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The (Re-)Emergence of Spatial Demography

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ABSTRACT

This paper consists of two parts. The first reviews the historical role that space and place has played in the discipline of demography in the United States. We argue that until approximately the middle of the 20th century nearly all of demographic analysis could be labeled "spatial demography." Beginning in the 1940s this pattern changed, as an increasing number of microdata files from large sample surveys began to provide attitudinal and behavioral data for individuals and families. The trend was further accelerated by release in the early 1970s of census data in the form of public use microdata sample files (PUMS). We argue that in addition to data availability, the drift away from analysis of aggregated census data was prompted by a conscious desire on the part of researchers to avoid the troublesome issues of aggregation bias and what came to be known in sociology as the ecological fallacy. Sometime around the 1950s to 1960s most population analysis in the U.S. shifted away from macro- (spatial) to micro-level research, although we acknowledge and document that in two small subfields of demography (rural demography and applied demography) fascination with aggregate (spatial) data analysis persisted.

In the second part of the paper, we argue that there has emerged in very recent years a renewal of interest in aggregate demographic data. Part of this re-emergence of interest in spatial demography is driven by awareness of developments in the fields of spatial econometrics and regional science that bring fresh approaches to the specification of traditional regression models and new software tools for estimating parameters in the presence of spatial externalities. By way of illustration, we provide a brief data analysis as various aspects of these new developments are discussed. Finally, we close the paper with an overview of how the earlier split between macro and micro approaches to data analysis are now being bridged with multilevel models that simultaneously consider both individual-level variables and aggregated contextual level variables for those areas where the individual lives or works.

The (Re-)Emergence of Spatial Demography

Social scientists have noted a re-emerging interest in issues concerning social processes embedded within a spatial context (e.g., Messner and Anselin, 2004). While some may argue that this movement is refreshing and new, we demonstrate that spatially focused demographic theories and research agendas clearly predate contemporary interest in these topics. We further assert that recent methodological advancements have merely emboldened and refined the expanding body of spatially oriented population research rooted in earlier traditions and practices. In this chapter we broadly discuss the role of geographic space, location or place, in the discipline of quantitative demography.[1] We argue in the following section that, until roughly the mid-20th century, virtually all demography in the United States was spatial demography. Here, we define spatial demography as the formal demographic study of areal aggregates, i.e., of demographic attributes aggregated to some level within a geographic hierarchy. In the second section, we argue briefly that in the years since approximately 1950 the scientific study of population came to be dominated by attention to the individual as the agent of demographic action. That is, spatial demography gave way to micro-demography.[2] We offer two, mutually enforced, explanations for this shift. During this period, those demographers whose research and writings primarily addressed aggregate demographic trends or comparisons among areal units – what we here call macro-level or spatial demography – slipped into a disciplinary minority. In section three we discuss how the tradition of spatial demography persisted during the latter half of the 20th century, despite the dominance of micro-demography, through the contributions of rural demographers and of others working in the sub-field of "applied" demography.

Following this, we include a substantial section in which we discuss the recent awakening that has come to spatial demographers from developments in other disciplines. This development is in regard to the specialized – some would say “spatialized” – set of statistical tools appropriate for the analysis of data aggregated to areal units. Attributes of spatially referenced data generally violate at least one of the assumptions underlying the standard regression model, which necessitates both caution regarding these violations and attention to methods designed to correct for them. We discuss the nature of the problem, how it arises, how to identify it, and methods by which one can press forward appropriately with the analysis of such data. This is followed by a section in which we briefly discuss the recent role played by the methods of multilevel modeling (hierarchical linear modeling) in bridging the 50-year-old split between micro-level and macro-level demography by introducing techniques which simultaneously consider individual (family or household) variation in demographic attributes or behavior as well as the broader geographic contexts in which individual demographic action occurs. Finally, we close with a concluding summary and a note of encouragement for those researchers analyzing georeferenced data.

TRADITIONAL DEMOGRAPHY WAS (MOSTLY) SPATIAL DEMOGRAPHY

Prior to the advent of public use microdata files from the decennial census, and before the arrival of large public use analytical files from major surveys (e.g., General Social Survey, National Longitudinal Study of Youth, Panel Study of Income Dynamics), most demography in the U.S. consisted of the analysis of population trends or comparisons among geographic entities (e.g., counties), or aggregates of such entities (e.g., states, census regions/divisions, or metropolitan/nonmetropolitan aggregates, etc.). With only a bit of exaggeration, one can make a convincing case that traditional demography was *spatial* demography.

Exceptions to this generalization are few.[3] They mostly involve the pioneering work of statisticians, actuarial scientists and early mathematical demographers who established the groundwork in renewal theory, the stable population model and the examination of formal relationships among demographic phenomena (e.g., Dublin and Lotka, 1925; Feller, 1941; Lotka, 1918, 1938, 1939, 1942, 1948). For these early quantitative demographers, these methods of studying populations were established as guidelines under which the less formal "empirical" approach to population analysis would serve as a concrete illustration (Lotka, 1938). Yet, the assumption was that the two approaches would complement one another and proceed in tandem, with the empirical analyses generally drawn from aggregate population information for specific geographic areas such as countries (Dublin and Lotka, 1925, 1930; Lotka, 1938) or individual states in the U.S. (Dublin and Baker, 1920; Dublin and Lotka, 1936; Lotka, 1936). Thus, even conceding this exception to our assertion, it must be acknowledged that spatial comparisons were a significant part even of this early formal demographic literature.[4]

Since *Demography*, the official journal of the Population Association of America, did not commence publishing until 1964, and *Population Index* (which dates from 1937) was primarily a bibliographic resource, one has to look more broadly in the social science, statistical and medical literatures to track the topical emphases in demography from its formal beginnings in the U.S. Lorimer's (1959) comprehensive overview of the origins of demography makes clear the difficulty and artificiality of trying to establish the precise origins of the demographic discipline in the U.S. Many different roots extend deep into European soil. The "political arithmetic" of the late 17th and 18th centuries, for example, was well advanced before the formal investigation of demographic phenomena emerged in America in the early 20th century. Certainly a strong and mature study of population dynamics had taken hold in the U.S. before the founding of the Population Association of America in 1931, but perhaps not much before that date.

The early years of empirical demography in the U.S. were dominated by analyses in which areal aggregates were the chief units of analysis. We mention some of these analyses in a later section of this paper. Many other studies, which for space limitations cannot be individually cited, appeared in the period roughly spanning 1940 to 1970 as state or regional Experiment Station bulletins (Voss, 1993).

In subfields of sociology closely related to demography, the analysis of aggregated social data also flourished. The classical theoretical foundations of human ecology date from the 19th century, but the emergence of the Chicago School in the 1920s and 1930s brought many of the concepts of biology and general ecology (e.g., adaptation, competition, interaction, division of labor) to the study of human "organisms" (Theodorson, 1961). The theoretical language used to describe such ecological processes often focused on the organism level. Yet, it is instructive to be reminded that Hawley's (1950) highly influential book on the subject was subtitled "A Theory of *Community* Structure" (emphasis added), and much of the research over ensuing decades that flowed from this disciplinary paradigm examined structure and change of social aggregates. Dozens of studies flowed from Shevky and Bell's (1955) early "social area analysis," which attempted to relate measures of social heterogeneity to ecological patterns and processes at different levels in the urban hierarchy. Studies in "factorial ecology" (e.g., Hunter, 1971) extended this line of research by applying such formal statistical routines as factorial analysis and principal components analysis to understand the latent structure underlying social systems. Around the same time, methodological sophistication was brought to the examination of residential segregation (Duncan and Duncan, 1955), a general line of social inquiry at the areal unit level that persists to this day. Despite the fact that general issues of spatial distribution and differentiation can be found in the sociological, human ecological and demographic literatures throughout the 20th century, we argue in the following section that sometime around mid-century a substantial share of demographers changed the lens on their research to focus not on spatial aggregates but on individuals, families and households.

THE SHIFT FROM MACRO-DEMOGRAPHY TO MICRO-DEMOGRAPHY

Two forces likely influenced the change of focus from macro- to micro-demography. One was the emergence of large scale microdata files that provided access to detailed individual/household-level data. The initial motivation for such data sets was a response to the low levels of fertility in the U.S. during the 1930s (Kiser and Whelpton, 1953). The continued analysis of “data of the census type,” while providing some understanding of “the relation of fertility to such factors as region, rural-urban residence, colour, nativity, occupation, education and other measures of socio-economic status,” could not yield information regarding the underlying “social and psychological factors affecting fertility” (Kiser and Whelpton, 1953:95). This recognition prompted the first ever large effort in the U.S. to study contraception practice and planned family motivations at the husband-wife level of analysis: the *Indianapolis Study of Social and Psychological Factors Affecting Fertility* was carried out in Indianapolis, in 1941 with 1,444 “relatively fecund” couples (Whelpton and Kiser, 1946, 1950). The success of this effort led to additional localized survey efforts such as the Detroit Area Study (see Freedman and Sharp, 1954; Freedman, Goldberg and Sharp, 1954) and later to national surveys, including initially (1) the Growth of American Families (GAF) studies carried out in 1955 and 1960 (see Freedman, Whelpton and Campbell, 1959; Whelpton, Campbell and Patterson, 1966), (2) the longitudinal Family Growth in Metropolitan America Study (see Westoff and Mishler, 1961), and (3) the series of six National Fertility Surveys. The value of microdata to analyze individual knowledge, values, beliefs and behaviors was well established by the 1970s.

Also by the 1970s, the U.S. Census Bureau had begun to release anonymized public use microdata sample (PUMS) files from the decennial census.[5] These complemented the microdata files from the long-running Current Population Survey, also conducted by the Census Bureau. By the 1980s more basic demographic research in the U.S. was being conducted using microdata files than from census files or reports presenting data for areal aggregates.

A second force behind the shift away from the analysis of spatial aggregates to micro analysis was the predicament presented by what came to be known in sociology as the "ecological fallacy." Gehlke and Biehl (1934), in a brief but pioneering study of scale effects in the analysis of census tract data, concluded that "a relatively high correlation might conceivably occur by census tracts when the traits so studied were completely dissociated in the individuals or families of those traits" (1934:170). It was Robinson (1950), however, who pressed this point forcefully in what became required reading for demography graduate students in the decades to follow. He demonstrated the pitfalls of using aggregated data to draw inferences about individual characteristics and relationships. Robinson's paper quickly led to a conscious desire on the part of demographers to avoid the trap of the ecological fallacy. Even more damaging for those who espoused ecological analysis, however, were the scale and aggregation biases inherent in the analysis of traits and relationships using areal aggregates. This was not good. If one's findings were strongly dependent on whatever specific areas (census tracts, counties, etc.) happened to be available to the researcher, and, additionally, acknowledging the often arbitrary boundaries of those units (whatever their spatial scale), what importance should be attached to those findings? Quantitative geographers were also wrestling with this dilemma (although by a different name: "the modifiable areal unit problem" – or MAUP), and today some argue that the inability of geographers to respond satisfactorily to critics who pointed to the problems of scale and zoning in geographical analysis actually precipitated a decline of interest in quantitative geography in the 1980s (Fotheringham, Brunsdon and Charlton, 2000).

But dilemmas abound, even when taking precautions against the ecological fallacy. It frequently is mentioned by those who study ecological aggregation biases (e.g., Jones and Duncan, 1996), that those who strictly eschew the analysis of areal aggregates (thereby avoiding the ecological fallacy) ironically run the risk of falling prey to the "atomistic fallacy." Here, the individual is considered in isolation of his/her environment. Alker (1969) points out that choosing to work at the individual level misses the context in which individual behavior occurs, while choosing to work only with areal aggregates fails to recognize that it is individuals, not aggregates, who act. We return to this issue in a later section in which we discuss the emergence of multilevel models. We simply note here that attention to the various analytical difficulties surrounding the matter of aggregation bias reinforced the inclination on the part of sociologists and demographers to take full advantage of the opportunities afforded by the increasing number of microdata files entering the public domain.

And so they did. The shift toward micro-level analyses established the preeminence of the individual, family or household as the demographic actor, and left only a small proportion of professional demographers continuing the serious scholarly inquiry of population change among demographic aggregates.

CONTINUED INTERSEST IN SPATIAL DEMOGRAPHY AMONG SOME DEMOGRAPHERS

Despite the shift in emphasis to micro-demography, there remained some demographers for whom ecological analyses continued to hold fascination. Much of this work falls into two categories: (1) migration and population distribution research, work carried forward predominantly by rural demographers, and (2) population estimation research, work which came to dominate the portfolio of many applied demographers.

Rural Demography

Much research regarding migration and population redistribution originated in the 1930s, perhaps due to the extensive social upheaval resulting from the Great Depression and the enormous disruption of the national economy, and of jobs and family life. Research into the determinants and consequences of human migration carried out by social scientists at the University of Pennsylvania and elsewhere (see, for example, Creamer, 1935; Goodrich, Bushrod and Thornthwaite, 1936; Thornthwaite, 1934), and by teams of research analysts assembled by the Division of Social Research of the Federal Works Progress Administration (see, for example, Lively and Taeuber, 1939; Webb, 1935; Webb and Brown, 1938), generated interest in migration that sparked the intellectual imaginations of scholars for the next several decades.

Research into the dynamics of internal migration was carried out largely in the context of massive metropolitanization in the U.S. It focused on the shifts of population into the Western region of the country, on the interregional flows of blacks from rural communities in the South to the expanding industrial centers of the Northeast and North Central regions, and on the exodus of populations from farms and rural communities throughout the nation. Much of this research was descriptive in nature. Almost all of it was spatial.[6]

A similar line of research was developed following the release of the 1970 and 1980 censuses, when it was discovered that patterns of internal migration had shifted and nonmetropolitan counties were growing at higher levels than their metropolitan counterparts (Beale, 1975; Fuguitt, 1985). By the 1980s natural population decrease, especially among nonmetropolitan counties, had also emerged as a subject of increasing interest among demographers. This development was the consequence of agricultural adjustments in rural America, declining rates of fertility everywhere, and migration patterns that pulled many young people out of rural areas upon graduation of high school and the "aging in place" of older rural residents (Beale, 1969; Johnson, 1993).

Returning for a moment to mid-century, the 1940s and 1950s witnessed another critical thread of research that was to be very important to the development of spatial demography in the U.S. Around this period, migration research began to focus on the migration *event*, per se, such as how to conceptualize migration, how to compute migration rates, and how to manipulate other variables to derive estimates of net migration for an area. This work was strongly rooted in substantive migration studies of the 1930s and 1940s (for example Hamilton, 1934; Hamilton and Henderson, 1944; Hutchinson, 1938; Shryock, 1943; Shryock and Eldridge, 1947). But in the 1950s, and on into the 1960s, several important methodological studies brought conceptual clarity to these issues and set in motion the routine production of methodologically sound estimates of net migration.

This research was important to spatial demography because migration was not a reported or registered event in the U.S. Instead, migration exchanges among areas had to be estimated from aggregated data. Eventually, component models for calculating population estimates and projections required that reasonable estimates of net migration and of net migration rates be made available, and these estimates increasingly were based on the analysis of population change among small geographic areas. Because the Census Bureau was not engaged in population estimation below the state level prior to the 1970s, and because it frequently fell to rural sociologists and agricultural economists in Land Grant colleges of agriculture (due to the mission of such institutions) to respond to the need for substate population estimates, many demographers in rural sociology departments around the country found themselves actively engaged in the production efforts of population estimation for relatively small areal units in the 1950s and 1960s (see Voss, 1993, for citations and a general overview of this literature). In the 1970s this work coalesced under a new rubric within the population sciences: applied demography.

