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A Companion to Political Geography

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Chapter 3

Spatial Analysis in Political Geography

John O'Loughlin

Unlike its sister disciplines of economics or political science, political geography has a relatively small amount of published research that contains quantitative analysis, or as I shall term it in this chapter, spatial analysis.[1] Political geography has reflected the rest of the geographic discipline in the flow and ebb in spatial quantitative modeling over the past 40 years. Early examples of correlation and regression analysis appeared in the other social sciences before 1945 but it was not until H. H. McCarty's (1954) analysis of the geographic patterns of the vote for Wisconsin's right-wing senator Joseph McCarthy that a spatial methodology for the examination of electoral results was widely introduced. Following McCarty's lead, the use of aggregate socioeconomic variables for geographic units (counties, wards, census tracts, or countries) as predictors of the political outcomes (votes, international behavior, or legislative votes) in a nonspatial regression framework, widely used in political science, was now complemented by a focus on the geographic pattern of the residuals (error terms, indicating the places that did not closely correspond to the general trend). Only in the late 1970s, thanks to the pioneering work of Cliff and Ord (1973) and extended by Anselin (1988) and Griffith (1987), did it become apparent that the classical statistical methodology was almost always inappropriate for geographic data because of their special nature and a new spatial statistical analysis developed in geography. Unfortunately, the misuse of classical statistical methods continues in geography, including political geography, despite two decades of evidence that these models can produce erroneous results.[2]

The "special nature of spatial data" (Anselin, 1988) requires a more complicated and extended modeling procedure than is usually found in basic statistics texts. Moreover, a significant debate about the nature of "context" (the environment in which political behavior is shaped and expressed) between political geographers and political scientists has propelled the search for new methodologies that will clarify whether place matters or (stated baldly) whether political geography as a discipline is sustainable. If contexts (places) matter little except as convenient units to map or visualize political behavior, political geography fits the role assigned to it by the political scientist, Gary King. "(T)hey (geographers) are skilful at pointing out what we do not understand.

Geographical tools are essential for displaying areal variation in what we know, but this is nowhere near as powerful as the role of geography in revealing features of data and the political world that we would not otherwise have considered" (King, 1996, p. 161). In this chapter, I will make the case that in order to remain a vital part of the wider social science enterprise to understand human behavior, political geography has to merge its central theoretical elements and methodological approaches with appropriate spatial and statistical modeling techniques. Failure to do so will consign the discipline to the kind of cartographic *cul-de-sac* that King envisions for the discipline or worse, further isolation from the other social sciences and continued retreat from the quantitative analysis of important social scientific questions.

The reasons for the relative paucity of quantitative work in political geography can be traced to dual trends that have been evident for the past 20 years and that can be easily recorded from a perusal of the contents of the journal, *Political Geography* (founded in 1982) (Waterman, 1998). First, like the rest of human geography, political geography has seen a rise in interest in poststructuralist and humanistic research methodologies as the 1970s heyday of positivism passed. Longley and Batty (1996, p. 4) believe that this trend is because "words are more persuasive than numbers," although it seems more likely that political geography is returning to the *status quo ante* where quantitative methodology is just one of a plethora of options on the research menu. Second, and connected to the first, quantitative geography (and shortly after, Geographic Information Science – GIS) was promoted as a response to the challenges of the day, especially economic stagnation in Western countries. By pursuing spatial analysis and GIS, and later merging these approaches, geography could certify its "scientific" status and show its uses to the corporatist state (Taylor and Johnston, 1995). Longley and Clarke (1995) stress the amount of "technical deskilling" that has occurred in geography in an era in which transferable skills and flexible specialization hold the keys to adaptability and change in a constantly restructuring labor market. Geography's relative abandonment of its spatial analysis/GIS birthright is allowing other disciplines to fill the labor and market niches.

Unfortunately, a gap developed early between GIS technology and spatial analytical methods and only in the past few years has a sustained effort been made to re-link them so that spatial analysis does not remain an afterthought in a GIS environment. The release of Arc 8© in spring 2001 contains a fully integrated module on geostatistics (useful for analysis of point patterns such as earthquake epicenters) but does not yet include regression-based analyses.[3] Longley and Batty (1996, p. 18) correctly identify the important challenge facing geography: "We are now at a crossroads: either we will make a significant effort to understand the workings and representation of spatial entities, locational processes, and system dynamics, or we will retreat to the margins of academic debate, denying the notion that spatial measures and analyses can ever mean anything, and sniping at the successes of non-geographers when even quite rudimentary spatial analytical techniques are shown to be applicable in planning contexts." Political geography stands at a similar junction.

Big Social Science Questions and Political Geography

Spatial analysis obviously requires some sort of spatially-coded data; these are most commonly areal (also called polygonal) data. But a fundamental problem of geographic data is that we usually collect them for existing political units that, despite their historical and governmental meaning, are less than optimal for spatial analysis. In order to answer the key question posed by Ann Markusen (1999) for policy research but relevant for all geographic research – "How will we know it when we see it?" – ("it" is explicitly conceptualized and empirically operationalized research), we need a dual-track approach in political geography that promotes a model-based methodology to tackle theoretical claims and a set of explanatory variables (i.e. data) to test them.[4] The geographic units that we use suffer from the MAUP (modifiable areal unit problem), visible in results that are scale-dependent. For example, if we correlate data on socioeconomic class and voting for the Republican party with the coefficient varying across the scales as a result of the number of data points and the geographic configuration of the districts, we cannot be sure which coefficient is correct (see the review of MAUP in Openshaw, 1996). If we had a realistic choice, we would gather data on the basis of districts that are arranged in a regular geometric pattern, such as on a grid or for a standardized worldwide unit of analysis, say a square kilometer lattice. Not only is political geography research plagued by a paucity of data in some sort of standardized collection scheme but further, we are hostage to data collection schema that are ill-designed for our purposes.[5]

The key concept related to geographic data is spatial autocorrelation. It is rare for a geographic dataset to lack spatial autocorrelation, defined as like objects clustering together in a nonrandomized manner. Spatial autocorrelation is a mixed blessing since without it, geography as we know it would hardly exist because the world would unquestionably be more idiosyncratic. Spatial modeling research is clearly divided into two camps, commonly referred to as "geostatistics" (analysis of point patterns) and "spatial econometrics" (regression analysis of areal data in a spatial framework). Geostatistics is typically concerned with making a generalized map surface from a sample of points (termed kriging) whereas spatial econometrics blends regression analysis with spatial autoregression methods that use geographic data coordinates to check if location has a significant impact on the compositional relationships (e.g. class on voting choice). As Griffith and Layne (1999, p. 469) note, an integration of the two schools of spatial analysis is long overdue since spatial autocorrelation is the "progenitor of both."

