PREAMBLE

Statistics are like alienists–
they will testify for either side.

F. H. LaGuardia, **Liberty**, (May, 1933)

In a fashion somewhat similar to that found in the subsequent chapter by Haining, Anselin addresses a debate focusing on different perspectives regarding geo-referenced data analysis. In doing so, he promotes model validation and sensitivity analysis. But what conclusion should a researcher state when a slight, modest, or even radical change in underlying assumptions produces an opposite statistical decision? In recent years, scholars seem to be increasingly bombarded with contradictory statistical evidence extracted from data sets. Such pairs of findings could be amusing if consequences of their coexistence were not so unfortunate. The purpose of this paper is to review and evaluate various approaches to modelling and analyzing spatial data, as well as the role spatial errors play in these endeavors. By fulfilling this goal, Anselin helps to resolve these troublesome themes of conflicting statistical implications obtained from geo–referenced data. Haining goes on to emphasize three of the points raised by Anselin, stressing the importance of substance over method as a guiding light in data analysis.

The Editor

What Is Special About Spatial Data? Alternative Perspectives on Spatial Data Analysis

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Overview: In this paper, some general ideas on fundamental issues are outlined, related to the distinctive characteristics of spatial data analysis, as opposed to data analysis in general. The emphasis is on the relevance for spatial data analysis of the ongoing debate about methodology in the disciplines of statistics and econometrics, and on the role of spatial errors in modeling and analysis. First, some general remarks are formulated on two opposing viewpoints regarding spatial analysis and spatial data: a data–driven approach versus a model–driven approach. This is followed by a review of a number of competing inferential frameworks that can be used as the basis for spatial data analysis. Next, the focus shifts to spatial errors and to the implications of various forms of spatial errors for spatial data analysis. Finally, some concluding remarks are formulated on future research directions in spatial statistics and spatial econometrics.

1. Introduction

The analysis of spatial data has always played a central role in the quantitative scientific tradition in geography. Recently, there have appeared a considerable number of publications devoted to presenting research results and to assessing the state of the art. For example, at an elementary level, Goodchild (1987a), Griffith (1987a), and Odland (1988) introduce the concept of spatial autocorrelation, and Boots and Getis (1988) review the analysis of point patterns. At more advanced levels, Anselin (1988a) and Griffith (1988) deal with a wider range of methodological issues in spatial econometrics and spatial statistics. Extensive reviews of the current state of the art for different aspects of spatial data analysis are presented in Anselin (1988b), Anselin and Griffith (1988), Getis (1988), Griffith (1987b), and Odland, Golledge and Rogerson (1989). In addition, spatial data analysis has received considerable attention as an essential element in the development of Geographic Information Systems (GIS), as outlined in Goodchild (1987b) and Openshaw (1987), and as an important factor in regional modeling, as argued in Anselin (1989a).

In this paper, I will take some distance from specific methods and techniques, and instead outline a few general ideas on fundamental issues related to the distinctive characteristics of spatial data analysis, as opposed to data analysis in general. I will focus on two issues that are often overlooked in technical treatments of the methods of spatial statistics and spatial

* Paper prepared for presentation at the Spring 1989 Symposium on Spatial Statistics, Past, Present and Future, Department of Geography, Syracuse University. The research reported on in this paper was supported in part by Grants SES 86-00465 and SES 87-21875 from the National Science Foundation, and by the National Center for Geographic Information and Analysis (NCGIA). An earlier version was presented at the NCGIA Specialist Meeting entitled "Accuracy of Spatial Databases," Montecito, CA, December 13-16, 1988.

econometrics. One is the relevance for spatial data analysis of the ongoing debate about methodology in the disciplines of statistics and econometrics. I will review and evaluate a number of different approaches towards modeling and analyzing spatial data, and put them in the context of the debate. Some recent examples of the opposing viewpoints that are taken in this debate can be found in Leamer (1978), Hendry (1980), Sims (1980, 1982), Lovell (1983), Swamy *et al.* (1985), Zellner (1985, 1988), Efron (1986), Pagan (1987), Kloek and Haitovsky (1988), and Durbin (1988). The second issue is much narrower and pertains to the role of spatial errors in modeling and analysis. This topic has recently received considerable attention in the context of GIS (*e. g.*, as evidenced in the 1988 Research Initiative of the National Center for Geographic Information and Analysis on "errors in spatial databases"), but many aspects of its relation to spatial data analysis remain to be explored.

