The Electoral Geography of Weimar Germany: Exploratory Spatial Data Analyses (ESDA) of Protestant Support for the Nazi Party

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For more than half a century, social scientists have probed the aggregate correlates of the vote for the Nazi party (NSDAP) in Weimar Germany. Since individual-level data are not available for this time period, aggregate census data for small geographic units have been heavily used to infer the support of the Nazi party by various compositional groups. Many of these studies hint at a complex geographic patterning. Recent developments in geographic methodologies, based on Geographic Information Science (GIS) and spatial statistics, allow a deeper probing of these regional and local contextual elements. In this paper, a suite of geographic methods—global and local measures of spatial autocorrelation, variography, distance-based correlation, directional spatial correlograms, vector mapping, and barrier definition (wombling)—are used in an exploratory spatial data analysis of the NSDAP vote. The support for the NSDAP by Protestant voters (estimated using King's ecological inference procedure) is the key correlate examined. The results from the various methods are consistent in showing a voting surface of great complexity, with many local clusters that differ from the regional trend. The Weimar German electoral map does not show much evidence of a nationalized electorate, but is better characterized as a mosaic of support for "milieu parties," mixed across class and other social lines, and defined by a strong attachment to local traditions, beliefs, and practices.

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1 Introduction

Despite attempts to bridge the epistemological and methodological gaps between the disciplines of geography and political science recently, lack of awareness of developments in geographic techniques by political scientists is still evident.[1] Some reasons can be proffered for this neglect, not the least of which is the nature of the data deployed by political methodologists in their analyses. Over time, data collected from surveys of individuals have become the norm and, partly because of difficulties of inference across levels, political scientists have tended to eschew aggregate data collected for geographic units (King 1997). The preponderance of individual-level data is of relatively recent vintage, however. A classic study of political behavior, V. O. Key's (1949) *Southern Politics in State and Nation*, used aggregate electoral data, whereas Pollock's (1944) study of Nazi party electoral success pointedly relied on a geographic analysis of the aggregate votes. King's (1997) ecological inference methodology was recently the subject of a forum in the leading U.S. geography journal, *Annals of the Association of American Geographers* (Vol. 90, No. 3, 2000). The reviews were generally favorable regarding the attempt to bridge the aggregate-individual scales, although important issues concerning the role of spatial autocorrelation still await resolution (see also Anselin 2000; Anselin and Cho 2002; and Davies-Withers 2001). It seems fair to assert that given the propensity of political scientists to rely on survey data of individuals and of geographers to rely on aggregate, often Census, data for small areal units, the gap between the preferred methodologies will likely continue.

This paper is an exercise in exploratory spatial data analysis and therefore no inferential models are used. Instead, attention is given to methods developed in the environmental sciences, especially environmental biology and physical geography, for uncovering underlying structures. The various methods point to the same general conclusions—that the Nazi party support was a mosaic of locally expressed factors and that no single explanation of the vote is expressed commonly across the country. In examining the nature of aggregate data distributions and possible causal relationships, this paper presents seven methods of exploratory spatial data analysis (ESDA; see Anselin 1995), most of which have been developed in the geographic sciences and are increasingly available in specialized mapping and analysis software for the environmental sciences. To clarify the relative advantages of each method, the support of the NSDAP in Weimar Germany is used as a comparative example. Most studies of the Nazi party have been case studies of one or a few localities (a small city or a rural area) using archival materials. Although these studies offer a great deal of information about the mechanisms of the party's strategy and successes, they do not provide much help in understanding the national picture.

Despite the addition of geographic modules to statistical software (such as the S-Plus module for *ArcView* GIS®), most of the users of such software seem to be environmental scientists (e.g., geologists, physical geographers, biologists, ecologists, engineers) interested in statistical data properties rather than social scientists with a bent towards the examination of aggregate data. Although survey data suffice nicely for most political subjects,

[1] Some key exceptions have been special issues of *Political Geography* devoted to contextual models of political behavior (Vol. 14, nos. 6/7, 1995) and to controversies in political redistricting (Vol. 19, no. 2, 2000). Both geographers and political scientists contributed to the volume edited by Ward (1992) on *The New Geopolitics*. Ongoing sponsorship of workshops by the National Center for Geographic Information and Analysis (www.ncgia.ucsb.edu) and the Center for Spatially Integrated Social Science (www.csiss.org) brings together practitioners from both disciplines. A special issue of *Political Geography*, complementing this special issue of *Political Analysis* and titled "Developments and Applications of Spatial Analysis for Political Methodology," was published as Vol. 21, no. 2, 2002.

some research questions force the use of aggregate data. These include analysis of historical political questions that predate the arrival of reliable survey data (including the forces behind the electoral success of the Nazi party in Weimar Germany), political behavior in countries without national-level survey data but with acceptable census data (much of the world falls into this category), and questions that focus on the context of political decisions, forcing a consideration to move from the individual to the neighborhood and larger scales. Events data in international relations, gathered for countries and substate units, can also be analyzed using spatial methodology (Murray et al. 2002).

Spatial autocorrelation is the most fundamental concept in geography and underlies the growing set of spatial statistical approaches. A geographic truism, often known as the First Law of Geography (Tobler 1970, p. 236), states that, "Everything is related to everything else but near things are more related than distant things." Across all specialized branches of geography, spatial autocorrelation underpins geographic assumptions, methods, and results. The (relative) order is generated by spatial autocorrelative processes. Because the distribution of phenomena on the earth's surface has been well documented in thousands of studies and simple observation, we know that clustering of like objects, people, and places is the norm. However, political scientists, including King (1996), have argued that these patterns and clusterings are not of intrinsic interest because it is the object of social science to explain them. The purpose of this paper, using the example of voting for the Nazi party in Weimar Germany, is to help bridge the gap by linking the methodological advances in geography and related environmental sciences to research questions in political science. Although much of spatial autocorrelation is extended to spatial econometric modeling in a regression framework (Anselin 1988), I confine my attention here to descriptive and exploratory methods of spatial analysis because extensive use of spatial econometric modeling to political data can be seen in O'Loughlin and Anselin (1991), O'Loughlin et al. (1994), and O'Loughlin et al. (1997).

Traditionally, the geographic factor (spatial autocorrelation) is modeled out of the regression equations, although geographers have been arguing since the 1970s that these practices—"a throwing out of the baby and keeping the bath-water" (Gould 1970, p. 444)—miss the point that human societies are not arranged in a statistically independent manner. Indeed, contra King (1996), geographers argue that the dynamics of human interaction in communities of kindred individuals, driven by needs of security and familiarity and/or by fears of the dissimilar, give rise to a "contextual" element that is more than simply the sum of the effects of the community composition. Examples of these contextual effects abound and the recent application of multilevel modeling of survey data of political attitudes has shown that typically 10–20% of the variance in the responses is attributed to contextual effects (Jones and Duncan 1998; O'Loughlin forthcoming). However, if the methods normally used do not specifically consider contextual elements in the distributions, it is little wonder that contextual models get short shrift.

Geostatistical methods are typically configured for large samples and are used widely by environmental scientists. In order to see wider use of these methods applied to human geography, we need both larger data sets (many aggregate geographic units, also called *polygons*) than those to which we are accustomed and a point sampling strategy. At a fine scale of resolution, every spatial distribution is discontinuous. The main difference between geostatistics and spatial autocorrelation is that the former deals with point sampling, usually on a grid, of a continuously geographic phenomenon (like a forest); the latter deals with a division of a geographic surface, thus producing an aggregation of geographic phenomena (Griffith and Layne 1999, p. 457). With a large number of polygons, say approaching 1000 units, a centroidal or some other point sampling strategy offers a reasonable approximation of a continuous surface that can be modeled using geostatistical methods, like *kriging* (a statistical interpolation method that predicts values for unsampled locations on a surface) and *trend surface analysis* (fitting a linear or polynomial trend to a latitude, longitude, and height surface).

In this article, geostatistical methods are heavily used. *Mantel correlation analysis* (correlating distance and difference vectors) and *variography* (the process of pattern description and modeling using the variance of the difference between the values at two locations) are used to understand the distribution of the Nazi party votes. *Vector mapping* (identifying local directional trends) and *directional spatial correlograms* (summary measures of association by major angles and distances) are added to the usual tools of spatial autocorrelation analysis—(Moran's I and G_i^*) measures of global and local spatial association—and GIS mapping in this paper. *Wombling analysis* (identification of statistically significant boundaries on a surface) is applied for the first time to a political geographic problem.

