Handbook of Applied Spatial Analysis
The Handbook is written for academics, researchers, practitioners and advanced graduate students. It has been designed to be read by those new or starting out in the field of spatial analysis as well as by those who are already familiar with the field. The chapters have been written in such a way that readers who are new to the field will gain important overview and insight. At the same time, those readers who are already practitioners in the field will gain through the advanced and/or updated tools and new materials and state-of-the-art developments included.

This volume provides an accounting of the diversity of current and emergent approaches, not available elsewhere despite the many excellent journals and textbooks that exist. Most of the chapters are original, some few are reprints from the Journal of Geographical Systems, Geographical Analysis, The Review of Regional Studies and Letters of Spatial and Resource Sciences. We let our contributors develop, from their particular perspective and insights, their own strategies for mapping the part of terrain for which they were responsible. As the chapters were submitted, we became the first consumers of the project we had initiated. We gained from depth, breadth and distinctiveness of our contributors’ insights and, in particular, the presence of links between them.

The chapters were rigorously refereed blindly by the contributors to this volume. Referee reports were sent to each author and changes made accordingly. We supervised this process to guarantee that authors received reviews that would be useful for finalizing their chapters. The soundness of the comments and ideas have contributed immensely to the quality of the Handbook. Fortunately, we were dealing with truly exemplary scholars, the most distinguished and sophisticated representatives of the fields of inquiry.

We thank the contributors for their diligence, not only in providing extremely thoughtful and useful contributions, but also in meeting all deadlines in a timely manner and in following stringent editorial guidelines. Moreover, we acknowledge the generous support provided by the Institute for Economic Geography and GIScience, Vienna University of Economics and Business. Thomas Seyffertitz greatly assisted in keeping the project well organized. Last but not at least, we have benefitted greatly from the editorial assistance he and Ingrid Divis provided. Their expertise in handling several word processing systems, formatting, and indexing, together with their care and attention to detail, helped immeasurably.

August 2009

Manfred M. Fischer, Vienna
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Introduction

Manfred M. Fischer and Arthur Getis

1 Prologue

The fact that the 2008 Nobel Prize in Economics was awarded to Paul Krugman indicates the increasing attention being given to spatially related phenomena and processes. Given the growing number of academics currently doing research on spatially related subjects, and the large number of questions being asked about spatial processes, the time has come for some sort of summary statement, such as this Handbook, to identify the status of the methods and techniques being used to study spatial data. This Handbook brings together contributions from the most accomplished researchers in the area of spatial analysis. Each was asked to describe and explain in one chapter the nature of the types of analysis in which they are expert. Clearly, having only one chapter to explain, for example, exploratory spatial data analysis or spatial econometric models, is a daunting task, but the authors of this book were able to summarize the key notions of their spatial analytic fields and point readers in directions that will help them to better understand their data and the techniques available to them.

Whether or not spatial analysis is a separate academic field, the fact remains that in the last twenty years spatial analysis has become an important by-product of the interest in and the need to understand georeferenced data. The current interest in environmental sciences is a particular stimulant to the development of new and better ways of analyzing spatial data. Environmental studies have become either an important subfield of or a major thrust in such fields as ecology, geology, atmospheric sciences, sociology, political science, economics, urban planning, epidemiology, and the field that sometimes characterizes itself as the archetype environmental science, geography. There is no shortage of articles in the applied journals of these fields where the analysis of spatial data is central.

Many researchers are busy developing techniques for the study of georeferenced data, and many more use spatial analytic tools. Following the adage ‘Necessity is the mother of invention,’ very often the developers are also the users. Thus, we see that in the fields mentioned above, new and tantalizingly imaginative techniques have been created for analytic purposes. Most often, but not exclusively, however, the fundamental principles for spatial analysis come from
mathematics, statistics, and econometrics. Applied spatial scientific studies require use of probability and statistics and, for model development, the techniques of the econometricians and geostatisticians.

Since the practical nature of spatial analysis is the driving force for the field’s development, it was inevitable that creating software would be a major activity of spatial analysts. Unlike most compendia, where principles are laid out first, followed by applications and notes on software, the editors of this Handbook placed software tools first. Some of the very best innovative techniques for spatial analysis come from the wide variety of software packages discussed in Part A. As the reader will deduce from perusing the table of contents, we approach spatial analysis as a series of surveys of what is available for the practical user. We want it to be possible for anyone new to the field to find relevant ideas and techniques for his/her research. In addition, our goal is to have seasoned researchers find new ideas or key references from unfamiliar spatial analytic fields. The fact that not everything available for spatial analysis is included in the discussions that follow has more to do with the background, research interests, and points of view of the editors than it does with space limitations.

Not unusual to academic research is the disciplinary boundaries surrounding some of the types of work being done in spatial analysis. For example, economists have a record of being reluctant to look at literature outside of their own field. It usually takes a strong societal interest in a given problem to encourage disciplinarians to consider, or become conversant, with other literatures. Although less true in a field such as spatial analysis, many are unwilling to get involved with names and ideas outside of their immediate research area. Fortunately, spatial analysis is the type of field that tends to break down those barriers. Especially with the development of GISystem software, user friendly software packages, National Institute of Health and National Science Foundation summer institutes in the US, interdisciplinary conferences and meetings, and internet activity, spatial analysis is taking on an ecumenical flavor. The difficulty that remains is the need for researchers to become familiar with the language of spatial analysis, the spatial point of view, and the techniques of those working on similar problems, but in other fields. We hope that this Handbook enhances the interdisciplinary nature of this field.

