FOREWORD

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Geographic information systems date from the 1960s, when computers were mostly seen as devices for massive computation. Very significant technical problems had to be solved in those early days: how did one convert the contents of a paper map to digital form (by building an optical scanner from scratch); how did one store the result on magnetic tape (in the form of a linear sequence of records representing the geometry of each boundary line as sequences of vertices); and how did one compute the areas of patches (using an elegant algorithm involving trapezia). Most of the early research was about algorithms, data structures, and indexing schemes, and thus had strong links to emerging research agendas in computer science.

Over the years, however, the research agenda of GIS expanded away from computer science. Many of the technical problems of computation were solved, and attention shifted to issues of data quality and uncertainty; the cognitive principles of user interface design; the costs and benefits of GIS; and the social impacts of the technology. Academic computer scientists interested in GIS wondered if their research would be regarded by their colleagues as peripheral – a marginally interesting application -- threatening their chances of getting tenure. Repeated efforts were made to have GIS recognized as an ACM Special Interest Group, without success, though the ACM GIS conferences continue to attract excellent research.

The entries in this encyclopedia should finally lay any lingering doubts to rest about the central role of computer science in GIS. Some research areas, such as spatiotemporal databases, have continued to grow in importance because of the fundamental problems of computer science that they raise, and are the subject of several respected conference series. Geopatial data mining has attracted significant attention from computer scientists as well as spatial statisticians, and it is clear that the acquisition, storage, manipulation, and visualization of geospatial data are special, requiring substantially different approaches and assumptions from those in other domains.

At the same time GIS has grown to become a very significant application of computing. Sometime around 1995 the earlier view of GIS as an assistant, performing tasks that the user found too difficult, complex, tedious, or expensive to do by hand was replace by one in which GIS became the means by which humans communicate what they know about the surface of Earth, with which they collectively make decisions about the management of land, and by which they explore the effects of alternative plans. A host of new issues suddenly became important: how to support processes of search, assessment, and retrieval of geospatial data; how to overcome lack of interoperability between systems; how to manage large networks of fixed or mobile sensors providing flows of real-time

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geographic data; how to offer useful services on the very limited platform of a cellphone; and how to adapt and evolve the technology to respond to emergencies and to provide useful intelligence. A revitalized research agenda for computer science emerged that shows no sign of diminishing, and is reflected in many of the topics addressed in this encyclopedia.

For example, computer scientists are engaged in the development of data structures, algorithms, and indexing schemes to support the hugely popular virtual globes (Google Earth, Microsoft's Virtual Earth, NASA's World Winds) that have emerged in the past few years and are stimulating a whole new generation of applications of geospatial technology. Research is ongoing on sensor networks, and the complex protocols that are needed to handle flows of real-time data from massive numbers of devices distributed over the Earth's surface, in areas of scientific interest such as the sea floor, in vehicles acquiring data on traffic movement, and in battlefields. Semantic interoperability, or the ability of systems to share not only data but the meaning of data, remains a thorny problem that will challenge the research community for many years to come.

As a collection of well-written articles on this expanding field, this encyclopedia is a welcome addition to the GIS bookshelf. The fact that its compilers have chosen to emphasize the links between GIS and computer science is especially welcome. GIS is in many ways a *boundary object* to use a term common in the community of science historians: a field that has emerged between two existing and recognized fields, in this case computer science and geography, and which has slowly established its own identity. As it does so, contributions such as this will help to keep those links alive, and to ensure that GIS continues to attract the interest of leading researchers in computer science.

IMPRECISION AND SPATIAL UNCERTAINTY

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DEFINITION

Spatial uncertainty is defined as the difference between the contents of a spatial database and the corresponding phenomena in the real world. Because all contents of spatial databases are representations of the real world, it is inevitable that differences will exist between them and the real phenomena that they purport to represent. Spatial databases are compiled by processes that include approximation, measurement error, and generalization through the omission of detail. Many spatial databases are based on definitions of terms, classes, and values that are vague, such that two observers may interpret them in different ways. All of these effects fall under the general term of spatial uncertainty, since they leave the user of a spatial database uncertain about what will be found in the real world. Numerous other terms are partially synonymous with spatial uncertainty. Data quality is often used in the context of metadata, and describes the measures and assessments that are intended by data producers to characterize known uncertainties. Vagueness, imprecision, and inaccuracy all imply specific conceptual frameworks, ranging from fuzzy and rough sets to traditional theories of scientific measurement error, and whether or not it is implied that some true value exists in the real world that can be compared to the value stored in the database.