Applied Demography

This brings us to an important second category of continuing work in spatial demography: population estimation research. In addition to advances in migration research, the 1950s was also a decade of major improvements in the development of population estimation models for application at the substate level (i.e., counties, cities, and even smaller geographic areas). There were three pivotal activities during this period, and each extended the focus on spatial units, thus continuing the role of space in the population sciences, even while many demographers had begun to shift their analytical efforts to the emerging microdata files.

First was the model development work that occurred primarily at the U.S. Census Bureau and in selected university settings. Indeed, it was the early 1950s that spawned small-area population estimation models that even today have been improved upon only modestly. Second was the production work (i.e., the production of small-area population estimates) that found its way into state and local agencies rather than the Census Bureau. Third were the few early tests of various estimation methods against the census counts of 1950 (see, for example, Schmitt 1952; Siegel, Shryock and Greenberg, 1954), and the significant advances in population estimation and forecasting during the 1960s.

In the 1970s, the emergence of state and local demography and, somewhat later, the field of business demography within the Population Association of America, brought a fresh perspective to the analysis of spatial units. This group of demographic practitioners appropriated for their work the term "applied demography," the distinguishing feature of which is that it involves almost exclusively the analysis of demographic data or the production of population estimates and forecasts for spatial units (see Merrick, 1987; Murdock and Ellis, 1991; Rives and Serow, 1984). Thus, applied demographers joined hands with rural demographers and brought renewed vigor to the study of the demography of space. Their work was aided enormously by the summary tape files from the 1970 census – the first census to place into the hands of demographic researchers huge electronic files of census data for geographic areas as small as census blocks. The importance of these files to the development of business demography in the U.S. has been chronicled by Russell (1984) and by Merrick and Tordella (1988).

The decade of the 1980s witnessed yet another boost to the analysis of spatially-arrayed data. The coming together in the late 1980s and early 1990s of five remarkable products radically changed the world of demography, including parts of demographic study not traditionally concerned with spatial variation. These products were (1) the Census Bureau's TIGER files – digital, seamless, block-level geographic databases for the U.S. released as a 1990 Census product, (2) the summary tape files from the 1980 and 1990 censuses, (3) extensive natural resource, crime, and epidemiological databases – all of which were largely outside the scope of traditional demographic interest, (4) incredibly powerful geographic information system (GIS) software for mapping and, importantly, for *integrating* spatially-arrayed data from diverse and disparate georeferenced systems, and finally, (5) the awesome, but affordable, computing hardware platforms on which to bring together these various elements. These elements, having converged so forcefully by the early 1990s, began to alter the way in which spatial demographic research was carried out. Together, these forces motivated the formation of new and broadly interdisciplinary collegial relationships on campuses and elsewhere, and began to foster the development of hypotheses and researchable questions in areas where only a few demographers and ecologists had previously ventured.[7]

RECENT RENEWED INTEREST IN SPATIAL DEMOGRAPHY

By the mid-1990s, demographers could be described as pursuing population science along two different lines.[8] The larger group consisted of those demographers whose research continued to mostly ignore the dimension of geographic space and focused the locus of demographic action on the individual, family or household. The smaller group, among them rural demographers and applied demographers, continued the much earlier tradition of spatial demography by focusing on areal aggregates as units of analysis. We argued in the preceding section that trends in technology during the 1980s and 1990s brought increasing sophistication to the work of demographers in the latter group. However, another important trend that emerged in the 1980s in the disciplines of geography, regional science and spatial econometrics was, until quite recently, largely overlooked by spatial demographers. In the following subsections we examine (i) the origins of formal statistical models to handle geographically referenced data, (ii) the role of regression analysis in spatial demography, (iii) the special nature of spatial data that requires modification to the standard regression model when "spatially autocorrelated" demographic attributes among geographic units are being analyzed, (iv) how and why spatial autocorrelation arises, (v) how these effects become manifest in large-scale and small-scale spatial processes, (vi) some of the emerging tools of exploratory spatial data analysis (ESDA) are aiding the analysis of such data, (vii) the need for attention both to "global" as well as local diagnostic tools, (viii) the role of geographically weighted regression as a new tool for exploring spatial variation in covariate relationships, and, finally, (ix) the emergence of multilevel models.

The statistical literature contains a number of critically important early works which form the theoretical bedrock of today's field of study known as spatial data analysis (Moran, 1950; Geary, 1954; Whittle, 1954; Besag, 1974). However, it was not until the publication by Cliff and Ord in 1973 of a monograph simply titled *Spatial Autocorrelation* (and its much expanded revision in 1981) that social scientists could turn to a comprehensive, thorough and systematic treatment of the topic.[9] Before the end of the 1980s, geographer and regional scientist Luc Anselin had brought together and synthesized the literature on "spatial econometrics" in his remarkably influential monograph, *Spatial Econometrics, Methods and Models* (1988). Other works also had appeared in the interim (e.g., Gaile and Willmott, 1984; Griffith, 1987; Ripley, 1981; Upton and Fingleton, 1985), and at decade end, the fields of spatial statistics and spatial data analysis were solidly established. Their influence was clearly felt in the scholarly analyses of georeferenced data throughout many of the social sciences, eventually including sociology and demography.

We also single out for special mention three seminal articles that appeared in the sociological literature in the early 1980s. Two thoughtful and well placed reviews by mathematical sociologist Patrick Doreian (1980; 1981) invited the attention of sociologists to the need for special treatment of spatial data in linear regression modeling. Around the same time, Loftin and Ward (1983) published a reanalysis of an earlier influential work (Galle, Gove and McPherson, 1972) highlighting the risk to analysts of ignoring spatial autocorrelation. Important as these early sociological treatments of spatial data were (and might have been in terms of influencing subsequent research in our discipline), the message did not immediately take. With but few exceptions from the early 1990s (e.g., Land and Deane, 1992; Land, Deane and Blau, 1991), sociologists and demographers did not begin seriously to grapple with the issue of spatially autocorrelated data in regression models until the mid- to late-1990s.

In leaving this brief section, we pause to pay homage to one other early, seminal work. This is the 1961 monograph by Duncan, Cuzzort and Duncan. Early as it was, and written by sociologists rather than geographers, the book clearly anticipated the developments in spatial statistics that unfolded over the ensuing 30 to 35 years. The authors did not address in detail such matters as spatial autocorrelation and spatial modeling. But the book does acknowledge the issues of aggregation bias, spatial dependence and spatial lags, and, in pointing to Whittle (1954) and Geary (1954), was bold enough to suggest "that a breakthrough to a solution [to the problem of spatial autocorrelation in data] may be imminent" (1961:11). That forecast was largely fulfilled a decade later with the first book by Cliff and Ord (1973).

Spatial is Special

When analyzing population change for a large number of spatial units (e.g., counties), it is the natural inclination of sociologists and demographers to move from simple descriptive analyses to begin asking such questions as: How might these data be modeled? How well can I account for variability in attribute values among geographic units by identifying other covariates of our attribute of interest? Such analysts have traditionally turned to multivariate regression modeling, the common, workhorse methodology in the social sciences, to answer such questions. Regrettably, standard regression approaches to data tied to spatial units bring special complications that have not always been understood or appreciated, even by spatial demographers. The idea that somehow "spatial is special" is a notion that has begun only slowly to enter the awareness of quantitative demographers.

Over the past two decades, increasing attention has been drawn to the fact that spatial data require special analytical approaches. Many of the techniques documented in standard statistics textbooks and taught in our "methods" classrooms unfortunately confront significant difficulties when applied to the analysis of geospatial data. These problems are summarized by language more familiar to geographers and regional scientists than to demographers: spatial autocorrelation, the modifiable areal unit problem, scale and edge effects. But the emphasis on "problems" fails to capture the fact that there also is a benefit arising from the special nature of spatial data. Aspects of space (e.g., distance, proximity, and interaction), when properly acknowledged and incorporated into one's model, can overcome the complications of space and error dependence, improve the specification of models based on spatial units, and provide estimates of parameters that are less subject to statistical bias, inconsistency or inefficiency. Further, such approaches can contribute to theoretical notions regarding the role of space in social relationships and processes.

Although rural demography has long maintained a strong focus on patterns and trends that vary spatially, the field has not been very sensitive to these more recent analytical issues, and rural demographers have largely failed to adopt the methods of formal quantitative spatial analysis that have emerged in the fields of geography, regional science and spatial econometrics during the past decade or so (Lobao and Saenz, 2002). It is encouraging that such insensitivity is waning, as evidenced by the spatial focus of a recent Rural Sociological Society presidential address (Lobao, 2004).

By way of illustration, we examine the correlates of county-level population change in the Great Plains between 1990 and 2000.[10] A thorough researcher will carefully begin by exploring the behavior of the variables of interest using the standard tools of exploratory data analysis (EDA) – and thus we begin. In the present example, one that will be used throughout the remainder of the paper, interest is focused on population change and a few potentially useful (theoretically based) covariates of population change: farm dependence, population age structure, climatological conditions, metropolitan status, county size (acreage) and county size (initial population). The latter two variables are of less substantive interest and are included in the model as possible controls for heteroskedasticity. When undertaking initial EDA explorations of spatial data, in addition to examining the univariate statistical distributions of the attributes (for normality, outliers, etc.) and their bivariate relationships with the dependent variable (for linearity), it also is worthwhile to develop a sense of the spatial distributions of the attribute values. As illustrated in Figure 1, the map of population change indicates that roughly 1-in-12 Great Plains counties suffered population loss over the decade of the 1990s in excess of 10% while more than 1-in-4 counties witnessed population growth of more than 10% during the same period. Growth characterizes many of the east-west boundary counties while loss is largely concentrated along a north-south axis among the central counties and along the northern edge of the region. These concentrations lead to two initial conclusions: First, there is sub-regional variation within the larger Great Plains region (something we discuss below as *spatial heterogeneity*). Second, there appears to be evidence of spatial clustering, such that counties experiencing growth seem to be near other counties experiencing growth while those suffering loss similarly are near other counties undergoing loss (which we discuss below as possible evidence of *spatial dependence*).

Although we have introduced the terminology earlier in our chapter, we have not yet discussed specific methods to quantify the extent of *spatial autocorrelation* in our data or how to deal with it. But by simply mapping our data, and reviewing the distributions of the variables across space, it becomes evident that spatial patterning (and, therefore, spatial autocorrelation) will have to be addressed in our modeling strategy. In addition, scatterplots and related EDA graphics suggest that the most useful form of the dependent variable will be the natural log of the ratio P_{2000}/P_{1990}. Two of the independent variables also were log transformed: County Acreage and Initial Population.

[Figure 1 About Here]

We now discuss more formally the topic of spatial autocorrelation. For those who have studied time-series analysis, the parallels to temporal autocorrelation will be recognized. For most social phenomena mapped in space, locational proximity usually results in value similarity. High values tend to be located near other high values, while low values tend to be located near other low values, thus exhibiting *positive* spatial autocorrelation (Cliff and Ord, 1973; 1981). Such appears to be the case of population change in the 1990s within the Great Plains. Less often, high values may tend to be co-located with low values (or vice versa), as “islands” of dissimilarity, or in a spatial “checkerboard” pattern that exhibits *negative* spatial autocorrelation. In either case, the units of analysis in spatial demography likely fail a formal statistical test of randomness and thus fail to meet a key assumption of classical statistics: independence among observations. With respect to statistical analyses that presume such independence (e.g., standard regression analysis), positive autocorrelation means that the spatially autocorrelated observations bring less information to the model estimation process than would the same number of independent observations. The greater the extent of spatial autocorrelation, the more severe is the information loss. Again, this fact has been known for several decades.[11]

Yet, examples of research where spatial autocorrelation is even acknowledged, much less explicitly incorporated into regression models, are embarrassingly absent from the sociological literature, generally, and from the literatures of sub-disciplines such as demography that consider themselves to be methodologically mature and rigorous. Exceptions to this blanket indictment can be found. Most notably, in sociology one would point to the work of Land, Deane, and Blau (1991), Baller and Richardson (2002), and Sampson (1988, 1991), to name just a few. While a handful of additional studies could be cited, the point still holds: These important additions to our methodological toolkits have not been widely adopted, and manuscripts which analyze spatially referenced data using standard regression approaches without acknowledgement of potential estimation problems arising from spatial autocorrelation continue to find their way into our major journals.[12]

How Does Spatial Autocorrelation Arise?

We have pointed out that *positive* spatial autocorrelation is very commonly a property of mapped social and economic data. Negative spatial autocorrelation is much less commonly observed, although there are interesting exceptions (Tolnay, Deane and Beck, 1996). A quick explanation for the presence of spatial autocorrelation can be found in the oft-cited "first law of geography" enunciated by Tobler in 1970: Everything is related to everything else, but near things are more related than distant things (1970:236). While useful as a short-hand reminder, Tobler's first law is somewhat unsatisfying because it doesn't tell us *why* this phenomenon arises in practice, or what difference it makes. Why, for example, do state sales tax levels tend to cluster regionally? Why does the percentage vote cast for presidential candidates show systematic geographic clustering? Why do high housing values cluster in some neighborhoods of a large city and low values in other neighborhoods? Or, as in the case of our example, why is relatively high growth concentrated in some sub-regions of the Great Plains and low growth (or decline) in others?

While there exist some helpful reviews on this topic (e.g., Wrigley et al., 1996:30-31; Brueckner, 2003), the answers to such questions can only be approximated with models of the spatial process that inevitably are imperfect. Such answers generally will be a function not only of the data being analyzed, but will depend strongly on the analyst's theory about the process, assumptions underlying both the data and the statistical model(s) selected to describe the nature of the relationships under investigation. For example, the four substantively interesting independent variables selected for our example (farm dependence, population age structure, climatological conditions, metropolitan status) and two additional control variables were not chosen at random, but have been identified in earlier work addressing population change. Our task is to appropriately analyze the nature of their joint relationship with population change while simultaneously accounting (or correcting) for spatial process relationships at work in the data.

Exploratory Spatial Data Analysis

While much of the growing literature in spatial data analysis focuses on matters of specification tests, parameter estimation and advanced tools such as Monte Carlo simulation, any proper empirical analysis must begin more simply by exploring and understanding one's data. Continuing our earlier discussion of EDA, many of the techniques first codified by John Tukey (1977) and later expanded by Tukey's colleagues (Hoaglin, Mosteller and Tukey, 1983, 1985) are also appropriate for the exploration of spatial data. Once again, however, some of the unique aspects of spatial data make exploratory *spatial* data analysis (ESDA) a field that has attracted considerable attention in and of itself. The science of creating and interpreting maps of spatial data, for example, is the topic of a large literature fostered by the development over the past 30 years of powerful geographic information systems (GIS) (Chou, 1997). In addition, software for creating and testing a variety of neighborhood weights matrices, for generating various measures of spatial autocorrelation (both global and local), and for obtaining diagnostic results concerning error dependence in standard regression models are now widely available.[13]

Global and Local Diagnostics

We have not said much on the topic of global and local measures, but we use these terms throughout this chapter and they deserve at least brief clarification. Global measurements – whether they are overall descriptions of attribute values, measures of statistical relationships, or model accuracy assessments – are derived using data for the entire study region. For example, a global Moran's *I* statistic is a single measure describing the general extent of spatial clustering of an attribute across the region, conditional on the specific neighborhood structure imbedded in the chosen weights matrix. The global Moran's *I* can be scaled to the interval (-1,1) where a strong positive value indicates value similarity among neighbors (clustering), and a strong negative value indicates value dissimilarity (dispersion). A value near zero suggests no spatial relationship. Tests for significance use z-scores and the standard normal distribution.[14] As commonly applied to a full data set, Moran's *I* yields an indication of the extent of spatial clustering of similar values on a given attribute. It is a "global" measure of spatial autocorrelation and, as such, cannot by itself identify *where* "hot spots" of value clustering exist within the study region. Since spatial data are easily mapped, it is thus only natural that techniques have been developed for generating and mapping *local* counterparts to many global measurements.