Though there are many issues and choices in spatial analysis that could be the subject of debate and discussion in this chapter, I will focus on the five topics that I think are central to political geography and, at the same time, are topical subjects in spatial analysis. I will begin with the contextual debate between geographers and political scientists about research on the use of aggregate data to infer individual behavior. Then I will look at recent developments in local indicators of spatial association (LISAs) and new methods of visualization and display. Finally, I will end with an exposition of multi-level modeling that offers a powerful methodology to political geographers who assert that relationships between scales are what separates our discipline from others and gives us a special role in the social science collective enterprise.

Context debates in political geography

What distinguishes spatial analysis from sociological, political or economic modeling is a consideration of both compositional and contextual elements of the problem.

Political studies typically lack any consideration of the context or environment in which the political process takes place. It is now common practice to see context carefully evaluated in epidemiological or educational studies, because environmental considerations (neighborhood, school, metropolitan area, region) have been dramatically significant in explaining variations in disease rates and school test scores. The contextual approach is not new in social science and Blakely and Woodward (2000) credit the first multi-scalar study to the sociologist Emile Durkheim, whose work on the environmental and personal factors underlying suicide was published in 1898. Over the past hundred years, social scientific and medical research moved away from reductionist environmental explanations of the style that simply adds a contextual variable to a set of compositional factors. In such a model, a dummy variable measuring the setting of the survey respondent or regional location of the geographic unit is added to the right-hand-side of the regression equation to the usual array of compositional factors (class, age, gender, religion, educational status, etc.). At best, such a model can demonstrate that there are "unexplained" effects emanating from environmental settings, but it cannot readily show the relative importance or interactive influence of these effects. A more formal and sophisticated modeling strategy is warranted that allows for interaction between the multiple scales; the effects of the ecological variables might be mediated by intermediate variables at the individual level (Blakely and Woodward, 2000, p. 368).

While geographers have argued that context counts (see Agnew, 1987 for the most complete statement; see also Agnew, 1996a,b; Cox, 1969; Johnston, 1991, 2001; Johnston et al., 1990; O'Loughlin and Anselin, 1991), political scientists have countered that contextual effects are either insignificant or bogus. (A bogus contextual effect is one that evaporates in a statistical analysis that incorporates many compositional elements or has a different functional form – non-linear, for example.) The most direct challenge to the geographers' position has come from Gary King's (1996, p. 161) conclusion that "if we really understood politics, we would not need much of contextual effects . . . [T]o understand political opinions and political behaviour, we are usually trying to show that context does not matter." King bases his position on the undoubtedly accurate assessment that while the geographic variation in political outcomes (say, percent Republican vote) is large to begin with, after compositional effects are introduced into the model accounting for geographic variation in the characteristics of the voters, there is little left for contextual effects.

There are three possible retorts from geographers to King's important challenge. The first is that one cannot know how important the contextual effects are until they are formally identified and measured; these checks are not usually carried out in political science or sociology. The impact of the context will vary from study to study and unless the contextual variables are considered, it is highly probable that their direct and indirect (mediated by compositional variables) impacts will go unmeasured. The second retort is that in aggregate data analysis, compositional estimates will probably be inefficient, biased, inconsistent, and insufficient (Anselin, 1988; Griffith and Layne, 1999). We cannot retain much confidence in the compositional coefficients if spatial autocorrelation is present, as is usually the case with aggregate geographic data. Third, King's challenge misses the important point that political geographers have reiterated for the past quarter-century. Agnew (1996a) calls this approach the "geo-sociological" model, a sharp contrast to King's concentration on individuals as separate from their environment. In the geo-sociological approach, geographic research focuses on "how individuals are spread around and divided into aggregates... [W]e can never satisfactorily explain what drives individual choices and action unless we situate the individuals in the social-geographical contexts of their lives" (Agnew, 1996b, p. 165). Herein lies the central quandary for geographers – although we argue the case for a geo-sociological approach in which individuals are embedded in their contexts, we do not specifically offer a methodology that allows measurement of the relative contribution of the direct and indirect effects of the environment on individual behavior. Until we have the methods and the trained personnel to use them correctly, we will be making an argument that will not carry much weight in the disciplines that are more quantitatively oriented, especially political science and economics. The importance of multi-level modeling (discussed below) as a way to bridge the gap with political science should therefore not be underestimated.

Inferring individual behavior from aggregate data

Related to the context debate, attempts to bridge the political scientists' emphasis on individuals and political geographers' focus on aggregate units are getting underway. The central problem is one of scale and is also related to the MAUP discussed earlier. Geographers usually resort to aggregate statistics and as a result, we have not been able to infer individual behavior from these large unit data. Since the early twentieth century, it has been noted that conclusions deriving from aggregate data often show significant differences to those based on individual data. In the 1950s, the term "ecological fallacy" came into common use and students were steered away from making any kind of inference to individual behavior from analysis of aggregate data. The result of the widespread recognition of the ecological fallacy was twofold. First, political scientists turned strongly to survey methods over the past 50 years to elicit attitudinal and behavioral characteristics of citizens. Second, geographers with recourse predominantly to aggregate data refrained from extending their conclusions to individuals, making generalizations only about populations or regions. A typical conclusion of quantitative geographic study is "Elderly voters in the southwest of the city are more likely to support the Republican candidate." Missing are any specific measures of the level of support over and above some baseline measure (such as all elderly in the city) as the regression coefficients are incapable of conveying this information.