The history of spatial analysis is noteworthy for its genesis in a number of different fields nearly simultaneously. Much of the development has been based on the types of data characteristic of the particular research being done in the respective fields. For example, geologists and climatologists tend to study continuous data. Economists and political scientists pay a great deal of attention to time series data. Geographers, anthropologists, and sociologists are especially fond of point and area (choropleth) data. Transportation planners favor network data. Many environmentalists use remotely sensed spatial data. The data-driven emphasis of spatial analysis helped to create specialized ‘schools of thought’ on spatial analysis methodologies. Our view is that in recent years these schools are being opened to include ideas and methods from other schools. We believe, too, that in the future the field of spatial analysis will become less discipline oriented as the need for interdisciplinary research teams becomes a greater part of the research
landscape. For example, no longer is it possible for a microbiologist or an epidemiologist alone to solve problems of disease transmission. Researchers well versed in the nuances of continuous or discrete spatial data must become members of the team. Moreover, the epidemiologist must be conversant with the techniques of analysis used to solve a disease transmission problem.

In the following section we briefly outline what may be called the points of view of the various schools of thought. Our goal, of course, is to have readers better understand how others approach spatial data. In this Handbook, these areas of interest are described, explained, and demonstrated.

2 Schools of thought on spatial analysis methodologies

*Exploratory spatial data analysis* (ESDA) is the extension of a Tukey-type data exploration (see Tukey 1977) to georeferenced data. ESDA represents a preliminary process where data and research results are viewed from many different vantage points, one of which is the display of data on maps. The power of computers to summarize and visualize large sets of georeferenced data has helped to stimulate the creation of amazingly evocative procedures for data manipulation. Science has always emphasized the need for high quality data and for researchers to have an informed sense of what problems may be in the offing once data are subjected to rigorous study. Computer programmers in a number of different fields have now made it possible to view data in a myriad of ways.

Of particular interest is GI software that allows for the mapping of data, making measurements on the mapped data, identifying weaknesses in the data, correcting incorrect data or data placed in incorrect locations, producing summary measures of data, manipulating point data into surfaces, viewing these surfaces from many different angles, and, if the data are time related, viewing data changes over time. The summary measures are the usual histograms and box plots, but the ability of the programs to, for example, identify a data outlier on a map at the same time as one views the location of the outlier in a histogram, in a cumulative distribution function, and in a three dimensional scatter diagram that can be viewed from any angle, gives ESDA a powerful role to play in much research.

Our view is that much of ESDA is used prior to the model building phase of research, but interestingly enough, some new techniques of ESDA act as model builders by allowing us to see how variables relate to one another in space. The field of data visualization, especially as related to maps, is just beginning to make an impact on research. There is a need to more closely unite those working on new techniques for data visualization with the actual needs of the various spatially-oriented fields of study.

The software discussed in Part A of the Handbook gives researchers an idea of the many tools and functions available for them to engage in ESDA. At one time it was anathema for many ‘purists’ to engage in exploratory work when preparing their data for analysis. The goal was to statistically test a model that was a direct descendant of well-documented theory. Now, awareness of all that is available in
the software stimulates us to create final models only after performing a good deal of exploration and experimentation. In a sense, ESDA and EDA represent a new wave of research methodology. The traditional six steps of hypothesis guided inquiry – problem, hypothesis, sampling distribution, test, results, decision – has been expanded to a seventh step, data exploration, but instead of squeezing data exploration between two of the former steps, exploration is now represented at nearly all stages of analysis.

**Spatial Statistics.** The roots of spatial statistics go back to Pearson and Fisher, but their modern manifestation is mainly due to Whittle, Moran, and Geary. The field is indebted to Cliff and Ord for explicating, extending, and making their work socially relevant. From Cliff and Ord’s papers and books of the late 1960s to the early 1980s comes the basic outline of what constitutes spatial statistics (see, for example, Cliff and Ord 1973, 1981). It probably is a stretch to call this area a school of thought, but the vast number of researchers who look to spatial autocorrelation statistics, for example, indicates a strong interest area. The point is that spatial statistics is also a part of ESDA, spatial econometrics, and remote sensing analysis, and to a lesser extent, geostatistics. One might ask the question, how can we model spatially varying phenomena without testing patterns on maps? The process of creating hypotheses and testing map patterns gives spatial statistics its raison d’être. Because of space limitations, this Handbook cannot cover in any detail all of the types of issues that spatial statistics practitioners address.

As a field, spatial statistics is concerned with map-related problems. Geometrically, one can think of point, line, and area patterns as well as mixtures of these three as the fundamental elements that are included in the use and study of spatial statistics. What is crucial, of course, is that these points, lines, and areas represent real world phenomena. How these phenomena pattern themselves and interact with one another has come to be an important element of scientific inquiry.

