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Applying spatial thinking in social science research

John R. Logan, Weiwei Zhang, and Hongwei Xu

Brown University, Providence, RI, USA

Abstract

Spatial methods that build upon Geographic Information Systems are spreading quickly across the social sciences. This essay points out that the appropriate use of spatial tools requires more careful thinking about spatial concepts. As easy as it is now to measure distance, it is increasingly important to understand what we think it represents. To interpret spatial patterns, we need spatial theories. We review here a number of key concepts as well as some of the methodological approaches that are now at the disposal of researchers, and illustrate them with studies that reflect the very wide range of problems that use these tools.

Keywords

GIS; Spatial methods; Spatial concepts

In the last 10 years there has been an explosion of interest in the applications of spatial concepts and techniques in the social sciences (Voss 2007). The development has been especially intense among those researchers who are used to working with data that are aggregated for a territorial unit (a county, city, or neighborhood). It is a natural step to take advantage of the new Geographic Information System (GIS) technologies that make it relatively easy to map those data. More important, visualizing information on a map tends to bring up other questions about how to understand the patterns. At this point, GIS gives way to a myriad of tools of spatial analysis that are well established in geography and in some applied fields such as biostatistics but that most social scientists are not yet familiar with.

We provide an overview of some important techniques with examples of their application. Some readers will find these examples directly relevant to their research interests, noticing that their data or their question is of the same form as one of those reviewed here, which can then be used as a template for their own analysis. We also have a theoretical purpose. Spatial analysis brings into play concepts like proximity or access, isolation or exposure, neighborhoods and boundaries, neighborhood effects, and diffusion. Informed use of spatial tools requires familiarity with these concepts, and the presentation is organized to clarify the spatial thinking that underlies them. We emphasize that very simple notions in the new spatial statistics toolbox, like distance, turn out to be theoretically complex in their use. When there are spatial patterns, there is usually more than one way that they could arise, so there is no shortcut for interpretation of findings.

Some key spatial concepts

Locating an observation on a map is of use when it is evaluated in relation to other observations. This is what draws our attention when we look at a well constructed map—the mapmaker has

helped us perceive a spatial relationship, to notice where some kinds of observations lie in relation to others. The map allows us to see (and allows a GIS program to calculate and store in a data file) these relative distances. What do these distances mean to us?

A core presumption for geographers is that like things tend to be near to one another, and the more alike, the nearer they are (Tobler's First Law of Geography). This is the phenomenon of spatial dependence on which much spatial analysis is built. Yet many different causal processes can lead to spatial dependence. It can result from the possibility that, for better or worse, the nearer two phenomena are to one another, the more likely they will come into contact or affect one another. In studies of intergroup relations exposure is often presumed to be a step toward reducing boundaries between groups, so it is positive. In epidemiological applications, in contrast, exposure to others leads to infection. Either way, if the access or the risk is consequential, it can make nearby phenomena more similar by virtue of exposure to the same stimulus. That is, proximity causes similarity. This causal path can operate in the opposite direction. We can think of locations in terms of the access or risk that accompany them. Proximity to a resource is thought of as better access; proximity to a hazard, as greater risk. As people or organization make locational choices they may take into account their differential proximity to resources or hazards, so the spatial pattern may be the result of their selectivity in location. Similarity, in other words, can cause proximity.

How close is close enough to make a difference? Many spatial statistics require taking a position on this question. It seems reasonable to assume that the relationship between two observations declines monotonically with the distance between them, perhaps very rapidly and perhaps disappearing entirely at some distance. Yet we rarely have enough information or theory to specify more clearly the functional form of this decline. Geographers have defined a number of options. It is popular to consider only adjacent observations to be close, or "spatially dependent." An alternative is to treat the "n" nearest neighbors as equally close, or to extend the analysis to a larger number of neighbors but to give greater weight to the nearest ones in the analysis. Rather than stipulate an answer to this question, some approaches directly investigate how patterns of similarity are related to distance. For example, one could specify a number of rings of different diameter (or band widths) around an observation and then evaluate how similarity changes (presumably it declines) across these bands. The result is not a single statistic, but a graph representing how the statistic varies at different distances.