Until the appearance of Gary King's 1997 book *A Solution to the Ecological Inference Problem*, attempts to bridge the aggregate–individual gap suffered from serious statistical and theoretical shortcomings and assumptions. Though King's solution is not a panacea for all methodological problems surrounding the ecological inference problem such as MAUP or spatial autocorrelation, it nevertheless offers a breakthrough for political geographers because it allows inference to individuals on the basis of fairly sparse aggregate data. Unlike the entropy-maximizing method promoted by Ron Johnston and Charles Pattie (2000), King's method does not require an overall system-wide value in order to get the estimates for the individual geographic units. Thus, in the example below, it is impossible to know what ratio of Protestants voted for the Nazi party in Weimar Germany in 1930 as this was an era before public opinion polls were conducted. In most historical circumstances and in many local elections, system-wide values that drive the entropy-maximizing estimating procedure will be unknown. King's method warrants further attention from geographers and although the estimates for individual units can be affected by the overall distributional statistics and should be used only after examination of the confidence bounds, the global estimates have been shown to be reliable.

The ecological inference problem and solution can be explained by illustration. What ratio of the Protestant population in Weimar Germany voted for the Nazi party in 1930? From previous studies, it is well known that the Protestant ratio in a district was positively correlated with support for the Nazi party (O'Loughlin et al., 1994). The data to be used for the inference is the ratio of Protestants in each of the 743 districts in Germany, the ratio of the vote for the Nazis, and the total number of voters in each district. Nationally, the Nazis received 18.3 percent at the 1930 election and the Protestant ratio in Germany was 62 percent. The global estimate will be the national percentage of Protestants that voted for the Nazis and the local estimates are the respective county (*Kreis* in German) ratios. Using King's notation, the independent variable X is the Protestant population and T is the national Nazi vote. For each county, we have the Protestant and Nazi totals from census and electoral archives but not the cell values that must be estimated (see table 3.1). Using the information in the marginals (the totals of each row and column), ecological modeling estimates the values for the question marks for the country as a whole and for each *Kreis*. Any estimates must meet the conditions of the marginals (must sum to these values). King's solution avoids the homogeneity pitfall that plagued Goodman's double regression method; the assumption of homogenous distribution of parameters across all geographic units is an untenable assumption for political geographers.

King's ecological inference method uses an identity from the modified Goodman formula to generate combinations of values for T_i (the Nazi vote in *Kreis i*) and X_i (the Protestant vote in the *Kreis*) in the form of $T_i = \beta_i^b X_i + \beta_i^w (1 - X_i)$. The purpose of the ecological inference modeling is to estimate β^b (the national ratio of Protestant voters who chose the Nazi party) as well as the estimates for the individual *Kreise*, β_i^b. Combined with information about the bounds of each district, found by projecting the line onto the horizontal axis (β_i^b, the Protestant vote for the Nazi party) and the vertical axis β_i^w (the non-Protestant vote for the Nazis), King's method combines the double regression approach with the information on bounds. Clearly the narrower the bounds, the higher the reliability of the estimates is likely

Table 3.1 The ecological inference problem for a typical *Kreis* in Weimar Germany

	Vote		
	Nazi	Non-Nazi	Totals
Protestant	?	?	13,261
Non-Protestant	?	?	6,735
Totals	8,423	11,573	19,996

to be. (Further information is found in O'Loughlin, 2000.) In the case of the 1930 election, the ecological estimate of 22.4 percent of Protestant voters who picked the Nazi party is 3.6 percent higher than the national average of 18.3 percent.

The individual ecological inferences for the 743 *Kreise* of Germany can be used in a further "second-level" analysis as dependent variables; there is significant variation in these ratios across Germany from 2 to 50 percent, showing that the Protestant support for the Nazis varied according to local conditions. The maps of these ecological inferences shows a concentration of high values in scattered locales in Northern Bavaria, Northwest Germany, and Saxony (O'Loughlin, 2002). These contextual anomalies suggest local circumstances that propelled the Protestant population to support the Nazi party far in excess of their national average. Like all methods, King's ecological inference procedure works best (giving most reliable estimates) if the districts are nearly homogenous on the predictor variable (Protestant ratio in this case), the units are small (precincts or some other small geography unit is most suitable) and there is a large number of districts (more than 100). In the USA, racially-homogenous districts are common and, therefore, the method has had its most publicized successes in this context (King, 1997).

Nonstationarity and directional analysis of spatial autocorrelation

In the example above, the mapping of the ecological inferential values for the Protestant support of the Nazi party indicates that a disaggregated approach to the study of political phenomena is valuable. Of course, there is a fine line between total disaggregation to each of the data points (complete uniqueness) and a study that remains at the global (most aggregated) level. Spatial analysis is clearly interested in the social scientific enterprise of drawing generalizations and making inferences to populations from samples but at the same time, geographers remain acutely aware that national-level statistics hide great regional and local variations. A way out of this impasse was suggested by Siverson and Starr (1991) who believe that "domain-specific laws," incorporating important local and regional circumstances under consideration in a general model, offers the most attractive alternative. Thus, in a study of the correlates of the Nazi party vote in 1930 Germany, O'Loughlin et al. (1994) were able to show that the specific mix of supporters of the party varied between six large cultural–historical regions of the country. In some regions, the middle-class was a significant base for the party but in other regions, the coefficients show that support was weak and nonsignificant. What was most evident in this study is that the national average hid great regional variation. Moreover, local effects in the form of small clusters of districts that stood out from surrounding values (high values in generally low-value regions and vice versa) were also visible in a spatial analysis and could therefore be modeled.