HISTORICAL BACKGROUND

Very early interest in these topics can be found in the literature of statistical geometry (Kendall, 1961), which applies concepts of probability theory to geometric structures. An early paper by Frolov and Maling (1969) analyzed the uncertainties present in finite-resolution raster representations, and derived confidence limits on measures such as area, motivated in part by the common practice of estimating measures of irregular patches by counting grid cells. Maling's analysis established connections between the spatial resolution of the overlaid raster of cells and confidence limits on area estimates. Maling's book (Maling, 1989) was a seminal venture into the application of statistical methods to maps, and helped to stimulate interest in the topic of spatial uncertainty. The growth of geographic information systems (GIS) provided the final impetus, and led to the first research initiative of the new U.S. National Center for Geographic Information and Analysis in 1988, on the topic of accuracy in spatial databases (Goodchild and Gopal, 1989).

The notion that spatial databases could be treated through the application of classical theories of measurement error soon proved too limiting, however. The definitions of types that are used in the compilation of maps of soil class, vegetation cover class, or land use are clearly open to interpretation, and such maps must be regarded as to some degree subjective and outside the normal bounds of scientific replicability. Concepts of fuzzy and rough sets were explored by researchers interested in these issues (Fisher and Unwin, 2005). While the definition of a given class may be vague, it is nevertheless helpful to think about degrees of membership in the class. For example, researchers interested in developing plain-language interfaces to GIS found that prepositions such as “near” had vague meanings that could be represented more formally through membership functions. This approach resonated well with the move in the early 1990s to introduce theories of linguistics and cognition into GIS research.

By the end of the 1990s the literature on spatial uncertainty had grown to include several distinct theoretical frameworks, including geostatistics, fuzzy sets, rough sets, and spatial statistics. Zhang and Goodchild (2002) published a synthesis, framed within the fundamental dichotomy between discrete objects and continuous fields that underlies much of GIScience. Research continues, particularly on such topics as spatial uncertainty in digital terrain data.

SCIENTIFIC FUNDAMENTALS

In the classical theory of measurement, an observed value x' is distorted from its true value z by a series of random effects. If these effects are additive, the distortion $\delta z = z' - z$ is expected to follow a Gaussian distribution, and each observed measurement is interpreted as a sample drawn from that distribution. The mean of the distribution is termed the bias or systematic error, and the root mean square of δz is termed the standard error. The standard deviation of δz with respect to its own mean is often termed precision, and a biased measurement device is thus said to be possibly precise but not accurate. However, precision can also refer to the number of numerical digits used to report a measurement, and imprecision is used in several ways in the literature on spatial uncertainty.

This analysis extends readily to measurement of position in two or three dimensions, and thus to measurements made by such technologies as the Global Positioning System (GPS), where the multivariate Gaussian is widely used to characterize positional uncertainty. Measurement errors in the two horizontal dimensions are commonly found to have equal variance, but errors in the vertical dimension typically have very different variance; and measurement errors in all three dimensions are commonly found to be uncorrelated.

This classical theory has been developed extensively within the discipline of surveying, under the rubric of adjustment theory, in order to understand the effects that errors in raw measurements may have on the inferred locations of items of interest. For example, errors in the measurement of bearing, elevation, and range will translate into errors in the inferred positions of the objects of the survey. Complications arise when closed loops are surveyed in the interests of reducing errors, which must then be allocated around the loop in a process known as adjustment. This body of theory has not had much influence on spatial databases, however, outside of the domain of traditional surveying.

Any spatial database will consist of large numbers of measurements. For example, a remotely sensed image may contain millions of pixels, each containing several measurements of surface reflectance. Although measurements made by simple devices such as thermometers can reasonably be assumed to have statistically independent errors, this is almost never true of data compiled across geographic space. Instead, strong and mostly positive correlations are observed between data values that are close together in space. These correlations may be induced by the production process, when nearby many data values inherit the errors in a smaller number of measurements through various forms of interpolation, or through the measurements themselves, which are distorted by effects that operate across areas of space. Such correlations are generally known as spatial dependence or spatial autocorrelation.