This Handbook reviews the fundamental knowledge required of the user of spatial statistics. Users are found in all of the social and environmental sciences and, to a lesser extent, the physical sciences. Hypotheses include conjectures about the mapped patterns of diseases and crime, the pattern of residuals from regression, the tendency for some phenomena to cluster or disperse, the differences among patterns, the spatial relationship between a given observation and other designated observations, and perhaps most important, how defined points, lines, and areas interact with one another, either statically or over time and space.

Since the field’s inception, certain particular problems have given rise to new statistical tests and routines. For example, the large data sets that began to emerge in the 1980s required researchers to find ways to reduce data redundancy or to subdivide regions into smaller units for statistical analysis. Eventually, the focused spatial tests developed and popularized in the 1990s became widely used, especially because spatial cluster analyses have come to depend on them. The ability of computers to create interaction data between all members of a population or sample has given rise to large sample statistics like the $K$ function of Ripley (see Ripley 1977). The fundamental patterns of Voronoi polygons have now
been studied using algorithms capable of manipulating tessellations of area patterns. The same is true of networks of lines.

Two of the most promising areas of spatial statistical analysis are the creation of defensible spatial weights matrices and the employment of spatial filters, discussed in the chapters of Section B of this Handbook. These new techniques are designed to facilitate understanding of what may be called the nature of spatial effects in any spatial system of variables. In addition, work is proceeding on ways to better test hypotheses concerning pattern representation. These include such tests as false discovery rates and simulation routines that create sampling distributions on which tests can be carried out.

**Spatial Econometrics.** Since Jean Paelinck and Leo Klaassen’s description of the field in 1979 and Luc Anselin’s influential volume *Spatial Econometrics*, published in 1988, spatial econometrics has blossomed. Before those auspicious events, economists with a spatial bent, such as Walter Isard (see Isard 1960), had begun to study the spatial manifestation of economic activities. The models that Anselin classified as spatial lag models and spatial error models (among several others), while related to the well-established field of econometrics, have become the fundamental regression tools of the spatial econometrician.

Although not deeply ingrained into the thinking characteristic of the discipline of economics, the discipline of regional science has become the home for spatial econometrics practitioners. Judging from the number of researchers who are in daily contact with Anselin’s website, this field is growing very rapidly. Today, such researchers originally educated in economics and/or geography, such as LeSage, Pace, Kelejian, Florax, and Rey, are expanding the field to Bayesian thinking, new spatial regression estimating techniques and tests, and time-space modeling.

An interesting and crucial overlap between spatial statistics and spatial econometrics is the need to apply spatial statistical tests in order to check for the validity of the assumption of spatial randomness among the residuals of spatial, and non-spatial diagnostic, models. Commonly the well known Moran’s $I$ statistic is used for testing purposes. In Anselin’s GeoDa software and in LeSage’s spatial econometrics toolbox, Moran’s $I$ and newly developed tests are prominent parts of the software capabilities.

A new and useful system of econometric study, described in this Handbook, is geographically weighted regression (GWR). The realization that the constant nature of regression coefficients seems to fly in the face of reality when a geographic system is being modeled, stimulated Fotheringham, Brunsdon, and Charlton to create a spatial econometric system that allows regression parameters to vary over space (see Fotheringham et al. 2002). The developers of GWR are continually improving the system to avoid some of the difficulties in dealing with georeferenced data. Related to, but in addition to GWR, are expositions in this Handbook on the expansion method and the new techniques of spatial hierarchical models.

**Geostatistics.** Evolving differently than the previous schools of thought is the field of geostatistics, which is outlined in this Handbook. Primarily as a way to describe and explain physical phenomena in a continuous spatial data environment, geostatistics is the principal methodology of analysis. From its roots in the
1950s as a way to predict gold ore quality to its current widespread use for the study of all manner of physical phenomena, including petroleum reserve locations, soil quality, and patterns of weather and climate, geostatistics has become a mainstay of most earth science departments both in the academy and in the business world.

The field includes both spatial data descriptive routines and sophisticated modeling. The major themes are the study of variograms and the use of predictive devices called kriging, named after the mining engineer, Krige (1951), who pioneered the techniques. Matheron (1963), and most recently Cressie (1993), have laid out the statistical principles on which the methodology is based.

Variogram analysis is based on the principle of intrinsic stationarity, that is, inherent in the nature of spatial effects is that as distance increases between observations on the same variable, variance will increase. The increasing variance continues with increasing distance until a particular distance is reached when the variance will equal the population variance. The semivariogram is a function represented in a diagram that shows the nature of this increasing function. Considered to be theoretical, the function is most often estimated from real world data. The large amount of software available for the study of geostatistics is one of the field’s features. Some GISystem modules include many exploratory features as well as capabilities for sophisticated modeling.

The second area of study, mentioned above – kriging – is a series of techniques that allows for the prediction of variable values or multi-variable interactions at locations where no data are available. Thus, via the simultaneous equation systems of kriging, point data can be used to create surfaces where each location in the study area is represented by a point estimate of the true value at that point. Kriging creates map surfaces and error surfaces, that is, surfaces that represent the confidence level in spatial point estimates. The manner in which kriging is carried out ranges from relatively simple procedures (simple and ordinary kriging) to complex prediction systems (co-kriging and disjunctive kriging). Given the enormous number of calculations that must be performed, the techniques require large samples and high levels of computer power.