The implication of these considerations is that even the simplest spatial measures reflecting what we see on a map—the relative distances among observations—require substantive interpretation. We will add one further complication. Suppose the important spatial patterns are not smooth surfaces, but instead are better represented as discontinuous areas with frontiers between them like the boundaries between two school districts. Imagine that on one side of the line is district x [X] and on the other side is district y [Y], potentially with great differences between the two. Then we need a theory not of distance between locations but of socially relevant geographic areas, or discrete places. As the following review will illustrate, this is not an uncommon case. Spatially oriented social scientists often think in terms of neighborhoods or zones, and though the boundaries between them may not be as explicit as political boundaries, they may be very distinct. Especially when we ask how about the consequences of living in this place versus a different one, we are implicitly defining places. There are also situations where the issue is not living a little nearer or a little further away, but in one place or in another. How do we define the places and determine their boundaries? Sometimes the definition is based on a measurement limitation—we have information about a given administrative unit, and we choose to treat it as the relevant place even though it has no substantive meaning. In such cases it may make sense to use tools that seek to convert discrete data observations into smooth surfaces and deploy the usual methods of studying distance.

When we have choices about spatial scale, there is a temptation to try all of them. Indeed a spatial pattern we observe at one scale may disappear at a smaller or larger scale, so searching for a pattern is sometimes rewarded. A version of this approach is to hedge one's bets by conducting the analysis at one geographic scale but then taking into account the observations in nearby units as another predictor (in spatial regressions, this is called "spatial lag"). But when this is done without a clear theory, we do not know how to interpret the result when neighboring places seem to matter. It could be that there are causal processes by which what happens in one place is influenced by what happens in its neighbors. In that case one would describe the result as showing diffusion across space, or perhaps one would comment that places are fatefully embedded in a larger context. But alternatively the spatial dependence revealed in the analysis may indicate that we conducted it at too narrow a geographic scale—that a given area and the areas around it are really components of the same place. Ultimately, as in so many methodological questions, the real issue is substantive and it cannot be settled empirically.

We now turn to a review of representative studies in several research domains: community health, population and environment, residential segregation, land use, fertility, and migration. These examples were chosen to reflect the wide range of substantive applications of spatial concepts in social science research, to illustrate a variety of useful spatial tools, and also to offer examples of how researchers interpreted their spatial data.

Community health

Research on population health often takes advantage of data on the incidence of disease, where the address of victims is known. Converting street addresses to points on a GIS map (geocoding) opens up many possibilities for how to analyze the spatial distribution of those points. One study of dengue infection in a city in central Brazil (Siqueira et al. 2004) collected survey data on 1,585 individuals. The survey included dengue infection status, medical condition history, and socioeconomic and demographic characteristics. Another component asked specifically whether there were zones of the city with significantly high concentrations of infection, which could then be targeted for public health interventions. For this purpose they used a technique called kernel density estimation that evaluates the proximity of infected persons to other infected persons as compared to non-infected persons. Locations with statistically significant clusters of infected persons can readily be mapped (as in Fig. 1). The kernel estimate map reveals such clusters in the northwestern, eastern, and southeastern parts of the city.

Another step in the analysis investigated the source of the spatial clusters that were observed. Are they random (wherever an infection occurs, for whatever reason, it tends to spread from there) or caused by some underlying factor (something about the people living in a given area or their environment)? Area-based indicators derived from census data were linked with individual data. These variables included average income, population density, housing density, and percent of households with an indoor water supply. There was no special effort to determine the appropriate scale at which to measure neighborhood characteristics; like most researchers, the Siqueira team applied administrative units from the Brazilian census. The resulting contextual or multilevel analysis provided clues about the processes that caused spatial clusters.