2 Weimar German Data and the Nazi Vote

Much is known about the NSDAP vote from a variety of authors (Childers 1983; Kater 1983; Falter 1986, 1991; Küchler 1992).[2] Highly relevant to this paper, researchers have generally concluded that the geographic pattern is very complex, with strong local and regional elements, and that the correlation between the vote and compositional factors (e.g., religion, class, occupation, gender) is relatively weak. Until 1928, the NSDAP aimed its platform at urban and industrial blue-collar workers, but it had unexpected success in rural areas. Thereafter, the NSDAP targeted farmers, skilled workers, shopkeepers, and civil servants, following a lower–middle class strategy that was bolstered by strong support for private property. Rural areas of Germany became bifurcated along the lines of inheritance traditions. In the Catholic areas of the south and west, where partible inheritance was common, the NSDAP platform fell on deaf ears, whereas in the northern and northeastern rural sections, where impartible inheritance was the norm, the party found much success (Brustein 1996). In addition, the composition of the NSDAP electorate varied from region to region as a result of local economic circumstances and external pressures. Most researchers accept that no one factor accounts for the success of the Nazi party and often combine models of economic interest with "political confessionalism"—attachment to a party based on social networks and historical traditions, such as the attachment of the urban and industrial working classes to the Communists. In the elections of May 1924, the NSDAP received 6.5% of the vote, decreasing to 3.0% in December 1924 and to 2.6% in 1928. The electoral breakthrough to

[2]Because of my use of methods based on point sampling, a data set with many cases is preferred for analysis, and ideally it should also retain substantive interest. I chose the example of voting in Weimar Germany for this study. The issue of how the NSDAP (*Nationalsozialistiche Deutsche Arbeiterpartei*) or Nazi party came to electoral prominence has spurred hundreds of local- and national-level studies since the 1940s. A data set available for aggregate analysis of Nazi support (German Weimar Republic Data, 1919–1933, no. 0042) is available from ICPSR (www.icpsr.umich.edu), but users are cautioned that this data set is replete with errors (Falter and Gruner 1981). A cleaned version is available from the *Zentralarchiv für empirische Forschung* of the *Universität Köln* (see Hänisch 1989, for an account of the data and levels of aggregations). The raw data set consists of electoral and census data for Weimar Germany from 1919 to 1934 for more than 6,000 spatial units. However, the data are sparse for many individual units and must be aggregated to the same geographic basis for matching of census and electoral data. Previous works (O'Loughlin et al. 1994, 1995) have used a data set of 921 units for study of the key breakthrough election, that of 1930 when the NSDAP increased their vote share to 18.3%. However, in this current study over a longer time span (1924–1933), the data are aggregated to 743 units, including both *Kreise* (counties) and cities of Germany. The data were collated by Colin Flint for his dissertation work (1995) that examined the diffusion of the NSDAP vote on a regional basis from 1924 to 1933. The number of cases varies from election to election because of boundary changes and aggregations.

18.3% in 1930 was doubled to 37.4% in July 1932 after the economic collapse in Germany. The vote dropped to 33.1% in November 1932 before peaking at 43.8% in the last Weimar election in 1933, with the NSDAP never having reached a majority.

For purposes of our earlier work, we divided Weimar Germany into six regions based on historical and cultural attachments; these regions overlap to some extent with the post–World War II Federal *Länder* that also were predicated on the notion of regional attachments. The regional boundaries are shown in Fig. 1. In this article, these regions are not used as predictors, but reference is made to them in describing the map patterns and probing the maps' spatial structures. The Nazi party took advantage of this regional mosaic by pushing a variegated appeal that was modified from locale to locale depending on specific conditions (Stachura 1980; Kater 1983; Brustein 1990, 1996; Brustein and Falter 1995; Ault and Brustein 1998; Heilbronner 1998). The Weimar data set is therefore satisfactory for detailed spatial analysis and offers a test of how far exploratory spatial data analysis can be carried to gain insights into a complex story that is still not fully understood, despite a massive effort by historians and social scientists. Simple models fail to account for its complexity. As shown by O'Loughlin et al. (1994), geographic-compositional models for

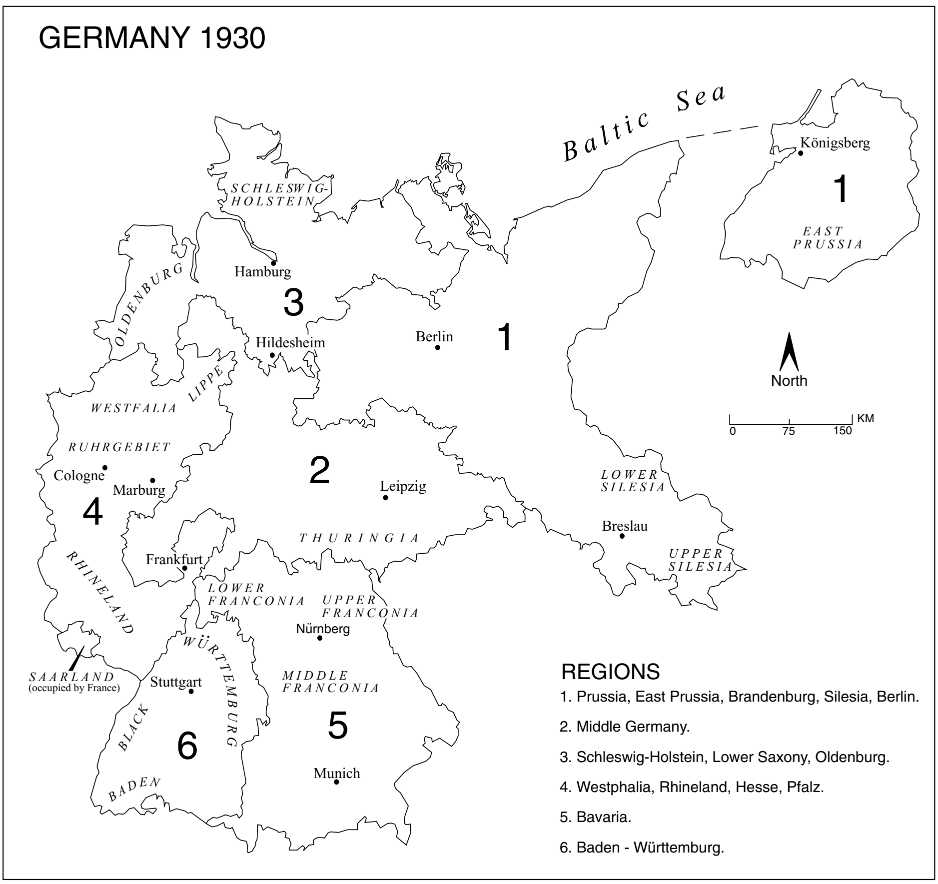

Fig. 1 Germany, 1930, with key locations mentioned in the text and boundaries of six cultural–historical regions. Note that Saarland was occupied by France in 1930 and no elections were held there.

the 1930 NSDAP vote must take this spatial heterogeneity into account; regression models with spatial autoregressive terms showed that different combinations of NSDAP supporters were distributed across the six regions.

Because the main purpose of this paper is to describe and highlight the geographic elements in the support for the NSDAP, I analyze a series of votes between 1924 and 1933, but I center the analysis on the 1930 Weimar parliamentary election. From just 2.6% in 1928, the NSDAP vote rose dramatically in 1930 to reach 18.3% of the total, making it the second largest party in the *Reichstag* (parliament) after the SPD (*Sozialdemokratische Partei*, Social Democrats). Therefore, 1930 is generally considered the "breakthrough election" for a party that had existed on the fringes of the parliamentary scene for a decade, and analyses of the changes between the years 1924–1928 and 1928–1930 allow for a better understanding of the spread of the party support.

The key dependent variable is the percentage of the 1930 valid vote received by the NSDAP in each of the spatial units. The distribution of the Nazi ratio of the 1930 vote is shown in Fig. 2. Although the map makes regional and local clusterings evident, it is lacking in wide bands of similar values. In general, strong Nazi party support corresponds to the Protestant regions of the country, with largest values in East Prussia, Schleswig–Holstein, Oldenburg, and Saxony. The Catholic areas of the Rhineland, Bavaria, and Upper Silesia, as well as big cities and industrial areas (notably Berlin, the Ruhr and Thuringia), were centers of opposition to the Nazi party, although in 1924, the party had received its strongest support in Bavaria, its initial center of mobilization and organization. However, within the north–northeast versus west–southwest–south divide, there are numerous islands of support and opposition distinguishing Catholic and Protestant areas; note the contrast between Upper

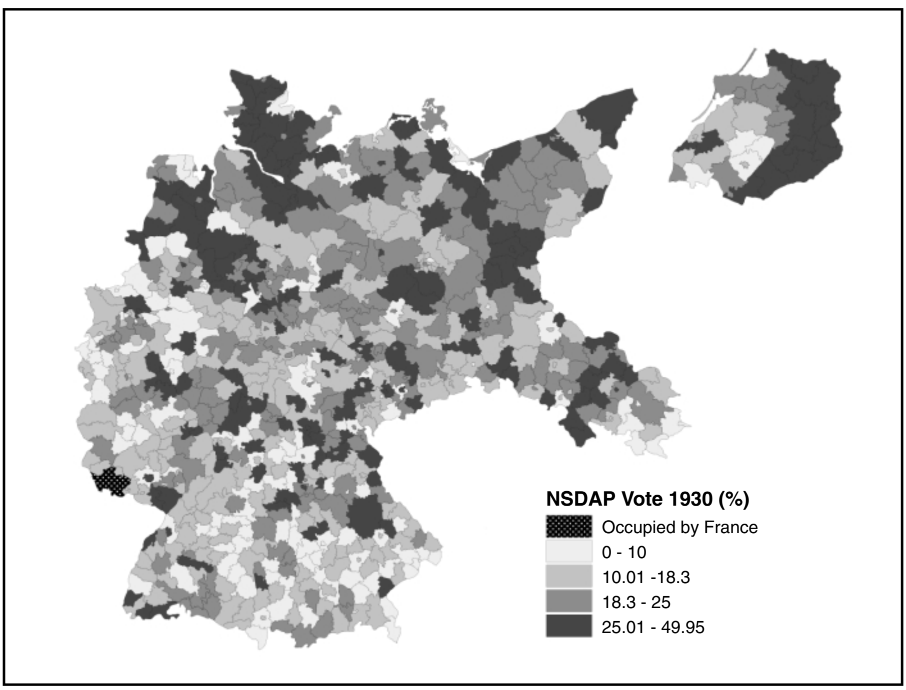

Fig. 2 The distribution of the NSDAP vote in Germany in 1930 by *Kreis*. The number of *Kreise* is 743.

and Lower Silesia or the eastern and central parts of the East Prussia exclave. It is this cartographic complexity that makes the electoral map of Weimar Germany both a social science puzzle and a candidate for detailed spatial analysis.