This tendency turns out to be quite useful. For example, consider a curved segment of a street, recorded in a spatial database as a sequence of coordinate pairs. Assume a measurement error of 10m, not unreasonable in today's street centerline databases. If each point was independently disturbed by 10m, the result would be impossibly and unacceptably erratic, and the segment's length as determined from the database would be severely overestimated. Instead, positive correlation between nearby errors ensures that the general shape of the street will be preserved, even though its position is disturbed. Similar arguments apply to the preservation of slopes in disturbed elevation models, and to many other examples of spatial data.

Several authors have drawn attention to an apparent paradox that follows from this argument. Consider a straight line, such as a straight segment of a street or property boundary, and suppose that the endpoints are disturbed by measurement error. If the disturbances are independent with known distributions, standard errors can be computed at any point along the line; and are found to be in general smaller away from the endpoints. If the disturbances have perfect positive correlation then standard errors are constant along the line; if they have identical and independent distributions then standard error is least at the midpoint where it is equal to 0.707 times the endpoint standard error; and if errors have perfect negative correlation then standard error will drop to zero at one intermediate point. Kyriakidis and Goodchild (2006) have generalized this problem to several other instances of linear interpolation. In practice, however, the straight line may itself be a fiction, and deviations of the truth from the straight line will tend to rise away from the endpoints, more than compensating for this effect.

Geostatistics (Goovaerts, 1997) provides a comprehensive theoretical framework for such spatial autocorrelation of errors. Variances between nearby errors are expected to increase monotonically up to a distance known as the range, beyond which there is no further increase. The variance at this range is termed the sill, and corresponds to the absolute error of the database; however relative error is less over distances shorter than the range, and near zero over very short distances. Mathematical functions provide models of the monotonic increase of variance with distance.

Such models provide a convenient and powerful basis for exploring the effects of errors in applications such as terrain databases. Just as one might simulate the effects of error by adding independent samples from a Gaussian distribution to an observed value, so the effects of error in such databases can be simulated by adding random fields with suitable spatial covariances. In such cases, however, and because of the strong spatial dependences present in virtually all spatial data, it is the entire database that must be simulated in each realization of the random process, not its individual measurements; and samples from the stochastic process are entire maps, not simple measurements. Such simulations have proven very useful in visualizing the effects of spatially autocorrelated errors in spatial databases, and in exploring the propagation of such errors during GIS analysis. Several studies have demonstrated the use of geostatistical techniques such as conditional simulation to provide models of error in spatial databases.

Progress has been made in modeling the ways in which uncertainties propagate through GIS operations based on this theoretical framework. Although simple queries may refer only to a single point, and require knowledge only of that point's marginal distribution of uncertainty, other operations such as the measurement of area, distance, slope, or direction require knowledge of joint distributions and thus covariances. Heuvelink (1998) has developed a comprehensive framework for the propagation of uncertainty, using both analytic and numeric methods, including Taylor series approximations.

Such approaches are fundamentally limited by their insistence on the existence of a truth that is distorted by measurement. They fit well with applications in terrain modeling, and the positional accuracy of well-defined featuers such as roads, but poorly to applications involving classifications of soil, vegetation cover, or land use. But progress has been made in analyzing these latter types of database using the theoretical frameworks of fuzzy and rough sets. Briefly, such frameworks suppose that although the exact nature of a class A may remain unknown, it is still possible to measure membership m(A) in the class. Zhu *et al.* (1996) have shown how maps of membership can be useful in characterizing inherently vague phenomena, and Woodcock and Gopal (2000) have shown how such maps can be useful in managing forests. Fisher and Unwin (2005) have explored more advanced versions of these simple frameworks. Fundamentally, however, and despite the simplicity and intuitive appeal of these approaches, the question remains: if A cannot be defined, how is it possible to believe that m(A) can be measured? Moreover, it has proven difficult to represent the fundamental spatial dependence properties of spatial data within these frameworks, so while marginal properties can be analyzed with some success, the joint properties that underlie many forms of GIS analysis remain the preserve of statistical methods and of frameworks such as geostatistics and spatial statistics.