The balance between global and local measures and approaches in statistical geography seems to have been resolved strongly in favor of local measures in recent years. Because most geographic datasets have large amounts of nonstationarity (relationships between variables vary across the dataset and are not consistent in all regions), we often tend to find multiple regimes of spatial association, as in the case of Nazi Germany above. We need more than one parameter estimate in these cases and the fitting of models according to a theory-derived regional division is indicated. Nonstationarity in spatial modeling can have a number of underlying causes: random sampling variations, the fact that relationships vary because of regional circumstances, a mis-specified model in which the measures are poor reflections of reality, or possibly because one or more of the relevant variables are omitted or are represented by the incorrect functional form (linear, rather than nonlinear) (Fotheringham, 1997).

Because of the widespread attention to nonstationarity, there has been a significant return to basics in spatial analysis, paralleling the rise in exploratory data analysis in social science in general. Rather than confirmatory procedures, such as regression of a theory-derived model, geographers tend carefully to tease out local trends in the data. To do this, specific indicators of local significance are derived, and as becomes clear in Anselin's (1995) work on LISAs (local indicators of spatial association), there is a clear linkage between global measures of clustering and local indicators. Local statistics are well-suited to (i) identifying the existence of pockets or "hot spots" that are significantly different than the regional or global trend (such as disease clusters or a congregation of supporters of a particular party), (ii) assessing assumptions of stationarity, and (iii) identifying distances beyond which no discernible spatial association is present (Getis and Ord, 1996). After dissecting global statistics to their local constituents, we can produce local statistics that can be mapped. But the dilemma is not resolved just by deriving local measures. As Openshaw (1996, p. 60) notes, "the confirmatory dilemma is as follows; either you test a single whole-map statistic against a null hypothesis or you test N hypotheses relating to zone or locality-specific statistics. In the former, the test is silly from a geographical point of view because of its "whole-map" nature, its dependency on the definition of the study region, and the nature of the underlying globally defined hypothesis. In the latter case, there is the problem of multiple testing." A reaffirmation of the confirmatory hypothesis-testing approach has been achieved by blending modeling procedures with diagnostic, exploratory, and interactive techniques.[6]

As well as being nonstationary, geographic data are often anisotropic. (Isotropic data means that spatial dependence – autocorrelation in other words – changes only with the distance between the values but not with their directional orientation with respect to each other.) In physical geography, prevailing winds in climatology, the spread of beetles in a pine forest from an external source or earthquake fault lines come to mind as examples of directional influences. In political geography, one might expect directional influences to be significant in a pattern that results from a diffusion process. It is plausible, for example, that war spreading directionally across a continent, the growth of a political party from a local core, or the diffusion of the democratic form of government will violate the isotropic assumption. Given these possibilities, it is necessary to identify and account for any anisotropic developments. While mapping the LISAs might conceivably show a directional trend, say a north-west trend caused by the migration of pine beetles in this direction as a consequence of local environmental (terrain or climatologic) conditions, it is better to use methods developed specifically for the measurement of directional bias. We need a statistic that incorporates the geographic coordinates, their angular relations with respect to a fixed bearing (e.g. east) and the values of the item of interest (in this case, the level of tree infestation by beetles) to determine if there is significant directional bias in the pattern.

Most of the direction-based methods come from genetics, animal ecology, and organismic biology, emanating from Oden and Sokal's (1986) introduction of directional spatial autocorrelation techniques by developing "distance/direction classes" to create a windrose correlogram; sectors represent the same distance but different angles grouped together in rings called annuli (Rosenberg, 1999, p. 270). The selection of spatial weights (measuring the attraction or contiguity of places to each other) has bedeviled spatial analysis because no commonly-agreed method for choosing the weights structure is available. In the bearing spatial correlogram, the weight variable incorporates not only the distance or contiguity between points (they could be areal centroids) but also the degree of alignment between the bearing of the two points and a fixed bearing. For each distance-class (predefined based on some theoretical conception of appropriate distance bands for the study), the weights matrix is determined by multiplying the nondirectional weight value (distance between the points) by the squared cosine of the angle between the points and the eastern bearing, or formally as $w'_{ij} = w_{ij} \cos^2(\alpha_{ij} - \theta)$, where w'_{ij} is the $i-j^{th}$ entry of the bearing weights matrix, w_{ij} is the distance weights between the capitals, α_{ij} is the angular direction between points i and j measured counterclockwise from due east, and θ is the angular direction of the fixed bearing. We can calculate the standard spatial autocorrelation statistic, Moran's I, in the normal manner using the w'_{ij} weights in the place of the usual nondirectional weights in the measure.[7] Examples of the methodology using an anisotropic lens to the study of political processes are O'Loughlin (2001a) for the diffusion of civil and political rights, and O'Loughlin (2002) for the study of the diffusion of the Nazi party vote in Germany 1924–33.

Visualization and displaying results

With the renewed emphasis on local measures of spatial association (autocorrelation) in recent years, new methods of visualization as a first step in spatial analysis have been proposed to highlight these circumstances. A useful distinction between private and public visualization has been noted by Cleveland (1993). In the early stages of the research, private visualization in the form of graphs, diagrams, maps, and descriptive indicators can be generated and saved as screen captures or low-quality prints. Most of the statistical software packages offer adequate visualization procedures (Q–Q plots for normality tests, histograms or box-plots for distributional displays, etc.), although Stata© and S-Plus© provide suites of trellising options that allow detailed exploration of the data structures. Trellis displays are tools for visualizing multidimensional datasets and trellis graphics display a large variety of one-, two- or three-dimensional plots in an automatically generated trellis layout of panels, where each panel displays the selected plot type for a slice on one or more additional discrete or continuous conditioning variables. Few trellis displays make it to the second kind of visualization, that of public presentation in the traditional print medium or as web documents where the emphasis is on presentation and the dissemination of knowledge. Good examples of trellis graphics are available in Cleveland (1993) while Tufte (1997) provides clear guidelines and magnificent examples of public visualization. In general, the purpose of visualization is to identify geographic clusters of similar data points, identify local and global outliers, and identify trends in the relationships (Fotheringham, 1999).