A related technique was used to identify clusters of childhood leukemia in west-central Lancashire in England during 1954–1992. Gatrell et al. (1996) geocoded and plotted the locations of children with and without leukemia. GIS tools were used to calculate the proportion of leukemia cases at various distances from each child. If leukemia were clustered, one would expect to find more leukemia cases within a given distance from a sick child than within the same distance from a healthy child. The K-function (Diggle 1983) is a statistic that summarizes

the density of these cases at a given distance or spatial scale. The difference between the K-functions for sick and healthy children is therefore a measure of clustering. Figure 2 graphs the result, with the difference in K-functions on the y axis and distance on the x axis. The graph seems to show that the difference is positive at every distance, and that it reaches a maximum at a distance of about 4 km. One might conclude, then, that there is clustering at that scale. But it turned out not to be statistically significant. The diagonal lines on the graph show a “simulation envelope” within which K-function values could be expected to fall by chance 95% of the time. A nice feature of the K-function is that it can easily be recalculated many times in a computer simulation, where leukemia cases are randomly assigned to children. That is the basis for the test of statistical significance.

Unfortunately individual-level data (points) are often not available. Kelsall and Wakefield (2002) had only aggregate data on colorectal cancer in 39 electoral wards in the U.K. West Midlands district of Birmingham in 1989. They were aware that aggregated data, especially for rare diseases and small geographic areas, are subject to much random variation between extremely high and low values. And in this case they were unwilling to assume that the administrative areas approximated “real” neighborhoods. Therefore they sought to convert the aggregate data to an estimate of what the underlying point data might be like, if the ward-level data were based on an underlying continuous risk surface of colorectal cancer. Their approach assessed values in each electoral ward as well as in its neighbors, taking advantage of the fact that neighboring areas tend to have similar values (the phenomenon referred to as spatial dependence or spatial autocorrelation). Specifically they assumed that the risk at any point could be approximated by a Gaussian random field model that has been much used in geostatistics (Diggle et al. 1998). Although there appeared to be great variation in cancer rates across electoral wards, once the data were “smoothed” in this way there was little spatial variation.

Population and environment

The main focus of the first set of studies was on the spatial pattern of a single variable: disease. A further step is to examine the relationship between a risk factor (like air pollution) and the composition of the population exposed to that risk. Pastor et al. (2004) studied the spatial distribution of sites in California that were known to release toxic emissions. Emissions sites were categorized as facilities reporting any type of toxic air release, facilities reporting emissions of “persistent bio-accumulative toxins” (PBT), and sites reporting releases of an EPA priority category of toxics known as 33/50 chemicals. These sites were geocoded, and GIS methods were used to create circular zones (distance buffers) of 1/2 mile, 1 mile, and 2 1/2 miles around each site. Then census tracts were categorized according to their zone of proximity to these exposures. Note that census tracts were accepted as proxies of neighborhoods, and the question was how close (in three distance intervals) various types of neighborhoods were to a risky location. The key finding is that neighborhoods with high proportions of Latino residents were most exposed.

A more sophisticated approach is to use a distance decay model, where “exposure” to a site is assumed to be proportional to one’s distance from it. Downey (2006) used this method to examine whether minority and lower income groups are disproportionately burdened by environmental hazards in Detroit. He began with a map showing the geocoded location of industrial facilities identified in the federal government’s 2000 Toxics Release Inventory. He overlaid this map with a census tract map, and calculated the distance from every toxic facility to each of many small grids within each tract. He then calculated the total hazard exposure for each grid, taking into account these distances and also the volume of toxic emissions from each facility, and aggregated the grid cells to calculate a total tract exposure. There are two hurdles for this analysis. The first is that Downey did not know what variation there was in population

composition of the many grid cells within each tract. He chose to presume that they were all the same (unlike Kelsall and Wakefield, who sought to model the variation). The second hurdle was to assess how distance should be related to exposure—should exposure decline linearly with distance, or should nearby facilities be counted even more heavily than more distant ones, and is there some distance beyond which there is no exposure? Because there is no obvious solution, Downey chose six different distance-decay functions and tested all of them. He used multiple regression analysis to determine that the percent of black residents in a tract is significantly related to toxic exposure, but only at distances of 1.5–2.5 miles. Black census tracts tended to be near but not directly adjacent to toxic facilities. Without a stronger theory about the expected distance band, the significance level of this finding is in doubt—if one tests several cutoff points, there is a probability that at least one of them will appear to be significant even if the distribution is random.