The discussion in this paper is not intended to be comprehensive, but it is selective in the sense that I will focus on issues that seem to be most relevant to current modeling practice and most promising to lead to future research advances. Clearly, this selective treatment reflects my own biases and interests, and is focused on applications in regional science and analytical human geography.

The remainder of the paper consists of six sections. First, I formulate some general remarks on two opposing viewpoints regarding spatial analysis and spatial data: a data–driven approach versus a model–driven approach. This is followed by a review of a number of competing inferential frameworks that can be used as the basis for spatial data analysis. Next, I focus on spatial errors and on the implications of various forms of spatial errors for spatial data analysis. I close with some concluding remarks on future research directions in spatial statistics and spatial econometrics.

2. Spatial Analysis and Spatial Data

In general terms, spatial analysis can be considered to be the formal quantitative study of phenomena that manifest themselves in space. This implies a focus on location, area, distance and interaction, such as is expressed in Tobler's (1979) First Law of Geography, where "everything is related to everything else, but near things are more related than distant things." In order to interpret what "near" and "distant" mean in a particular context, observations on the phenomenon of interest need to be referenced in space (*e. g.*, in terms of points, lines or areal units). There are two opposite approaches towards dealing with spatially referenced data (Anselin, 1986b; Haining, 1986). In one, which I will call the data–driven approach, information is derived from the data without a strong prior notion of what the theoretical framework should be. In other words, one lets the "data speak for themselves" (Gould, 1981). In this largely inductive approach information on spatial pattern, spatial structure and spatial interaction is derived without the constraints of a pre–conceived theoretical notion.

In most respects, this approach falls under the category of "exploratory data analysis" (EDA) popularized by Tukey (1977) and Mosteller and Tukey (1977). It is also similar to the philosophy underlying time series analysis and forecasting of the Box–Jenkins (1976) type, and its extensions to vector autoregressive processes and the like (*e. g.*, Doan *et al.*, 1984; and the critique of Cooley and LeRoy, 1985).

The data–driven approach in spatial analysis is reflected in a wide range of different techniques, such as point pattern analysis (Getis and Boots, 1978; Diggle, 1983), indices of

spatial association (Hubert, 1985; Wartenberg, 1985), kriging (Clark, 1979), spatial adaptive filtering (Foster and Gorr, 1986), and spatial time series analysis (Bennett, 1979). All these techniques have two aspects in common. First, they compare the observed pattern in the data (*e. g.*, locations in point pattern analysis, values at locations in spatial autocorrelation) to one in which space is irrelevant. In point pattern analysis this is the familiar Poisson pattern, or "randomness," while in many of the indices of spatial association it is the assumption that an observed data value could occur equally likely at each location (*i. e.*, the null hypothesis for many tests for spatial autocorrelation, based on a normal or randomization approach).

The second common aspect is that the spatial pattern, spatial structure, or form for the spatial dependence are derived from the data only. For example, in spatial time series analysis, the specification of the autoregressive and moving average lag lengths is derived from autocorrelation indices or spatial spectra.

The data–driven approach is attractive in many respects, but its application is not always straightforward. Indeed, the characteristics of spatial data (dependence and heterogeneity) often void the attractive properties of standard statistical techniques. Since most EDA techniques are based on an assumption of independence, they cannot be implemented uncritically for spatial data. In this respect, it is also important to note that dependence in space is qualitatively more complex than dependence in the time dimension, due to its two–dimensional and two–directional nature. As a consequence, many results from the analysis of time series data do not apply to spatial data. As discussed in detail in Hooper and Hewings (1981), the extension of time series analysis into the spatial domain is limited, and only applies to highly regular processes. It goes without saying that most data in empirical spatial analysis for irregular areal units do not fit within this restrictive framework.