3 Structure of the handbook

This volume is not intended as a textbook or research monograph, nor does it attempt to cover the field of spatial analysis exhaustively, or in great depth. It does attempt, though, to provide a useful manual or guidebook to spatial analytic fields, and to offer a wide range of views on spatial analysis that may lead the reader to inquire more deeply into specific areas that are touched on herein. It is intended that this Handbook should be as accessible as possible, especially to those who are relatively unfamiliar with this area of work.

The material in this volume has been chosen to provide an accounting of the diversity of current and emergent models, methods, and techniques, not available elsewhere despite the many excellent journals and text books that exist. The inter-
national collection of authors was selected for their knowledge of a subject area, and their ability to communicate basic information in their subject area succinctly and accessibly.

The volume is structured as a series of parts ranging from software tools over spatial statistical and geostatistical approaches to spatial econometric models and techniques, and finally to applications in various domain areas. The parts are as follows:

- **Part A**: GI software tools,
- **Part B**: Spatial statistics and geostatistics,
- **Part C**: Spatial econometrics,
- **Part D**: The analysis of remotely sensed data,
- **Part E**: Applications in economic sciences,
- **Part F**: Applications in environmental sciences, and
- **Part G**: Applications in health sciences.

where the chapters in **Part D** to **Part G** represent in many ways an application of models, methods, and techniques discussed in the preceding chapters.

**Part A: GI software tools**

The focus of **Part A** is on GI software packages, from which some of the very best innovative techniques for spatial analysis come. This part is composed of ten contributions, viz:

- Spatial statistics in ArcGIS (Chapter A.1),
- Spatial statistics in SAS (Chapter A.2),
- Spatial econometric functions in R (Chapter A.3),
- GeoDa: An introduction to spatial data analysis (Chapter A.4),
- STARS: Space-time analysis of regional systems (Chapter A.5),
- Space-time intelligence system software for the analysis of complex systems (Chapter A.6),
- Geostatistical software (Chapter A.7),
- GeoSurveillance: A GIS-based exploratory spatial analysis tool for monitoring spatial patterns and clusters (Chapter A.8),
- Web-based analytical tools for the exploration of spatial data (Chapter A.9), and
- PySAL: A Python library of spatial analytical methods (Chapter A.10).

The first chapter, written by Lauren M. Scott and Mark V. Janikas, provides an overview of the tools in the ArcGIS spatial statistics toolbox, an extendible set of feature pattern analysis and regression analysis tools, specifically designed to work with spatial data. There are four core analytical toolsets: measuring geo-
graphic distributions, analysing patterns, mapping clusters, and modeling spatial relationships. The chapter not only provides an overview of the tools, but presents also application examples and references, and outlines strategies for extending ArcGIS functionality through custom tool development.

The next chapter, by Melissa I. Rura and Daniel A. Griffith, describes ways SAS has been used in the past for spatial statistical analyses. It covers recent work that explicitly includes spatial information and geographic visualization, and gives two SAS implementation examples, namely the calculation of Moran’s I and the eigenvector spatial filtering spatial statistical technique. First, SAS’s embedded spatial functionality is discussed in terms of function options and procedures like PROC VARIOGRAM and PROC MIXED. Next, SAS’s GISystem module functionality, including map display and data import, is described. Then PROC NLIN-based spatial autoregressive code capabilities are discussed. Finally, two example implementations and their necessary input and output data are described. An example calculation of Moran’s I is presented, and an implementation of eigenvector spatial filtering is described, in order to illustrate how customized SAS can be created to put spatial statistical techniques into practice. Several sources are summarized from which a user may download or look up freely available spatial statistical SAS implementations. This chapter seeks to show how the use of a mature statistical programming language like SAS can enable advanced spatial analysis.

Placing spatial econometrics and more generally spatial statistics in the context of an extensible data analysis environment such as R exposes similarities and differences between traditions of analysis. This can be fruitful, and is explored in Chapter A.3, written by Roger S. Bivand, in relation to prediction and other methods usually applied to fitted models in R. R is a language and environment for statistical computing and graphics, available as Free Software under the terms of the Free Software Foundation’s GNU General Public License in source code form. It compiles and runs on a wide variety of UNIX platforms and similar operating systems (including Linux), Windows, and MacOS. Objects in R may be assigned a class attribute, including fitted model objects. Such fitted model objects may be provided with methods allowing them to be displayed, compared, and used for prediction, and it is of interest to see whether fitted spatial models can be treated in the same way.

Chapter A.4, by Luc Anselin, Ibru Syabri, and Younghin Kho, presents an overview of GeoDa™, a free software program intended to serve as a user-friendly and graphical introduction to spatial analysis for non-GIS specialists. It includes functionality ranging from simple mapping to exploratory data analysis, the visualization of global and local spatial autocorrelation, and spatial regression. A key feature of GeoDa is an interactive environment that combines maps with statistical graphics, using the technology of dynamically linked windows. A brief review of the software design is given, as well as some illustrative examples that highlight distinctive features of the program in applications dealing with public health, economic development, real estate analysis and criminology.
Space-Time Analysis of Regional Systems (STARS) is an open source software package designed for the dynamic exploratory analysis of data measured for areal units at multiple points in time. STARS consists of four core analytical modules: exploratory spatial data analysis; inequality measures; mobility metrics; spatial Markov. Developed using the Python object oriented scripting language, STARS lends itself to three main modes of use. Within the context of a command line interface (CLI), STARS can be treated as a package which can be called from within customized scripts for batch oriented analyses and simulation. Alternatively, a graphical user interface (GUI) integrates most of the analytical modules with a series of dynamic graphical views containing brushing and linking functionality to support the interactive exploration of the spatial, temporal and distributional dimensions of socioeconomic and physical processes. Finally, the GUI and CLI modes can be combined for use from the Python shell to facilitate interactive programming and access to the many libraries contained within Python. Chapter A.5, by Serge J. Rey and Mark V. Janikas, provides an overview of the design of STARS, its implementation, functionality and future plans. A selection of its analytical capabilities is also illustrated that highlight the power and flexibility of the package.