KEY APPLICATIONS

The literature on imprecision and spatial uncertainty now encompasses virtually all types of spatial data. As noted earlier, the literature on uncertainty in terrain data is voluminous. Several authors have demonstrated the use of representations of uncertainty in spatial decision support (*e.g.*, Aerts, Goodchild, and Heuvelink, 2003), and have discussed the many sources of uncertainty in such applications. Interesting methods have been devised for visualizing uncertainty, including animation (Ehlschlaeger, Shortridge, and Goodchild, 1997). To date, however, the implementation of these methods in GIS software remains limited. Duckham (2002) and Heuvelink (2005) have described efforts to build error-aware systems, and data quality is now an important element of metadata. But the mainstream GIS products continue to report the results of calculations to far more decimal places than are justified by any assessment of accuracy, and to draw lines whose positions are uncertain using line widths that are in no way representative of that uncertainty. Indeed, GIS practice seems still to be largely driven by the belief that accuracy is a function of computation, not representation, and that the last uncertainties were removed from maps many decades ago.

FUTURE DIRECTIONS

Uncertainty has been described as the Achilles' Heel of GIS (Goodchild, 1998): the dark secret that once exposed, perhaps through the arguments of clever lawyers, will bring down the entire house of cards. While this sounds extreme, it is certainly true that the results of GIS analysis are often presented as far more accurate than they really are. As GIS moves more and more into the realm of prediction and forecasting, the dangers of failing to deal with uncertainty are likely to become more and more pressing. At the same time the accuracy of databases is steadily improving, as more accurate measurements become available. Nevertheless we possess an enormous legacy of less accurate data that is sure to continue to find application for many years to come.

While much has been learned over the past two decades about the nature of spatial uncertainty, a large proportion of the literature remains comparatively inaccessible, due to the complexity of its mathematics. Some progress has been made in making the work more accessible, through visualization and through the comparatively straightforward methods of Monte Carlo simulation. In time, such approaches will result in greater awareness of what is possible, and to greater adoption of these methods within the wider community.

Progress is also needed on the construction of suitable data models for error-sensitive spatial databases. The simple expedient of adding values representing uncertainty to the entire database in its metadata, or to individual objects as additional attributes, fails to capture all of the complexity of spatial uncertainty, particularly its essential spatial dependence. Goodchild (2004) has argued that this problem is profound, stemming from the complex structures of spatial dependence; that it presents fundamental and expensive barriers to any attempt to improve spatial databases through partial correction and update; and that it can only be addressed by a radical restructuring of spatial databases around the concept of measurement, in what he terms a measurement-based GIS. In practice, the almost universal use of absolute coordinates to define position in spatial databases ensures that any information about spatial dependence, and the processes used to compute or compile such positions, will have been lost at some point during the production process.

CROSS REFERENCES

Spatial Statistics, Representation of Inexact Spatial Information, Spatial Data Quality, Metadata, Generalization and Aggregation,

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SPATIAL DATA ANALYSIS

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DEFINITION

Spatial data analysis refers to a set of techniques designed to find pattern, detect anomalies, or test hypotheses and theories, based on spatial data. More rigorously, a technique of analysis is spatial if and only if its results are not invariant under relocation of the objects of analysis—in other words, that location matters. The data that are subjected to spatial data analysis must record the locations of phenomena within some space, and very often that is the space of the Earth's surface and near-surface, in other words the geographic domain. However, many methods of spatial data analysis can prove useful in relation to other spaces; for example, there have been instances of methods of spatial data analysis being applied to the human brain or to the space of the human genome. The terms spatial data analysis, spatial analysis, and geographic analysis are often used interchangeably. Spatial data analysis overlaps very strongly with spatial data mining. Some authors use the latter term to refer specifically to the analysis of very large volumes of data, and to imply that the purpose is the detection of pattern and anomalies—in other words hypothesis generation—rather than the testing of any specific hypotheses or theories. In this sense spatial data mining is more strongly associated with inductive science than with deductive science. However to authors the terms data analysis and data mining are essentially synonymous.