The second approach, which I will call model–driven, starts from a theoretical specification, which is subsequently confronted with the data. The theory in question may be spatial (*e. g.*, a spatial process or a spatial interaction model, as in Haining, 1978, 1984) or largely aspatial (*e. g.*, a multiregional economic model, as in Folmer, 1986), but the important characteristic is that its estimation or calibration is carried out with spatial data. The properties of this data, namely spatial dependence and spatial heterogeneity, necessitate the application of specialized statistical (or econometric) techniques, irrespective of the nature of the theory in the model.

Most of the methods that I would classify under this category deal with estimation and specification diagnostics in linear models in general, and regression models in particular (*e. g.*, Cliff and Ord, 1981; Anselin, 1980, 1988a). The main conceptual problem associated with this approach is how to formalize the role of "space." This is reflected in three major methodological problems, which are still largely unresolved to date: the choice of the spatial weights matrix (Stetzer, 1982a; Anselin, 1984, 1986a); the modifiable areal unit problem (Openshaw and Taylor, 1979, 1981); and the boundary value problem (Griffith, 1983, 1985; Griffith and Amrhein, 1983).

In order for the data–driven or the model–driven approaches to be operational, the various tests, diagnostics and estimators need to be incorporated in an inferential framework. More precisely, the uncertainty associated with a random variable, sampling error, or any other stochastic aspect of the data analysis needs to be assessed within a consistent framework that forms a logical basis for decisions. A number of competing frameworks have been suggested. They are discussed next.

3. Inferential Frameworks in Spatial Data Analysis

Spatial data analysis is not immune from the implications of the philosophical debates that go on in the broader disciplines of statistics and econometrics. Although the results of applied and empirical work are often presented as if only one particular view of statistics existed, there are in fact many competing perspectives (or even paradigms). Rather than repeating the various philosophical arguments, I will outline five dimensions of conflict or competition, and discuss some implications of the alternative viewpoints for spatial data analysis. Some of these dimensions are more fundamental than others, but all have direct applications to the practice of spatial statistics and spatial econometrics.

3.1. Classical versus Bayesian inference

The debate between the classical (Neyman–Pearson) and Bayesian approaches to statistical inference (or decision making) is undoubtedly the most fundamental one ongoing in the discipline. The arguments of both sides are well known and a compromise does not seem likely in the near future (*e. g.*, Efron, 1986; Durbin, 1988; Zellner, 1988). In a nutshell, the classical approach is "objective," and practical, but fraught with philosophical problems when applied in a strict sense: problems with multiple comparisons, the need to assume a "true" model, and the such. On the other hand, the Bayesian approach is generally considered to be superior in terms of overall consistency and as a perspective on "learning," but is "subjective" and difficult to apply to many practical problems, due to the need to construct complex prior distributions and to carry out numerical integration in multiple dimensions.

In spatial data analysis, the Bayesian perspective is the exception, and it has found only limited application. Some Bayesian concepts are fairly familiar in image processing of remotely sensed data (Richards, 1986), but applications to spatial data analysis in human geography are fairly rare (some exceptions are provided in March and Batty, 1975; Odland, 1978; Hepple, 1979; and Anselin, 1982, 1988b). Although the classical approach reflected in the Neyman–Pearson inferential framework is by far the dominant one in geography, its uncritical application to spatial data analysis is inappropriate in a lot of respects. The many assumptions, judgements and multiple comparisons carried out in the practice of estimation and data analysis (both data–driven as well as model–driven) make a mockery out of the rigorous and elegant probabilistic calculus that underlies the classical approach (for more details, see Anselin, 1988b). It therefore would seem, at least from a conceptual viewpoint, that a number of spatial "problems" could be most fruitfully attacked from a Bayesian perspective. Examples are pattern recognition, or "learning" from data in general, the prior assumptions about a spatial weights matrix, spatial interpolation, and dealing with boundary effects. However, the practical implementation of a Bayesian analysis of these issues is not straightforward. Specifically, it has so far not been possible to develop useful prior distributions for the full range of patterns of spatial dependence (spatial weight matrices) that would be operational in spatial data analysis. Overall, dealing with the two–directional nature of spatial dependence in a Bayesian framework is still very much an unresolved research topic.