Three regression-type models are now available to political geographers who wish to build local spatial relationships into the usual compositional models of the political scientists. First, the mixed spatial–structural model adds a spatial autoregressive term to the usual regressors if there are indications in the data that significant spatial autocorrelation is present that is not simply the result of omitted variables. In analysing the distribution of conflict in Africa between 1966 and 1978, O'Loughlin and Anselin (1991) show how a spatial autoregressive term (measuring the effects of neighboring states at war) is an important addition to a regression with other characteristics of states (colonial history, ethnic fractionalization, nature of government, economic status, etc.). While not every research problem in political geography will benefit from the incorporation of a spatial autoregressive term, extensive experience now indicates that every dataset should be carefully checked for the presence of spatial autocorrelation. If spatial autocorrelation is near zero, the traditional statistical model with only compositional variables will suffice but as noted earlier, a significant danger of biased parameters will result from ignoring the presence of sizeable autocorrelation.

Two alternative forms of local spatial measurement in multivariate relationships are now readily available. The expansion method (Jones and Casetti, 1992) allows parameter drift so that if the parameters of the regression model are functions of geographic location (say, latitude and longitude), the trends in parameter estimates over space can then be measured. A more recent alternative is geographic weighted regression (GWR), where localized parameter estimates can be produced and, also, localized versions of all the regression diagnostics can be developed (Brunsdon et al., 1996). GWR is based on the assumption that data are weighted according to their proximity to point i and the weights are not constant but vary with proximity to point i. These parameters can be mapped to see the geographic pattern and possibly lead to further analysis of the residuals. Like the discussion of nonstationarity and the use of multiple regimes, these methods are motivated by the belief that strong evidence of regional heterogeneity will normally be a feature of geographical data.

In the environment of exploratory spatial data analysis (ESDA), one of the motivations behind the visualization push is to redress one of the troubling aspects of quantitative analysis, the growing gap between those who use spatial models and the rest of the discipline. Unlike the situation at the height of the quantitative revolution in Geography, graduate students in the discipline can now finish a Ph.D. without being obliged to pass a course in statistical methods. The splintering of the discipline has led to the acceptance of alternative methods courses (qualitative, feminist, field) in lieu of the quantitative requirement. The development is enforcing an increasingly fractionalized discipline, with a small or no common core of knowledge and a lack of understanding of the language and methods of each sub-discipline. Because the theory and language of spatial analysis is increasingly arcane, not only to fellow geographers but also to colleagues in other social sciences, it places additional pressure on modelers to write in an accessible style and include more materials that present statistical results in a visual manner. Nonlinear modeling generates coefficients that can be difficult to interpret and logit models benefit from conversion of the coefficients by anti-logs to render them meaningful. Too frequently, spatial analysts simply regurgitate the output from their computer packages. Maps are wonderful tools for making sense of complex data, though clearly the choices of metric, color schemes, analytical methods, scale, and symbols are critical in presenting results that can be understood and evaluated. In political science, a similar separation between the methodologists and the rest of the discipline has propelled a re-thinking of the way in which statistical results are presented. Gary King and his colleagues have written a series of programs in Stata© to convert results from nonlinear models into values that can be graphed using a simulation technique.[8] Thus, for example, O'Loughlin (2001b, p. 29) used box-plots of simulated values to show the ranges of the estimated probability of support for the free market by household finances and by region in Ukraine 1996. While households with "better finances" in western Ukraine had a mean probability of supporting the free market at a rate of 0.62, families with poor finances in the south of the country only had a 0.21 probability of supporting the free market. These huge differences by region and family finances are thus easily understandable to readers without statistical training, though the logit coefficients may not be especially meaningful to them.

Multilevel modeling and scale effects

As will hopefully be clear by this point in the chapter, the problems posed by aggregate data organized on a geographic basis are formidable. Not only do issues connected to spatial autocorrelation require attention but for political geographers, scale problems in the form of identification of individual and contextual variations also must be tackled. If all political outcomes are the result of individual choices and behaviors in an atomized world, then political geography is severely under threat. But an atomized world-view is highly implausible and it can be countered by a "geo-sociological" imagination (Agnew, 1996a). While offering a counter model to the political scientists and public opinion pollsters is a start, it is unlikely to carry political geography very far in the face of a sceptical audience that wants statistical evidence of scale and context effects. Recent developments in multilevel modeling allow the calculation of statistical variance at each scale (individual, local, regional) and thus, enable the researcher to determine if the geo-sociological imagination holds any value. The interaction effect (individual-context) offers an additional element of variance explanation and thus, the hypothesis of a geo-sociological imagination can be tested statistically. As Jones and Duncan (1996, p. 80) note, there has been too much stress in spatial analysis on the stereotypical and the average and not enough on variability because the underlying trend has been sought by ignoring difference. The multilevel approach preserves between-place heterogeneity and does not annihilate space as context in a single equation that is fitted for all places and all times.

Multilevel modeling extends the technique of ordinary least-squares (OLS) to explore the variation among units defined at the various levels of a hierarchical structure. I will illustrate using the example of the political attitudes of residents of 17 neighbourhoods (*rayoni* in Russian) in Moscow in March 2000. (The notation and review is modified from Bullen et al., 1997; Goldstein, 1995; and Kreft and de Leeuw, 1998.) The simple regression relationship is expressed as $y_i = \beta_0 + \beta_1 x_i + e_i$, where subscript i ranges from 1 to n_j, the number of respondents in the j^{th} neighborhood in Moscow. For the i^{th} respondent, y_i is the dependent variable (willingness to protest in this case) and x_i is an independent predictor, say age. In the usual single-level model, e_i is the residual, that part of the dependent variable not predicted, and with only one level, the variation is simply the variance of these e_i.