Pais and Elliott (2008) used similar methods to investigate the effects of another type of environmental risk: three major hurricanes during the early 1990s. What population shifts in neighborhoods (again operationalized as census tracts) were caused by wind damage? This study relied on sophisticated climatological applications of GIS methods to estimate the maximum wind speeds experienced in every census tract within the study region. The researchers combined these estimates with information about the tract's demographic composition (population size, in-migration, and number of housing units) in 1990 (before the storm) and 2000 (afterwards). Their regression procedure adds a special feature that qualifies it as a “spatial regression.” To control for the fact that census tracts near one another tend to have similar characteristics, and also tend to have suffered similar levels of wind damage, they included a spatial error term in their model to correct for spatial autocorrelation. They also specifically investigated several spatial factors. Most interesting, it turned out that there was robust population growth in all the areas hit by these hurricanes, but especially in those areas just outside the zone of greatest damage. There was, in a sense, displacement of resources to nearby, less damaged zones.

Residential segregation

A common feature of all these studies is that they rely on an implicit concept of neighborhood, reflected in clusters of points or in administratively defined wards or census tracts. Scholars have given the definition of neighborhoods more explicit attention in studies of residential segregation and its effects. Although there is a long history of segregation research that relies on aggregate data for administrative units, it is only recently that demographers have attempted systematically to take into account the spatial configuration of those units. An example is a study by Reardon et al. (2008). These researchers point out that the geographic scale of segregation may vary greatly from city to city. This notion is illustrated in Fig. 3. The figure shows stylized patterns of segregation for a city that is 50% white and 50% black. Starting at a random point within this city, the figure shows the percent of neighbors who are black within a ring of a given radius. Region A, for example, has many small neighborhoods (areas with a 1–2 km radius) that are as low as 30% black or as high as 70% black, but at any 4 km radius every neighborhood is 50% black. At another extreme, Region D has large neighborhoods (with a radius of about 16 km) that are predominantly white or black. In both cases the city could be described as racially segregated, but the spatial scale of segregation is quite different.

Reardon et al. proposed using a spatial information theory index as a measure of segregation. Such indices are based on the density distribution of a particular group, measured in this case at the block level. Like Downey's risk exposure measure, it includes a distance decay function, so that adjacent blocks are more strongly weighted than those farther away. And to assess variation in the geographic scale of segregation the Reardon index counts blocks within four different radii, ranging from 500 m (what they describe as a “walking neighborhood” scale to

4 km, a much more macro scale). In the cities they study the level of segregation is consistently higher at smaller scales, as one would expect. More interesting, some cities (Pittsburg) have most of their segregation at a small geographic scale (small racially homogeneous neighborhoods near other with very different composition), while others (Atlanta) are characterized by segregation at a large scale.

This study emphasizes that the measure of segregation depends on what the researcher considers to be a “local” neighborhood area. A related direction for research is to seek to define explicitly the boundaries of neighborhoods, freed from the assumption that all neighborhoods have the same scale. This is the goal of a project by Logan et al. (2002) that asked which group members were likely to live within ethnic neighborhoods in New York and Los Angeles for several largely immigrant groups, such as Chinese and Mexicans. To do this required as a first step to identify the neighborhoods. Maps of census tract data for both regions revealed that the areas of concentration for these groups tended to extend over multiple tracts. But what criterion could be used to determine where the concentration ended—at what point was the next adjacent tract “outside” of the neighborhood?