3 The NSDAP in Weimar Germany

In this study, I examine Protestant support for the NSDAP in Germany using seven analytical steps: 1) global indicators of spatial autocorrelation; 2) distance analysis; 3) variance pattern analysis; 4) local indicators of spatial association; 5) directional spatial autocorrelation analysis; 6) vector mapping; and 7) wombling (barrier identification). (In some analyses, the percentage of the vote for the NSDAP is used for comparison because the variation in this vote provides a benchmark for the comparison with the Protestant support of the party.) The general indicator of the NSDAP vote in a conglomerate of the support of various constituencies for the Nazi party and one of several key correlates of Nazi party support, identified in previous studies, is the Protestant population. To estimate the Protestant support ratio for the 743 geographic units, I used the EzI version of the King program that does not require the use of the Gauss program. *EzI: A(n Easy) Program for Ecological Inference* by Kenneth Benoit and Gary King is available from http://gking.harvard.edu/stats.shtml.

The Ecological Inference (EI) method has gained a great deal of press and familiarity in political science since it was first introduced by Gary King (1997). King has promoted his ecological inference technique as a method that allows disaggregation of the global (whole study region) estimates to the individual units that comprise the aggregate.[3] These estimates can be mapped, as King (1997, p. 25) illustrates for the white turnout in the 1990 New Jersey elections, and can also be the subject of further "second-order analysis." In this study, the EI estimates are only considered in descriptive, exploratory spatial data analyses.[4] King's EI method, although now well known to political scientists, has only recently been introduced to geography. Although its potential is recognized (Fotheringham 2000; O'Loughlin 2000; Davies-Withers 2001), no application of it designed to tackle key human geographic questions has yet been published.

From previous research, it is clear that a key compositional predictor of the NSDAP vote in Weimar Germany is the Protestant ratio of the local population. After 1928, the NSDAP gained a large proportion of the support of the DNVP (*Deutsche National Volkspartei*, German National People's Party), a mostly Protestant party in the north and east of the country whose vote was collapsing. The Catholics also had their own conservative party, the *Zentrum* (Center) party, whose core support was in Bavaria. One of the main explanations

[3] An alternative method of inferring subunit values published in this journal from Johnston and Pattie (2000) is not feasible because one of the key data requirements for its implementation, the national estimate of the ratios from survey data, is not available for the era of the Weimar republic.

[4] Using the EI methodology, I am interested in whether the group of interest, the Protestant population, showed significant support (compared to Catholics) for the NSDAP. Knowing the marginals (votes for the NSDAP and non-NSDAP parties, the Protestant and non-Protestant populations), EzI can be used to estimate the Protestant support for the NSDAP using the accounting identity (King's notation):

$$T_i = \beta_i^b X_i + \beta_i^w (1 - X_i),$$

where T_i is the proportion of Protestants supporting the NSDAP in each *Kreisunit*, X_i is the Protestant proportion of the population, $1 - X_i$ is the non-Protestant proportion of the population, β_i^b is the proportion of the Protestants who voted for the NSDAP, and β_i^w is the proportion of Protestants who voted for other parties. The purpose of the EzI modeling is to estimate β^b (the aggregate turnout rate for Nazi voters for the whole country); one can also get estimates for the individual counties and cities (*Kreisunits*), β_i^b. Both T_i and X_i are known values, and β_i^b and β_i^w are the unobservable parameters of interest to be estimated using King's ecological inference method (full details are available in King 1997).

Table 1 Regional pattern of EzI estimates for Protestant ratio and NSDAP vote, 1930

Region	*Number of cases*	*EzI estimate*	*Protestant ratio*	*NSDAP 1930 ratio*	*Regional gain/loss*	*National gain/loss*
Prussia	193	.216	.786	.214	+.002	+.033
Central Germany	144	.203	.829	.199	+.004	+.020
Northwest Germany	74	.271	.837	.243	+.028	+.088
Rhineland	124	.211	.458	.155	+.056	+.028
Bavaria	150	.289	.270	.167	+.122	+.106
Baden-Württemburg	58	.174	.549	.152	+.022	−.009

Note. The mean national percentage for the NSDAP was 18.3%, for a total number of cases of 743.

of the rise to prominence of the NSDAP focuses on political confessionalism and the role of the religious loyalties in local communities that existed before the rise of a national electorate after 1945 (Passchier 1980; Hamilton 1982; Grill 1983, 1986). The argument states that the NSDAP was relatively weak in Catholic areas because of the special role of agricultural relations (the nature of inheritance) and sociocultural conflict about Catholic schools in the southern and western regions of the country that tied voters to the *Zentrum* party (Stone 1982; Brustein 1996; Heilbronner 1998). Since the earliest work by Pollack (1944), the correlation of the NSDAP vote and the Protestant ratio has colored all subsequent studies.

EzI estimates indicate a 3.6% gain to the NSDAP from Protestant voters in 1930, the breakthrough election for the party. By the July 1932 election, the advantage had risen to 9.0%. The advantage is calculated as the difference between the overall NSDAP vote ratio of 18.3% and the EzI estimate of Protestants voting for the NSDAP of 21.9%. In 1932, the respective figures were 37.4% and 46.4%. Data presented in Table 1, however, suggest that German voting patterns were in fact quite complicated and that strong regional attachments remained. The comparisons to the national and regional means for the NSDAP clearly indicate the variegated nature of the core relationship.

Although caution is warranted for the estimates from Northwest Germany and Baden–Württemburg as a result of the small number of cases, the regional variation in the advantage to the NSDAP from the Protestant proportion is large, from an advantage of only 0.2% in its core support region, Prussia, to 12.2% in Bavaria. In the two most Catholic regions (Bavaria and the Rhineland), Protestant support for the NSDAP was the strongest (regional advantage over the mean of 12.2% and 5.6%, respectively). That the Protestant population's support of the NSDAP was not uniformly similar across the country is undoubtedly connected to the tensions between the populations in mixed areas. For example, Heilbronner (1998) shows this conflict for the Black Forest region of southwest Germany, and Stone (1982) illustrates the same for Franconia (the northern part of Bavaria). In these mixed regions, the religiously based political parties acted as proponents of the confessional economic interests and politics took on a decidedly local, village-level, focus. Although the parties were competing nationally, the election can also properly be seen as thousands of local and regional contests for control. The Nazi party recognized this phenomenon in their appointment of *Gauleiters* (regional leaders), who in turn appointed local party organizers for the culturally defined divisions of the state (Freeman 1995). Hitler's speeches and the party flyers also tailored the Nazi party message to local circumstances (Brustein 1996). As is evident from all the maps and statistics in this paper, the German electorate was highly disaggregated in a geographic manner, partly as a result of the splintered nature of the

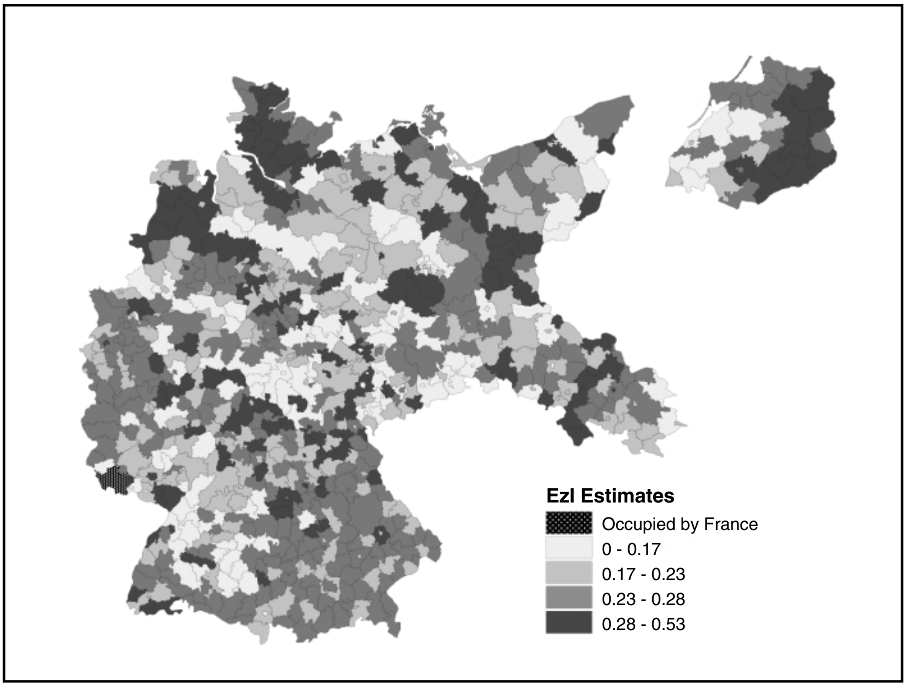

Fig. 3 EzI estimates of the ratio of Protestants in Germany who voted for the NSDAP in 1930, by *Kreis*.

German Reich (only unified for about 60 years), partly as a result of the strong culturally defined effects that promoted distinct place-based uniqueness, and partly as a result of the electoral strategies of the parties.

The EzI estimates for the 743 *Kreisunits* are derived from simulations, using a number of random samples from the distribution of values within the bounds of each *Kreisunit* that are set by the marginal totals of the cross-tabulations for each (King 1997). The geographic distribution of these estimates for 1930 Weimar Germany is shown in Fig. 3 (support of Protestants for the NSDAP). The pattern is not cohesive, and no macroregional elements (and fewer localities) stand out in the map that highlights the extreme values. In the language of spatial analysis, this map has less spatial heterogeneity and more spatial dependence. The mean value for Germany is 0.219; only scattered *Kreisunits* in northern Bavaria, East Prussia, and Central Germany (mixed Protestant–Catholic regions) are evident as strongholds for Protestant support for the party. In contrast, in the Catholic areas of the Rhineland, Westphalia, and Württemburg, very low ratios of Protestants chose the NSDAP in the 1930 election.