Two useful ESDA tools in spatial data analysis are the Moran Scatterplot (Aneslin, 1996) and so-called LISA statistics (for Local Indicators of Spatial Association) such as the "local" Moran's *I* (Anselin, 1995). These devices are extremely valuable for gaining an understanding of the extent and nature of spatial clustering in a data set, and their use logically should precede and inform the process of hypothesis construction, model specification, estimation, and statistical inference. Rather than producing a single global statistic or parameter, local analysis generates statistics or parameters that correspond with researcher-specified smaller scale local areas (commonly called "neighborhoods"). It is helpful to re-emphasize this point. It is the researcher, not the data or some software program, who defines what is meant by a local neighborhood. As indicated earlier, this is done by specifying a matrix of weights (≤ 1) that characterizes the structure of local dependence.[15]

Figure 2 shows the Moran scatterplot for the Great Plains dependent variable: Log Percent Growth (for counties) 1990 to 2000.[16] In this exploratory view, the data are standardized so that units on the graph are expressed in standard deviations from the mean. The horizontal axis shows the standardized value of the log percent change for each county. The vertical axis shows the standardized value of the *average* log percent population change for that county's "neighbors" as defined by the weights matrix. Neighbors for this illustration are defined under the "first-order queen" convention, meaning that the neighbors for any given county "A" are those other counties that share a common boundary (or single point of contact) with "A" in any direction.[17] The upper right quadrant of the Moran scatterplot shows those counties with above average growth which also share boundaries with neighboring counties that have above average growth (high-high). The lower left quadrant shows counties with below average growth and neighbors with below average growth (low-low). The lower right quadrant has counties with above average growth surrounded by counties with below average growth (high-low), and the upper right quadrant has the reverse (low-high). Anselin (1996) has demonstrated that the slope of the regression line through these points conveniently expresses the global Moran's I value which, for our Great Plains example, is 0.54. This statistic is strongly positive, indicating powerful *positive* spatial autocorrelation (clustering of like values). Most counties are found in the high-high or low-low quadrants.

[Figure 2 About Here]

In Figure 3 we show a LISA cluster map which displays in a different way the same data as the Moran scatterplot of Figure 2. The map shows where in the Great Plains region the various combinations of high-high, low-high, etc. counties are found. Counties where the local Moran statistic is not significant (at the .05 level, based on a randomization procedure) are not shaded. Hotspot clusters of high growth counties surrounded by high growth counties are apparent in the sprawling east-central Texas region connecting metropolitan areas of Dallas-Fort Worth, Austin, San Antonio and Houston-Galveston. Another large high-high cluster connects the Denver-Boulder, Colorado Springs and Pueblo metropolitan areas, and a small high-high cluster is found mostly in the Missouri counties southeast of Kansas City. Coldspots include the (low-low) clusters of counties of central North and South Dakota, central Nebraska and Kansas, and two or three small clusters in the Texas Panhandle region and other areas of east-central Texas.

[Figure 3 About Here]

Individual high-low counties appear as islands throughout a central band running north-south through the Great Plains. Often these include small, somewhat isolated, metropolitan counties – e.g., Burleigh County (Bismarck) and Cass County (Fargo) in North Dakota. A few statistically significant (at the .05 level) low-high counties are also present in the region. These defy easy summarization, save for the fact that they are largely found along or near the borders of the region (and thus may suffer from unknown but troublesome edge effects). While this exploratory view of the data may suggest hypotheses for the analyst to confirm in the inferential part of any further analysis, perhaps the principal message for us at this point is that, taken together, the maps in Figure 1 and Figure 3 confirm that the process of growth in the Great Plains in the 1990s has somehow conspired to partition the region into identifiable sub-regions of growth and decline. Such spatial heterogeneity must be addressed in any further analysis of the data, and we begin by examining whether there might be parameter regimes that can be associated with the patterns observed in Figures 1 and 3.

Geographically Weighted Regression

One of the more recent and fascinating developments in the design of local statistics is the theoretical/conceptual background, and associated software, to explore how regression parameters and regression model performance varies across a study region. Geographically Weighted Regression (GWR) is similar to a global regression model in that the familiar constant, regression coefficients, and error term are all present within the regression specification. There are two ways in which GWR differs from standard (global) regression, however. First is the fact that a separate regression is carried out at each location (observation) using only the other observations that lie within a user-specified distance from that location. Second, the regression specification includes a statistical device which weights the attributes of nearby counties more highly than it does the attributes of distant counties. The result is a set of *local* regression parameters for each county. Otherwise stated, the regression is *localized* through the inclusion in the regression specification of the spatial coordinates of the units of analysis, and at each of these points is generated the full set of regression parameters and diagnostics based on the model specification and on methods by which units across space are swept into the localized regression estimation. The precise implementation of GWR is controllable by the analyst and is far too detailed for discussion here (see Brundson et al., 1996, 1998a, 1998b; Fotheringham et al., 1996, 1997a, 1997b, 1998, 1999, 2000, 2002). The important feature to emphasize, however, is that the output file enables the researcher to examine and map local parameter estimates and local regression diagnostics, thereby enabling assessment of the utility of the model for various portions of the larger study region.

Examples of such maps are illustrated in the various panels of Figures 4 through 6. Local R-squared statistics are mapped over the sample region in Figure 4, illustrating those areas where the model performs well versus those where the model "fit" is less precise. The local R-squared statistic in this example ranges widely from 0.230 to 0.740. We note that the model's highest performance is found roughly in southern Oklahoma and in the northwestern Plains counties in western North Dakota and eastern Montana. Lower model fits are generally found among the boundary counties but specifically in the Texas Panhandle region, in southern Iowa and, to a lesser extent, in western Nebraska. When referring back to the distribution of population growth (Figure 1), variation in model fit does not appear to associate closely either with areas of growth or areas of loss. For instance, the model fits relatively poorly (low R-squared values) both in the loss (Panhandle) and the growth (southeastern) clusters of Texas counties.

[Figures 4 through 6 About Here]

GWR parameter estimates and t-values can also be mapped and compared to gain further insight regarding spatial variation in relationships. We stress that these tools are exploratory in nature as opposed to explanatory. GWR can be a useful guide in showing where particular covariates of the response variable contribute strongly and where they do not. Figures 5 and 6 contain two panels each representing, respectively, the values of a locally estimated parameter (Panel A) and the local t-values (Panel B) for gauging significance.[18] The parameters shown are the intercept term (Figure 5) and that for one of the independent variables, Farm Employment (Figure 6). The linked spatial distributions of parameter and t-statistics are striking.

The map showing the distribution of the intercept parameter (Panel A in Figure 5) indicates that even after controlling for the response to predictive variation from the independent variables, the levels of population change reflected in the local intercept values varies across the Great Plains. According to the local intercept values, the model correctly picks up the higher levels of growth in the band of counties from southern Texas to northwestern Missouri. It also correctly picks up the higher growth in the area around (and north of) the Denver metropolitan area. It appears that the model over-estimates growth (i.e., the regression hyperplane floats too high) in western Montana and North Dakota.[19] The model appears to under-estimate growth (i.e., the regression hyperplane is too low) in northern Texas, southwestern Kansas and southern Minnesota, although Panel B (showing t-values) suggests that only the areas with the darkest shading likely achieve (corrected) statistical significance. That is, for this model, areas where the local intercept values are the highest may be the only areas where the t-values for the local intercept are sufficiently high.

The maps in Figure 6 reveal considerable variation across the region in the response of Log Population Growth to the extent of Farm Employment (net of other variables). The parameter varies from a low of -1.62 to a high of +0.51, although for nearly all parts of the region the parameter has a negative value, as hypothesized in the research. The corresponding local t-values suggest that only in sub-regions of the Great Plains where the t-value shading is the lightest can much stock be placed on the local parameter levels – although we note that this includes large areas of wheat growing territory in the western Plains.

These maps, also, become particularly telling when compared to the spatial distribution of change (Figure 1) and to one another. Smaller parameter estimates and lower significance levels for Farm Dependence are especially found among counties losing population between 1990 and 2000. Further, the distribution of lighter shading in Figure 5, indicating negative intercepts or estimated population loss, also appear in lighter shading in Figure 6, indicating a lower growth response from the extent of farm employment.

A GWR approach to regression analysis is a highly useful exploratory device for understanding parameter heterogeneity in one's data. The GWR software designed by Fotheringham and his colleagues offers the analyst options for various types of distance-decay weights, and also offers a number of options relating to the type of regression carried out and the number of units brought into a given regression.

Spatial Heterogeneity versus Spatial Dependence

As hinted at in the preceding section, large scale regional differentiation is an important component of spatial variation. Most treatments of spatial data analysis refer to such sub-regional variation as "spatial heterogeneity." We follow the usual convention of referring to spatial heterogeneity as the lack of stability across space of one or more attribute values (more formally expressed as lack of stability in the moments of the joint probability distribution of the attributes), or as lack of stability of relationships among the attributes as measured by correlation statistics or regression parameter values (see Anselin, 1988).[20] The term "heterogeneity" simply gives recognition to the common observation that values of a variable, or values of relationships among variables, are not the same across space. That is, few social processes are spatially *homogeneous*. In our example, the nature and extent of population change and its associations with correlated factors is distributed unequally across the Great Plains. In particular, the term spatial heterogeneity applies to large-scale variation in a spatial process, where "large-scale" is taken to mean scales involving distances that extend well beyond any "neighborhood" structure imposed on the data (as discussed further below). Spatial heterogeneity often is also referred to as "first-order variation" or as "first-order spatial effects" in a spatial process (Bailey and Gatrell, 1995). The inclusion in a regression model of one or more variables might satisfactorily account for the observed spatial heterogeneity. If population growth is mainly concentrated in specific types of counties, for example, and if this is the spatial process dominating our data, then inclusion of a dummy variable to identify these counties would not only boost the explanatory value of the model, but also would reduce the extent of spatial heterogeneity and, ideally, also reduce or eliminate heteroskedasticity and spatial autocorrelation among the residuals.

"Spatial dependence" ("second-order variation") refers to small-scale spatial effects that manifest as a lack of independence among observations. The assumption is that dependence among the observations derives from spatial interaction among the units of analysis which ideally can be defended theoretically and which can be statistically captured by a spatially lagged "neighborhood" effect in a model of the spatial process. Such spatial lags may involve the dependent variable, one or more of the independent variables, the error term, or some combination of all three. Properly specified and estimated, such a model with spatial lags is able to "borrow information" or "borrow strength" from neighboring observations because of the spatial autocorrelation among the units of analysis (Haining, 2003:36).[21] In our example, a carefully selected variable to account for spatial heterogeneity in the data might boost the explanatory value of the model and largely remove the large-scale spatial process, but spatial autocorrelation would persist if a spatial dependence process also were indicated. In other words, there would remain in the data a more complicated, interactive spatial relationship among neighbors that suggests the requirement for some type of autoregressive term in the regression specification.

While the preceding discussion appears to present a sequential, orderly, step-by-step process, in practice the situation is more complex. Often the data suggest a combination of both first-order and second-order effects or fail to give unambiguous clues to one or the other. For example, the map of recent population change in the Great Plains (Figure 1) reveals an uneven gradation of population growth and decline in the 1990s that defies any simple and immediate explanation. Several clusters of counties with high growth are apparent (e.g., east-central Texas, central Missouri, eastern Colorado) – certainly very different counties in terms of topography, cultural history, and industrial base. Clusters of slow growth or population decline are apparent across the most northern Plains counties (Montana, North Dakota and northwestern Minnesota), in much of Nebraska and Kansas and in the Texas Panhandle. Might these clusters be accounted for by established historical or legacy effects, and might they be "explained" by a few well chosen independent variables? Or might there exist neighbor influences among these counties (e.g., spatial spillovers or diffusion) that account for the spatial pattern? The first question inquires about possible spatial heterogeneity; the second about possible spatial dependence.

For whatever reasons, some parts of the Great Plains reveal growth (some with relatively high growth) and other parts show low growth or population decline. The goal of the researcher is to identify potential covariates of population change in the region and to explain the variation in growth among Great Plains counties using a combination of traditional modeling approaches and newer spatial modeling approaches.

Regardless of the analyst's theoretical notions about the process giving rise to the observed spatial pattern, the analysis generally proceeds along an established path. First, based on a combination of theory and review of the relevant literature, a defensible OLS regression model is fit to the data, and a test for autocorrelation in the residuals is carried out. Tests for spatial error dependence generally take two forms: (1) a general test for spatial autocorrelation of residuals against the alternative of no autocorrelation, and (2) a set of tests against a specific *form* of spatial process. The first such generalized test usually is the calculation of a region-wide, or “global,” measure of spatial autocorrelation such as the Moran *I* statistic, as discussed above. The second set of specific tests is based on the maximum likelihood principle (see Anselin, 2001; Anselin and Bera, 1998). We comment on these tests in interpreting the regression model results, below.[22]

Unfortunately, in the cross sectional context, there do not exist statistical tools to inform the analyst which spatial process, heterogeneity or dependence, has generated the data at hand. If repeated observations (over time) are available for cross sectional data, the story is less bleak and there may be sufficient data to distinguish between the two spatial processes. Moreover, the distinction between large-scale variation and small-scale variation in an attribute is rarely easily determined. It depends in part on how the analyst has chosen to define “neighborhood” structure. As described earlier, the latter is expressed formally in a proximity or weights matrix. This matrix captures the researcher’s view of the *nature* of neighboring influences. The actual *degree* of such influences is captured by the data and a parameter to be fitted along with other parameters. A strong theoretical framework and some testing of alternatives should guide the choice of spatial weights, as they play a strong role in determining statistics or parameters derived using a specific weights matrix. This matrix is required for the calculation of spatial autocorrelation statistics, such Moran’s *I*, and for specifying and estimating regression models incorporating spatial dependence terms to account for spatial autocorrelation in the data.

Thus far in our discussion, spatial autocorrelation has been described as something that arises from a substantive spatial process. In the case of spatial heterogeneity, there are presumed forces (geophysical, cultural, social or economic) that somehow work to constrain or otherwise serve as influences causing individuals (or families) with similar attribute bundles to find themselves (by choice or otherwise) to be physically located near one another. In the case of spatial dependence, presumed *interaction* among individuals results in spatial clustering. The large body of literature springing from the theory of social adoption/diffusion (Rogers, 1962), for example, captures well the notion of spatial dependence.[23]

However, spatial autocorrelation can also arise as a nuisance (Anselin 1988). Most commonly this occurs when the underlying spatial process creates regions of value clustering that are much larger than the units of observation chosen by (or available to) the analyst. An example of such nuisance autocorrelation might be present in the distribution of population growth in the Great Plains. The large cluster of high growth counties in central Texas (Figure 1) is discussed above as a sub-region contributing to spatial heterogeneity, and this sub-region contributes heavily to the fairly high global Moran's *I* statistic. Stepping back from the data for a moment, one quickly observes that this sub-region of high growth is considerably more extensive than is the particular lens (counties) through which the process is viewed. When units of analysis are smaller than the boundaries of areas having high or low attribute values, spatial autocorrelation in the observations is inevitable. Such nuisance autocorrelation must somehow be recognized and eventually brought into the formal analysis of the data. Customarily this is handled in models of spatial heterogeneity with the use of dummy variables to identify different "spatial regimes" (Anselin, 1988).