This question is very similar to the one raised in health studies above (where are the areas of significant spatial clustering?), but with a greater emphasis on establishing a boundary. Logan employed an increasingly popular method of analyzing spatial clusters for aggregated data (where the units of analysis, like tracts, are polygons). This is the local Moran’s I (Anselin 1995), which evaluates the spatial distribution of local area values on a single variable and identifies locations where there are clusters of areas with high values whose neighbors are also significantly high (and also areas with low values whose neighbors are also significantly low). Logan treated high–high clusters (such as tracts with a high share of Chinese residents surrounded by other highly Chinese tracts) as ethnic neighborhoods.

Having identified the neighborhoods, Logan could then describe their characteristics, and also estimate models of which group members lived in their group’s ethnic neighborhood vs. a less segregated location. Findings for some groups did not match the expectations of standard immigration theories, which posit that group members concentrate initially in neighborhoods with lower costs but greater ethnic solidarity. For example, the Afro-Caribbean neighborhoods of New York were in many respects more advantaged than the non-ethnic neighborhoods where Afro-Caribbean people lived. And for some groups, it is the more affluent members who live in ethnic neighborhoods, apparently because they have a preference for that living environment.

Neighborhood effects

Another rapidly growing interest among social scientists is whether neighborhoods have effects on their residents. As already noted, most often neighborhoods are defined according to the available administrative geography (like a census tract), although some progress has been made in methods of combining small units into socially meaningful neighborhoods. But in rare cases researchers have point data for individuals and therefore have greater flexibility in their analysis. To investigate the relationship between neighborhood-level deprivation and individuals’ mental disorders, Chaix et al. (2005) used data for all 65,830 residents aged 40–59 years in Malmö, Sweden, geocoded at their place of residence. Figure 4 shows the spatial distribution of predicted risk for mental disorder based on these data. This map is based on a sophisticated “geoadaptive logistic model,” where individual risk is predicted as a function of their spatial location (see Wood 2004), and variation across individuals is “smoothed out.” Clearly disorder was highly concentrated in neighborhoods in the northern part of the city. How is this risk related to neighborhood deprivation? A standard approach would be to estimate a multilevel model (Raudenbush and Bryk 2002), including some individual predictors (age, gender, marital status, education, income) along with a measure of neighborhood income level

based on Malmö's 100 administrative neighborhoods. Results from that approach, correcting for spatial autocorrelation, showed significant effects of the mean neighborhood income. Chaix's team then took another step, reasoning that people might be especially affected by their closest surroundings. Using their individual-level data, they drew their own "spatially adaptive areas" around each person, experimenting with areas that included only the 25 nearest neighbors, then the 100 closest, up to the 1,500 closest. The effect of income measured for these areas was much stronger than when measured in administrative neighborhoods—about twice as strong in the most tightly drawn areas.

Researchers have begun asking broader questions about neighborhood effects, especially whether people are affected only by their own local neighborhood but also by characteristics of larger surrounding areas. These are often called "spatial lag" effects. Chaix fitted a model in which this lag effect could be estimated using the same sort of distance decay function employed by Downey above. That is, it was assumed that adjacent neighborhoods had stronger effects than more distant neighborhoods. It turned out, after controlling for individual predictors and the effect of neighborhood income level, that there was significant association in levels of mental disorder between neighborhoods that were as much as 700 m apart.

Land use

Spatial methods are natural in studies of land use, where a central question is how different forms of agriculture or forage are distributed across a region. Remote sensing from satellites is being exploited as a central data source. For example Chomitz and Gray (1996) conducted a spatial analysis of land use in Belize between 1989 and 1992. The land use data are derived from a land cover map based on satellite imagery. Remote sensing signals are coded into three categories of land use: (1) "semisubsistence" agriculture, comprising milpa and other nonmechanized annual cultivation; (2) "commercial farming", comprising mostly pasture and mechanized farming of annuals; and (3) "natural vegetation", comprising forest, secondary growth, wetlands, and natural savanna. In the rural area that they studied, they felt free to ignore administrative boundaries entirely, and instead they placed a 1-km rectangular grid over the territory and drew a sample of nearly 12,000 land points. To this they overlaid information on the soil's physical and chemical characteristics from a series of land resource assessments based on a combination of aerial photography and field surveys. They also added the road network from topographic maps.