4 Global Indicators of Spatial Association

In spatial analysis, global summary measures of distributions are now as common as statistical distribution measures that are typically presented in the social sciences (Rogerson 2000). The limitations of the usual mean and variance statistics are evident when a simple choropleth map (the spatial units are shaded according to the value of a variable for that area) of the distribution of the NSDAP vote shows regional clustering. Moran's I measure is now most commonly presented as a summary of spatial distribution, although there

Table 2 Moran's I for spatial autocorrelation in district EzI estimates of NSDAP vote, 1930

Variables	*Lag 1*	*Lag 2*	*Lag 3*	*Lag 4*	*Lag 5*
NSDAP30	.260	.164	.112	.071	.062
Turnout	.203	.151	.131	.105	.092
(*Turnout_ezi*)	.156	.108	.079	.058	.038
Protestant	.566	.491	.409	.323	.239
(*Protestant_ezi*)	.120	.015*	.016*	.017	.011

*Not significant at $a = .05$.

are alternative measures of spatial patterns (see Cliff and Ord 1981; Bailey and Gatrell 1995).[5]

Moran's I is derived from:

$$I = (N/S_o)\Sigma_i \Sigma_j w_{ij} x_i x_j / \Sigma_i x_i^2 \tag{1}$$

where w_{ij} is an element of a spatial weights matrix $\mathbf{W}$ that indicates whether i and j are contiguous. The spatial weights matrix is row-standardized such that its elements sum to 1 and x_i is an observation at location i (expressed as the deviations from the observation mean). S_o is a normalizing factor equal to the sum of all weights ($\Sigma_i \Sigma_j w_{ij}$). Moran's I, as a product-moment coefficient, usually falls in the range of $+1$ to -1, with positive values indicating spatial autocorrelation (clustering pattern of similar values) and negative values indicating a chessboard-like arrangement of alternating dissimilar values. The choice of weights is important because they influence the index and its significance. Typically, the researcher uses an intuitive notion of how geographic proximity should be measured for the specific problem—by distance-based weights such as the inverse of intercentroidal distance, by contiguity measures (regardless of where the boundaries touch), by cost, or by some combination of these. The significance of the Moran's I is assessed by a standardized z score that follows a normal distribution and is computed by subtracting the theoretical mean from I and dividing the remainder by the standard deviation. *Spacestat* version 1.90 was used for the calculation of the spatial statistics (Anselin and Bao 1997; Anselin 1998).

Although the Nazi map patterns are complex and apparently disorganized, calculation of the Moran's I measure of spatial correlation suggests otherwise. The values for five spatial lags are presented in Table 2. Because contiguity is defined here as a shared *Kreisunit* boundary, a fifth-order neighbor would be reached in five spatial steps across the separating geographic units. Although the issue of the choice of contiguity metric is debated not only in geography (Harvey Starr and colleagues have written widely on the subject of measuring contiguity in international relations; Siverson and Starr 1991; Starr 2002), it is generally agreed that the nature of the data should dictate the choice of metric. Thus, distance metrics are typically presented for indices of spatial autocorrelation for trade whereas border contiguity is more plausible for international conflict analyses (O'Loughlin 1986; Griffith

[5]The most common alternative summary measures are Geary's c coefficient, which is a squared difference coefficient and is related to variogram analysis, described in Section 5 of this paper. Details are available in Anselin (1988). Descriptive statistics for point patterns are typically dispersion indices indicating the distribution of points across quadrats; details are in Diggle (2002).

and Layne 1999). In earlier work on Weimar Germany, O'Loughlin et al. (1994) used an intercentroidal distance of 56 kilometers as the definition of *Kreisunit* contiguity.

The correlograms for five spatial lags (e.g., first-order neighbor, second-order neighbor) of the five variables of interest follow the classic pattern in spatial analysis: decreasing positive values with increasing lags, with the greatest decline from the first to the second lag. Because the number of cases varies from lag to lag (some *Kreisunits* did not have higher order neighbors), comparison of the Moran's I values requires caution. The population distribution variable (Protestant ratio) is clearly—and unsurprisingly—more geographically clustered than any of the other variables. Because of centuries of religious conflict and accommodation, political compromise and geographic allocation, the religious map of Germany in 1930 still reflected to a great extent the preindustrial pattern. Only in the large metropolitan areas was a more recent mixing of the two predominant religious groups evident. A second comparison of the EzI estimates with the percentage figures shows the effect of variable controls on the distributions. Because the geographic patterning of Protestant supporters of the NSDAP is noticeably less clustered than the distribution of Protestants, one way to press this comparison is to examine the level of clustering across the six cultural–historical regions of the country.

The Moran's I values for the first-order lags of the six cultural-historical regions are presented in Table 3; again, caution in comparison is warranted because of the variable number of cases. The main contrast in this table is between the regions with significant positive spatial autocorrelation (Prussia and Bavaria) and the other four regions. Bavaria and Prussia were the most homogenous regions of Germany in religious, cultural, and historical terms (most consistent boundaries), and are often considered as polar opposites within the country. In the mixed regions of the center of the country, the pattern of NSDAP support is random in Northwest and Central Germany, as can be seen in the map in Fig. 2. This randomness is due to local political–confessional loyalties. Like the correlograms in Table 3, the autocorrelation for the EzI estimates of Protestant support for the NSDAP is less clustered than the raw data, except for Baden–Württemburg.

A consistent feature of Moran's I values for political geographic data is one of positive and significant spatial autocorrelation. Clustering of geographically distributed phenomena is the norm and has been documented for many political variables across an array of contexts. Voting surfaces are marked by positive spatial autocorrelation, especially for small-scale units such as wards or precincts. As the size of the unit increases, it typically becomes more heterogenous and the Moran's I values tend toward indications of less clustering. The Weimar case study is interesting not only for its historical significance, but also because the base map (distribution of the NSDAP vote in 1930) shows regional heterogeneity, local dependence (spatial autocorrelation), national trends (northeast to southwest), and a complex association between the predictor and dependent variables. Is it an amalgam of

Table 3 Moran's I test for spatial correlation—variables and district EzI estimates, 1930

Variable (EzI estimate)	*Prussia*	*Central Germany*	*Northwest Germany*	*Rhineland*	*Bavaria*	*Baden–Württemburg*
Number of Cases	193	144	74	124	150	58
NSDAP 1930	.349	−.060*	.106*	.204	.181	.286
Protestant	.541	.040	.348	.384	.521	.035
(*Protestant_ezi*)	.134	−.050*	−.078*	.211	.150	.154

*Not significant at $a = .05$.

Table 4 Distribution of Moran's I values for the NSDAP vote in all elections

Elections and changes between elections	*Lag 1*	*Lag 2*	*Lag 3*	*Mantel test* Coefficient	*Mantel test* z score
May 1924	.313	.058	−.065	−.032	−1.59
December 1924	.175	.028	−.043	.010	0.46
1928	.210	.013	−.025	−.014	−0.07
1930	.161	.025	.012	.082	4.94*
July 1932	.202	.057	.037	.070	4.89*
November 1932	.176	.023	.010	.042	2.82*
1933	.113	.027	.019	.072	4.68*
Change 5/24–12/24	.272	.056	−.029	−.022	−1.06
Change 12/24–1928	.128	.046	.025	.052	2.45*
Change 1928–1930	.219	.128	.096	.202	13.17*
Change 1930–7/32	.157	.027	.017	.013	0.85
Change 7/32–11/32	.139	.084	.072	.042	2.09*
Change 11/32–1933	.301	.100	.054	.058	2.92*

*z score significant at .05 level.

local stories with no common denominator, or a macro-level process with local deviations? The methods of spatial analysis can help determine the answer.

A final analysis of nondirectional global statistics concerns the changing Moran's I values over time. It is worth remembering that the NSDAP support ranged from 6.5% in their first national effort in 1924 to 43.8% at the last Reichstag election of 1933. Several trends are immediately apparent from the lagged Moran's I values of Table 4. As expected, the values drop consistently with increasing lags, and the values at the third lag for the early elections (before 1930) are negative and significant, indicating a chessboard-like pattern of high and low values. The most extreme Moran's I value is that for the first election, May 1924, when the NSDAP was a small minority and had only scattered support throughout Germany, with a more concentrated nucleus of support in Bavaria (Freeman 1995; Stögbauer 2001). Similarly, the first lag value for the changes between the May 1924 and November 1928 elections and for the changes between the 1932 and 1933 elections are the largest, indicating a strong contagious diffusion effect as party support grew into adjoining districts at the beginning and the end of its rise to power. Because all of the values for the changes between elections are significant at the first- and second-order lags, the evidence is consistent with a model of geographic spreading from core *Kreise* that were scattered throughout Germany. Obviously, not all of Germany was equally susceptible to the NSDAP appeal. Strong resistance was particularly noticeable in the major cities, especially Berlin, and in the majority of Catholic regions, where political confessional loyalties were strongest between socioeconomic groups and the parties representing their interests. In order to discern these localities of resistance, it is necessary to disaggregate the global indicator into its local components, using local indicators of spatial autocorrelation.

5 Global Analysis of the Voting Surfaces—Mantel Analysis and Variograms

Geography has been often and crudely described as a "discipline in distance." Two specific tests for this general proposition are used here. Global spatial association is measured by a widely used test (Mantel 1967) that examines the relationship between two square matrices, typically a distance matrix (in this study, the distances between the centroids of the *Kreise*) and some other measure of (dis)similarity between the points (here, the difference in their NSDAP percentage and change between elections). The analytical question is whether the value of the index indicates that the distance similarity is significantly related to the compositional similarity. A permutation procedure is used to estimate if the test statistic is significant by resorting the rows and columns of one of the matrices at random and comparing the resulting values. A variogram is a display of the spatial properties of the data, and a general upward curve to a threshold (or sill) is expected for spatial data with increasing distance (Bailey and Gatrell 1995).