The goal of the researcher is to specify and estimate models that reasonably account for the spatial effects present in the data, and, generally, these effects are modeled as spatial heterogeneity and/or spatial dependence. When first examining a spatial relationship, the researcher must ask whether the association appears to be a *reaction*, characteristic of heterogeneity, or an *interaction*, indicative of spatial dependence. Anselin, referring to earlier studies, discusses this difference using the terms "apparent contagion" (spatial heterogeneity) and "real contagion" (spatial dependence) (1988:15).

If the association is merely a reaction to some geophysical, cultural, social, or economic force that works to create spatial patterning, then a modeling strategy with a standard regression structure may be appropriate. Often it is discovered that independent variables in the model (themselves spatially autocorrelated) can account satisfactorily for the observed spatial autocorrelation in the dependent variable. In such a situation, regression residuals generally are found to be negligibly autocorrelated, and standard regression approaches are adequate. At other times, the researcher might introduce a variable or variables that capture the influence of the geophysical or other forces underlying the spatial effect. Fotheringham, Brunsdon and Charlton provide several examples – GWR among them – of how this particular issue might be approached (2002:15-24). As a general matter, it is wise practice to model, perhaps with a simple regression specification, the heterogeneity of a spatial process before spatial dependence modeling is undertaken. The reason for this is that spatial dependence modeling assumes a homogeneous (technically, stationary) process. One good option for a second, spatial dependence, model is to take the residuals from the first regression as the new dependent variable for the model incorporating a spatial dependence term – a strategy we employ below for the Great Plains population growth model.

If, on the other hand, the association is an interaction suggesting some type of formal dependency among areal units, then a modeling strategy with a spatially dependent covariance structure is the way to proceed. In this instance, controlling for heterogeneity likely will not fully remove the spatial effects within the data. An alternative is needed – a spatially oriented approach that formally commonly incorporates a spatially lagged dependent variable or spatially lagged error term. In a conceptual way this approach is a spatial analogue to the treatment of temporal variables in time series analysis. The added dimensionality of geographic space and the absence of any form of natural order in spatial data, however, render many statistical procedures in time series analysis inappropriate in spatial analysis. For details on spatial dependence modeling, the reader is advised to begin with Anselin (1988), Anselin and Bera (1998), and Anselin (2003). This literature presently is expanding at a very rapid pace.

Concluding our discussion of population change in the Great Plains, we attempt to bring several of these thoughts together by presenting some regression results in Tables 1 and 2. Each table has three columns of regression parameter values and some useful diagnostic terms.

[Table 1 About Here]

In Table 1, we approach our task without first attempting to account for spatial heterogeneity in the data. As often is done in such analyses, we advance immediately to the search for a properly specified regression model. In this table, we take the dependent variable discussed above (Log Population Growth) and regress this on the six independent variables also previously discussed. The first column shows the results of a standard OLS regression. The demographic theory behind the model is not discussed here, but can be found in White (2003). It should be mentioned in passing that we recognize, but do not further discuss, the complications of using a ratio dependent variable where the denominator of the dependent variable is also included among the independent variables.[24] The OLS model performs reasonably well. Several parameter estimates are strongly significant, parameter signs are as anticipated, and the adjusted R^2 statistic achieves a respectable level of 0.347. Having anticipated and checked for it, however, we quickly note a critical flaw: the regression residuals show strong autocorrelation (Moran's $I = 0.368$), a clear indication that the model is in violation of the standard iid assumption regarding regression errors. The regressors have not satisfactorily accounted for obvious spatial heterogeneity and/or dependence in the data, and a correction to the model clearly is indicated. But what type of correction?

At this point one's theory of the process under investigation is asked to do some heavy lifting. Does the residual dependence in the model likely stem from omitted variables on the right-hand side of the regression specification, thus suggesting the utility of a spatial error model? If so, what variables? On the other hand, might there be spillover influences among growing counties or declining counties that directly influence the growth rates of their neighbors? Fortunately, to supplement our theory about the process, we receive some additional guidance from other diagnostic statistics applied to the residuals in the OLS regression.

Two such regression diagnostics are shown at the bottom of the first column: Lagrange Multiplier test statistics which, for this example, weakly suggest a preference for a spatial lag specification (a lagged dependent variable term on the right-hand side) over a spatial error specification (a lagged error term).[25] While often very helpful, these diagnostic statistics are also known to be unreliable in the presence of unresolved heterogeneity in the model. We therefore present both models (columns 2 and 3 of Table 1) partly as a concession to our uncertainty about the process but partly, also, to see what additional understanding we might glean from examination of both the spatial error and lag specifications.

We comment first on the results of the spatial error model shown in column 2. In this specification the error variance-covariance matrix is assumed to have non-zero off-diagonal terms (thus permitting the extent of autocorrelation in the errors to be estimated by a parameter, **8**). The underlying assumption in the model (apart from those assumptions justifying a linear specification and the particular set of selected independent variables) is that spatial autocorrelation in the dependent variable is caused by one or more spatially autocorrelated "omitted variables" on the right-hand side of the regression specification. Such a specification is often appropriate in the absence of a theoretical rationale for assuming interaction dependence in the dependent variable. If indeed a spatial error specification is the "correct" specification for the process, then the estimated parameters from the OLS regression are unbiased but inefficient (the standard errors of the parameter estimates are downwardly biased). We note that the parameter estimates in column 2 (compared to column 1) are modestly different. Troubling, perhaps, is the sign reversal for the parameter estimate for the initial population variable. A higher likelihood and lower AIC score in column 2 are encouraging, but the pseudo R^2 statistic is considerably lower than achieved in the OLS run. We note two additional desirable features of this model: the spatial error parameter (**8**) is strong and the model has eliminated any diagnostic evidence of a remaining spatial lag influence (i.e., the Lagrange Multiplier test for lag specification is small and not statistically significant. The model appears to be a plausible alternative to the OLS specification.

We now comment on the spatial lag model shown in column 3. In this specification, a lagged version of the dependent variable appears on the right-hand side of the regression specification. As discussed above, the particular form of the spatial lag is determined by the researcher through a definition of "neighborhood," operationalized by a weights matrix. The strength of the lag effect is estimated by the lag parameter, ρ. A spatial lag specification is particularly appropriate when there is structured spatial interaction involving the dependent variable and when the analyst is concerned about measuring the strength of that interaction or is concerned about having "correct" estimates of the regression parameters which can be obtained only after removal of the effect of spatial autocorrelation in the process. If a spatial lag model is the "correct" specification for the process at hand, then the incorrect OLS specification will suffer from biased and inconsistent parameter estimates.

We note modest changes in the estimated regression parameters, including the observation that inclusion of the lag term has removed the importance of the initial population variable. The spatial lag parameter (ρ) is strong and significant and, of the three models, this specification has the highest likelihood and lowest AIC score. No indication of residual error correlation is apparent. Our inclination at this point is to prefer the lag specification over the error specification, and we are not at all uncomfortable with the implied theoretical position that sprawl and residential spillover growth into neighboring counties (and, elsewhere, spillover influences of population loss) are likely the source of difficulty in the OLS misspecification. However, we introduced Table 1 with the admission that we had not first attempted to remove the apparent spatial heterogeneity in process before proceeding directly to spatial regression modeling. As spatial dependence analysis is unreliable in the face of strong spatial heterogeneity, we seek now to atone for our indiscretion by first attempting to remove at least some of the heterogeneity in our dependent variable.

We proceeded as follows. First, a simple dummy variable was created to indicate counties with above and below average growth. Our dependent variable (log growth) was then regressed on this indicator variable and the residuals from the regression were saved. We have little interest in the substance of this regression. It was carried out simply as a means of reducing spatial heterogeneity before embarking on a second set of spatial regressions – this time taking as the dependent variable the residuals from the simple dummy variable regression. The results are shown in Table 2.

Perhaps the most striking finding comes from a comparison of the OLS results in Table 1 and Table 2. Farm Employment, a highly strong and significant predictor in Table 1, vanishes from importance in what we will call the "residual regression." (We delay our discussion of this finding until the alternative spatial regressions are introduced.) We also note that after removing some of the spatial heterogeneity in the model, the regression residuals still reveal dependence (a Moran coefficient of 0.212). While highly significant, this is much reduced from the Moran coefficient in Table 1 suggesting that the correction for heterogeneity, as intended, removed a substantial amount of spatial autocorrelation in the spatial process. The R^2 statistic is much smaller in Table 2, which we interpret as the strength remaining in the model after removing much of the predictive power in the first-stage dummy variable regression. The Lagrange Multiplier statistics again (weakly) support the alternative spatial lag regression. Columns 2 and 3 of Table 2 parallel those of Table 1. We discuss only the results of the spatial lag regression, column 3. This seems to be a reasonable specification. The likelihood is the highest of the six regressions in Tables 1 and 2, and the AIC is the lowest, as desired. The spatial lag parameter (ρ) is strong and significant. Not much of substance remains in the model, however. Only one independent variable (Temperature Range) has a significant parameter estimate in this final model suggesting that portions of the Great Plains with the widest annual variation in temperature are those with the lowest growth rates (implying population decline). Of course this typifies counties in the northern Plains – those most affected by continental temperature extremes. Whether this is yet one more demographic corroboration of the general appeal of Sunbelt over the Frostbelt climates is unclear. That it is the only variable of substance in the final model is a bit discouraging. We fully anticipated that Farm Employment would remain a strong predictor of population change. That is, high farm dependency would be associated with lower rates of growth (decline) in the Plains in the 1990s What happened between Table 1 and Table 2? It appears that the attempt to correct for spatial heterogeneity accomplished in the dummy variable regression completely swallowed up this influence. Systematic variation in rates of population change reflected in Figure 1 are so inextricably linked to farm dependency, that in our simple-minded effort to reduce spatial heterogeneity we have unwittingly also removed the farm dependency effect. Said another way, in our particular approach to these data we have serendipitously revealed a potential candidate for identifying what commonly are called "spatial regimes" – sub-regions revealing systematic differences in the relationships under investigation. In the interest of closure, we do not proceed down this path here, but it would be good to point the way. At this juncture, we likely would want to carefully examine the bivariate relationship between Log Population Growth and Farm Employment. Sub-regions where this relationship is substantively different are likely candidates for identification of a spatial regime. Then the spatial regression software SpaceStat™ will easily handle the regression task for us where each of the coefficients takes on a different value in each of the spatial regimes. (See the SpaceStat™ Tutorial, page 56, at http://www.terraseer.com/products/spacestat/docs/spacestat_tutorial.pdf.)

MULTILEVEL MODELING

In the first few sections of this chapter, we discussed how the maturing of demographic science in the U.S. witnessed a shift around 1950 from an interest in population change among geographic areas to an interest in individual-level demographic behavior. We also discussed the re-emergence in recent years of interest in areal data brought about by growing awareness of the tools and techniques for properly specifying and estimating statistical models based on geospatial data. We now close our chapter with a brief discussion of how these two perspectives, macro- and micro-demography, are presently being bridged by new interest in multilevel modeling techniques.

These methods deal with data organized hierarchically (such as individuals within neighborhoods, pupils within schools, or crimes within census tracts) and provide the opportunity to simultaneously study variation at different levels of the hierarchy. Such models acknowledge that individuals are embedded in social units (schools, tracts, neighborhoods, regions, etc.). As such, they blur the artificial boundaries between micro and macro analyses. Many examples of multilevel modeling are found in sociological and demographic research since the 1980s (e.g., Cotter, 2002; DiPrete and Grusky, 1990; Entwisle and Mason, 1985; Entwisle et al., 1984; Entwisle et al., 1986; Hirschman and Guest, 1990; Mason et al., 1983-84; Raudenbush and Bryk, 1986; Sampson, 1988, 1991; Sampson and Wooldredge, 1987). Comparable to the experience with spatial analysis, technological advances in software capabilities have greatly facilitated an already existing interest in hierarchical data analysis. The motivation for the development of these analytical tools also is strikingly similar to that underlying the expansion of spatial methods: "Almost all data collected in the social sciences have some form of inherent hierarchical structure, and this structure should be reflected in the statistical models that are used to analyze them" (Paterson and Goldstein, 1991, in Westert and Verhoeff, 1997:7). Broadly, the hierarchical structure might refer to individuals within non-spatial structures such as companies or organizations. Spatially, the hierarchical structure includes some geographic unit such as census tracts, counties and the like.

As with spatial regression modeling, however, multilevel strategies bring their own distinct set of methodological issues and cannot be analyzed by conventional statistical approaches. Hox and Kreft (1994) provide a useful summary of the problems that arise when applying single level models to multilevel data (see also Bryk and Raudenbush, 1992; Raudenbush and Bryk, 2002). Only one stochastic error component is allowed in a single level model, and is assumed independent, normal, and homoskedastic. If the data are multilevel, the unmodeled group variation will produce a residual error term at the group or higher level that assumes a nonzero covariance between the residual error terms of individuals comprising the group. In doing so, it incorrectly assumes independence between the observations. Because the data contain observations nested within a shared spatial unit, the data are in effect dependent; households residing within the same neighborhood are likely to have more similar characteristics relative to households within another neighborhood. This dependency, and the accompanying error structure, is not accounted for in a single level model. Therefore, the assumption upon which standard errors and variances are determined is violated and the model produces inefficient estimates of standard errors and overall "explained" variance. Such single level model estimates are biased and unreliable for multilevel data structures.

Consequently, in recent years, software development has resulted in many statistical packages offering tools to specify and properly model hierarchical data. The most focused and well known is Hierarchical Linear and Non-Linear Modeling (HLM) (Raudenbush et al., 2000), but other packages including SAS (SAS Institute, 1999-2001) and S-Plus (Insightful Corporation, 1987-2001) also enable the analysis of multilevel data. Equipped with these tools, contemporary demographic research bridges the important gap between micro- and macro-level processes. These methods allow the analyst to simultaneously address the ecological and atomistic fallacies by appropriately modeling the social processes at both levels in addition to estimating the relationships between the two levels. In essence, the associations estimated for one level (e.g., child's school performance and SES) are interacted with the second level, thereby allowing for variation in the parameters, or the nature and magnitude of the association, according to the second-level values (e.g., neighborhood SES). Such an approach takes full advantage both of individual (family or household data) and geospatial data.

SUMMARY

In this chapter, we have discussed the role of geographic space in quantitative demography. We have argued that until sometime around mid-20th century, nearly all of quantitative demography used geographic units as the unit of analysis. As more microdata files became available, beginning in the 1940s and 1950s, a majority of demographers shifted their attention to behavioral process in population studies. We argue that the motivation behind this shift was not simply the availability or novelty of microdata, but also the desire to avoid the analytical problems associated with areal data such as aggregation biases and the ecological fallacy. We also recognize and highlight a counter trend: the continued fascination with demographic processes linked to areal units, what we refer to as spatial demography, that characterized the research agendas of many rural demographers since the 1950s and of applied demographers, beginning in the 1970s. The latter sub-discipline, in fact, was largely defined by its attention to geographic units – particularly the smaller units near the bottom of the U.S. census geographic hierarchy. We then shifted our focus to the re-emerging interest in spatial demography that slowly is beginning to appear as an increasing number of demographers seek to adopt the formal tools of spatial econometrics to improve on traditional regression models of demographic processes operating in space.[26] We introduced the concept of spatial autocorrelation and ways to correctly specify multiple regression models in the presence of spatial autocorrelation. This lengthy section is made more concrete through an illustration of spatial modeling of county level growth during the 1990s in the U.S. Great Plains region. Finally we draw attention to ways of bridging the split between macro-demography and micro-demography by the further adoption of multilevel models.