3.2. Parametrics versus non–parametrics and/or robustness

In applied spatial data analysis, the standard assumptions of normality and of perfect knowledge of the model specification are often rather crude abstractions of reality. Consequently, the relevance of a strict parametric approach has been increasingly questioned, and a nonparametric, qualitative or robust perspective has sometimes been suggested as an alternative, by, among others, Gould (1981), Costanzo (1983), Nijkamp, Leitner and Wrigley (1985) and Knudsen (1987). However, it is not as if nonparametric and robust procedures have not been introduced into spatial analysis. On the contrary, a number of well known indices for spatial association have been based on randomization, permutation and other nonparametric techniques. Examples range from a robust Moran index in Cliff and Ord (1973), and Sen and Soot (1977), to the general measures of spatial association in Hubert *et al.* (1981, 1985). Most of these methods would fall under the data–driven category of spatial data analysis. However, there have been some recent applications in the model–driven category as well, primarily based on the use of the Jackknife and bootstrap estimation techniques (Stetzer, 1982b; Folmer and Fischer, 1984; Anselin, 1989b).

In spite of the concerns about its appropriateness, the parametric approach remains the most common one in spatial data analysis. Most tests are based on an underlying distribution which is normal (for values) or Poisson (for point patterns) and the estimation method of choice is the maximum likelihood technique. As is well known, the parametric approach is optimal in a number of ways if the underlying assumptions are indeed satisfied. It is when this is not the case that problems occur. Since the robust and nonparametric techniques are not grounded in such a restrictive set of assumptions, they remain valid in a wider range of situations. However, this robustness comes at the cost of a loss in generality and precision. For example, the spatial association indices that are based on a permutation approach only pertain to the data at hand, and cannot be generalized to hold for a "population." Similarly, the variance estimates for parameters obtained by means of the bootstrap or Jackknife will tend to be larger than for the maximum likelihood (ML) approach, and thus will lead to a more conservative inference (*i. e.*, it will be "harder" to find significant coefficients). Clearly, when the assumptions underlying the ML approach do hold (primarily normality of the distribution), the larger variances of the robust approach will be inefficient and the parametric approach is superior. However, this is likely to be the exception rather than the rule in spatial data sets.

An important obstacle for the acceptance of robust or non–parametric techniques in spatial data analysis is that a great many of the techniques developed in mathematical statistics and econometrics (*e. g.*, as reviewed in Huber, 1981; Koenker, 1982; Efron, 1982; and Robinson, 1988) are not directly transferable, since they are based on an assumption of observational independence. An appropriate "spatial" theoretical framework for robust analysis remains to be developed.

3.3. Random sample versus stochastic process

The dependence that is inherent in many (if not most) spatial data runs directly counter to the postulate of a random sample of independent observations upon which most common statistical procedures are based. Nevertheless, much applied spatial data analysis still proceeds as if the standard assumptions hold (see Anselin and Griffith, 1988), and notions of sampling error, sampling variance, and the such, abound in the empirical literature. Clearly, this is

incorrect, and the loss of information that results from the dependence in the observations should be accounted for.

In most instances, the proper perspective is not to consider spatial data as a random sample with many observations, but instead as a single realization of a stochastic process. In contrast to the sampling approach, where each observation is taken to provide an independent piece of information, the dependence (and heterogeneity) embodied in a stochastic process implies that only one observation is available, which is the full spatial pattern (or space–time pattern) of values. Provided that the underlying stochastic process is sufficiently stable (stationary, isotropic, *etc.* ...) or that the structure of the instability (nonstationarity) is known, the observed pattern will yield information on the characteristics of that process. In contrast to the random sampling approach, where the notion of independence is exploited in order to derive exact statistical properties for estimates and hypothesis tests, an asymptotic reasoning is needed in the stochastic process approach. Specifically, the theory of mixing processes, which allows a degree of dependence as well as heterogeneity, forms a solid basis for the inference for spatial stochastic processes (for details see Anselin, 1988a, Chapter 5).