The basic Mantel statistic is the sum of the products of the corresponding elements of the matrices

$$Z = S_i S_j X_{ij} Y_{ij} \tag{2}$$

where $S_{ij} S_{ij}$ is the double sum over all i and all j, $j \neq i$. X_{ij} is the matrix of intercentroidal distances, and Y_{ij} is the difference in the NSDAP percentages between the respective geographic units. Like any product–moment coefficient, it ranges from -1 to $+1$ and its significance can be tested through a t test after randomly permuting the order of the elements of one of the matrices (Dutilleul et al. 2000). Illustrating the Mantel test using the same sequence of elections as the Moran's lagged values, shown in Table 4, the same general results for the two tests are evident. This is expected because both are product–moment coefficients, but in this instance, they use different measures of distance (i.e., border contiguity for the Moran's I values; intercentroidal distance for the Mantel tests). Election patterns after 1930 and interelectoral change after 1924, especially between 1928 and 1930, are strongly related to distance between the spatial units, further evidence of the contagious spatial diffusion inherent in the growth of the Nazi party.

Variogram analysis is often referred to as *geostatistical analysis* because of the central role that this methodology plays in physical and environmental geography. The focus is on the graph of the empirical semivariogram computed from half of the average of $(i - j)^2$ for all pairs of locations separated by distance h, calculated from the square root of the sum of the squared differences in the x and y coordinates. Rather than plotting all pairs, making it impossible to distinguish the graphs in a large data set, the data are grouped by distance bands and the empirical semivariogram is the graph of the averaged values. Every spatial statistical package includes a module for the calculation and display of variograms (Bailey and Gatrell 1995; Kaluzny et al. 1998; Griffith and Layne 1999; Johnston et al. 2001) and variography has been widely disseminated through the work of Cressie (1991) and Diggle (2002). Variogram computation and display is the first step in developing predictive models of spatial surfaces and for interpolating data locations, such as with kriging. The analysis here was completed using *Surfer7*® (Golden Software 1999). Variograms are often computed for different directions if there is a suspicion of anisotropy (directional biases and trends in the data); the models plotted here are omnidirectionally calculated and are the simplest models with no assumptions of directionality.

The plot for the NSDAP vote in 1930 (Fig. 4a) shows a classic variograph pattern, indicating the presence of a large-scale trend or nonstationary stochastic process in the data. In contrast, the plots of the EzI estimates for the Protestant support for the NSDAP (Fig. 4b) show no distinct trend with distance, and these surfaces can be considered to be stationary. In a stationary process, the variogram is expected to rise to an upper-bound, called the *sill*; the distance at which the sill is reached is the *range*. Centroids that are separated by less than the value of the range are spatially autocorrelated, whereas those with intercentroidal distances beyond the value of the range are uncorrelated.

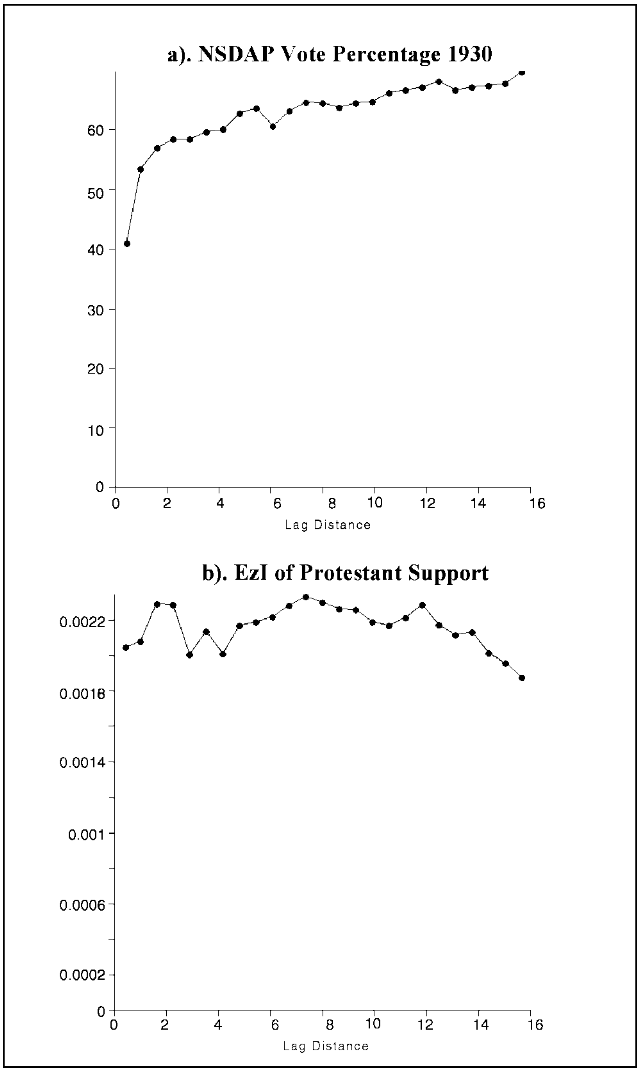

Fig. 4 Variographs of the distribution of the NSDAP vote and the ratio of Protestants who voted for the NSDAP in 1930.

A comparison of the ranges of the two graphs shows that the range (lag distance) is reached at a value between 2 and 4 (converting to 20–40 km) for the EzI estimate graph (Fig. 4b); thereafter, the variogram is flat, oscillatory, or decreasing. By contrast, the graph of the NSDAP vote percentages (Fig. 4a) continues to increase at a range of 13–14 (more than 130 km), a clear indication of a large-scale spatial autocorrelation. King (1997) considered how spatial autocorrelation affects the ecological inference estimates; it is clear from these variographs and from the spatial measures (Moran's I and local indicators explained later) that the EzI estimates of NSDAP turnout and the Protestant support for the Nazi party are much less spatially autocorrelated than the dependent variable and the individual predictors. This conclusion does not preclude the possibility of local anomalies or some regional trends; it simply accounts for the fact that a control in the form of the EzI predictor removes much of the geographic patterning. King (1996), in a debate with political geographers, argued that similar socioeconomic factors account for what underlies the geographic pattern of political phenomena and that identifying and removing these trends should be the aim of the geographic discipline.

6 Local Measures of Spatial Association

A recent trend in spatial analysis has been to disaggregate global statistics in order to uncover local clusters, or "hot spots." If there is significant positive spatial autocorrelation evident in the Moran's I values (significant negative autocorrelation would indicate a checkerboard pattern of alternating high and low values), local measures are used to identify the exact location of clusters of unexpectedly high or low values that contribute to the size and direction of the global statistic (Anselin 1995; Ord and Getis 1995; Fotheringham 1997; Rogerson 2000). Two other developments are pushing more use of local indicators of spatial association (LISAs). First, as more data for smaller geographic units have become available and manageable in GIS databases, it is common to generate highly significant global measures of spatial autocorrelation, such as Moran's I or Mantel coefficients, in situations with hundreds of data units. However, whether these statistics are substantively interesting is hard to say without recourse to other, more disaggregated analyses. Second, the modified areal unit problem (MAUP), a function of the essentially arbitrary nature of geographic boundaries in dividing up a surface into subunits, means that global statistics remain somewhat arbitrary. Consider that a different spatial arrangement and the reaggregation of the geographic subunits would produce a different Moran's I because the contiguity matrix and the number of cases would be altered. A focus on local statistics (LISAs) helps highlight and clarify these dilemmas of geographic data.

A common tactic to identify local outliers prior to the development of the LISAs was to map and inspect large residuals from regression, frequently by adding spatial autoregressive terms to the equations (Cliff and Ord 1981; Anselin 1988). The most commonly used LISA is the G_i^* (Ord and Getis 1995), which is defined by

$$G_i^* = \frac{\sum_j w_{ij}x_j - \sum_i (w_{ij} + w_{ii})_i^* \bar{x}}{\hat{\sigma}_x \sqrt{n \sum_j w_{ij}^2 - \sum_i w_{ij}^2 \big/ (n-1)}}, \; j \neq i \tag{3}$$

where w_{ij} denotes element i, j in a binary contiguity matrix and x_j is an observation at location j. The G_i^* measure is normally distributed and indicates the extent to which similarly valued observations are clustered around a particular observation i. A positive value for the G_i^* statistic at a particular location implies spatial clustering of high values around that location; a negative value indicates a spatial grouping of low values. The values can then be mapped as shown in Fig. 5, with extreme values identified as hot spots.

The attraction of the LISA method as a tool to identify the clusters of low–low and high–high values in a geographic distribution is immediately obvious from the map in Fig. 5. Most values are nonsignificantly associated with neighboring *Kreisunits*, and the patches of neighboring high–high and low–low values are typically small, scattered around the country and not clearly associated with any underlying cultural–historical feature. Instead, they appear to be associated with local phenomena. Small clusters of high and low z scores are evident in Fig. 5. Of the 70 G_i^* values less than -1.5 for the EzI estimates of Protestant support for the NSDAP, 33 are found in the Rhineland (western border of the country) and another 14 are in Baden–Württemburg (using the regional boundaries in Fig. 1). Of the 50 regions with G_i^* values greater than $+1.5$, 21 are in Bavaria and another 12 are in central Germany, a mixed religious zone. Traditionally high Protestant support