In the multilevel case, where the 17 *rayoni* (districts) are regarded as a random sample of all neighborhoods in Moscow, we can express the multiple relationships as: $y_{i1} = \beta_{01} + \beta_1 x_{i1} + e_{i1}$, $y_{i2} = \beta_{02} + \beta_1 x_{i2} + e_{i2}$, etc. These equations can be generalized to $y_{ij} = \beta_{0j} + \beta_1 x_{ij} + e_{ij}$, where in the final general expression the subscript j takes values from 1 to 17, one for each *rayon*, and the first subscript now refers to respondent i in *rayon* j. In a multilevel analysis, the level-2 groups (*rayoni*), are treated as a random sample. We therefore re-express the last equation as $y_{ij} = \beta_0 + \beta_1 x_{ij} + u_j$, where u_j is the departure of the j^{th} *rayon*'s actual intercept from the overall mean value. It is thus a level-2 residual. (β_0 has no level subscript, indicating that it is constant across all *rayoni*; β_{0j} is specific to *rayon* j, but is the same for all respondents in that *rayon*.) The full model for actual scores can be re-expressed as $y_{ij} = \beta_0 + \beta_1 x_{ij} + u_j + e_{ij}$. In this equation, both u_j and e_{ij} are random quantities, whose means are equal to zero. The quantities β_0 and β_1 are fixed and must be estimated. The presence of the two random variables u_j and e_{ij} in the last equation make it a multilevel model and their variances, σ_u^2 and σ_e^2, are referred to as random parameters of the model. The quantities β_0 and β_1 are known as the fixed parameters. A multilevel model of this simple type, where the only random parameters are the intercept variances at each level, is known as a variance components model. For political geographers, the real interest is the relative contribution of the second-level variance σ_u^2 to the overall model.

In a multilevel model, between-place differences can be examined in relation to the social characteristics of individuals in combination with the characteristics of places. For example, a voter of low social class may vote quite differently according to the social class composition of the neighborhood in which he or she lives (Taylor and Johnston, 1979). Using the example of Moscow, a person's attitude towards protest (dependent variable) is modeled as a function of (i) the person's characteristics (age, gender, ideology, education, etc.), (ii) the neighborhood in which the person lives, and (iii) the compositional/contextual interactions. Data on the characteristics, civic behavior and political preferences of 3,476 Muscovites in 17 sample neighborhoods were collected in door-to-door interviews in March 2000 just after the Russian Presidential election that elected Vladimir Putin. Four key characteristics of voters (educational level, age, whether they voted for Vladimir Putin, and whethe[r] they support the rapid transition to the free market) are used to explain whether th[e] respondent was willing to take part in protest or not. Only 9.9 percent of the 3,47[6] respondents were willing to take part in protests against falling living standards.

In multilevel modeling, the first stage is to measure the level-2 (neighborhood variance; in this study of Moscow, the value was rather large and significant. The[n] the characteristics of the level-1 units (respondents in this case) are added to th[e] model and, as in the usual regression format, only significant independent predicto[rs] are included in the equation. All of the four variables are in the expected directio[n] and significant; the chance of protest increases with age, educational level, votir[ng] for Putin and with distrust of the market economy. Overall, the model indicates th[at] the second-level variance contributes 7 percent of the total variance while t[he] interaction term (across the two levels) accounts for 4 percent, and as usual, t[he] overwhelming proportion, 89 percent, is attributed to the individual-level varianc[e]

This study thus supports the claims of geographers that a contextual effect exists over and above the varied distribution of voters among geographic units and that the geo-sociological model which emphasizes interaction effects across the levels is also useful in helping to explain the political choices of citizens. Similar interaction and contextual effects have been identified by Jones et al. (1998) for the Labour vote in the 1992 British election. The multilevel individual–context interaction model parallels the explanation offered by Pattie and Johnston (2000) that extensive and intensive local contacts help to shape political opinions and choices. Contextual effects account for a significant part of the overall explanation and compositional models that ignore context are likely to offer only partial explanations.

Conclusions

This review of developments in spatial analysis in political geography has stressed key developments and challenges. Sceptical challenges to quantitative political geography emanate from two sources: from within the discipline from those who are antithetical to hypothesis-testing and empirical data analysis; and from outside the discipline where, though sympathetic to quantitative analysis, researchers have not yet been persuaded that significant and measurable contextual and geo-sociological effects exist. To answer these critics, political geographers need to develop further training and expertise in the spatial analysis of aggregate data, the collection of survey data, the conversion of statistical results into visual and accessible formats, and the matching of appropriate methodologies to specific research questions. Each of these desiderata are formidable and time-consuming but without their implementation, I fear that political geography will become marginalized in a small discipline and excluded from the social science enterprise.

Political geographers, unfortunately, have come to rely on aggregate data collected by government agencies on the basis of pre-existing geographic units. Not only does this reliance magnify the modifiable areal-unit problem (MAUP), but it also forces political geographers to turn to complex analytical techniques because the usual statistical models are inappropriate for spatial data. Of course, misapplications of OLS models to geographic data continue to appear in the literature, and not only in political geography. For aggregate data, often available in circumstances for which no other information is available like the example of Nazi Germany in the 1930s, it is high time to follow tried and true procedures. Griffith and Layne (1999) list the steps from descriptive statistics and visual plots to measures of local and global spatial autocorrelation to semi-variogram plots for geostatistics, and spatial econometric modeling for aggregate data, and they conclude (p. 478) that "now is the time for all good spatial scientists to begin implementing appropriate spatial statistical specifications."

Many core political geographic questions, however, cannot readily be answered by the use of aggregate data and must be tackled instead through survey methodologies. Few political geographers receive formal training in the design, selection, sampling, analysis, and pitfalls of survey data. Unlike the many large databases and panel data designed for political scientists and economists, political geographic research tends to tweak these data rather than designing specialized surveys from the start of projects. Recently, Shin (1998) and Secor (2000) conducted surveys in Central Italy and Istanbul, respectively, to elicit information about contemporary political changes in these sites and to determine the role of local contexts in helping to shape opinions and behaviors. Both survey samples were chosen on the basis of neighborhood typologies so instead of sampling randomly, these researchers developed a systematic design that covered the range of possible context effects. Although the time and effort of such enterprises exceed those of mining pre-existing aggregate data (from census offices or archives), they compensate by allowing the researcher to match the methodology to the nature of the research questions.