The consequence of spatial dependence, or, more precisely, positive spatial dependence is that the observations contain less information than if there had been independence. In other words, in order to obtain approximately the same degree of information as in an independent set of observations, a larger data set of (positively) dependent observations will be needed. Sometimes, the latter can be transformed into the former, by deleting observations that are contiguous or within a given distance of each other. For example, if only those observations are selected that are far enough apart so that no marked dependence can reasonably be expected (*i. e.*, dependence related to distance only) this new "sample" can be considered to be independent for most practical purposes. This "re–coding" lies at the basis of the so–called "conditional" approach to spatial modeling (Haining, 1986). Its advantage is that most standard statistical techniques can be applied unchanged to the re–coded data. However, the re–coding itself is not unique and somewhat arbitrary. Also, this is only a practical approach if the loss of information from discarding the "dependent" observations is not critical. Unfortunately, in many practical situations such a luxury does not exist, and the "simultaneous" (joint probability) stochastic process approach is the only feasible parametric framework.

A related issue is the extent to which spatial data constitute a sample, a realization of a stochastic process, or instead form the complete population of interest. It is sometimes argued that the latter is the only correct perspective, and not only that no inferential statistics are possible, but also that a descriptive approach is the only valid one (*e. g.*, Summerfield, 1983). Although this may be an acceptable viewpoint in the case of extreme heterogeneity (*i. e.*, each place is "unique" and no generalization is possible), it is more the exception than the rule. There are two crucial issues that need to be considered. The first pertains to the imperfect nature of measurement, and the inherent error (or noise). Since a mixture of signal and noise is observed in empirical practice, the stochastic nature of the data can be easily generated from the randomness in errors of measurement. As a consequence, the population in question pertains to the family of stochastic processes that may have generated a particular error pattern. Thus, a "statistical" approach is the only way in which conclusions can be formed about the underlying "signal" and an understanding of spatial errors is crucial.

The second issue pertains to the nature of space as a framework within which observations are ordered. In essence, the spatial unit of observation needs to be a representative unit for the phenomenon that is under study. Only then will it be possible to formulate and test general statements about "space." The real issue is whether the observations at hand are compatible with the complexity of the phenomenon of interest. If they are not, this does not mean that a statistical approach should be rejected, but rather that other types of data are needed. For example, this may necessitate the collection of micro–behavioral data to avoid problems of ecological fallacy, or may require the extension of a cross–section into the time dimension in order to formulate general conclusions about a specific region.

3.4. Finite sample versus asymptotics

The stochastic process approach to spatial data analysis is based on asymptotic properties for an "abstract" and infinitely large data set. This conceptual framework contrasts sharply with the reality of small data sets with a finite number of observations. Two issues merit some consideration. The first is practical and pertains to the extent to which the asymptotic properties are valid in finite samples. As is well known, this is not necessarily the case, and many properties of equivalence and optimality of asymptotic tests and estimators are not reflected in realistic data sets. Moreover, few analytic results are available and the properties of a number of approximations are questionable (see, for instance Taylor, 1983; and also Anselin, 1988b for spatial data). In other words, considerable caution (a conservative inference) is needed when interpreting the findings of spatial data analysis that are based on asymptotic properties.

The second issue related to asymptotics is more conceptual and pertains to the relevance of the notion of an infinitely large data set for spatial analysis. In essence, an asymptotic reasoning is only meaningful if an infinitely large number of replications of the observed spatial units can be conceived of. While this is fairly straightforward in the case of a continuous process that is observed on regularly spaced points or grids, it is not at all obvious for discontinuous processes or observations for irregular areal units (*e. g.*, a given set of counties in a state). There are two approaches to this conceptual problem. In one, the data for irregular spatial units are transformed (interpolated) to regular spatial units. Although this forms an elegant solution to the problem, it is only valid if the underlying process is sufficiently smooth and homogeneous. In the other approach, the dependence and heterogeneity in the data are recognized as a limiting factor, and the only way to obtain meaningful information from the observations is by adding an additional dimension (*i. e.*, the time dimension). In other words, by pooling time series data for a fixed set of cross–sectional units, the asymptotics in the time dimension provide the framework to carry out statistical inference about the spatial dimension. In either case, it is necessary to evaluate whether the complexity of the proposed hypotheses or models is compatible with the information available in the data. Unfortunately, in many situations encountered in applied empirical work this will not be the case. In those instances the stochastic framework for inference will be suspect, and give rise to legitimate concerns about the relevance of a "statistical" approach.