The development and implementation of software tools that account for both spatial and temporal dimensions, and that provide advanced visualization and space-time analysis capabilities is recognized as an important technological challenge in Geographic Information Science. Chapter A.6, written by Geoffrey M. Jacquez, provides an overview of space-time intelligence system (STIS) software that has been developed by BioMedware with funding from the National Institutes of Health. STIS is founded on space-time data structures for representing points, geospatial lifelines, polygons and rasters, and how they morph through time. Linked windows, cartographic and statistical brushing are time-enabled, as are visualizations including tables, maps, principal coordinate plots, histograms, scatterplots, variogram clouds, and box plots. Spatial weight relationships that change through time for points, geospatial lifelines and polygons include nearest neighbors, inverse distance, geographic distance, and adjacencies. These are used by advanced space-time analysis methods including clustering, regression (linear, logistic, Poisson, and step-wise), geographically-weighted regression, variogram models, kriging, and disparity statistics, among others. STIS allows researchers to span the analytical continuum for space-time data on one software platform, from visualization, animation, exploratory space-time data analysis, through hypothesis testing and modeling.

During the last two decades one has witnessed an increasing interest in the application of geostatistics to the analysis of space-time datasets. A critical issue for many novice users is the availability of affordable and user-friendly software that offer basic (for example, variogram estimation and modeling, kriging) and advanced (for example, non-parametric kriging, stochastic simulation) algorithms for geostatistical modeling. The chapter, by Pierre Goovaerts, presents a brief overview of the main geostatistical software, stressing their advantages and weak-
nesses in terms of flexibility and completeness. Concomitant with the growing range of geostatistical applications, the software market is expanding and nowadays fairly general software or add-on modules that are open source but have limited graphical capabilities coexist with highly visual commercial software that are often tailored to specific applications, such as 2D health data or 3D assessment of contaminated sites. In particular, when geostatistics is combined with classical statistical techniques, such as regression analysis for trend modeling, the user often will have to rely on several programs to accomplish the different steps of the analysis.

Chapter A.8, written by Gyoungju Lee, Ikuho Yamada, and Peter Rogerson, describes GeoSurveillance, a GIS-based exploratory spatial analysis tool for monitoring spatial patterns and clusters over time. During the past decade, significant methodological advances have been made in assessing geographic clustering and in searching for local spatial clusters based on diverse statistical models. Recently, prospective surveillance models have been proposed to detect spatial pattern changes over time quickly, in contrast with traditional retrospective tests. As frequent updates of spatial databases are now made possible on a regular basis with the rapid development of GISystems, the development of prospective methods for monitoring emerging spatial clusters of geographic events (for example, disease outbreak) has been facilitated. GeoSurveillance provides a statistical framework integrated with a GISystem platform, where both retrospective and prospective tests for spatial clustering can be carried out effectively. To demonstrate the program, illustrations are given for Sudden Infant Death Syndrome (SIDS) in North Carolina and breast cancer cases in the northeastern part of the US.

In the next chapter, Luc Anselin, Yong Wook Kim, and Ibru Syabri deal with the extension of internet-based geographic information systems with functionality for exploratory spatial data analysis. The specific focus is on methods to identify and visualize outliers in maps for rates or proportions. Three sets of methods are included: extreme value maps, smoothed rate maps and the Moran scatterplot. The implementation is carried out by means of a collection of Java classes to extend the Geotools open source mapping software toolkit. The web based spatial analysis tools are illustrated with applications to the study of homicide rates and cancer rates in US counties.

PySAL is an open source library for spatial analysis written in the object oriented language Python. It is built upon shared functionality in two exploratory spatial data analysis packages: GeoDA and STARS and is intended to leverage the shared development of these components. This final chapter of Part A, written by Serge J. Rey and Luc Anselin, presents an overview of the motivation behind and the design of PySAL, as well as suggestions for how the library can be used with other software projects. Empirical illustrations of several key components in a variety of spatial analytical problems are given, and plans for future development of PySAL are discussed.
Part B: Spatial statistics and geostatistics

This part of the Handbook shifts attention to spatial statistical and geostatistical approaches, methods and techniques, and includes the following chapters:

- the nature of georeferenced data (the Chapter B.1),
- exploratory spatial data analysis (Chapter B.2),
- spatial autocorrelation (Chapter B.3),
- spatial clustering (Chapter B.4),
- spatial filtering (Chapter B.5), and
- the variogram and kriging (Chapter B.6).