SYNONYMS

Spatial analysis, geospatial analysis, geographical analysis, spatial data mining

HISTORICAL BACKGROUND

Modern interest in spatial data analysis dates from the 1960s, when the so-called quantitative revolution in geography was at its peak. A number of authors set about systematically collecting techniques that might be applied to the analysis of geographic data, in other words to patterns and phenomena on the Earth's surface, drawing from the literatures of statistics, geometry, and other sciences. Berry and Marble (1968) published one of the first collections, and included discussions of spatial sampling, the analysis of point patterns, the fitting of trend surfaces to sample data in space, measures of network connectivity, Monte Carlo simulation, and measures of spatial dependence. Other early texts were written by Haggett (1966), Haggett and Chorley (1969), King (1969), and Taylor (1977). The topic of spatial dependence quickly surfaced as one of the more unique aspects of geographic pattern, and Cliff and Ord (1973) unified and extended earlier work by Moran and Geary into a comprehensive treatment.

Many of these early efforts were driven by a desire to find general principles concerning the distribution of various types of phenomena on the Earth's surface. For example, Central Place Theory had postulated that under ideal geographic and economic conditions settlements on the Earth's surface should occur in a hexagonal pattern. Many methods of point pattern analysis were developed and applied in order to detect degrees of hexagonality, without success. Other researchers were interested in the morphological similarity of patterns across a wide range of phenomena, and the implications of such patterns for ideas about process. For example, Bunge (1966) describes efforts to compare the geometric shapes of meandering rivers with roads in mountainous areas, and others compared river and road networks to the geometry of branching in the human lung.

Another quite different direction might be described as normative, or concerned with the design and planning of systems on the Earth's surface. The field of location-allocation modeling developed in the 1960s as an effort to develop techniques for the optimal location of such central facilities as schools, fire stations, and retail stores (Ghosh and Rushton, 1987). Other researchers were concerned with the optimal design of voting districts or the optimal routing of power lines or roads across terrain.

Another large literature developed around the modeling of spatial interaction. The numbers of visitors to central facilities such as retail stores is observed to decline systematically with distance from home. Spatial interaction models attempt to predict such flows based on the characteristics of the home neighborhood, the characteristics of the destination, and the characteristics of the trip (Fotheringham and O'Kelly, 1989). They have been applied successfully to the modeling of migration, social interaction, and many other types of spatial interaction.

Interest in spatial data analysis has grown rapidly in recent years, in part because of the increasing availability of spatial data and the popular acceptance of tools such as Google Earth, Google Maps, and Microsoft Virtual Earth. Geographic information systems (GIS) are designed to support the manipulation of spatial data, and virtually all known methods of spatial data analysis are now available as functions within this environment. There has been some success at achieving interoperability between the many brands of GIS and formats of spatial data, so that today it is possible to submit spatial data to analysis in a uniform computing environment that is also equipped to perform the necessary ancillary tasks of data preparation, along with the visualization of results. Increasingly the results of spatial data analysis are portrayed through generic services such as Google Maps, which allow them to be "mashed" or combined with other information, allowing the user to explore the geographic context of results in detail.

SCIENTIFIC FUNDAMENTALS

Statistical analysis evolved in domains where location was rarely important. For example, in analyzing the responses to a questionnaire it is rarely important to know where respondents live. It is possible in such situations to believe that the members of a sample were selected randomly and independently from some larger population. But when dealing with spatial data this assumption is rarely if ever true. The census tracts of Los Angeles, for example, clearly were not drawn randomly and independently from some larger set. Spatial data analysis must confront two tendencies that are almost always present, yet rarely present in other types of analysis: spatial dependence, or the tendency for local variation to be less than global variation; and spatial heterogeneity, or the tendency for conditions to vary over the surface of the Earth. Technically, these tendencies lead to an overestimation of the numbers of degrees of freedom in a test, and to an explicit dependence of results on the bounds of the test.

Faced with this reality, some texts on spatial data analysis have focused first on the normal assumptions of statistics, and then attempted to show how the reality of spatial data imposes itself. It is in many ways more satisfactory, however, to proceed in reverse—to first discuss the spatial case as the norm, and then to introduce the assumptions of independence and homogeneity.

It is helpful to define spatial data rigorously, since the definition of spatial data analysis depends on it. Data may be defined as spatial if they can be decomposed into pairs of the form <**x**,**z**> where **x** denotes a point in space-time and **z** denotes one or more properties of that point. It is common to distinguish between spatial or geographic analysis, conducted in two or three spatial dimensions, and spatio-temporal analysis in which the temporal dimension is also fundamental; thus spatial data analysis may involve two, three, or four dimensions.