Their purpose was to understand how soil characteristics and distance to market affect land use. Like some other studies discussed above, their multivariate model included controls for spatial autocorrelation. Less distance to market is associated with higher probabilities of land being in semi-subsistence and commercial agriculture. Higher soil nitrogen and phosphorus are related to higher probabilities of both types of agriculture, while an excessively low or high pH is related to decreased probabilities of both types. Other geographic characteristics associated with location (proximity to a river, slope of the land) also have significant effects.

Social scientists more often wish also to take population data into account. Pan et al. (2007) conducted such a study to analyze the effect of changes in population size, density, and distribution on forest cover in Ecuador's northern Amazon region. A first round of survey data were collected from migrant farmers in 1990, yielding a sample of 470 settler plots in 64 settlement sectors with interviews with both the economic head and the spouse. These surveys covered a wide range of topics, including detail on land use, agricultural and non-agricultural work, and household socioeconomic and demographic backgrounds. Then a follow-up survey was conducted in 1999, providing an opportunity to examine changes in population structures and land use. Additional community and spatial data were collected in 1999 and 2000. Locations of all relevant community structures (e.g., markets, health care centers, community

centers, and schools), farms, and each household were geocoded using the global positioning system (GPS) receivers. Primary and secondary roads were also digitized.

Pan estimated an initial ordinary least squares (OLS) regression seeking to explain which farms had experienced the greatest loss of forest cover. Diagnostic statistics (Moran's I and Lagrange multiplier tests) showed that there was a high degree of spatial autocorrelation (farms with more forest loss tended to be near one another). One standard response would be to estimate a spatial error model, where correlated errors across farms are accounted for by their proximity to one another. This requires creating a spatial weights matrix that identifies distances between every pair of cases, which fortunately has become relatively straightforward through the use of GIS software. Another response, and one that worked well in this case, is to understand the source of spatial dependence and control for it more directly. Here spatial dependence mostly reflected clustering of farms within settlement areas, so it could be accommodated through a random effects model (Snijders and Bosker 1999) that allows intercepts to vary by settlements. This model helps to control for spatial dependence and clustering of farms within sectors. All three types of models showed that an increase in population size is significantly related to a decrease in forest cover, deforestation rates are higher among more recently established farms, but proximity to markets has no independent effect.

Fertility

We complete this review by turning to two of the most traditional demographic topics, fertility and migration. Both phenomena are known to have a spatial structure, and understanding that structure can lead to new conclusions about population processes.

A remarkable study by Skinner et al. (2000) used GIS techniques to analyze 1% microdata from China's 1990 census. Skinner showed that cities and towns in China can be arrayed on both a core-periphery structure and an urban-rural continuum. The urban-rural distinction categorizes 12,000 places in terms of size and volume of economic activity into classes ranging from an "apex metropolis" (9 cities with an average of 4 million urban residents) to "central towns" (nearly 3,000 places with an average of about 4,000 residents). The core-periphery distinction classifies places into categories ranging from "inner core" (places with very high levels of education, manufacturing employment, and economic productivity) to "far periphery." Note that this classification was clearly spatial, but the actual measures used to produce it did not include distance. Figure 5 below illustrates this scheme for the Lower Yangtze region centered on Shanghai. Skinner's team then applied this model to the fertility information from the 1990 census. They demonstrated a strong association between both dimensions of regional structure and fertility rates—the share of women over age 30 with 3 or more children ranges from less than 20% in the most urban/inner core places to over 65% in the rural/far periphery. Additional analyses suggested that the fertility transition diffused over time from the former to the latter type of place.

Skinner's work shows a close affinity between demography and the analysis of regional systems. Another study of fertility assesses the causal impact of spatial location on contraceptive use. Entwisle et al. (1997) report on a long-term program of research on 51 villages in rural Thailand. The Nang Rong data included a full census of the villages conducted in 1984 that gathered information on married women's contraceptive use and method (e.g., pill, IUD, and sterilization). The data also included information about many characteristics of communities that were believed to be related to reproductive choices or adoption of innovations; hence a multilevel analysis could be conducted. Explicit spatial predictors were the presence of a district health center in the village and proximity to Nang Rong's main town. Presence of a health center turned out to be positively related to being sterilized between 1984 and 1988 and also (among non-sterilized women) with using the pill vs. no birth control.