In the first chapter of Part B, Robert Haining identifies various types of georeferenced data but focuses attention on the spatial data matrix. He considers the relationship between it and the complex, continuous geographic reality from which it is obtained and the difficulties that need to be addressed in constructing a spatial data set for the purpose of undertaking practical spatial data analysis. The links between each of the stages involved in the construction of the data matrix and the properties of spatial data are described. The author continues to discuss the implications of these findings for the conduct of exploratory and confirmatory data analysis and for the interpretation of results. The chapter concludes by discussing the role of models in influencing the types of georeferenced data that are needed and the consequences for model inference.

The focus of Chapter B.2, written by Roger S. Bivand, is on exploratory spatial data analysis, an extension of exploratory data analysis geared especially to dealing with the spatial aspects of data. This chapter presents the underlying intentions of ESDA, and surveys some of the outcomes. It challenges the frequently drawn conclusion that ESDA can somehow replace proper modeling. Exploratory spatial data analysis remains a key step prior to the model building phase of research, but interestingly enough, some new techniques of ESDA act as model builders by allowing us to see how variables relate to one another in space. A fundamental concept for the study of spatial phenomena is spatial autocorrelation. The concept has played a pivotal role in the development of the field of spatial analysis.

Chapter B.3, written by Arthur Getis, reviews the literature on spatial autocorrelation and explains its various representations. Most definitions of the concept concern the spatial relationships among realizations of a random variable. The uses of spatial autocorrelation are many, including its major role in testing for model mis-specification and for testing hypotheses concerned with spatial relationships. The cross product statistic, a fundamental spatial autocorrelation structure, is used to record the geometrical relationships and the variable relationships among the spatial units under study and to assess the degree of similarity between the two relationships. The spatial weights matrix represents the geometric relationships. Each matrix element records the spatial association among the spatial
units under study. Many tests and indicators of spatial autocorrelation are available. Chief among these is Cliff and Ord’s extension of Moran’s spatial autocorrelation statistic. At the local scale, Getis and Ord’s statistics and Anselin’s LISA statistics enable researchers to evaluate spatial autocorrelation at particular sites. Also at the local level, geographically weighted regression is an entire system devoted to the study of stationarity in spatial relationships among variables by location. Many software packages are available for the study of various aspects of spatial autocorrelation, including exploratory, global, local, time-space, and spatial econometric.

Chapter B.4, by Jared Aldstadt, reviews techniques for spatial clustering analysis. Emphasis is placed on the most commonly used techniques and their direct precursors. Some attention is given to recently developed clustering routines. These techniques may not yet be in wide use, but they are relevant because they overcome deficiencies in existing methodologies. They also indicate the direction of current research. Following the path of development, global clustering indices are covered first, followed by local clustering techniques. When applicable, test statistics are presented in the general cross-product form. In this format the similarities between and distinguishing characters of the clustering statistics are apparent.

Chapter B.5, written by Daniel A. Griffith, directs attention to spatial filtering, a spatial statistical methodology that enables spatial autocorrelation effects to be accounted for while preserving conventional statistical model specifications. A spatial filter is a synthetic variate that is constructed from locational information independent of the thematic nature of affiliated georeferenced data, being based upon the underlying geographic configuration of the data georeferencing. The primary idea is that some spatial proxy variables extracted from a spatial relationship matrix are added as control variables to a standard statistical model specification. To date, four principal approaches to spatial filtering have been implemented: autoregressive linear operators (à la Cochrane-Orcutt prewhitening), Getis’s $G_i$-based specification, linear combinations of eigenvectors extracted from either distance-based principal coordinates of neighboring matrices, or topology-based spatial weights matrices. Not only does spatial filtering allow a more detailed analysis of spatial autocorrelation effects for geographic distributions of attribute variables, but it also supports sounder geographically varying coefficients analyses, spatial interpolation, and the analysis of spatial autocorrelation effects in geographic flows data. Spatial filtering can be employed with both the normal probability model, and the entire family of probability models affiliated with generalized linear models.

The final chapter of Part B, by Margaret Oliver, shifts focus to the variogram and kriging, the two central techniques of geostatistics. The variogram describes quantitatively how a property changes as the separation between places increases. Its values are estimated from data for a set of separating distances or lags to give the experimental variogram. This may then be modeled by a limited set of mathematical functions. Methods of estimating the variogram and the models that are
fitted most frequently in the earth sciences are described and illustrated with a case study of soil data. The parameters of the models fitted to the variograms are used with the data to predict by employing kriging techniques. Kriging is a best linear unbiased predictor; it provides predictions and estimates of errors at each prediction point. Kriging is now a generic term that embraces several types of kriging that have been developed to solve particular problems in prediction. The emphasis in this chapter is on ordinary kriging, which is the type of kriging most often used. Factorial kriging is also described because of its value when the variation has more than one spatial scale.

**Part C: Spatial econometrics**

Part C is concerned with estimation and testing problems encountered when attempting to implement regional economic models. The problems often are characterized by the difficulties associated with assessing the importance of spatial dependence and spatial heterogeneity in a regression setting. Seven chapters represent the diversity of spatial econometric approaches, methods and techniques:

- spatial econometric models (Chapter C.1),
- spatial panel data models (Chapter C.2),
- spatial econometric methods for modeling origin-destination flows (Chapter C.3),
- spatial econometric model averaging (Chapter C.4),
- geographically weighted regression (Chapter C.5),
- expansion method, dependency, and multimodeling (Chapter C.6), and
- multilevel modeling (Chapter C.7).