3.5. Analytics versus computing power

A final issue that has come to the fore as a result of the recent advances in computer technology is the choice between procedures based on rigorous analytics and those that replace the analytics by numerically intensive computation. The latter have led to the development

of combinatorial methods and resampling schemes in which the stochastic properties are derived from a large number of replications of pseudo–data (*e. g.*, Efron, 1979; Hubert, 1985; Knudsen, 1987). With the advent of large spatial data bases and geographic information systems, the distinction between description, analysis, modeling and simulation has become blurred. The technological possibilities are virtually unbounded, and have opened up new horizons for spatial data analysis. An example of a recent development in this respect is the creation of a so–called "geographical analysis machine" (GAM), as a combination of a GIS, a spatial statistical analysis and expert system that is designed to carry out an automated spatial data analysis (Openshaw *et al.*, 1987). This concept has many attractive features, but in its current form, the GAM is still rudimentary and limited to a specific application. Also, the statistical properties of the results obtained from a sequence of multiple comparisons (as in the GAM) are unclear. As is well known, a naïve impression of "significance" can always be obtained after a large number sequential tests. Consequently, important further developments are needed before this a–theoretical approach will be able to replace (or complement) the more traditional analytic approach for a wide range of spatial data analysis problems.

4. Spatial Errors

Basic to both the data–driven and the model–driven analysis of spatial data is an understanding of the stochastic properties of the data. The use of "space" as the organizing framework leads to a number of features that merit special attention, since they are different from what holds for aspatial or time series data. The most important concept in this respect is that of error, or, more precisely for data observed in space, spatial error. The distinguishing characteristics of spatial error have important implications for description, explanation, and prediction in spatial analysis. Some of these issues will be discussed in the next section. In this section, I present a simple taxonomy of the nature of spatial errors, and outline some alternative perspectives on how error can be taken into account.

4.1. The nature of spatial errors

Spatial errors can be due to a variety of sources. For spatial data analysis, the most relevant types of error are measurement error and specification error. Measurement error occurs when the location or the value of a variable are observed with imperfect accuracy. The former is an old cartographic problem and is still very relevant in modern geographic information systems (*e. g.*, errors due to a lack of precision in digitizing). The main problem is that the geometric and graphical representation of the location of points, lines or areal boundaries (*i. e.*, a map) gives an imperfect impression of the uncertainty associated with errors in the measurement of these features. Since these locational features are important elements in the evaluation of distance and relative position, and in the operations of areal aggregation and interpolation, the associated measurement error will affect many of the "values" generated in a spatial information system as well. Although similar errors occur in the time dimension, they are much simpler to take into account since they only propagate in one dimension and one direction. Moreover, spatial measurement errors, in contrast to the classical case, will tend not to balance out.

Other spatial errors of measurement have to do with the imperfect way in which data on socio–economic phenomena are recorded and grouped in spatial units of observation (*e. g.*, various types of administrative units). This interdependence of location and value in spatial data leads to distinctively spatial characteristics of the errors. These are the familiar spatial

dependence and spatial heterogeneity. Dependence is mostly due to the existence of spatial spill–overs, as a result of a mis–match between the scale of the spatial unit of observation and the phenomenon of interest (*e. g.*, continuous processes represented as points, or processes extending beyond the boundaries of administrative regions). Heterogeneity is due to structural differences between locations and leads to different error distributions (*e. g.*, differences in accuracy of census counts between low–income and high–income neighborhoods).

Specification error is particular to the model–driven approach in spatial data analysis. It pertains to the use of a wrong model (*e. g.*, recursive versus simultaneous), an inappropriate functional form (*e. g.*, linear as opposed to nonlinear), or a wrong set of variables. In essence, it is no different from misspecification in general, but it generates spatial patterns of error due to the use of spatial data. These spatial aspects can occur as a result of ignoring location–specific phenomena, spatial drift, regional effects or spatial interaction. When a false assumption of homogeneity is forced onto a model in those instances, spatial heterogeneous errors will result. Similarly, when the spatial scale or extent of a process does not correspond to the scale of observation, or when the nature of a process changes with different scales of observation, spatial dependent errors will be generated.

