot spot" that did not exhibit increased homicides are characterized as highly rural or agricultural. The western barrier counties for the St. Louis urban core also exhibit a distinctive socioeconomic makeup: these are among the most affluent (least deprived) counties in the region.

In closing, we remind the reader that ESDA is a starting point for analysis. As the label states, it represents the *exploratory* phase of research. If one wishes to entertain the notion of spatial diffusion, it must be shown that the distribution is nonrandom. We have done this. However, spatial diffusion is not the only mechanism through which spatial nonrandomness occurs. Rigorous testing of diffusion processes requires identification of specific mechanisms and formal modeling in a spatial multivariate regression approach. The spatial diffusion of homicide is based on an argument that the observed rates of homicide are systematically related to rates of homicide in neighboring areas. Alternatively, spatial nonrandomness could be due to a spatial "error" process (where the important unmeasured predictors of homicide account for the observed clustering) or spatial heterogeneity (where different causal processes are thought to operate in subregions of the geography, e.g., urban versus rural areas, that produce similar levels of homicide in those areas). Indeed, spatial heterogeneity and spatial dependence can be observationally equivalent and detection of one must be tested while the other is controlled for (Anselin, 1988; Anselin and Bera, 1998). Nevertheless, ESDA is an extremely useful set of inductive techniques for pursuing an hypothesis of diffusion. By combining graphical and statistical tools in an interactive computing environment, researchers can discover suggestive spatial patterns warranting further empirical investigation and theoretical interpretation. Our analyses illustrate how this inductive approach can be profitably applied to enhance understanding of the phenomenon of homicide.

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