The first chapter, written by James P. LeSage and R. Kelley Pace, provides an introduction to spatial econometric models and methods in a cross-sectional context. The authors show how conventional regression models can be augmented with spatial autoregressive processes to produce models that incorporate simultaneous feedback between regions located in space, and discuss methods estimating these models that are useful when modeling cross-sectional regional observations. The authors conclude the chapter in showing that for models containing spatial lags of the explanatory or dependent variables, interpretation of the parameters becomes richer and more complicated than in a least squares regression context with independent observations. Interpretation of parameter estimates and inferences requires an interpretation based on a steady-state equilibrium view, where changes in the explanatory variables lead to a series of simultaneous feedbacks that produce a new steady-state equilibrium. Because of working with cross-sectional sample data, these model adjustments appear as if they are simultaneous. The authors argue that these spatial regression models can be viewed as containing an implicit time dimension.
Chapter C.2, written by J. Paul Elhorst, focuses on the estimation of the spatial fixed effects model and the spatial random effects model extended to include spatial error autocorrelation or a spatially lagged dependent variable, including the determination of the variance-covariance matrix of the parameter estimates. In addition, it deals with robust LM tests for spatial interaction effects in standard panel data models, the estimation of fixed effects and the determination of their significance levels, a test for the fixed effects specification against the random effects specification using Hausman's specification test, the determination of goodness-of-fit measures, and the best linear unbiased predictor when using these models for prediction purposes. Finally, it briefly discusses possibilities for testing for endogeneity of one or more of the explanatory variables and to include dynamic effects.

Spatial interaction models of the gravity type are used in conjunction with sample data on flows between origin and destination locations to analyse international and interregional trade, commodity, migration, and commuting patterns. The focus of Chapter C.3, by James P. LeSage and Manfred M. Fischer, is on problems that plague empirical implementation of conventional regression-based spatial interaction models and econometric extensions that have appeared in the literature. The new models replace the conventional assumption of independence between origin-destination flows with formal approaches that allow for spatial dependence in flow magnitudes. Particular emphasis is laid on discussing problems, such as efficient computation, spatial dependence in origin-destination flows, large diagonal flows matrix elements, and the zero flows problem.

Model specification decisions represent a source of uncertainty typically ignored in applied modeling when we conduct statistical inference regarding model parameters. Chapter C.4, written by Olivier Parent and James P. LeSage, discusses formal methods that can be used to incorporate model specification uncertainty into inferences about model parameters. The focus is on how this can be accomplished in the context of spatial regression models, with an applied illustration involving the relation between local government expenditures and population migration.

Chapter C.5, by David Wheeler and Antonio Páez, deals with geographically weighted regression (GWR), a local form of spatial analysis drawing from statistical approaches for curve fitting and smoothing applications. GWR is based on the idea of estimating local models using subsets of observations centered on a focal calibration point. Since its introduction in 1996, GWR rapidly captured the attention of many in spatial analysis for its potential to investigate non-stationary relations in regression models. The basic concepts of GWR have also been used to obtain local descriptive statistics and other spatially weighted models, such as for Poisson regression. GWR has been instrumental in calling attention to the existence of potentially complex spatial relationships in linear regression. At the same time, there have been a number of issues raised concerning the nature and range of applications of the method, including its application for formal statistical inference on regression relationships. The available evidence suggests that GWR is an effec-
tive tool for spatial interpolation, but that it is problematic for inferring spatial processes. Collinearity has been shown to exacerbate inferential issues in GWR, but diagnostic tools have been developed to highlight local collinearity. In addition, other available approaches are discussed, such as hierarchical Bayesian regression models.

Chapter C.6, by Emilio Casetti, shows that the expansion method can provide an avenue for remedying residual spatial dependence, and, moreover, that within a multimodel frame of reference the expansion method can be used to identify the correlates and determinants of spatial dependence. The expansion method is a technique for widening the scope of a simpler initial model by expansion equations that redefine some or all of the initial model’s parameters into functions of contextual variables. By replacing the parameters of the initial model with their expansions a terminal model is produced that encompasses both the initial model and a specification of its contextual variation. An initial model that upon estimation and testing displays significant residual spatial autocorrelation can be often expanded into terminal models that upon estimation and testing display no significant autocorrelation. Thus, the expansion method may provide an avenue to remedy the problem of spatial dependence. Omitted variables can produce autocorrelated residuals. The variables added to a terminal model by expansions obviously do not appear in its initial model. If upon estimation and testing, significant autocorrelation is found in the initial model’s residuals but not in the terminal model’s residuals, it follows that the variables generated by expansions are what makes the difference. These results can be used to investigate which properties and attributes of the models are associated with the occurrence of spatial dependence.