With the continued growth in the use (and misuse) of GIS technology and the slow integration of GIS and visual displays, it is likely that greater attention will be given to improving the presentation of research results, the public visualization at the end of a project. Undoubtedly, private visualization will allow more insights into the structure of data and help to route scholars around the potholes of inappropriate statistical tools. More use of color, web animation, dynamic links, and free software and data downloads, as well as continued presentation in the print medium, will make research results both more accessible and comparative. (See O'Loughlin et al., 1998 for an example.) Compared to political science, little replication of the research of others or attention to the accumulation of research results occurs in political geography. Hopefully, the trend of isolation will be reversed as standard procedures become more formalized and accepted.

To paraphrase Longley and Batty (1996), quantitative political geography now stands at a junction. Either it will be integrated more intensively with the rest of political geography (this has to be a two-way street and will only succeed if non-quantitative political geographers accept our approaches and research results) and more generally with other quantitative social science, or it will become further isolated. After four decades of development, we now have accumulated expertise and powerful analytical software and display tools to answer many lingering questions regarding the role of place and space in political behavior. Although political geographic theory has raced ahead of empirical tests and statistical expertise over the past 20 years, the gap can be narrowed and many untested theoretical propositions can be checked. As this chapter has shown, political geography is an important part of the enterprise that is trying to understand human behavior; now is the time to challenge the atomizing model and reassert the contextual/geo-sociological one in a hypothesis-testing spatial analytical mode.

ENDNOTES

1. By spatial analysis, I mean the analysis of data that have spatial coordinates or geographic locations such as data for electoral precincts, countries, regions, cities, or locational attributes of voters (street address, work location, personal networks, etc.).
2. In the interests of full disclosure and self-criticism, I admit that I followed McCarty's methodology in my Masters thesis at Penn State (1971), although I introduced a strong spatial focus by close examination of the residuals in the analysis of the Mayoral elections in Philadelphia.
3. Luc Anselin has developed an interface between his spatial econometrics package, Spacestat®, and ArcView3.2©. See Anselin (1999) and the website www.spacestat.com.

4. I agree with Paul Plummer (2001) who makes a similar case for economic geography and who is also responding to Markusen's call for an end to fuzziness and a clearer conceptual base for empirical research.
5. Gary King and his colleagues have engaged in a massive effort to collect, standardize, and make accessible electoral data for the past 20 years in a GIS format. The political units range from precincts to congressional districts in the US. Called the ROAD project (Record on American Democracy), the data are available from the project website www.data.fas.harvard.edu/ROAD.
6. A good example of the multiple options for spatial analysis is Luc Anselin's Spacestat® program.
7. The standard global measure of spatial autocorrelation, Moran's I, is given by $I = (N/S_o) \sum_i \sum_j w_{ij}x_ix_j / \sum_i x_i^2$, where w_{ij} is an element of a spatial weights matrix W that indicates the new bearing weight matrix for i and j; x_i is an observation at location i (expressed as the deviations from the observation mean); and S_o is a normalizing factor equal to the sum of all weights ($\sum_i \sum_j w_{ij}$). PASSAGE (Pattern Analysis, Spatial Statistics, and Geographic Exegesis) is a directional analysis computer program from Michael Rosenberg, available from www.public.asu.edu/-mrosenb/Passage.
8. The program is called CLARIFY and is available from Gary King's webpage at http://gking.harvard.edu. It is described in King et al. (2000).

BIBLIOGRAPHY

Agnew, J. A. 1987. *Place and Politics: The Geographical Mediation of State and Society.* Boston, MA: Unwin Hyman.
Agnew, J. A. 1996a. Mapping politics: How context counts in political geography. *Political Geography*, 15, 129–46.
Agnew, J. A. 1996b. Maps and models in political studies: A reply to comments. *Political Geography*, 15, 165–8.
Anselin, L. 1988. *Spatial Econometrics: Methods and Models.* Dordrecht: Kluwer.
Anselin, L. 1995. Local indicators of spatial association – LISA. *Geographical Analysis*, 27, 93–115.
Anselin, L. 1999. *Spacestat Manual, Version 1.91.* Ann Arbor, MI: TerraSeer Inc.
Blakeley, T. A. and Woodward, A. J. 2000. Ecological effects in multi-level studies. *Journal of Epidemiology and Public Health*, 54, 367–74.
Brunsdon, C. F., Fotheringham, A. S., and Charlton, M. E. 1996. Geographically weighted regression: A method for exploring spatial non-stationarity. *Geographical Analysis*, 28, 281–98.
Bullen, N., Jones, K., and Duncan, C. 1997. Modelling complexity: Analysing between-individual and between-place variation – a multilevel tutorial. *Environment and Planning A*, 29, 585–609.
Cleveland, W. S. 1993. *Visualizing Data.* Summit, NJ: Hobart Press.
Cliff, A. D. and Ord, J. K. 1973. *Spatial Autocorrelation.* London: Pion.
Cox, K. R. 1969. The voting decision in a spatial context. *Progress in Geography*, 1, 81–118.
Fotheringham, S. 1997. Trends in quantitative analysis: Stressing the local. *Progress in Human Geography*, 21, 88–96.
Fotheringham, S. 1999. Trends in quantitative geography III: Stressing the visual. *Progress in Human Geography*, 23, 597–606.
Getis, A. and Ord, J. K. 1996. Local spatial statistics: An overview. In P. Longley and M. Batty (eds.) *Spatial Analysis: Modelling in a GIS Environment.* New York: Wiley, 261–78.
Goldstein, H. 1995. *Multilevel Statistical Models.* London: Edward Arnold.