This atomic form of spatial data is rarely observed, however, because in principle an infinite number of points can be identified in any geographic domain—only in the case of data sampled at a finite number of points is this form actually analyzed. In other cases spatial data consist of aggregate statements about entire lines, areas, or volumes. For example, summary census data are statements about entire counties, tracts, or blocks, since issues of confidentiality prohibit publication of data about individuals. Moreover, data about interactions are statements about pairs of such objects; for example, a state-to-state migration table contains 2500 entries, each giving the number of migrants between a pair of states. The rich variety of forms of aggregation that are used to publish spatial data lends complexity to the field, and has led many authors to organize surveys on this basis.

For example, Bailey and Gatrell (1995) organized their text into four major sections based on data type. Patterns of undifferentiated points were the basis for the first, and techniques are described for estimating a surface of point density, for comparing patterns of points to a statistical model of randomness, and for detecting clusters in spatial and spatio-temporal point patterns. Such methods are widely employed in the analysis of patterns of disease and in biogeography. The second major section also focuses on points, but as samples of continuous phenomena that are conceptualized as fields. Geostatistics provides the theoretical basis for many of these techniques, since one of the most popular tasks is the interpolation of a complete surface from such sample point data. The third major section concerns areal data, typified by the aggregate statistics reported by many government agencies. Such data are widely used to estimate multivariate models, in the analysis of data on crime, economic performance, social deprivation, and many other phenomena. Several specialized techniques have been developed for this domain, including various forms of regression that are adapted to the special circumstances of spatial data. Finally, the last major section is devoted to the analysis of spatial interaction data and to various forms of spatial interaction modeling.

The widespread adoption of GIS has had profound effects on all aspects of spatial data analysis. Several authors have discussed this relationship, and texts that have appeared in the past decade, such as that by O'Sullivan and Unwin (2003), are clearly informed by the theories and principles of geographic information science (GIScience). Recent texts on GIS (*e.g.*, Longley *et al.*, 2005) also place spatial data analysis within this increasingly rigorous framework.

GIScience draws a clear distinction between two alternative conceptualizations of space: as a set of continuous fields, and as a collection of discrete objects occupying an otherwise empty space. The field/object dichotomy is clearly evident in the work of Bailey and Gatrell (1995), but becomes explicit in more recent texts. Continuous fields must be discretized if they are to be represented in digital systems, in one of a number of ways. In principle one would like the methods and results of spatial data analysis to be independent of the method of discretization used, but in practice each method of discretization has its own methods of analysis, and much effort must be expended in converting between them. The most convenient discretization is the raster, in which fields are represented as values of a regular square grid, and Tomlin (1990) and others have shown how it is possible to achieve a high level of organization of the methods of spatial analysis if this discretization is adopted. The isoline discretization, in which a field is represented as a collection of digitized isolines, is far less convenient and comparatively few methods have been developed for it. The irregular sample point discretization has already been discussed in the context of geostatistics.

Longley *et al.* (2005) adopt a quite different way of organizing spatial data analysis, based on a hierarchy of conceptual complexity, and within the context of GIS. The simplest type in their scheme consists of query, in which the analyst exploits the ability of the GIS to present data in different views. This is in large part the basis of exploratory spatial data analysis, a subfield that provides the user with multiple views of the same data as a way of gaining additional insight. For example, the multiple views of a spatial data set might include a map, a table, a histogram, or a scatterplot. Anselin's GeoDa (geoda.uiuc.edu) is a current example of this style of computing environment, and supports many other types of view that are designed to expose potentially interesting aspects of data. Indeed, GIS has been defined as a system for exposing what is otherwise invisible in spatial data. In GeoDa views are dynamically linked, so that a user-defined selection in the map window is automatically highlighted in all other open windows.

Longley *et al.*'s second type is measurement, since much of the motivation for the original development of GIS stemmed from the difficulty of making manual measurements of such spatial properties as length, area, shape, and slope from maps. The third is transformation, and occurs whenever spatial data analysis results in the creation of new views, properties, or objects. For example, density estimation results in the creation of a new continuous field of density from a collection of discrete points, lines, or areas, and spatial interpolation results in the creation of a new continuous field from point measurements.