4.2. Perspectives on spatial errors

The treatment of spatial errors in data analysis is fundamentally different between the data–driven and the model–driven approaches. In the data–driven approach, errors are considered to provide information. The focus of attention is on how the spatial pattern of the errors relates to data generation processes. For example, in attempts to provide measures of uncertainty for spatial information in a GIS, the spatial pattern of errors is related to data collection and manipulation procedures. The spatial pattern of errors can often provide insight into the form of the underlying substantive spatial process, such as is exploited in the model identification stage of a spatial time series analysis. Important and still unresolved research questions deal with the formulation of useful spatial error distributions, in which error is related to location, distance to reference locations, area, and the such.

In the model–driven approach to spatial data analysis, error is considered to be a nuisance. The main focus is on how to identify the spatial distribution of the error process, and how to eliminate the effect of errors on statistical inference. In other words, once errors are identified, they are eliminated by means of transformations, corrections, or filters. Alternatively, robust estimation and test procedures can be applied that are no longer sensitive to the effect of errors. A major research question in this respect is how diagnostics can be developed that are powerful in detecting various types of errors, and are able to distinguish between them (*e. g.*, to distinguish between spatial dependence and spatial heterogeneity, or "real" versus "apparent" contagion).

5. Implications of Spatial Errors for Spatial Data Analysis

The presence of errors with a distinctive spatial pattern has obvious implications for the analysis of spatial data. These implications vary between the analysis of spatial pattern, the estimation and prediction of spatial models, and their validation.

5.1. Analysis of spatial pattern

Given the importance of distance and contiguity in the analysis of spatial pattern, errors of measurement in the location of points, lines, and areal units will greatly affect the distributional properties of tests and other indices. This aspect of spatial error is largely ignored in current statistical practice, but merits closer attention, particularly in light of the increased availability of large computerized spatial data bases with the explosion of the GIS field. Some indices of spatial pattern and spatial association that are routinely derived in a GIS (*e. g.*, based on nearest–neighbors) provide a misleading sense of precision, since they ignore the uncertainty associated with the location of spatial units themselves. Conceptually, the solution to this problem is straightforward, in that a spatial distribution needs to be specified for each location (and the associated values). However, the choice of the most appropriate distribution and its effect on the properties of the various spatial statistics are still largely unresolved topics of research.

5.2. Estimation and prediction

The effect of spatial errors on the estimation and prediction of standard linear models is probably the best understood aspect of spatial data analysis. In particular, for the linear regression model with normally distributed disturbance terms, many tests and estimators have been developed (see Anselin and Griffith, 1988, for a review). In those models, the error is taken to pertain to the dependent variable only and its effect is incorporated in the regression disturbance term. The more realistic situation where error is present in both dependent and independent variables has received much less attention, and is considerably more complex. The specification of interaction between the various spatial errors is largely unresolved, and so far only a robust estimation approach seems to hold promise.

Most methodological results obtained so far also are limited to the normal distribution case. Spatial effects in models with limited dependent variables, censored and truncated distributions, or in models for count data have been largely ignored. A major problem in this respect is that multivariate dependent distributions other than the normal are highly complex. Moreover, their application in an operational context is often hampered by limitations on carrying out numerical integration in multiple dimensions. Since the non–normal case is probably the rule rather than the exception in actual spatial data, a considerable agenda of research questions remains to be addressed.

5.3. Model validation

In model validation, the focus is on assessing the uncertainty associated with the output (interpretation) of alternative specifications. Clearly, this will be a function of the probabilistic model that has been adopted for the underlying (unobserved) spatial errors. A particular problem in spatial data analysis is how to provide a meaningful summary measure of spatial accuracy. If spatial heterogeneity is present, the accuracy is likely to vary systematically by location. On the other hand, if spatial dependence is present, the accuracy at one location will be affected by the accuracy associated with "neighboring" locations. A summary or holistic measure of accuracy will be an imperfect reflection of this partitive (observation by observation) accuracy. What is needed is a meaningful objective function (loss or risk function) that incorporates the relative importance of accuracy for particular locations or regions in space. It is unlikely that such an objective function can be developed with uni-

versal applicability, but instead, a flexible approach can be taken that is consistent with the use of spatial information systems as decision support systems.