Proximity to the town was, as expected, positively related to being sterilized, but negatively associated with using the pill.

Yet the most interesting spatial conclusion is the high degree of homogeneity within villages. The pseudo- R^2 for the model for choice of contraceptive was .146 with both individual and community variables. Replacing the community variables with a set of 50 dummy variables to represent villages—a maximal estimate of variation across villages—raises this to .332. Evidently there is an unmeasured social process that causes differences between villages. Focus group interviews in several villages led to the conclusion that contraceptive use is guided by local social networks. Women within a village talk openly and often about family planning, but there is less contact between women of different villages and less opportunity for intimate discussion. Social scientists have only begun to study the spatial character of social networks or their implications for population outcomes, though GIS methods have potential to facilitate such work. Remarkably here there seems to be a strong boundary around the village, so that “distance” needs to be replaced with the concept of discrete “places.”

Migration

Migration is of course inherently about location, with an origin and a destination. Johnson et al. (2005) used county-level age-specific net migration estimates over five decades (1950–2000) to describe how patterns have evolved over time. They distinguished several types of counties that were expected to have different migration experience, similar in some ways to Skinner’s classification of Chinese cities and towns. These are metropolitan core counties (those containing a central city), metropolitan non-core counties, formerly non-metropolitan counties that were reclassified as metropolitan after 1963, and non-metropolitan counties (distinguishing those with a recreational economy from those where agriculture predominates). The analysis confirmed the continuation into the 1990s of distinct net migration “signature patterns” for counties, although there was temporal variation in the overall volume of migration. For example, in every decade the metropolitan core counties experienced most net in-migration by people in their 20s, while “new” metropolitan counties experienced substantial losses in that age range but gains among people in their 30s and early 40s, plus children. The core–periphery or urban–rural classification is implicitly spatial but deals with categories of locations rather than distances.

In addition, Johnson’s team conducted an analysis of how counties that experienced net in-migration or out-migration clustered together, this time taking distances explicitly into account. They employed the same statistic, local Moran’s I , that Logan used to study ethnic neighborhood clusters. Figure 6 illustrates the results for the decade of 1980–1990. It identifies large, geographically contiguous regions of net in-migration (in particular, Florida and the Southwest) and geographically contiguous regions of net out-migration (especially the Great Plains, in particular). In most respects these are the same areas identified in other decades, though with some changes over time. For example the Southwestern cluster of in-migration in the 1990s shifted away from California and toward New Mexico and Colorado.

Migration can also be studied as an individual phenomenon, asking who moves and where they move. Tolnay et al. (2005) used data from the 1920, 1940, and 1970 Census Public Use Microdata Samples to investigate the distances traveled by men who moved from the Southern states. Length of migration was measured as the distance between the center of the migrant’s state of birth and the center of the migrant’s state of residence at the time of census enumeration. Predictors are individual-level variables from the census. They found that white migrants moved significantly farther than black migrants, which is related to the greater propensity for white migrants to move west, rather than north in this period. In this case it appears that distance is mainly a proxy for direction.

A more local study by Wiseman and Virden (1977) examined intra-urban migration by persons aged 60 years or older in Kansas City, Kansas. From an intensive individual-level survey they obtained the most recent previous and present residential locations for the sample households and plotted addresses on a map of the metropolitan area. They calculated three distance measures: distance to Central Business District (CBD) from the present residence; distance to the CBD from the former residence; and distance between the present and former residences. They then could classify 76% of moves as being away from the CBD. Figure 7 displays the moves by persons who left the CBD for more suburban locations. The figure also shows two ellipses (Wong 1999). The smaller ellipse summarizes the pattern of initial locations of these people; the larger one summarizes their destinations. These ellipses are useful for showing the overall direction of movement and the greater spatial dispersion of destinations.