The fourth is descriptive summary, or the calculation of summary statistics from spatial data. A vast number of such measures have been described, ranging from the spatial equivalents of the univariate statistics (mean, median, standard deviation, *etc*.) to measures of fragmentation and spatial dependence.

Recently several new methods have been described that disaggregate such measures to local areas, reflecting the endemic nature of spatial heterogeneity. Such place-based methods are typified by the local Moran statistic, which measures spatial dependence on a local basis, allowing the researcher to see its variation over space, and by Geographically Weighted Regression (Fotheringham, Brunsdon, and Charlton, 2002), which allows the parameters of a regression analysis to vary spatially.

Longley *et al.*'s fifth category is design, or the application of normative methods to geographic data, and includes the optimization methods discussed earlier. The sixth, and in many ways the most difficult conceptually, is statistical inference, addressing the problems discussed earlier that can render the assumptions of normal statistical inference invalid. Several method have been devised to get around these assumptions, including tests based on randomization, resampling so that observations are placed sufficiently far apart to remove spatial dependence, and the explicit recognition of spatial effects in any model.

KEY APPLICATIONS

Spatial data analysis is now commonly employed in many areas of the social and environmental sciences. It is perhaps commonest in the sciences that employ an inductive rather than a deductive approach, in other words where theory is comparatively sparse and data sets exist that can be explored in search of patterns, anomalies, and hypotheses. In that regard there is much interest in the use of spatial data analysis in public health, particularly in epidemiology, in the tradition of the well-known work of Snow on cholera (Johnson, 2006). Mapping and spatial data analysis are also widely employed in criminology, archaeology, political science, and many other fields. Goodchild and Janelle (2004) have assembled a collection of some of the best work from across the social sciences, while comparable collections can be found in ecology, environmental science, and related fields.

Spatial data analysis is also widely employed in the private sector and in administration. It is used, for example, by political parties to analyze voting behavior; by insurance companies to measure the geographic distribution of risk; and by marketing companies in organizing direct-mail campaigns and in planning retail expansions. The field of geodemographics focuses on the use of spatial data analysis to create and use detailed information on social, economic, and purchasing patterns in support of retailing and other forms of commercial activity.

FUTURE DIRECTIONS

Spatial data analysis provides a particular kind of lens for viewing the world, emphasizing the cross-sectional analysis of snapshots rather than the longitudinal analysis of changes through time, or approaches that ignore both the spatial and temporal dimensions and their power in organizing information and providing context. This is a time of unprecedented opportunity for spatial data analysis, for a number of reasons. First, spatial data and the tools needed to support spatial data analysis have evolved very rapidly over the past decade or so, and researchers are now able to perform a wide variety of powerful forms of analysis with considerable ease. Second, and not unrelated to the first point, interest in a spatial perspective has grown rapidly in recent years, and there have been many comments on the appearance of a spatial turn in many disciplines. Within this context, spatial data analysis is part of a much larger interest in space, that extends from tools and data to theory, and might be summarized under the heading of spatial thinking. The widespread availability of sophisticated tools such as Google Earth (earth.google.com) has~~ve~~ drawn attention to the need for education in the basic principles of a spatial approach.

The past decade has witnessed a fundamental shift in the nature of computing, and in how it is used to support research and many other forms of human activity. Many of the tools of spatial data analysis are now available as Web services, obviating the need for individual researchers to acquire and install elaborate software and data. Many agencies now offer primitive forms of spatial data analysis over the Web, allowing users to map, query, and analyze the agency's data in a simple, easy-to-use environment and requiring nothing more than a Web browser. Large software packages are now typically constructed from reusable components, allowing the functions of different packages to be combined in ways that were previously impossible, provided each is compliant with industry standards.

Spatial data analysis is now evolving into much stronger support of the spatio-temporal case, through the construction of packages such as Rey's STARS (stars-py.sourcforge.net), and through the development of new and powerful techniques. In this arena much remains to be done, however, and the next decade should see a rapid growth in spatio-temporal techniques and tools.

CROSS REFERENCES

Spatial Statistics, Spatial Reasoning, Spatial Econometrics, Spatial Thinking, Spatial Data Mining

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