We take particular delight in these latter two developments. It is our belief that as our own statistical models become more sophisticated, as spatial processes are brought into empirical demographic studies to correct for potential misspecification, and as our work begins to add in significant ways to the larger literature on spatial data analysis, we will have moved the science of spatial demography forward in very exciting ways. The growing interest in the field of spatial econometrics among several disciplines in the social sciences, of which the re-emergence of interest in spatial demography is a part, suggests an exciting future for quantitative demographers. Clearly the future will involve more interdisciplinary efforts – scholars from different disciplines brought together because of a common interest in scientific exploration of processes taking place in space. Spatial demographers will have many opportunities to lend their expertise to these efforts, including the understanding of the spatial data from, and the geographic hierarchy of, the decennial census (and hopefully from the emerging American Community Survey), and of the special demographic perspectives and insights that demographers will bring to such efforts.

ENDNOTES

[1] We focus our attention on demography as practiced in the United States, although we assert that the general argument holds as well for demography as practiced outside the U.S.

[2] Our choice of words here may be confusing to some readers, as the term "micro-demography" has earlier been used by Bogue to mean, "the study of…local area" (Bogue, 1957:46). Bogue's definition would apply to our use of the term areal demography, macro-level demography, or, our preferred term, spatial demography. In this chapter our use of the term "micro-demography" follows more recent convention of reference to the statistical analysis of individual-level (or family- or household-level) records from a microdata file, such as a census PUMS file.

[3] We do not allow as exception to our thesis the work of early population forecasters who used exponential models (e.g., Bonynge, 1852), polynomial models (e.g., Pritchett, 1891) or logistic functions (e.g., Pearle and Reed, 1920) to "fit" a set of census counts and then to extrapolate population change into the future. Dorn (1950) provides a helpful review and critique of these early forecasting efforts. While this work predates much of what today is considered the modern science of demography, we simply note in passing that, by definition, it involved reference to populations attached to geographic space.

[4] Our review of this extensive literature is necessarily brief and deliberately parochial. Since the focus of this chapter is on spatial demography in the U.S., we have omitted from this review important contributions by population scientists elsewhere (e.g., Gini, 1924; Henry, 1957; Rhodes, 1940; 1941).

[5] The first such file was released in 1971 based on a large sample from the 1970 census. Shortly thereafter, in 1973, the Census Bureau released a public use microdata sample file from the 1960

census. Since these early releases, the Census Bureau has worked in conjunction with various sociologists and demographers to create PUMS files corresponding with most U.S. decennial censuses. Today, files spanning most decades between 1850 and 2000, in addition to international PUMS data files, are available in machine-readable format free of charge through the Minnesota Population Center at http://www.ipums.org.

[6] For a recent interesting and encompassing review of the early history of migration research, the reader is directed to Greenwood and Hunt (2003).

[7] One example of such collaboration is the emergence of demographers working in the area which has become known as "environmental demography" (see, for example, Dietz and Rosa, 1994; Lutz, 2002; Lutz, Prieto, and Sanderson, 2000; O'Neil, MacKellar, and Lutz, 2001; Schnaiberg, 1980; Schnaiberg and Gould, 1994). Florax and Vlist (2003), among others, have drawn particular attention to the way in which recent increases and availability of spatially referenced data have partly driven the research agendas of several disciplines and have fostered new interdisciplinary collaborations.

[8] This obviously is an oversimplification. Both the demographic discipline (as a course of study) and the demographic profession (which defines the areas of pursuit and practice of various population scientists) are mature and multifaceted. That said, we maintain that the division here described applies readily to most demographic research and practice today, regardless of the specific substantive foci of the efforts, which are many.

[9] Our focus in this chapter is on the analysis of data tied to geographic areas, known more formally in the literature as "lattice" data. Consequently, we ignore in this review other developments in the spatial statistical literature that focus on "point" data (see, for example, the review of early literature by Boots and Getis, 1988:10-12) or on continuous field or

"geostatistical" data (see Webster and Oliver, 2001:6-8, for a brief overview of the origin this field of study).

[10] Details regarding the sample and measures can be found in White (2003). The county boundaries used throughout this example refer to the 1900 boundaries as the example is taken from a larger, historic project.

[11] Early recognition of this problem is found in a brief paper by census statistician Frederick Stephan who, when referring to the use of census tract data in social research, introduced the problem by analogy to classical sampling theory: "Data of geographic units are tied together, like bunches of grapes, not separate, like balls in an urn" (1934:165).

[12] Sociologists and demographers have not been alone in their seeming resistance to these developments. The hesitancy of regional scientists to adopt a formal spatial econometric perspective was the subject more than 15 years ago of a lament by Anselin and Griffith (1988).

[13] This literature is large and dynamic. Perhaps the best citation that can be provided is to invite the reader's attention to the website of the Center for Spatially Integrated Social Science (CSISS), a center whose mission is to serve as an ongoing clearinghouse for software tools, literature and training opportunities in spatial data analysis (http://www.csiss.org).

[14] Our goal for this chapter is to present some of the concepts of spatial data analysis and to indicate for interested readers where greater detail can be found. Specifically, we have sought to minimize the presentation of technical material including formulae and equations. With respect to how to compute and interpret Moran's *I*, for example, interested readers will easily find the formula, some discussion of the measure and article/text citations on the internet simply by entering the term in any web search engine. The reader will also discover that the Moran statistic is but one of several measures of spatial autocorrelation.

[15] There exists a large literature on the topic of selecting a weights matrix. Griffith (1996) is but one helpful resource.

[16] We refer to the independent variable as log percent population change as a matter of convenience. In fact, it is the natural log of the ratio P_{2000}/P_{1990}, where P stands for population census count. In addition, we repeat that the "counties" used here are based on boundaries that existed in 1900.

[17] "A" is not considered a neighbor of itself and is excluded from the average. Counties on the border of the Great Plains region, as shown in Figure 1, are permitted only to have neighbors within the region. This restriction creates some boundary problems ("edge effects") in this analysis, but the topic is not addressed further in this overview. The reader is referred to any of several articles or texts on spatial data analysis for further information and ways of dealing with such problems (e.g., Martin, 1987).

[18] Caution is advised when attributing statistical significance to the local parameter values because of the high degree of multiple hypothesis testing in GWR. Some type of Bonferroni-like adjustment to the critical values clearly is appropriate. Fotheringham and colleagues suggest rejection of the Null only when t-values approach 4.5 and greater (2002:135).

[19] One would normally wish to corroborate this interpretation by examining the residuals, say, from a global regression across the region.

[20] Spatial heterogeneity often is a concept referred to somewhat casually or vaguely. A more precise sense of what is captured in the notion of spatial heterogeneity is contained in the statistical concept of spatial stationarity in its various forms (Cressie, 1993).

[21] We do not present the details, but once a spatial lag is included in a regression model to account for spatial dependence in the data, maximum likelihood estimation (MLE) is usually the appropriate estimator (see Anselin and Bera, 1998).

[22] We have not said much about software in this chapter. To do so would involve us and the reader in a long digression that would divert us from our principal goal. In many respects the development of software for spatial data analysis has proceeded haltingly, and presently no single software package or programming language is the clear front runner. SpaceStat™ delivers considerable capability for estimating models of spatial dependence, but it is clumsy to run and its future development and support is uncertain. SpaceStat™ is distributed by TerraSeer, Inc. and details can be found on the Internet at http://www.terraseer.com. GeoDa™ has been jointly developed at Luc Anselin's Spatial Analysis Laboratory at the University of Illinois, Urbana-Champaign (http://sal.agecon.uiuc.edu) at the Center for Spatially Integrated Social Science (CSISS) at the University of California, Santa Barbara (http:/www.csiss.org). This easy to use software promises to replace much of the SpaceStat functionality, but is not yet there, and other promising developments are occurring on several fronts. The open source cross-platform programming language R is powerful and offers many spatial analysis routines in the spdep package developed by Roger Bivand and collaborators (http://cran.r-project.org). There exists a free, long established, spatial econometric toolbox developed by James LeSage using MathWorks' MATLAB software (http://www.spatial-econometrics.com), and a new, presently in development, open source software initiative called PySpace (http://sal.agecon.uiuc.edu) also holds promise. PySpace is an effort by Anselin and colleagues to implement spatial statistical and spatial regression analyses using the object-oriented programming language Python and

Numerical Python. Generally speaking, each of the latter three options requires considerable intellectual investment on the part of the novice spatial data analyst.

[23] We are aware of the dangers in this paragraph of using language that threatens the charge of "ecological fallacy." We are simply stating that the multitude of behavioral decisions or responses of individuals holding various social and economic attribute bundles ultimately are reflected in the demographic summary statistics of areal units.

[24] For further details, the reader is directed to Fuguitt and Lieberson (1974).

[25] There is a fairly large and growing literature regarding Lagrange Multipliers and other so-called "score" diagnostics. We refer the reader to the on-line tutorial for SpaceStat™, (available at http://www.terraseer.com/products/spacestat/docs/spacestat_tutorial.pdf) the software used to produce the parameter estimates and diagnostics shown in Tables 1 and 2.

[26] We take fascination in the fact that a recent article by Messner and Anselin (2004) makes precisely the same claim for empirical studies seeking to explain spatial heterogeneity of homicide rates. The authors assert that early interest in areal analyses shifted to studies that were "largely insensitive to spatial context." They go on to say, "The field has changed dramatically in recent years, and criminologists are increasingly applying formal tools of spatial analysis to describe and explain variations in levels of homicide (and other crimes)" (2004:127).

REFERENCES

Alker, Hayward R. 1969. "A Typology of Ecological Fallacies." Pp. 64-86 in Mattei Dogan and Stein Rokkan (eds.) *Quantitative Ecological Analysis*. Cambridge, MA: MIT Press.

Anselin, Luc. 1988. *Spatial Econometrics, Methods and Models*. Dordrecht: Kluwer Academic.

_____. 1995 "Local Indicators of Spatial Association—LISA." *Geographical Analysis* 27:93-115.

_____. 1996. "The Moran Scatterplot as an ESDA Tool to Assess Local Instability in Spatial Association." Pp. 111- 125 in Manfred Fischer, Henk J. Scholten and David Unwin (eds.) *Spatial Analytical Perspectives on GIS*. London: Taylor & Frances.

_____. 2001. "Rao's Score Test in Spatial Econometrics." *Journal of Statistical Planning and Inference* 97:113-139.

_____. 2003. "Spatial Externalities, Spatial Multipliers, and Spatial Econometrics." *International Regional Science Review* 26(2):153-166.

Anselin, Luc and Anil Bera. 1998. "Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics." Pp. 237-289 in Aman Ullah and David Giles (eds.) *Handbook of Applied Economic Statistics*. New York: Marcel Dekker.

Anselin, Luc and Daniel A. Griffith. 1988. "Do Spatial Effects Really Matter in Regression Analysis?" *Papers of the Regional Science Association* 65:11-34.

Bailey, Trevor C. and Anthony C. Gatrell. 1995. *Interactive Spatial Data Analysis*. Harlow Essex: Longman Scientific & Technical.

Baller, Robert D. and Kelly K. Richardson. 2002. "Social Integration, Imitation, and the Geographic Patterning of Suicide." *American Sociological Review* 67(6):873-888.

Beale, Calvin L. 1969. "Natural Decrease of Population: The Current and Prospective Status of an Emergent American Phenomenon." *Demography* 6:91-99.

_____. 1975. "The Revival of Population Growth in Nonmetropolitan America." Washington, D.C.: U.S. Department of Agriculture, Economic Research Service, ERS-605.

Besag, Julian. 1974. "Spatial Interaction and the Statistical analysis of Lattice Systems." *Journal of the Royal Statistical Society B* 36(2):192-225.

Bogue, Donald J. 1957. "Micro-demography." Pp. 46-52 in Donald J. Bogue (ed), *Applications of Demography: The Population Situation in the U.S. in 1975*. Scripps Foundation Studies in

Population Distribution, Study No. 13. (Oxford, OH: The Scripps Foundation, Miami University).

Bonynge, Francis. 1852. *The Future Wealth of America*. New York: Francis Bonynge.

Boots, Barry N. and Arthur Getis. 1988. *Point Pattern Analysis*. Newbury Park: Sage Publications.

Brueckner, Jan K. 2003. "Strategic Interaction Among Governments: An Overview of Empirical Studies." *International Regional Science Review* 26(2):175-188.

Brundson, Chris, A. Stewart Fotheringham and Martin E. Charlton. 1996. Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity." *Geographical Analysis* 28:281-298.

_____. 1998a. "Spatial Non-Stationarity and Autoregressive Models." *Environment and Planning A* 30:957-973.

_____. 1998b. "Geographically Weighted Regression—Modelling Spatial Non-stationarity." *The Statistician* 47:431-443.

Bryk, Anthony S. and Stephen W. Raudenbush. 1992. *Hierarchical Linear Models: Applications and Data Analysis Methods*. (1st Ed). Newbury Park: Sage Publications.

Chou, Yue-Hong. 1997. *Exploring Spatial Analysis in Geographic Information Systems*. Santa Fe, NM: OnWord Press.

Cliff, Andrew D. and J. Keith Ord. 1973. *Spatial Autocorrelation*. London: Pion Limited.

_____. 1981. *Spatial Processes: Models and Applications*. London: Pion Limited.

Cotter, David A. 2002. "Poor People in Poor Places: Local Opportunity Structures and Household Poverty." *Rural Sociology* 67(4):534-555.

Creamer, Daniel C. 1935. *Migration and Planes of Living*. Philadelphia, PA: University of Pennsylvania Press.

Cressie, N. A. C. (1993). *Statistics for Spatial Data (revised edition)*. New York: Wiley.

Dietz, Thomas and Eugene A. Rosa. 1994. "Rethinking the Environmental Impacts of Population, Affluence and Technology." *Human Ecological Review* Summer/Autumn (1):277-300.

DiPrete, Thomas A. and David B. Grusky. 1990. "The Multilevel Analysis of Trends with Repeated Cross-Sectional Data." *Sociological Methodology* 20:337-368.

Doreian, Patrick. 1980. “Linear Models with Spatially Distributed Data: Spatial Disturbances or Spatial Effects?” *Sociological Methods & Research* 9(1):29-60.

_____. 1981. “Estimating Linear Models with Spatially Distributed Data”, pp. 359-388 in S. Leinhardt (Ed.), *Sociological Methodology.* San Francisco: Jossey-Bass.

Dorn, Harold F. 1950. “Pitfalls in Population Forecasts and Projections.” *Journal of the American Statistical Association* 45(251):311-334.

Dublin, Louis I. and Gladden W. Baker. 1920. “The Mortality of Race Stocks in Pennsylvania and New York, 1910.” *Quarterly Publications of the American Statistical Association* 17(129):13-44.

Dublin, Louis I. and Alfred J. Lotka. 1925. “On the True rate of Natural Increase.” *Journal of the American Statistical Association* 20(151):305-339.

_____. 1930. “The Present Outlook for Population Increase.” *Publication of the American Sociological Society* 24(2):106-114.

_____. 1936. *Length of Life: A Study of the Life Table*. New York: Ronald Press.

Duncan, Otis Dudley and Beverly Duncan. 1955. “A Methodological Analysis of Segregation Indexes.” *American Sociological Review* 20:210-217.

Duncan, Otis Dudley, Ray P. Cuzzort and Beverly Duncan. 1961. *Statistical Geography: Problems in Analyzing Areal Data*. Glencoe, IL: Free Press.

Entwisle, Barbara, Albert Hermalin, Peerasit Kammuansilpz and Apichat Chamratrithirong. 1984. “A Multilevel Model of Family Planning Availability and Contraceptive Use in Rural Thailand.” *Demography* 21(4):559-574.

Entwisle, Barbara and William M. Mason. 1985. “Multilevel Effects of Socioeconomic Development and Family Planning Programs on Children Ever Born.” *American Sociological Review* 91(3):616-649.