6. Conclusion

The wide array of philosophical and methodological dilemmas that confront the analysis of spatial data necessitates an eclectic perspective. Many different ways of looking at a data set or at a model specification should be compared, and sensitivity analysis should play a central role. In other words, the extent to which the results are affected by changes in the underlying assumptions (as in fragility analysis) needs to be assessed. If different approaches yield the same qualitative conclusions, one can be more confident that meaningful insights have been gained. On the other hand, if the statistical findings turn out to be very sensitive to the approach taken, there is likely to be something wrong with the data and/or with the model, and not much faith should be put in the precise quantitive results.

The characteristics of errors that affect observations of spatial data clearly motivate the need for a specialized methodology of spatial statistics and spatial econometrics. However, much of the current state–of–the–art in these fields pertains to highly artificial and rather simplistic data structures. A major emphasis of future research should be to focus on realistic perspectives on spatial data. With the vast power of a user–friendly GIS increasingly in the hands of the non–specialist, the danger is great that the "wrong" kind of spatial statistics will become the accepted practice. Since the "easy" problems have more or less been solved, a formidable challenge lies ahead.

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DISCUSSION

"What is special about spatial data? alternative perspectives on spatial data analysis"

by Luc Anselin

Anselin has given an interesting review of issues underlying the analysis of spatial data. I will comment on three areas of his discussion, namely model–driven versus data–driven approaches to data analysis, problems raised by data accuracy, and the role of robust analyses in spatial data analysis.

Data analysis involves the stages of model specification, parameter estimation and model validation. The dangers inherent in the model–driven approach are first that data properties play a reduced role in the first and last stages, and second, as a consequence, there is a tendency to confirm or re–enforce existing theoretical 'prejudices'. In the case of the data–driven approach, analysis tends to emphasize current experience (the data) and disregard the results of previous analyses, and as a consequence there is a risk of reporting results that are mere artifacts of a particular data set. Data analysis in the social sciences tries to strike a balance between these two approaches, which lie at two ends of a continuum. The case against a purely model–driven approach in the social sciences is the dearth of good theory, while the case against a purely data–driven approach are first the conditions under which much data are collected (non–experimental, complex interactions), and second the accuracy of much social science data. These concerns make model specification, purely on the basis of data properties, an uncertain exercise.

Data accuracy is a major concern in all areas of inductive science. The rising tide of spatially referenced data (collected through both government and commercial agencies) offers both opportunities and pitfalls. The accuracy of these data, in terms of both spatial referencing and the reported values, should be a matter of concern. Although methods are being developed to reduce the influence of unusual or suspect values, in later stages of analysis this is hardly a substitute for the specification of minimal criteria for the procedure of data collection and the careful screening of data prior to and during computerized data storage. The question as to whether it is worthwhile analyzing large data sets, particularly those that may not satisfy such minimum criteria, is an important one. The increase in data allows us to be more discriminating in what we analyze, and should not necessarily lead to more analysis. There is a danger that the more data we have, the less we will know.

The following are two classes of problems that confront the data analyst: those that arise when statistical assumptions are not satisfied, and those that arise from the nature of the data. Robust and resistant estimation methods have been developed that provide improved estimates where the data follow some skewed distribution, or the data contain outliers or extreme values. Most of these estimation methods assume that observations are independent. Robust and resistant estimation methods are required for situations where observations are not independent in order to provide estimates of the parameters of spatial models (where there may be several different parameter sets associated with different aspects of the model). Not only the presence of extreme values but also their spatial distribution may affect parameter estimation when standard 'non–robust' methods are used on such spatial models.

Lastly, in addressing the issues raised in Anselin's paper and identifying directions for future research, it is important not to lose sight of the reason for developing these methods within any subject field such as geography or regional science. The importance of any methodological area of research ultimately depends upon the extent to which it better enables users to tackle substantive questions. The concern of statisticians is largely with the development of statistical theory and the methodology of data analysis. The concern of the applied scientist is with the development of the theory and methods in relation to important substantive issues within the specific field of study.

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