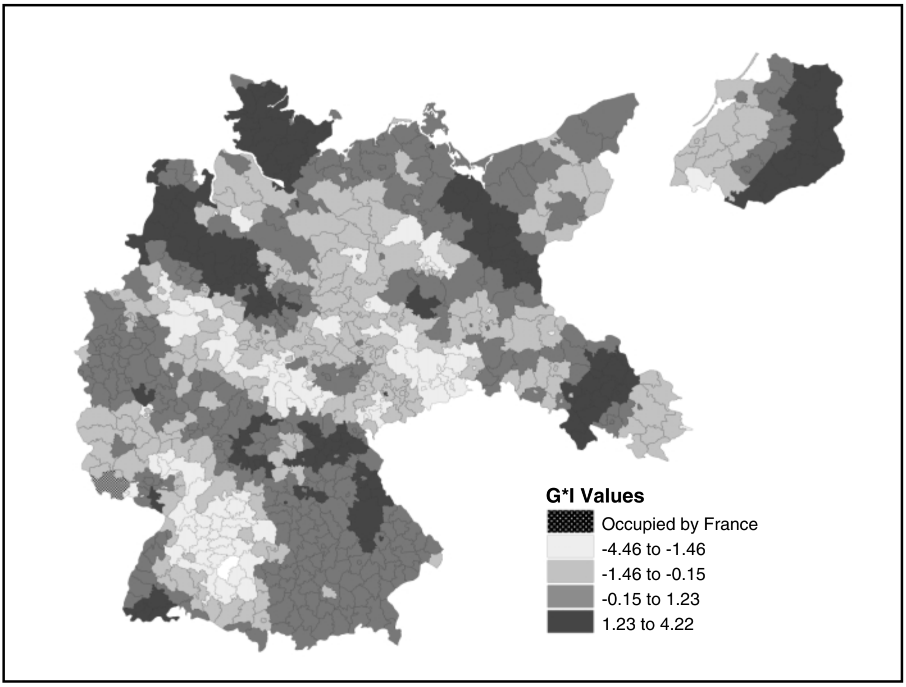

Fig. 5 Spatial clustering of the EzI estimates of the ratio of Protestants in Germany who voted for the NSDAP in 1930, by *Kreis*.

regions (i.e., Franconia, Silesia, east Prussia, Brandenburg, Schleswig–Holstein, Oldenburg) show clustering of high voter turnout and are undoubtedly related to local tensions and political–confessional competition. Larger areas of low Protestant support for the NSDAP are found in the mostly Catholic regions of industrial Westphalia and Württemburg, and also in Berlin. Why these regions should exhibit such clustering and other Catholic regions have no significant clustering is not immediately evident.

Use of the most common measures of spatial analysis indicates a pattern of NSDAP support that is both highly localized and weakly regionalized, except for a general northeast–southwest trend. Unlike many contemporary electoral geography maps, the NSDAP distribution (and its correlates) is more localized and not as regionalized. There are two possible explanations for this difference. First, the elections in Weimar Germany were the first set of relatively free and open contests, and as such, electoral preferences and trends had not stabilized. Over time, according to the nationalization thesis, minor parties are marginalized and disappear or are absorbed by larger parties, whereas the big parties campaign nationally and typically do not write off any locality. The result is that local and regional nuances are eroded and gradually disappear. Agnew (1988) criticizes this interpretation and has shown that in many European countries, local attachments and regional protest parties survive and prosper even in a time of national campaigning. The second interpretation is that Weimar Germany was simply a complex mosaic of culturally identifiable microregions, a product of a long history of local principalities, weak central authority, and intense political–confessional competition. Fewer than seven decades of the Second German-Empire after unification in 1871 had not yet dispersed these attachments. In this environment, parties (with the notable exception of the Communists) did not generally have a strong class base, but instead should be viewed as "complex constellations of social, religious and regional factors that had emerged into comparatively stable socio-cultural milieus" (Rohe 1990, p. 1). These *milieuparteien* had strong cultural associations, and this nexus was assisted by the omnipresence of *heimatbezogene Gemeinschaften* (locally based associations) that helped to develop a local consciousness in the Weimar period, continuing a preunification tradition. Further spatial analysis can unravel and clarify these regional and local idiosyncrasies.

7 Directional Spatial Autocorrelation

To this point, I have used global and local measures of spatial association. These measures do not consider the possibility of any directional trend in the pattern. To analyze geographic trends, trend-surface analysis is often used, in which the independent predictors are the location coordinates (east–west and north–south). Furthermore, by making the surface more complex by adding terms (e.g., quadratic, cubic), surface models can often be developed that fit the pattern well. If the surface is more complex with many ridges, valleys, and depressions, one quickly reaches the point of diminishing returns in adding terms. Recent developments in spatial analysis blend location and structural indicators (the socioeconomic attributes of the geographic units) as independent predictors in regression models.[6]

Prominent among these new spatial methods has been a search for measures of spatial association that also take direction into account. In many environmental geographies, such as climatology (e.g., wind direction) or biogeography (e.g., diffusion of a tree infestation, the spread of a noxious plant), directionality is a crucial factor in anticipating future developments and in generating strategies to ameliorate the impending trends. In these circumstances, the global spatial association measures are disaggregated by direction so that it is possible to determine predominant modes and routes of change. In this way, spatial association is not only a factor of contiguity, but also of the angle of direction between the spatial units. The location coordinates of the geographic centroids of the spatial units are the key controls, and contiguity is measured by circular bands of increasing distance (called *annuli*) around the centroids.

To this point, we assume *isotropy* (interaction is equally possible and predictable in all directions with no evidence of directional bias) in the global models of spatial autocorrelation. In the case of the NSDAP votes, this assumption is questionable because the maps show some northeast to southwest trends. One method to determine whether this trend is significant—whether these angular directions are more prominent than others—is to model autocorrelation using a bearing spatial correlogram. This method is one of a family of disaggregated autocorrelation measures that help to determine anisotropic spatial patterns (variable directional bias in the spatial pattern; Rosenberg 2000).

Bearing analysis is the term given by Falsetti and Sokal (1993) to the related methods that determine the direction of greatest correlation between data distance and geographic distance. The data distance matrix V is usually the difference between the values of two cells (in this case, in their percentage of voters who chose the NSDAP). The usual geographic distance matrix (intercentroidal distance) D is transformed into a new matrix $G_?$ by multiplying each entry of D by the squared cosine of the angle between the fixed bearing (θ) and that of each pair of points:

$$G_{ij} = D_{ij} \cos^2(\theta - a_{ij}) \tag{4}$$

[6]See Jones and Cassetti (1991) for the spatial expansion model. Fotheringham and Brunsdon (1999), Brunsdon et al. (1998), and Fotheringham et al. (2000) explain geographically weighted regression.

where G_{ij} is the ij^{th} element of matrix G, D_{ij} is the ij^{th} element of matrix D, and a_{ij} is the angular bearing of points i and j. If the two bearings (θ and a_{ij}) are the same, $\cos^2$ equals 1; if the bearings are at right angles to one another, the function of $\cos^2$ equals zero (Rosenberg 2002). Typically, the reference angle θ is due east and the correlation between V and G_θ is calculated via a Mantel test and repeated for a set of θ. Rather than calculating the bearing correlogram for all angles between 0° and 180°, the values are usually calculated for a set of standard values (10, 20, 30, etc. degree angles from θ). Other directional methods use wind-rose correlograms (Oden and Sokal 1986; Rosenberg et al. 1999) in which the classes are based on both distance and direction.

In the bearing spatial correlogram, the weight variable incorporates not only the distance or contiguity between points (centroids or capital coordinates of a country), but also the degree of alignment between the bearing of the two points and a fixed bearing; in this article, the fixed bearing is the east direction. All analyses were completed using *PASSAGE* (Pattern Analysis, Spatial Statistics, and Geographic Exegesis), a program by Michael Rosenberg.[7] Use of these methodologies has proved useful in tracking genetic drift in Japan and in identifying prostate cancer clusters and trends in Europe (Sokal and Thompson 1998; Rosenberg 2000).

A bearing correlogram can be constructed in the same way as the usual correlogram for spatial autocorrelation, except that the distance is weighted by direction. Distance bands are used to assign weights—each distance class has an associated weights matrix W that indicates whether the distance between a pair of centroids falls into that class. The weight matrix is converted into a new matrix W' by multiplying each entry by the squared cosine of the difference between the fixed bearing and that of a pair of points, as in Eq. (4). Pairs of points that do not fall into the distance class have an initial weight of zero and are unaffected by the transformation. Pairs that fall into the distance class are down-weighted according to their lack of association with the fixed bearing, θ. In the bearing correlogram, rather than simply presenting the coefficients in a table (as in Table 4), the bearing coefficients are plotted against the angle. Each distance class (annulus) is represented by a concentric circle—or semicircle because the other half is redundant in a symmetric plot—and each coefficient is plotted above or below the annulus ring. The distance from the ring represents the size of the coefficient, whereas a shading or symbolic scheme can indicate its level of statistical significance (see Rosenberg 2000, 2002 for more detailed descriptions).

Three bearing correlograms are presented in Fig. 6. On each of the semicircular diagrams, the coefficient is plotted every 18° (10 per 180° arc), whereas the annuli lines plot out the values for each distance band. Because autocorrelation is typically larger at smaller spatial distances, a greater density of annuli is shown for small distances in the plots. The three plots illustrate the geographic diffusion of the NSDAP in the period of electoral breakthrough, 1928–1930, as well as the pattern for the Protestant NSDAP support. In the period 1924–1928, when the NSDAP vote decreased by 0.4% (from 3.0% to 2.6%), there is strong evidence of localized spreading for the first two annuli (to 35 km) and to the north–northwest for the third ring (45 km). As is typical of spatial patterns, high and significant negative coefficients are seen in all directions for the longer intercentroidal distances.

The clustering of growth in the NSDAP vote continued between 1928 and 1930 (rise in the vote from 2.6% to 18.3%). The first four annuli (up to 54 km) show significant positive spatial autocorrelation in all directions and to the northwest for the fifth, sixth, and seventh bands (up to 84 km). The cline is most evident in this direction (northwest–southeast) and

[7]Available from www.public.asu.edu/-mrosenb/Passage/.