Griffith, D. A. 1987. *Spatial Autocorrelation: A Primer.* Washington DC: Association of American Geographers Resource Publications.
Griffith, D. A. and Layne, L. J. 1999. *A Casebook for Spatial Statistical Analysis: A Compilation of Analyses of Different Thematic Data Sets.* New York: Oxford University Press.
Johnston, R. J. 1991. *A Question of Place: Exploring the Practice of Human Geography.* Oxford: Blackwell.
Johnston, R. J. 2001. *Electoral geography in electoral studies: An overview on putting voters in their place.* Workshop on Political Process and Spatial Methods, Florida International University, Miami, FL.
Johnston, R. J. and Pattie, C. 2000. Ecological inference and entropy-maximizing: an alternative procedure for split-ticket voting. *Political Analysis*, 8, 333–45.
Johnston, R. J., Shelley, F. M., and Taylor, P. J. (eds.). 1990. *Developments in Electoral Geography.* New York: Routledge.
Jones, J. P and Casetti, E. (eds.). 1992. *Applications of the Expansion Method.* London: Routledge.
Jones, K. and Duncan, C. 1996. People and Places: the multilevel model as a general framework for the quantitative analysis of geographical data. In P. Longley and M. Batty (eds.) *Spatial Analysis: Modelling in a GIS Environment.* New York: Wiley, 79–104.
Jones, K., Gould, M. I., and Watt, R. 1998. Multiple contexts as cross-classified models: The Labor vote in the British general election of 1992. *Geographical Analysis*, 30, 65–93.
King, G. 1996. Why context should not count. *Political Geography*, 15, 159–64.
King, G. 1997. *A Solution to the Ecological Inference Problem: Reconstructing Individual Behavior from Aggregate Data.* Princeton, NJ: Princeton University Press.
King, G., Tomz, M., and Wittenberg, J. 2000. Making the most of statistical analyses: Improving interpretation and presentation. *American Journal of Political Science*, 44, 341–55.
Kreft, I. and de Leeuw, J. 1998. *Introducing Multilevel Modeling.* Thousand Oaks, CA: Sage Publications.
Longley, P. and Batty, M. 1996. Analysis, modeling, forecasting and GIS technology. In P. Longley and M. Batty (eds.) *Spatial Analysis: Modelling in a GIS Environment.* New York: Wiley, 1–16.
Longley, P. and Clarke, G. 1995. Applied geographical information systems: developments and prospects. In P. Longley and G. Clarke (eds.) *GIS for Business and Service Planning.* Cambridge: Geoinformational International, 3–9.
Markusen, A. 1999. Fuzzy concepts, scanty evidence, policy distance: the case for rigour and policy relevance in critical regional studies. *Regional Studies*, 33, 317–70.
McCarty, H. H. 1954. *McCarty on McCarthy: The Spatial Distribution of the McCarthy Vote 1952.* Iowa City, IA: Department of Geography, University of Iowa.
Oden, N. L. and Sokal, R. R. 1986. Directional autocorrelation: an extension of spatial correlograms in two dimensions. *Systematic Zoology*, 35, 608–17.
O'Loughlin, J. 2000. Can King's ecological inference method answer a social scientific puzzle: who voted for the Nazi party in Weimar Germany. *Annals, Association of American Geographers*, 90, 592–601.
O'Loughlin, J. 2001a. Geography and democracy: the spatial diffusion of political and civil rights. In G. Dijkink and H. Knippenberg (eds.) *The Territorial Factor in Politics.* Amsterdam: Amsterdam University Press, 77–96.
O'Loughlin, J. 2001b. The regional factor in contemporary Ukrainian politics: scale, place, space or bogus effect? *Post-Soviet Geography and Economics*, 42, 1–33.
O'Loughlin, J. 2002. The electoral geography of Weimar Germany: exploratory spatial data analysis (ESDA) of Protestant support for the Nazi party. *Political Analysis*, 10, 217–43.

O'Loughlin, J. and Anselin, L. 1991. Bringing geography back to the study of international relations: spatial dependence and regional context in Africa, 1966–1978. *International Interactions*, 17, 29–61.

O'Loughlin, J., Flint, C., and Anselin, L. 1994. The geography of the Nazi vote: context, confession and class in the Reichstag election of 1930. *Annals, Association of American Geographers*, 84, 351–80.

O'Loughlin, J., Ward, M., Lofdahl, C. et al. 1998. The spatial and temporal diffusion of democracy, 1946–1994. *Annals, Association of American Geographers*, 88, 545–74.

Openshaw, S. 1996. Developing GIS-relevant zone-based spatial analysis methods. In P. Longley and M. Batty (eds.) *Spatial Analysis: Modelling in a GIS Environment*. New York: Wiley, 55–73.

Pattie, C. and Johnston, R. J. 2000. "People who talk together vote together": an exploration of contextual effects in Great Britain. *Annals, Association of American Geographers*, 90, 41–66.

Plummer, P. 2001. Vague theories, sophisticated techniques and poor data. *Environment and Planning A*, 33, 761–64.

Rosenberg, M. S. 2000. The bearing correlogram: a new method of analyzing directional spatial autocorrelation. *Geographical Analysis*, 32, 267–78.

Secor, A. J. 2000. *Islamism in Istanbul: Gender, Migration and Class in Islamist Politics*. Ph.D. dissertation. Department of Geography, University of Colorado at Boulder, CO.

Shin, M. E. 1998. *Rossa, ma non troppo: Contextual Exploration into the Geography of Italian Voting Behavior, 1987–1996*. Ph.D. dissertation. Department of Geography, University of Colorado at Boulder, CO.

Siverson, R. M. and Starr, H. 1991. *Opportunity, Willingness and the Diffusion of War*. Columbia, SC: University of South Carolina Press.

Taylor, P. J. and Johnston, R. J. 1979. *Geography of Elections*. New York: Holmes & Meier.

Taylor, P. J. and Johnston, R. J. 1995. GIS and geography. In J. Pickles (ed.) *Ground Truth: The Social Implications of Geographic Information Systems*. New York: Guilford Press, 51–67.

Tufte, E. R. 1997. *Visual Explanations: Images and Quantities, Evidence and Narrative*. Cheshire, CT: Graphics Press.

Waterman, S. 1998. *Political Geography* as a reflection of political geography. *Political Geography*, 17, 373–88.