The final chapter of Part C, by S.V. Subramanian, continues to discuss the concept of multilevel statistical models as it relates to understanding place effects and more generally contextual effects. The chapter begins by identifying what constitutes a multilevel data analysis followed by a discussion on how a range of data structures that are observed in the real word or due to sampling design can be accommodated within a multilevel framework. After laying down the substantive motivation to utilize multilevel methods, some key statistical models are specified with a description of the property of each of the model. In particular, multilevel models are contrasted with fixed effect models. Finally, the chapter closes with a discussion of the substantive as well as the technical advantages of using a multilevel modeling approach to statistical analysis.

Part D: The analysis of remotely sensed data

Part D deals with the analysis of remotely sensed data. Remote sensing is the acquisition and analysis of data about an object or area acquired from a device that is not in contact with the object or area. Most of the remote sensor devices are placed in earth-observing satellites and both high and low flying aircraft. Much of the spatial analysis that is carried out on the data must take into account the
usually very large number of observations, sometimes in the billions, and the size of the fundamental observations (the pixels). Increasingly, spatial statistics has become an integral part of the remote sensing experience. The main issues facing researchers are that results differ by spatial scale and that typical study regions (landscapes) vary appreciably, even over short distances. The type of data sensed is usually values on the electromagnetic spectrum condensed into pixels of a particularly scale. A principal task is to aggregate refined data or select a sensor that will capture data at a scale appropriate to the problem being solved. Spatial variation is often modeled by covariance, variograms or fractals. Surfaces are constructed using Fourier transforms of the covariance. Variograms are often used to model topography, vegetation indices, and soil properties. GISystems and data based management systems provide the computing capability for organizing and storing what usually are very large data sets. Analysis is dependent on visualization techniques designed to extract information from the massive data sets. Issues of spatial sampling, especially with regard to spatial scales are an ongoing research question.

Part D of the Handbook is made up of three major constituent chapters, viz:

- ARTMAP neural network multisensor fusion model for multiscale land cover characterization (Chapter D.1),
- model selection in Markov random fields for high spatial resolution hyperspectral data (Chapter D.2), and
- geographic object-based image change analysis (Chapter D.3).

Land cover characterization is one of the primary objectives in using and analyzing geospatial information gathered by remote sensing. Land cover characterization is essential for terrestrial ecosystem modeling and monitoring, as well as climate modeling and prediction. To improve estimates of proportions or mixtures of land cover at a global scale, it is necessary to exploit information from multiple sensors and develop models that explicitly handle scale effects in data fusion. In Chapter D.1, Sucharita Gopal, Curtis Woodcock, and Weiguo Liu present a framework for multisensor fusion using an ARTMAP neural network to extract sub-pixel information from coarser resolution imagery. The framework is applied to the extraction of the proportion of forest cover using an image pair-TM (30M) and MODIS (one K) imagery for a region of North Central Turkey. The ARTMAP neural network multisensor fusion model is compared to a conventional linear mixture model and shows its superiority in terms of estimation of sub-pixel class proportion. This research suggests that nonlinear mixture models hold considerable promise for land cover mapping using information from multiple sensors.

Chapter D.2, written by Francesco Lagona, implements Markov random fields, implemented for the analysis of remote sensing images to capture the natural spatial dependence between band wavelengths taken at each pixel, through a suitable adjacency relationship between pixels, to be defined a priori. In most cases several adjacency definitions seem viable and a model selection problem
arises. A BIC-penalized pseudo-likelihood criterion is suggested which combines good distributional properties and computational feasibility for analysis of high spatial resolution hyperspectral images. Its performance is compared with that of the BIC-penalized likelihood criterion for detecting spatial structures in a high spatial resolution hyperspectral image for the Lamar area in Yellowstone National Park.

The objective of Chapter D.3, by Douglas A. Stow, is to provide an overview of the use of multi-temporal remotely sensed image data to map earth surface changes from an object-based perspective. An initiation of research activity on GEOBICA techniques for detecting, identifying, and/or delineating earth surface changes has occurred over the past five or six years. Such techniques may be referred to as geographic object-based image change analysis or GEOBICA. GEOBICA is based on quantitative spatial analytical methods and generates data sets that can support spatial analysis of geographic areas. The chapter provides background and details on: (i) reasons and purposes for conducting GEOBICA, (ii) image acquisition and pre-processing requirements and types of image data that are input to GEOBICA routines, (iii) image segmentation and segment-based classification, (iv) approaches to multi-temporal image analysis, (v) GEOBICA strategies, (vi) post-processing techniques, and (vii) accuracy assessment for object-based and land cover change maps.

**Part E: Applications in economic sciences**

The focus of Part E is on applications in economic sciences in general and regional economics in particular. Three chapters have been chosen to demonstrate the range of spatial analytical applications in economic research:

- the impact of human capital on regional labor productivity in Europe (Chapter E.1),
- income distribution dynamics and cross-region convergence in Europe (Chapter E.2), and
- a multi-equation spatial econometric model, with application to EU manufacturing productivity growth (Chapter E.3).

The focus of Chapter E.1, by Manfred M. Fischer and associates, is on the role of human capital in explaining labor productivity variation among 198 European regions. Human capital is measured in terms of educational attainment using data for the active population aged 15 years and older that obtained the level of tertiary education. The existence of unobserved human capital that is excluded from the model but correlated with the included educational attainment variable and most likely exhibiting spatial dependence motivates the use of a spatial regression relationship that is known as spatial Durbin model. The chapter outlines the model along with the associated methodology for estimating the impact of human capital