Wiseman and Virden then used a step-wise multiple discriminant analysis to identify six socioeconomic and attitudinal variables that most effectively distinguish inward from outward movers. They found that the outward migrants tend to be wealthier, socially more active, residentially more stable, and more likely to be home and auto owners, whereas the inward movers are more likely to have an unstable residential history, and to be relatively poorer, socially inactive, and less likely to own home or automobile.

Conclusion

This overview is intended to introduce some of the many ways in which spatial concepts and methods are being incorporated into social science research. It illustrates some common analytical tools, all of which rely heavily on GIS techniques. Once an area is systematically mapped in a GIS system, it is straightforward to create a visual display of features as points (such as locations of individual events) and polygons (such as characteristics of census tracts or counties). Researchers commonly use such maps as an exploratory and descriptive tool, noticing patterns that would otherwise easily be missed and raising questions and hunches about what social process underlies those patterns.

GIS techniques facilitate the creation of new spatial measures. These include simple measures such as distances between two locations. They also include more complex measures such as exposures, where proximity to many different locations has to be taken into account, along with information about the features of those locations and assumptions about how exposure decays with greater distance. Such new measures can be added to an existing dataset and analyzed using any other methodology.

Very often there is spatial dependence in social science data, which can be seen visually on a map and confirmed by analyses of spatial clustering. Statistical methods like those discussed here are being developed to draw conclusions about spatial structures, such as the existence of non-random clusters of population phenomena. Some of these are purely descriptive. Others, like Moran's I, have a statistical basis that allows the researcher to discern which clusters are unlikely to be random. Approaches to estimating spatial regressions that correct for statistical problems due to spatial autocorrelation are now widely used. A newer direction of research seeks to build models of the sources of spatial dependence, such as diffusion from one place to surrounding areas or effects of a wider local context on processes occurring within neighborhoods.

As researchers move beyond exploring spatial patterns to testing social theories, they also need to clarify their understanding of space. That is the main point of this essay. The studies reviewed here make reasonable use of a wide range of tools. Some of them are thoughtful in their treatment of concepts like distance, exposure, and places. Others make choices that seem to work, but are not clearly based on theory. Although many applications may seem to be

straightforward, their informed use requires thinking through questions such as what we mean by proximity, how we expect the impacts of proximity to vary across shorter or longer distances, and whether we conceive of space as a continuous surface or discontinuous places with more or less clear boundaries. How do we define neighborhoods, and how do we distinguish between the effects of adjacent neighborhoods and the misspecification of neighborhood scale? As more scholars find new questions that require spatial methods, there will be growing demand for approaches that are more finely attuned to the way problems are being thought about and attacked.

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Fig. 1.
Kernel estimate of dengue prevalence in Goiânia, Brazil, 2001

Fig. 2.
Difference between K functions (*bold line*) and simulation envelope (*lighter lines*) for childhood leukemia and 'population at risk'

Fig. 3.
Stylized racial distribution in four hypothetical regions

Spatial smooth term in the empty model

- Below the first quartile of risk [-2.34, -0.38]
- Between the first and the second quartiles of risk [-0.38, 0.04]
- Between the second and the third quartiles of risk [0.04, 0.47]
- Between the third quartile and the ninth decile of risk [0.47, 0.76]
- Above the ninth decile of risk [0.76, 1.20]

Standard error of the spatial smooth term

- First quartile [0.08, 0.11]
- Second quartile [0.11, 0.13]
- Third quartile [0.13, 0.20]
- Fourth quartile [0.20, 1.26]

Fig. 4.

Smoothed map of the prevalence of mental disorders due to psychoactive substance use (*top*) and associated standard errors (*bottom*)

Fig. 5.
Core-periphery structure of the Lower Yangtze macroregion, showing high-order cities and major waterways, 1990

Fig. 6.
Spatial autocorrelation of net migration in US counties

Fig. 7.
Moves showing origin and destination in the Kansas City area, for outwardly moving elderly residents