Entwisle, Barbara, William M. Mason and Albert I. Hermalin. 1986. “The Multilevel Dependence of Contraceptive Use on Socioeconomic Development and Family Planning Program Strength.” *Demography* 23(2):199-216.

Feller, Willy. 1941. “On the Integral Equation of Renewal Theory.” *The Annals of Mathematical Statistics*, 12(3):243-267.

Florax, Raymond J. G. M. and Arno J. van der Vlist. 2003. “Spatial Econometric Data Analysis: Moving beyond Traditional Models.” *International Regional Science Review* 26(3):223-243.

Fotheringham, A. Stewart, Chris Brunsdon and Martin E. Charlton. 1996. “The Geography of Parameter Space: An Investigation into Spatial Non-Stationarity.” *International Journal of Geographical Information Systems* 10:605-627.

_____. 1997a. “Two Techniques for Exploring Non-stationarity in Geographical Data.” *Geographical Systems* 4:59-82.

_____. 1997b. “Measuring Spatial Variations in Relationships with Geographically Weighted Regression,” in M.M. Fischer and A. Getis (eds.), *Recent Developments in Spatial Analysis: Spatial Statistics, Behavioral Modeling and Computational Intelligence*. Berlin: Springer-Verlag.

_____. 1998. “Geographically Weighted Regression: A Natural Evolution of the Expansion Method for Spatial Data Analysis.” *Environment and Planning A* 30:1905-1927.

_____. 1999. “Scale Issues and Geographically Weighted Regression,” in N. Tate (ed), *Scale Issues and GIS*. Chichester: Wiley.

_____. 2000. *Quantitative Geography: Perspectives on Spatial Data Analysis*. London: Sage Publications.

_____. 2002 *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. Chichester: Wiley.

Freedman, Ronald, David Goldberg and Harry Sharp. 1954. “Ideals About Family Size in the Detroit Metropolitan Area.” *Milbank Memorial Fund Quarterly* 33(2):187-197.

Freedman, Ronald and Harry Sharp. 1954. “Correlates of Values About Ideal Family Size in the Detroit Metropolitan Area.” *Population Studies* 8(1):35-45.

Freedman, Ronald, Pascal K. Whelpton and Arthur A. Campbell. 1959. *Family Planning, Sterility and Population Growth.* New York: McGraw-Hill Book Company, Inc.

Fuguitt, Glenn V. 1985. “The Nonmetropolitan Population Turnaround.” *Annual Review of Sociology* 11:259-280.

Fuguitt, Glenn V. and Stanley Lieberson. 1974. “The Correlation of Ratios or Difference Scores Having Common Terms.” Pp. 128-144 in Herbert L. Costner (ed.) *Sociological Methodology* 1973-1974. San Francisco: Jossey-Bass.

Gaile, Gary L. and Cort J. Willmott (eds.). 1984. *Spatial Statistics and Models*. Dordrecht: D. Reidel Publishing Company.

Galle, Omer R., Walter R. Gove and J. Miller McPherson. 1972. “Population Density and Pathology: What are the Relations for Man?” *Science* 176(4030):23-30.

Geary, R.C. 1954. "The Contiguity Ratio and Statistical Mapping." *The Incorporated Statistician* 5:115-45.

Gehlke, C. E. and Katherine Biehl. 1934. "Certain Effects of Grouping Upon the Size of the Correlation Coefficient in Census Tract Material." *Journal of the American Statistical Association* 29(185):169-170.

Gini, C. 1924. "Premières Recherches sur la Fécondité de la Femme." *Proceedings of the International Mathematical Congress* (2):889-892.

Goodrich, Carter, Bushrod W. Allin and C. Warren Thornthwaite. 1936. *Migration and Economic Opportunity*. Philadelphia, PA: University of Pennsylvania Press.

Greenwood, Michael J. and Gary L. Hunt. 2003. "The Early History of Migration Research." *International Regional Science Review* 26(1):3-37.

Griffith, Daniel A. 1987. *Spatial Autocorrelation: A Primer*. Washington, DC: Association of American Geographers.

_____. 1996. "Some Guidelines for Specifying the Geographic Weights Matrix Contained in Spatial Statistical Models." Pp. 65-82 in Sandra Lach Arlinghaus (ed.) *Practical Handbook of Spatial Statistics*. Boca Raton: CRC Press.

Haining, Robert. 2003. "Issues in Analyzing Spatial Data." Chapter 2 in *Spatial Data Analysis in the Social and Environmental Sciences*. Cambridge: Cambridge University Press.

Hamilton, C. Horace. 1934. *Rural-Urban Migration in North Carolina, 1920–1930*. Bulletin 295. Raleigh, NC: North Carolina Agricultural Experiment Station, February.

Hamilton, C. Horace and F. M. Henderson. 1944. "Use of the Survival Rate Method in Measuring Net Migration." *Journal of the American Statistical Association* 39(June):197–206.

Hawley, Amos H. 1950. *Human Ecology: A Theory of Community Structure*. New York: The Ronald Press.

Henry, Louis. 1957. "Fécondité et Famille: Modèles Mathématiques (I)." *Population* 12(3):413-444.

Hirschman, Charles and Philip Guest. 1990. "Multilevel Models of Fertility Determination in Four Southeast Asian Countries: 1970 and 1980." *Demography* 27(3):369-396.

Hoaglin, David C., Frederick Mosteller and John W. Tukey (eds.). 1983. *Understanding Robust and Exploratory Data Analysis.* New York: John Wiley & Sons.

_____. 1985. *Exploring Data Tables, Trends, and Shapes*. New York: John Wiley & Sons.

Hox, J.J. and I.G.G. Kreft 1994. "Multilevel Analysis Methods." *Sociological Methods and Research* 22(3):283-299.

Hunter, Albert. 1971. "The Ecology of Chicago: Persistence and Change, 1930-1960." *American Journal of Sociology* 77(3):425-444.

Hutchinson, Edward P. 1938. "The Use of Routine Census and Vital Statistics Data for the Determination of Migration by Age and Sex." Pp. 368–400 in Dorothy S. Thomas (ed.), *Research Memorandum on Migration Differentials*. Social Science Research Council Bulletin 43. New York: Social Science Research Council.

Insightful Corporation. 1987-2001. *S-Plus 6*. Seattle, WA: Insightful Corporation.

Johnson, Kenneth M. 1993. When Births Exceed Deaths: Natural Decrease in the United States." *International Regional Science Review* 15(2):179-198.

Jones, Kelvyn and Craig Duncan. 1996. "People and Places: The Multilevel Model as a General Framework for the Quantitative Analysis of Geographical Data." Pp. 79-104 in Paul Longley and Michael Batty (eds.) *Spatial Analysis: Modelling in a GIS Environment*. Cambridge: GeoInformation International.

Kiser, Clyde V. and P. K. Whelpton. 1953. "Resume of the Indianapolis Study of Social and Psychological Factors Affecting Fertility." *Population Studies* 7(2):95-110.

Land, Kenneth C. and Glenn Deane. 1992. "On the Large-Sample Estimation of Regression Models with Spatial- Or Network-Effects Terms: A Two-Stage Least Squares Approach." *Sociological Methodology* 22:221-248.

Land, Kenneth C., Glenn Deane and Judith R. Blau. 1991. "Religious Pluralism and Church Membership: A Spatial Diffusion Model." *American Sociological Review* 56(2):237-249.

Lively, Charles E. and Conrad Taeuber. 1939. *Rural Migration in the United States*. Washington, DC: Works Progress Administration.

Lobao, Linda. 2004. "Continuity and Change in Place Stratification: Spatial Inequality and Middle-Range Territorial Units." *Rural Sociology* 69(1):1-30.

Lobao, Linda and Rogelio Saenz. 2002. "Spatial Inequality and Diversity as an Emerging Research Area." *Rural Sociology* 67(4):497-511.

Loftin, Colin and Sally K. Ward. 1983. "A Spatial Autocorrelation Model of the Effects of Population Density on Fertility." *American Sociological Review* 48(1):121-128.

Lorimer, Frank. 1959. "The Development of Demography." Pp. 124-179 in Philip M. Hauser and Otis Dudley Duncan (eds.) *The Study of Population: An Inventory and Appraisal*. Chicago: The University of Chicago Press

Lotka, Alfred J. 1918. "The Relation Between Birth Rate and Death Rate in a Normal Population and the Rational Basis of an Empirical Formula for the Mean Length of Life given by William Farr." *Publications of the American Statistical Association* 16(123):121-130.

_____. 1936. "The Geographic Distribution of Intrinsic Natural Increase in the United States, and an Examination of the Relation Between Several Measures of Net Reproductivity." *Journal of the American Statistical Association* 31(194):273-294.

_____. 1938. "Some Recent Results in Population Analysis." *Journal of the American Statistical Association* 33(201):164-178.

_____. 1939. "On an Integral Equation in Population Analysis." *The Annals of Mathematical Statistics* 10(2):144-161.

_____. 1942. "The Progeny of an Entire Population." *The Annals of Mathematical Statistics* 13(2):115-126.

_____. 1948. "Application of Recurrent Series in Renewal Theory." *The Annals of Mathematical Statistics* 19(2):190-206.

Lutz, Wolfgang. 2002. "Population: A Global Challenge for the Twenty-First Century." Pp. 126-148 in Hans van Ginkel, Brendan Barrett, Julius Court and Jerry Velasquez (eds.) *Human Development and the Environment: Challenges for the United Nations in the New Millennium*. New York: United Nations University Press.

Lutz, Wolfgang, Lionel Prieto and Warren C. Sanderson. 2000. *Population, Development, and Environment on the Yucatan Peninsula: From Ancient Maya to 2030*. Research Report RR-00-14. Laxenburg, Austria: IIASA.

Martin, R. J. 1987. "Some Comments on Correction Techniques for Boundary Effects and Missing Value Techniques." *Geographical Analysis* 19:273-282.

Mason, William M., George Y. Wong and Barbara Entwisle. (1983-84) "Contextual Analysis through the Multilevel Linear Model." *Sociological Methodology* 14:72-103.

Merrick, Thomas W., 1987. "Preface." Pp. viii-ix in David A. Swanson and Jerry W. Wicks (eds.), *Issues in Applied Demography*. Bowling Green, OH: PSRC Press.

Merrick, Thomas W. and Stephen J. Tordella. 1988. "Demographics: People and Markets." *Population Bulletin* 43(1):49.

Messner, Steven F. and Luc Anselin. 2004. “Spatial Analyses of Homicide with Areal Data.” Pp. 127-144 in Michael F. Goodchild and Donald G. Janelle (eds.) *Spatially Integrated Social Science*. Oxford: Oxford University Press.

Moran, P.A.P. 1950. “Notes on Continuous Stochastic Phenomena.” *Biometrika* 37:17-23.

Murdock, Steve H. and David R. Ellis. 1991. *Applied Demography: An Introduction to Basic Concepts, Methods, and Data*. Boulder, CO: Westview Press.

O'Neil, Brian C., F. Landis MacKellar and Wolfgang Lutz. 2001. *Population and Climate Change*. Cambridge, U.K.: Cambridge University Press.

Paterson, L. and H. Goldstein. 1991. “New Statistical Methods for Analysing Social Structures: An Introduction to Multilevel Models.” *British Educational Research Journal* 17:387-393.

Pearle, Raymond and Lowell J. Reed. 1920. “On the Rate of Growth of the Population of the United States since 1790 and its Mathematical Representation.” *Proceedings of the National Academy of Science* 6:275-288.

Pritchett, H. S. 1891. “A Formula for Predicting the Population of the United States.” *Quarterly Publications of the American Statistical Association* 2(14):278-286.

Raudenbush, Stephen W. and Anthony S. Bryk. 1986. “A Hierarchical Model for Studying School Effects.” *Sociology of Education* 59(1):1-17.

_____. 2002 *Hierarchical Linear Models: Applications and Data Analysis Methods*. (2nd Ed). Thousand Oaks: Sage Publications.

Raudenbush, Stephen W., Anthony S. Bryk, Yuk Fai Cheong and Richard T. Congdon. 2000. *HLM 5: Hierarchical Linear and Non-Linear Modeling*. Chicago: Scientific Software International.

Rhodes, E. C. 1940. “Population Mathematics (Parts I, II, and III).” *Journal of the Royal Statistical Society* 103(1; 2; 3):61-89;218-245;362-387.

Rhodes, E. C. 1941. “Secular Changes in Death Rates.” *Journal of the Royal Statistical Society* 104(1):15-42.

Ripley, Brian D. 1981. *Spatial Statistics*. New York: John Wiley & Sons.

Rives, Norfleet W., Jr. and William J. Serow. 1984. *Introduction to Applied Demography: Data Sources and Estimation Techniques*. Sage University Paper No. 39. Beverley Hills, CA: Sage Publications.

Robinson, William S. 1950. "Ecological Correlations and the Behavior of Individuals." *American Sociological Review* 15(3):351-357.

Rogers, Everett M. 1962. *Diffusion of Innovation*. New York: The Free Press.

Russell, Cheryl. 1984. "The Business of Demographics." *Population Bulletin* 39:3. Washington, DC: Population Reference Bureau, Inc.

Sampson, Robert J. 1988. "Local Friendship Ties and Community Attachment in Mass Society: A Multilevel Systematic Model." *American Sociological Review* 53(5):766-779.

_____. 1991. "Linking the Micro- and Macrolevel Dimensions of Community Social Organization." *Social Forces* 70(1):43-64.

Sampson, Robert J. and John D. Wooldredge. 1987. "Linking Micro- and Macro-Level Dimensions of Lifestyle-Routine Activity and Opportunity Models of Predatory Victimization." *Journal of Quantitative Criminology* 3(4):371-393.

SAS Institute. 1999-2001. *The SAS System 8*. Cary, NC: SAS Institute, Inc.

Schmitt, Robert C. 1952. "Short-Cut Methods of Estimating County Population." *Journal of the American Statistical Association* 47(June):232–38.

Schnaiberg, Allan. 1980. *The Environment: From Surplus to Scarcity*. New York: Oxford University Press.

Schnaiberg, Allan and Kenneth Alan Gould. 1994. E*nvironment and Society: The Enduring Conflict*. New York: St. Martin's Press.

Shevky, Eshref and Wendell Bell. 1955. *Social Area Analysis*. Stanford: Stanford University Press.

Shryock, Henry S., Jr. 1943. "Internal Migration and the War." *Journal of the American Statistical Association* 38(March):16–30.

Shryock, Henry S., Jr. and Hope Tisdale Eldridge. 1947. "Internal Migration in Peace and War." *American Sociological Review* 12(February):27–39.

Siegel, Jacob S., Henry S. Shryock, Jr. and Benjamin Greenberg. 1954. "Accuracy of Postcensal Estimates of Population for States and Cities." *American Sociological Review* 19(August):440–46.

Stephan, Frederick F. 1934. "Sampling Errors and Interpretations of Social Data Ordered in Time and Space." *Journal of the American Statistical Association* 29(185 Supplement):165-166.

Theodorson, George A. (ed.). 1961. *Studies in Human Ecology*. Evanston: Row, Peterson and Company.

Thornthwaite, C. Warren. 1934. *Internal Migration in the United States*. Philadelphia, PA: University of Pennsylvania Press.

Tobler, Waldo R. 1970. “A Computer Movie Simulating Urban Growth in the Detroit Region.” *Economic Geography* 46:234-240.

Tolnay, Stewart E., Glenn Deane and E.M. Beck. 1996. “Vicarious Violence: Spatial Effects on Southern Lynchings, 1890-1919.” *American Journal of Sociology* 102(3):788-815.

Tukey, John W. 1977. *Exploratory Data Analysis*. Reading, MA: Addison-Wesley Publishing.