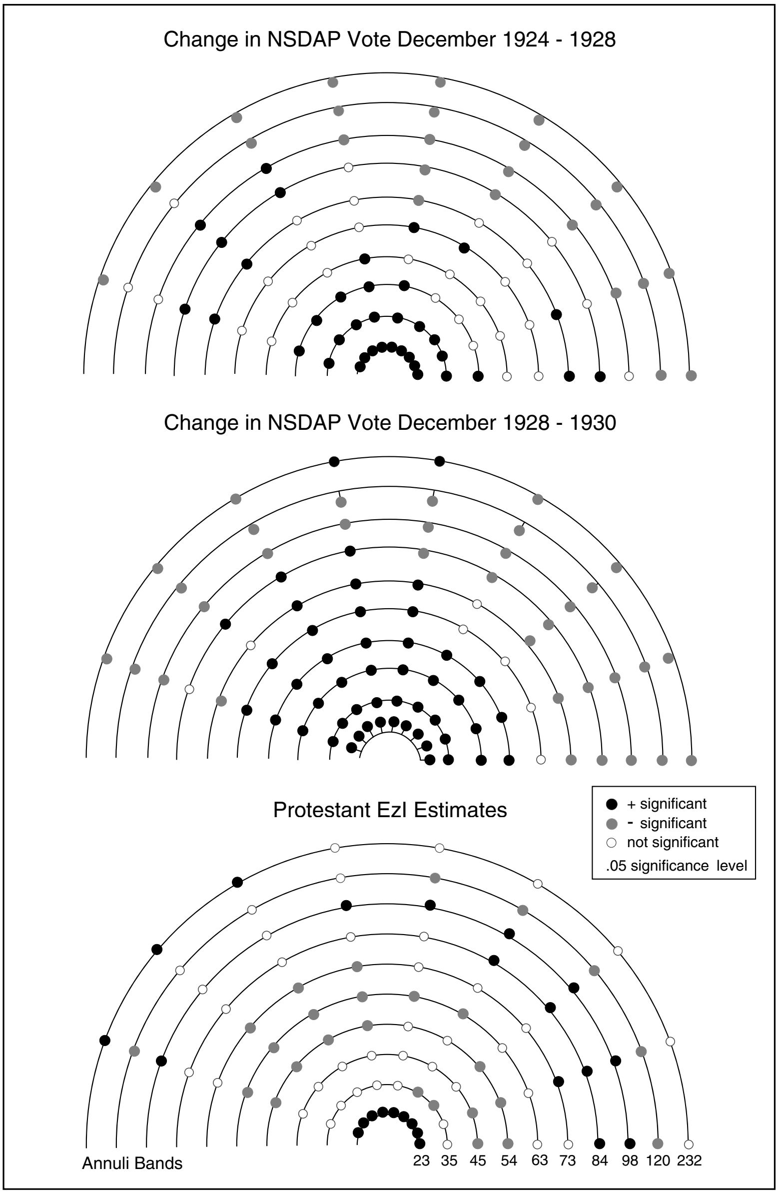

Fig. 6 Bearing correlograms of the NSDAP vote. Top: Change in the NSDAP vote between November 1924 and 1928 elections. Middle: Change in the NSDAP vote between the 1928 and 1930 elections. Bottom: EzI estimates of the ratio of Protestants who voted for the NSDAP in 1930.

the diffusion of the NSDAP support demonstrates a trend along this axis. Party gains in the northern and northwestern regions (i.e., Schleswig, Holstein, Lower Saxony, Oldenburg) contributed to this diffusion. By 1932 (not shown here), change is more localized in all directions and no further regional trends are evident. In the directional correlogram for the Protestant support for the NSDAP (Fig. 5c), the correlogram is remarkably clear. All directions of the first-order lag show significant positive values, but beyond the immediate vicinity of each polygon, the correlogram switches to significantly negative to the east (at the second- and third-order lags). Thereafter, the values are inconsistent with a weak trend to the north–northwest at the fourth-, fifth-, and sixth-order lags. We can conclude that the directional correlogram of Protestant support for the NSDAP shows no consistency; the pattern is highly localized.

Bearing correlograms are useful devices for disaggregating global autocorrelation measures like Moran's I. In many spatial applications, association varies not only by distance, but also by direction. Bearing correlograms can help determine if trend surfaces are significant, but they also suffer from the fact that, as a general measure, the local components that constitute or bias the trends cannot be determined from the general measure. Just as the Moran's I (global) statistic can be deconstructed and LISAs can be mapped, we now turn to vector fields as a way of examining the local trends that cumulatively constitute the national directional autocorrelations.

8 Vector Mapping

The use of vector mapping is helpful to visualize the directions of flows.[8] Akin to maps showing dominant wind direction and using the same symbolization (arrows of various widths and lengths pointing in the direction of dominant flow), vector maps have been widely used for portraying trade and migration flows, as well as other interactional data such as telephone calls, mail flows, and international cooperation–conflict (see the examples in Bailey and Gatrell 1995, Chapter 9). Tobler (1976) pioneered this methodology in human geography and developed the concept of *vector fields*. Vectors, shown by arrows of variable width and length, link origins and destinations by indicating the direction of net flows. Repeating this for all flows shows the "wind of influence" at each origin—a vector showing the sum of all flows and directions. If there are enough data points, an interpolation can be made to a regular spatial grid of locations.

In the example of NSDAP voting in this article, we are not using interaction data, although the analogy to interactional data is useful. Instead, a vector map contains two components, direction and magnitude, calculated from analyzing the gradient of the surface grid. Perhaps the best analogy is a contour map in which arrows point in the direction of steepest descent (downhill), and the direction that the arrows change from grid to grid depends on the topography surrounding the grid node. The magnitude of the arrows change depending on the steepness of the slope, in which longer vectors indicate steeper slopes (Golden Software 1999, p. 243). In a highly patterned map with a large-scale and even change of gradients from a few prominent nodes, the direction and magnitudes of the vectors are consistent and dramatic.[9] By contrast, a vector map of slope gradients in a complex contour surface, such as cancer distribution in a metropolitan area, shows a random pattern of small arrows pointing in multiple directions, reflecting the lack of a dominant angular bias. The surface vector mapping of the NSDAP vote and the EzI estimates for the NSDAP voter turnout and the Protestant supporters of the NSDAP were completed using *Surfer7*©.

The directional correlogram for Protestant support for the NSDAP had shown only local autocorrelation in all directions. This statement is consistent with the vector map in Fig. 7, also highly complex with multiple "sinks" and "ridges" in the surfaces. Although it is well known that the aggregate correlation of the NSDAP vote and the Protestant population

[8]Thanks to Ron Johnston and Mike Ward for suggesting that the directional biases underlying the bearing correlograms be examined.

[9]An example is intercensal elderly population flows in the United States, with Arizona and Florida acting as powerful magnets.

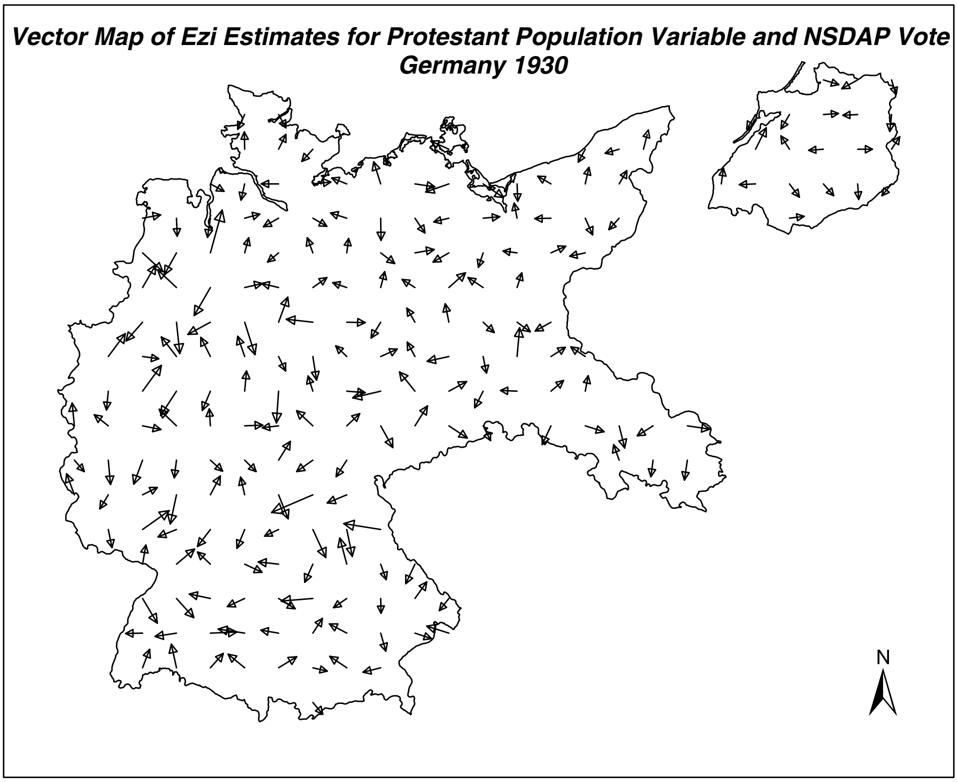

Fig. 7 Vector map of the EzI estimates of the ratio of Protestants who voted for the NSDAP in 1930.

distribution is significant, the EzI estimates do not show dramatic variations in the ratio of Protestants who voted for the NSDAP (range from .04 to .51). The maps are highly localized and only small pockets of higher and lower support than the national average are visible. Lower values (sinks in the vector map) are seen in Upper Silesia, Württemberg, the industrial Ruhr cities, and central Bavaria. Ridges of higher support are visible in the Rhineland (a Catholic region), northern Baden, Franconia, and the northern tier of regions (Oldenburg, Holstein, and the Mecklenburg region east of Hamburg). The complexity of the cultural–economic map of Weimar Germany reflects a mosaic of historical traditions and an un-nationalized electorate in the 1920s. Such traditions are frequently identified in electoral geographic studies of contemporary Western Europe, such as Shin (2001) for central Italy and Agnew (1987) for Scotland and Italy.