Upton, Graham J. G. and Bernard Fingleton. 1985. *Spatial Data Analysis by Example*. Chichester: John Wiley and Sons.

Voss, Paul R. 1993. “Applied Demography and Rural Sociology.” Pp. 145-170 in David L. Brown, Donald R. Field and James J. Zuiches (eds.) *The Demography of Rural Life*. University Park, PA: Northeast Regional Center for Rural Development.

Webb, John N. 1935. *The Transient Unemployed: A Description and Analysis of the Transient Relief Population*. Washington, DC: Works Progress Administration.

Webb, John N. and Malcolm Brown. 1938. *Migrant Families*. Washington, DC: Works Progress Administration.

Webster, Richard and Margaret A. Oliver. 2001. *Geostatistics for Environmental Scientists*. Chichester: John Wiley & Sons, Ltd.

Westert, Gert P. and Rene N. Verhoeff. 1997. *Places and People: Multilevel Modelling in Geographical Research*. Utrecht: The Royal Dutch Geographical Society.

Westoff, Charles F. and E. G. Mishler. 1961. *Family Growth in Metropolitan America*. Princeton: Princeton University Press.

Whelpton, Pascal K. and Clyde V. Kiser. 1946. *Social and Psychological Factors Affecting Fertility, Vol I, The Household Survey in Indianapolis*. New York: the Milbank Memorial Fund.

_____. 1950. *Social and Psychological Factors Affecting Fertility, Vol. II, The Intensive Study: Purpose, Scope, Methods, and Partial Results*. New York: the Milbank Memorial Fund.

Whelpton, Pascal K., Arthur A. Campbell and John E. Patterson. 1966. *Fertility and Family Planning in the United States*. Princeton, New Jersey: Princeton University Press.

White, Katherine J. Curtis. 2003. “A Century of Population Change in the U.S. Great Plains.” PhD dissertation, University of Washington.

Whittle, P. (1954) “On Stationary Processes in the Plane.” *Biometrika* 41:434-449.

Wrigley, Neil, Tim Holt, David Steel and Mark Tranmer. 1996. “Analysing, Modeling, and Resolving the Ecological Fallacy.” Pp. 23-40 in Paul Longley and Michael Batty (eds.) *Spatial Analysis: Modelling in a GIS Environment*. Cambridge: GeoInformation International.

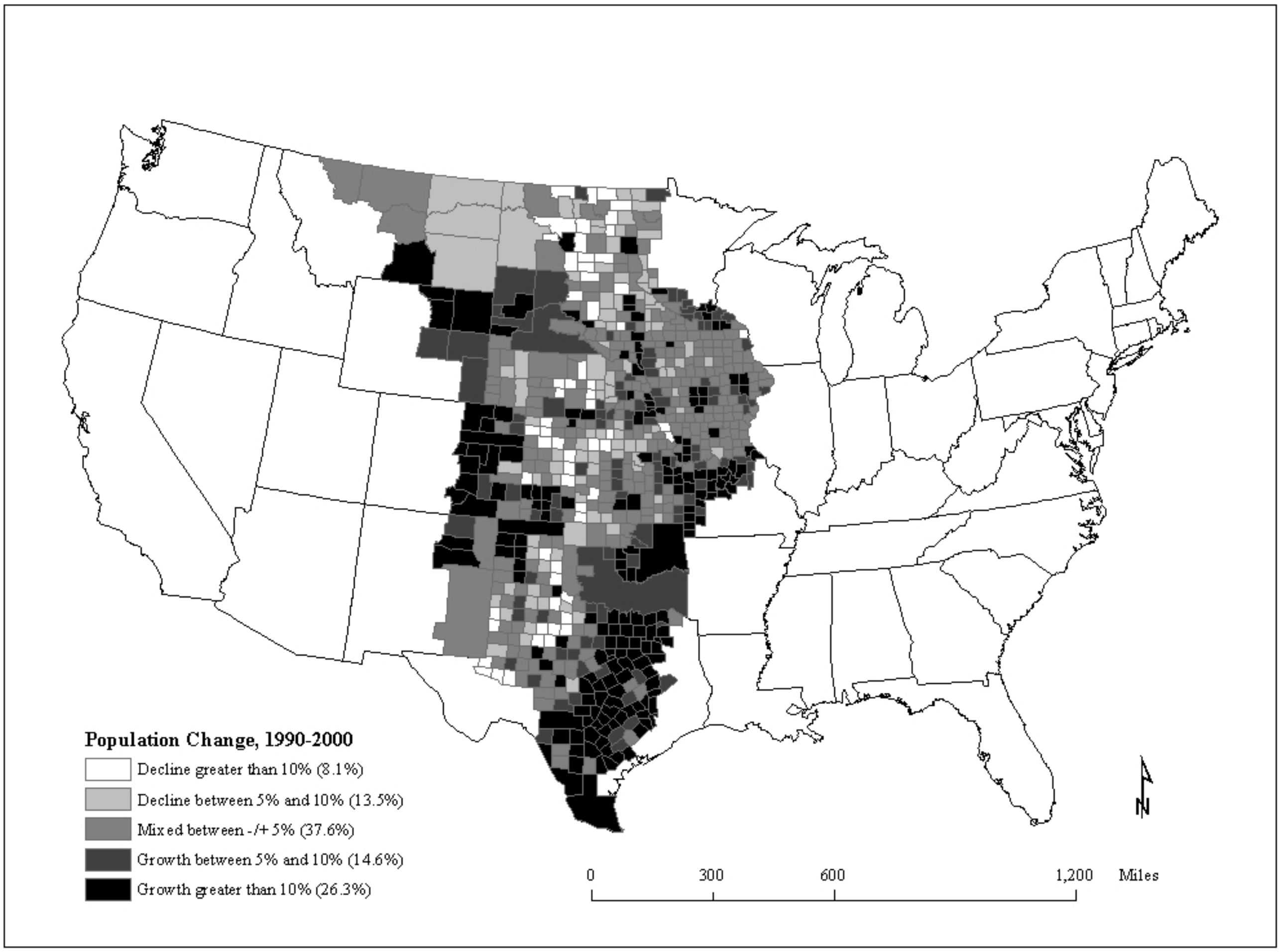


Figure 1. Spatial Distribution of Population Change among Great Plains Counties, 1990-2000

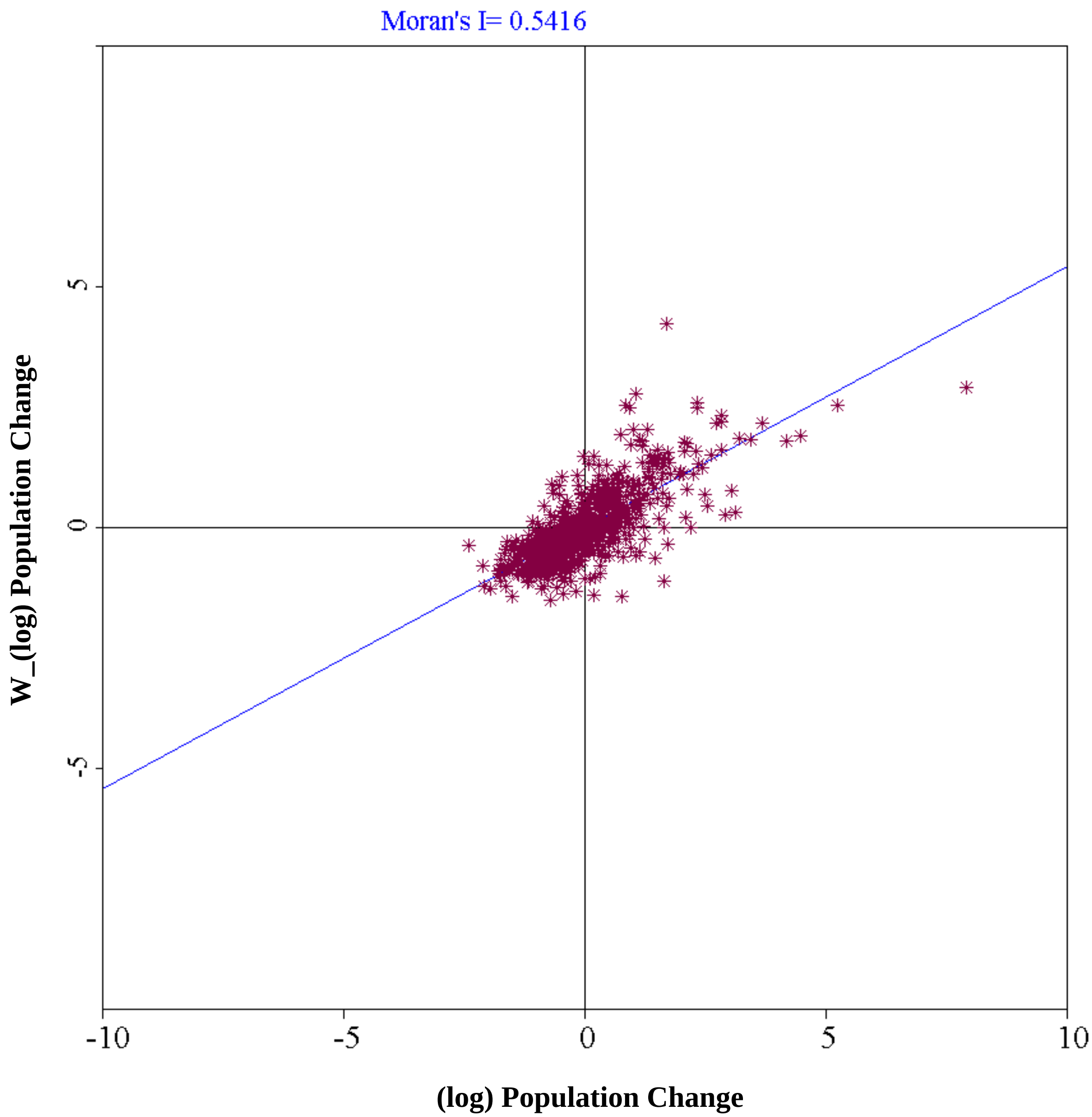


Figure 2. Moran Scatterplot of Population Change

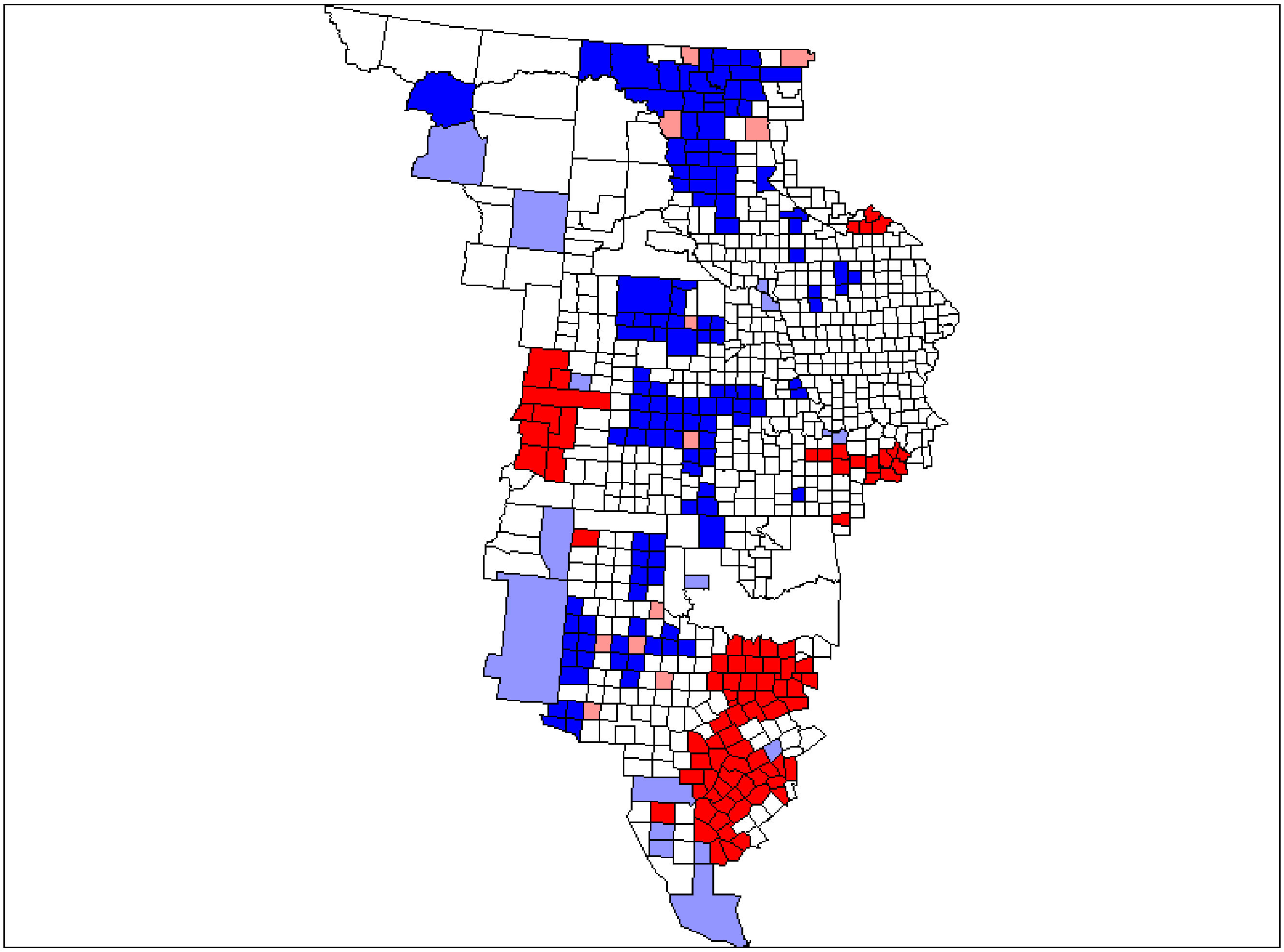


Figure 3. LISA Cluster Map of Population Change

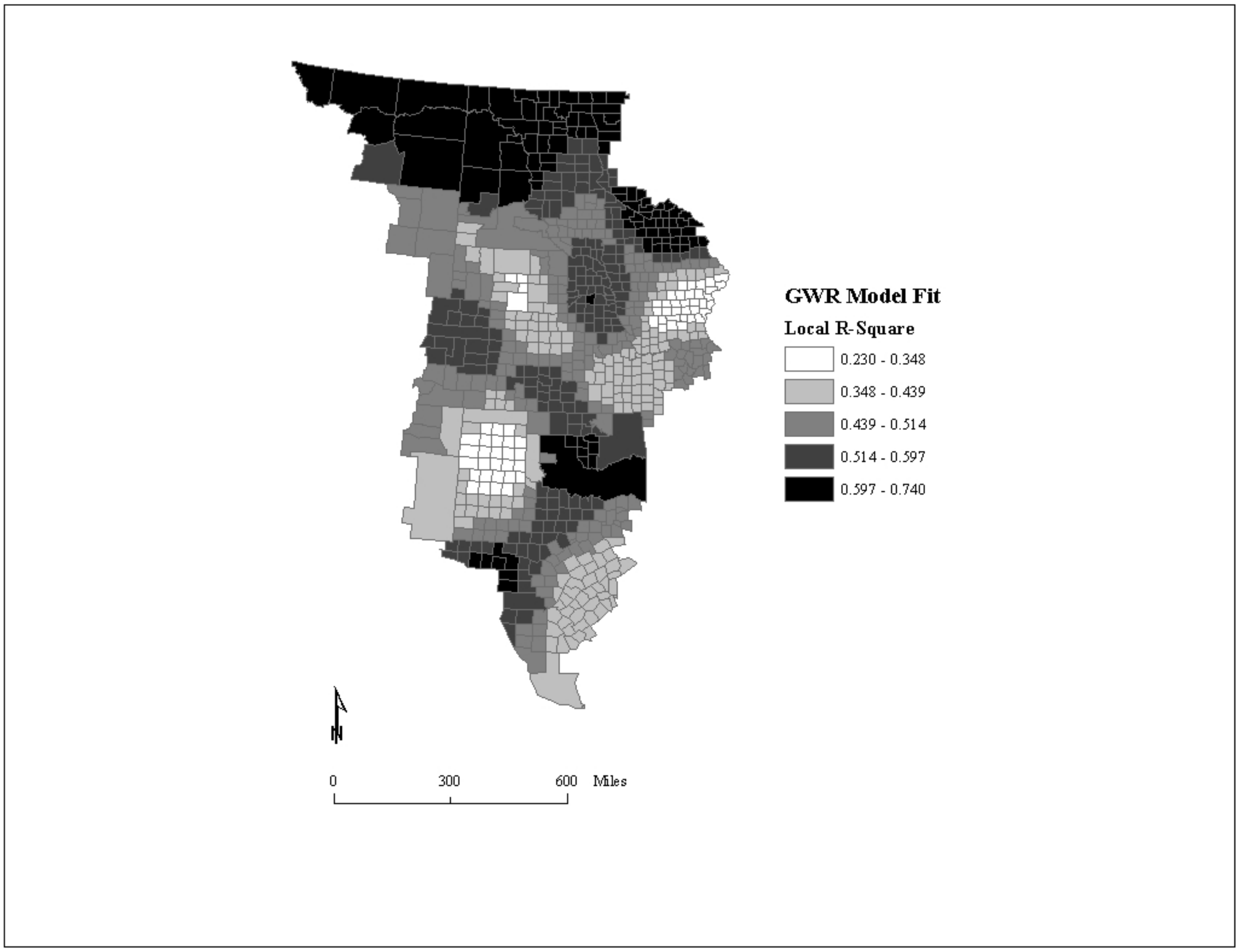
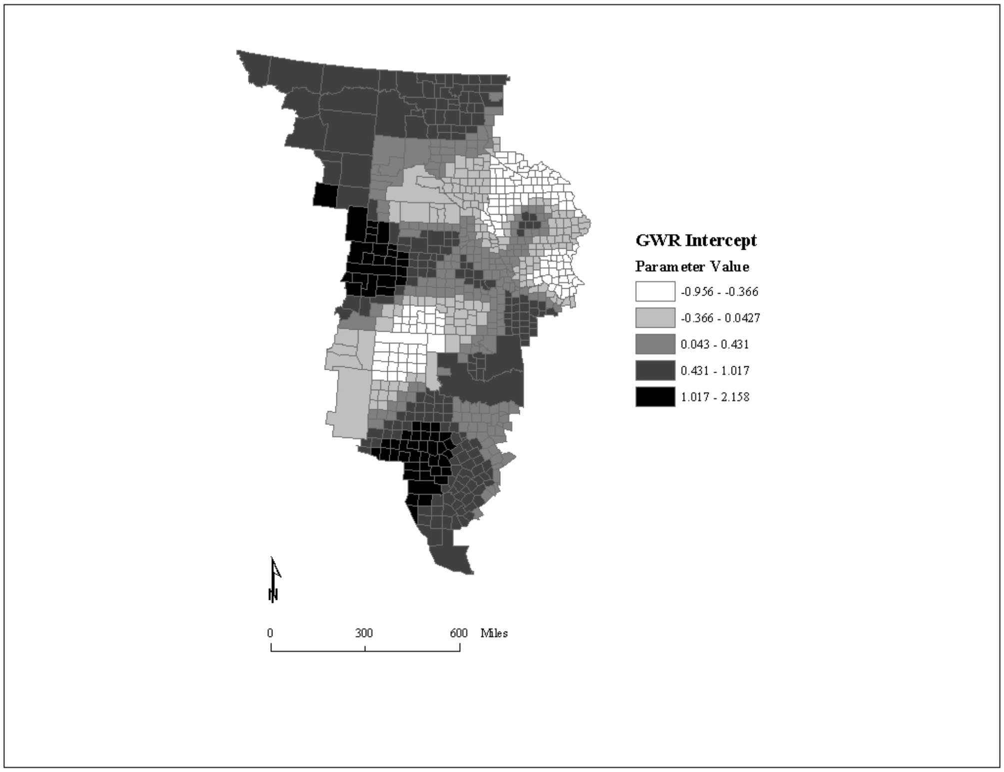
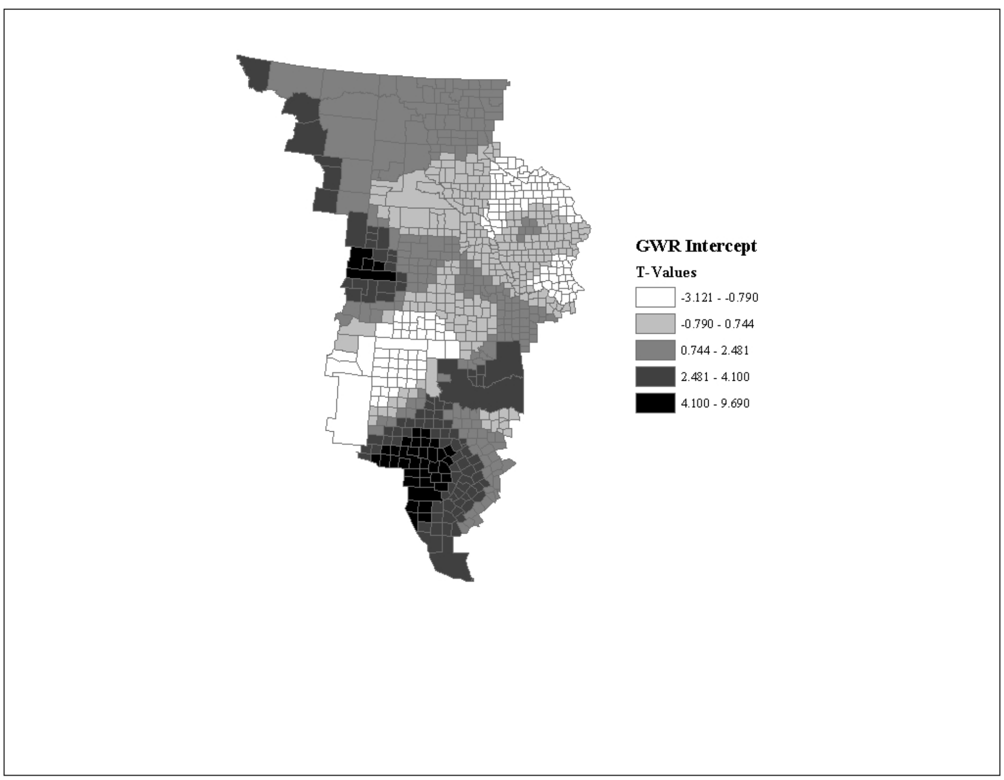


Figure 4. GWR Derived Distribution of Local R^2 Estimates

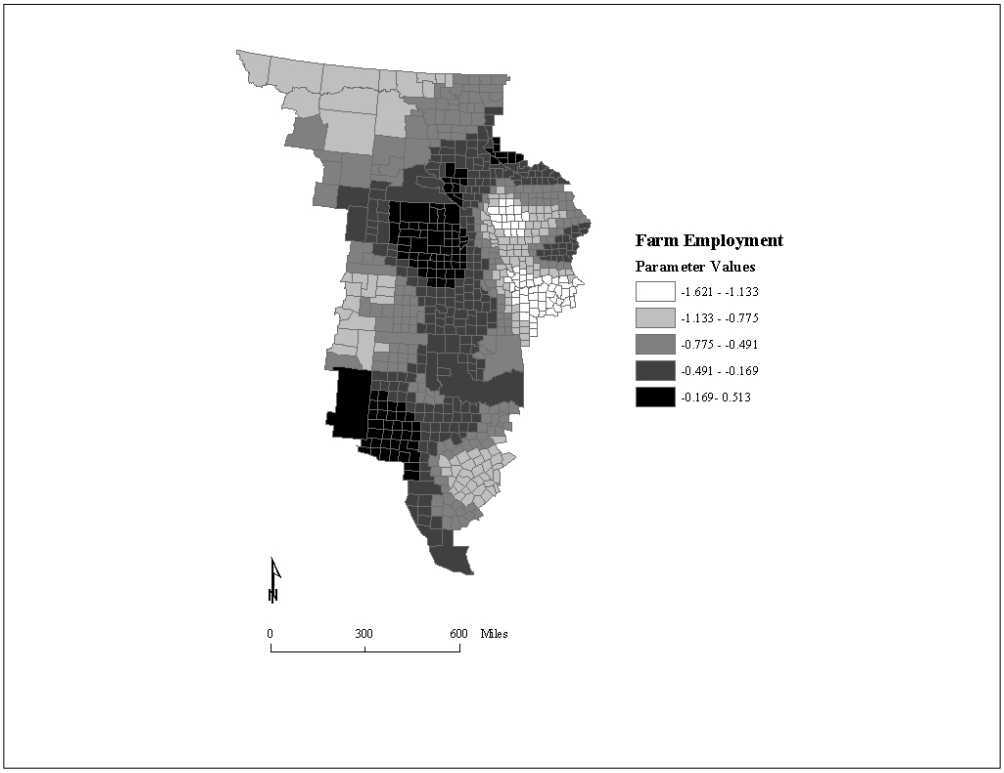


Panel A

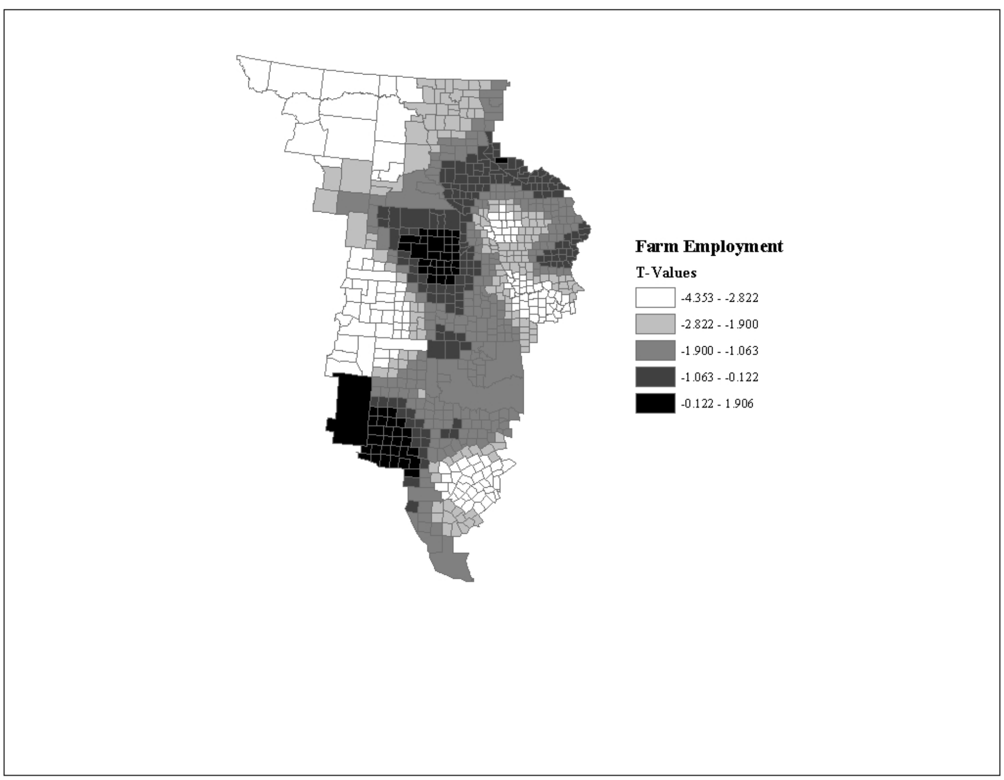


Panel B

Figure 5. GWR Derived Distribution of Intercept Parameter and Significance Estimates



Panel A



Panel B

Figure 6. GWR Derived Distribution of Farm Employment Parameter and Significance Estimates

Table 1. Non-Spatial and Spatial Regression Models of County Population Change, 1990-2000
Dependent Variable = log (Percent Population Change)

	OLS		Spatial Error		Spatial Lag	
Farm Employment (β)	-0.359	***	-0.477	***	-0.388	***
	(0.092)		(0.080)		(0.074)	
Proportion of Pop < 18 (β)	0.075		0.057		0.071	
	(0.123)		(0.112)		(0.099)	
Temperature Range (β)	-0.009	***	-0.010	***	-0.002	***
	(0.001)		(0.002)		(0.001)	
City Status (β)	0.017		0.009		0.015	
	(0.012)		(0.010)		(0.010)	
log County Acreage (per 100,000) (β)	-0.002		-0.002		0.003	
	(0.007)		(0.008)		(0.005)	
log Initial Population (per 1,000) (β)	0.021	***	-0.002	***	0.004	
	(0.006)		(0.006)		(0.005)	
Intercept (β)	0.397	***	0.518	***	0.127	**
	(0.056)		(0.089)		(0.048)	
Spatial Error Parameter (λ)			0.681	***		
			(0.033)			
Spatial Lag Parameter (ρ)					0.635	***
					(0.032)	
Pseudo R2	0.347		0.254		0.481	
Moran's I (error)	0.368	***				
Likelihood	625		742		748	
AIC	-1236		-1469		-1481	
Heteroskedasticity†	158	***	157	***	181	***
Robust Lagrange Multiplier (error)	5.951	*			2.497	
Robust Lagrange Multiplier (lag)	30.319	***	0.268			

* p ≤ .05, ** p ≤ .01, *** p ≤ .001 (two-tailed tests)
† Breusch-Pagan Test for Heteroskedasticity

Table 2. Non-Spatial and Spatial Regression Models of County Population Change, 1990-2000
Dep. Var. = Residual of Regression of (log % Population Change on Growth Dummy Var.)

	OLS	Spatial Error	Spatial Lag
Farm Employment (β)	-0.005	-0.100	-0.051
	(0.073)	(0.072)	(0.067)
Proportion of Pop < 18 (β)	0.063	0.044	0.061
	(0.098)	(0.100)	(0.090)
Temperature Range (β)	-0.004 ***	-0.005 ***	-0.002 **
	(0.001)	(0.001)	(0.001)
City Status (β)	0.003	0.002	0.004
	(0.010)	(0.009)	(0.009)
log County Acreage (per 100,000) (β)	-0.006	-0.005	-0.003
	(0.005)	(0.006)	(0.005)
log Initial Population (per 1,000) (β)	0.013 **	-0.002	0.006
	(0.006)	(0.005)	(0.004)
Intercept (β)	0.152 ***	0.226 ***	0.083 *
	(0.044)	(0.061)	(0.042)
Spatial Error Parameter (λ)		0.471 ***	
		(0.045)	
Spatial Lag Parameter (ρ)			0.457 ***
			(0.045)
Pseudo R2	0.099	0.104	0.16
Moran's I (error)	0.212 ***		
Likelihood	795	835	836
AIC	-1575	-1655	-1655
Heteroskedasticity†	166 ***	167 ***	164 ***
Robust Lagrange Multiplier (error)	0.498		3.399
Robust Lagrange Multiplier (lag)	6.632 *	1.623	

* $p \leq .05$, ** $p \leq .01$, *** $p \leq .001$ (two-tailed tests)
† Breusch-Pagan Test for Heteroskedasticity

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