9 Wombling (Barrier Analysis)

A final spatial analytical method that focuses on regional differences across shared boundaries to identify significant "barriers" (major differences across the line) can help determine the geographic extent and influence of these barriers. If the voting surface barriers correspond to other regional lines (e.g., cultural regions), then we can attribute significance to these historical bounds.[10] Methods of detecting difference boundaries are called *wombling*

[10] In landscape topographies, steep gradients (indicated by closely spaced contour lines) are the zones of greatest surface changes. In genetic study, such as those of allele (a genetic marker) frequencies, barriers are important

techniques because they were first quantified by Womble (1951). Wombling methods vary. The magnitudes of the derivatives of the surfaces can be added together to get a composite picture of the barriers (if one has more than one measure, such as alleles) (Sokal and Thompson 1998). In this study, a simpler measure of difference uses a distance metric to measure the difference between the values at the polygon centroids; only adjacent polygons (sharing a boundary) are used in the dissimilarity calculations. Because the locations of the polygon (*Kreise*) boundaries are known, so-called crisp boundaries can be delineated.[11] Barriers mark the edge of a homogeneous area, demarcating it from different regions.

In order to link subboundaries using BoundarySeer (available from www.terraseer.com), certain criteria must be met for a polygon boundary element to qualify as part of a defined barrier. Boundary Likelihood Values (BLVs) are spatial rate of change indicators derived from gradient magnitudes; in this case, the gradient is the difference in the value of the variable under consideration (e.g., Protestant support for the NSDAP in 1930) between the centroids representing the polygons. By introducing a percentage threshold (e.g., top 5% of BLV values represent a significant barrier and top 20% represent a modest barrier), a consideration of significance can be introduced (Barbujani and Sokal 1990, 1991). The benefits of *a priori* determination of the cutoff values, with some preferring to use the histogram of values to find the thresholds, is debated in the literature (Bocquet-Appel and Bacro 1994). Because I am interested in comparing the barriers across the different wombling maps, I opted for consistent percentage cutoffs.

A second criterion in marking a barrier is a consideration of the angular alignment of the subboundary units. Gradient angles are the direction of the maximum change in the BLV at a specific centroid. The angle is calculated relative to a horizontal vector pointing east from the candidate centroid. The calculation is repeated for the second candidate centroid. If the angular threshold for the maximum angle between gradient vectors is more than 90°, the boundary joining the centroids is no longer considered to be part of a defined barrier. A second angular calculation is similar to the bearing correlogram procedure discussed previously and measures the angle of the vector connecting the two centroids and due east. Two adjacent boundary elements are connected to form a subboundary if the average differences in their gradient angles and their connection angle with the subboundary are within thresholds set by the user. In this study, 30° is the maximum angle threshold for the connecting centroidal vector and due east. Especially useful in diffusion studies, in which the concept of barriers assumes central importance, the wombling technique allows a spatial comparison of different types of barriers (e.g., linguistic, cultural, religious, genetic, political, topographic) so that a correlation of boundary effects can be made and hypotheses about the effects of biological or physical features on sociodemographic characteristics can be tested (Bocquet-Appel and Bacro 1994). In this study, the barriers were identified only for the univariate case. A distinct line of high values separated from a region of low values would be identified as a significant barrier across many *Kreise*.

By setting the thresholds at 5% and 20% (of the BLVs), barriers at two levels are identified in Fig. 8. All of the 5% barriers are included within the 20% set of barriers. Like the previous displays, the dominant feature of the maps is the specificity of the locations and the lack of extended barriers across multiple *Kreise*. The map displays barriers that divide culturally distinctive regions, in which support of Protestants for the NSDAP was higher (or lower) than

to identify because they show the areas over which genetic flow (population movement) is reduced or stopped (Sokal and Thompson 1998).

[11] Fuzzy boundaries are appropriate when only point data are available and interpoint boundary interpolation is used.

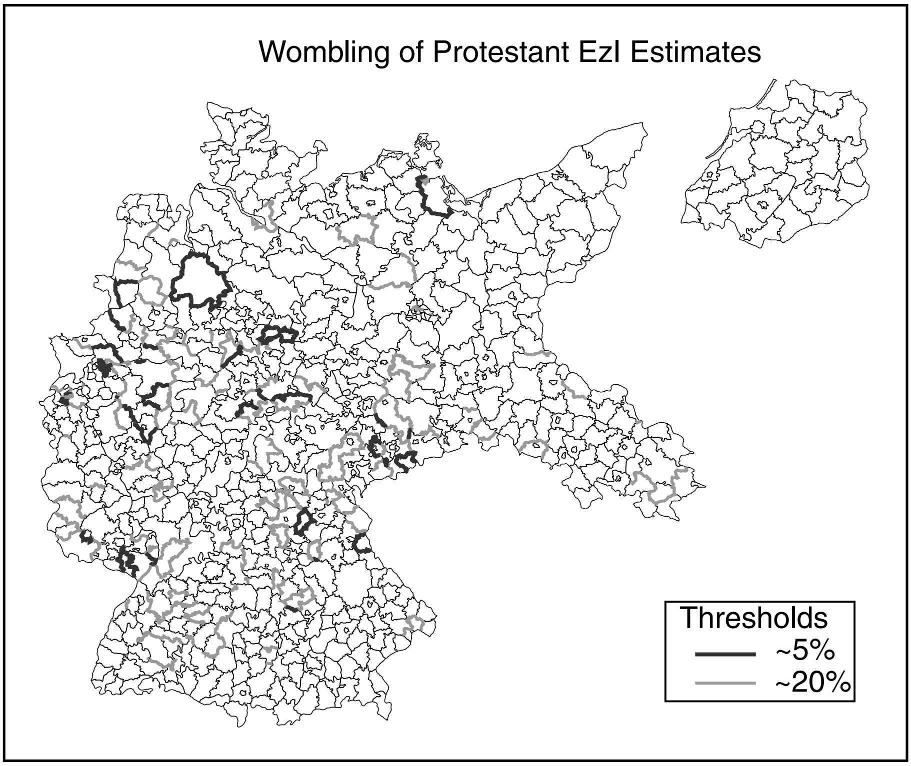

Fig. 8 Wombling (significant boundary identification) of the EzI estimates of the ratio of Protestants who voted for the NSDAP in 1930.

neighboring regions. High regions of Protestant support for the NSDAP in Upper Franconia and the adjoining region of Thuringia are visible. Similarly, low values concentrate in the Ruhr region, in northern Württemburg, and in Upper Silesia. The rest of the barriers isolate individual *Kreise* from their surroundings. Islands of higher values are clearly marked, but the lack of conjoined, extensive lines is still noticeable.

The wombling analysis confirms previous exploratory spatial data analysis conclusions about the lack of geographic pattern in the Weimar Germany voting surfaces. Numerous islands that are distinctive from surrounding regions, urban–rural differences, weak relationships between voting and sociodemographic characteristics, and lack of countrywide trends are consistent across the maps of this paper. Although most analysts use multiple measures to define barriers, I opted for the univariate modeling because the multivariate barriers are often hard to explain and correlate with other map features. Wombling offers much more potential use than has been the case in social science, perhaps hampered by the lack of accessible software. With the growing use of exploratory spatial data methods that include recognition of clusters ("hotspots") and barriers, especially in epidemiologic study (Bailey and Gatrell 1995; Griffith et al. 1998), diffusion of these methodologies into the rest of human geography can be expected.

10 Conclusion

In this article, I stress the benefits of exploratory spatial data analysis (ESDA) methods for examining a puzzle of long standing in the social sciences: Who voted for the Nazi party in Weimar Germany? In many ways, the Weimar German data set, consisting of both census and electoral data at the level of *Kreise*, provides as complete an aggregate account of the phenomenon as might be expected, and in some ways, it exceeds in coverage and detail the data files for contemporary societies in its geographic coverage, small scale, and temporal match between census and electoral data. Previous studies of the Nazi party phenomenon were motivated by the concern to check hypotheses about the propensity for different groups (e.g., religious, sociodemographic, age, occupational) to vote for the Nazis, but the conclusions to date have only been partial. Problems such as multicollinearity, scale of analysis, spatial autocorrelation, and accurate census measures of the predictive factors continue to plague the quantitative historical studies of Weimar Germany. This study shows that the country did not have a nationalized electorate and that a very complex cultural–historical mosaic underlies the electoral map. Clearly, any modeling of the NSDAP vote has to take this mosaic into account. Searching for a single explanation (a univariate model) of the Nazi phenomenon is likely to prove to be a futile endeavor.

Typically, the first step in any geographic analysis is mapping—using a variety of techniques to explore the structure of the spatially distributed data. The methods used in this article rank among the most common, although the use of point-based (centroidal) data is still relatively uncommon in human geography because most census data are collected for polygons (spatial entities). Since about 1980, there has been a retreat in geographic analysis from complex multivariate modeling (factor analysis and canonical correlation enjoyed their heyday in the 1970s) to a more focused attempt to understand basic distributive properties of the key variables (Fotheringham et al. 2000). It seems fair to conclude, however, that the trend has been to build models with more geographic terms and fewer compositional (sociodemographic) ones, partly as a result of a recognition of collinearity and the emphasis on parsimony, but also because the geographic models are complex and include multiple terms (see Griffith et al. 1998 for an example).

In 1980, Jean Laponce pointed out that geography was a net importer from political science (in turn, a net importer from economics). My guess is that this net flow is still the same. What has changed is the revolution in geographic methodologies of aggregate data analysis—some of which are used in this paper—the integration of statistical and GIS methodologies, and the theoretical conceptualization of context. Unfortunately, many political scientists continue to adhere to an out-moded conceptualization of space, place, and region. Over time, as political scientists have moved more to survey-based data analysis, the advantages of aggregate data in certain circumstances have not been noticed. Previous avoidance of these data as a result of perceived problems of ecological fallacy, inadequate methods for handling spatial autocorrelation, and insufficient experience in mapping geographic data is increasingly unwarranted. Further rapprochement of geographers and political scientists in tackling issues of mutual interest is to be welcomed.

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