Reflections on the current state of spatial statistics education in the United States: 2014

Daniel A. GRIFFITH*

School of Economic, Political and Policy Sciences, University of Texas at Dallas, 800 W. Campbell Road, GR31, Richardson TX 75080, USA

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This paper surveys the current state of teaching spatial statistics in the United States (US), with commentary about the future teaching of such a course. It begins with a historical overview, and proposes what constitutes suitable content for a contemporary spatial statistics course. It notes that contemporary university-level spatial statistics courses are mostly taught across myriad units, including biology/ecology, climatology, economics (as spatial econometrics), environmental studies, epidemiology/public health, forestry, geography, geosciences/earth sciences, geospatial information sciences, mathematics, quantitative social science, soil science, and statistics. It discusses the diffusion of this course across the US, which began in the mid-1980s. One result it reports is a model spatial statistics course offering.

Keywords: spatial statistics; spatial statistics education; spatial statistics courses; the United States

1. Introduction

Spatial statistics comprises a broad range of specialized statistics topics that treat correlated data tied together topologically or geometrically in such a way that they are tagged to locations on a surface (e.g. the Earth’s surface). The correlation arises from these topological or geometric linkages, and is labeled spatial autocorrelation because its source is spatial relationships and it occurs within a single variable, among observations. The general categories of spatial statistics topics are: spatial autoregression, which involves regression techniques that account for spatial autocorrelation; geostatistics, which involves describing patterns in geographic variance attributable to spatial autocorrelation; point pattern analysis, which involves analysis of geographic distributions of point phenomena; and, spatial filtering, which involves the separation of spatial and aspatial effects. Spatial econometrics relates to this first category of techniques. The dominant focus of spatial statistics is spatial autocorrelation, differentiating it from quantitative geography, which frequently includes an introductory treatment of spatial autocorrelation, but mostly applies traditional methodology to locationally tagged observations without accounting for spatial effects.

Because quantitative geography courses were historically overlooked, the correlated nature of geographic data, and consequently quantitative geography in practice tended to yield statistical decisions that were less reliable than expected, a need emerged for teaching spatial statistics courses. The offering of such courses was encouraged further by the success of time series courses, which address the correlated nature of time-sequenced data. Furthermore, the publication of Cliff and Ord’s 1973 book, entitled Spatial Autocorrelation (1), furnished a feasible textbook for an inaugural spatial statistics course. The principal remaining obstacle at that time was a lack of software for implementing even rudimentary spatial statistics. But many spatial scientists were writing their own FORTRAN code to complete spatial statistics calculations. Journals, in turn, began publishing some of this code as computer algorithms (e.g. Goodchild’s work in 1980 (2)). By the early 1980s, the stage was set for spatial statistics courses to be offered. The appearance of introductory books by Goodchild (3), Griffith (4), and Odland (5) attests to this contention.

One of the first courses dedicated to teaching spatial statistics, which was taught at the graduate level, was offered by J. Keith Ord at The Pennsylvania State University during the spring semester of 1985. The textbook for his course was the classic Cliff and Ord book entitled Spatial Processes (6), which emphasizes point pattern analysis, distribution theory for the Moran Coefficient and the Geary Ratio, and spatial autoregression. Griffith began teaching a spatial autoregressive version of spatial statistics at the State University of New York at Buffalo in the late 1980s (using the pre- and then the published version of his Advanced Spatial Statistics (7)), and then at Oregon State in 1993, and helped launch a spatial statistics course at Cornell University in 1997. Meanwhile, disseminating the geostatistical work pioneered by Matheron in Paris, Journal brought this part of spatial statistics to Stanford University in 1978.1 Spatial autoregression and geostatistics had parallel, but divorced developments, finally being integrated in part by Cressie’s 1991 book entitled Statistics for Spatial Data (8) (which has a 1993 revised edition (9)), and in part by Griffith’s work in the late 1990s (10). Nowadays, spatial statistics courses are taught in a large number of
United States (US) universities (see Table 1), mostly focusing on geostatistics and spatial autoregression, and sometimes on point pattern analysis. The purpose of this paper is to describe the nature of this US education, selectively addressing books supporting it as well as its pedagogy.

2. Background

Geostatistics largely was popularized by Isaaks and Srivastava’s 1989 book (12), and by such classes as Cressie and Clark’s (13) American Statistical Association (ASA) Continuing Education workshop. Its implementation was popularized by softwares such as GEO-EAS (14) and GSLIB (15). Meanwhile, Anselin’s book (16) was the most successful promoter of spatial econometrics, with his SpaceStat (17) software making its implementation much more widely accessible. Similarly, Griffith’s (18) monograph helped to disseminate the implementation of spatial autoregression within the context of spatial statistics. Today, many of these specialized softwares have been eclipsed by modules available in GeoBUGS, GeoDa, ArcGis/Geostatistical Wizard (ESRI), R, S+, SAS, Stata, and other commercial software packages.

Table 2 enumerates many of the important books used to teach spatial statistics courses over the years. Paelinck and Klaassen coined the term “spatial econometrics.” Bartlett’s book concentrates on the conditional autoregressive model (CAR). Ripley’s 1981 book (21) focuses on geostatistics, whereas his 1988 book (26) has more of a spatial autoregressive focus. Upton & Fingleton’s first volume treats point patterns and spatial autoregression (simultaneous autoregression – SAR; autoregressive response – AR), whereas their second volume treats categorical and directional data. Haining’s books are a blend of geostatistics and spatial autoregression. In contrast with Anselin’s book (16), LeSage and Pace’s book (30) has a strong Bayesian emphasis. Finally, Cressie and Wikle’s book (32) points to the future direction of spatial statistics courses, which most likely will have far more space-time data analytic content.

3. What should a spatial statistics course contain?

The ASA and the Mathematical Association of American jointly released the guidelines for teaching introductory statistics courses (33). With some minor translation, points made in this document also pertain to the teaching of introductory spatial statistics courses.

First, a modern introductory spatial statistics course should introduce students to: concepts underlying the design of spatial statistical studies, and the reasoning needed to interpret results of spatial statistical analyses. Its essentials include: the necessity of spatial data for good decision-making, the value of sound spatial data production, the omnipresence of variability in underlying spatial processes, and the understanding and quantification of spatial uncertainty. Such a course should question assumptions underlying spatial statistical models that explain, predict, and interpolate – and qualify their use with measures of uncertainty. For example, a kriged map

Table 1. Universities with geography units supporting the teaching of spatial statistics.

| Listed departmental specialty | Listed faculty specialty |
|-------------------------------|--------------------------|
| Central Michigan U.           | Arizona State U.: Balling|
| Florida State U.              | Ball State U.: Yang      |
| Oregon State U.               | California State U./Northridge: Sun |
| San Francisco State U.        | California State U./Sacramento: Roberts |
| SUNY/Albany                   | Central Michigan U.: Ha  |
| U. of California/Santa Barbara| Clark U.: Polsky, Pontius, Ogneva-Himmelberger |
| U. of Idaho                   | Florida State U.: Elsner |
| U. of Louisville              | George Mason U.: Leslie  |
| U. of Miami                   | Indiana U.: Huang        |
| U. of Texas at Dallas         | Northern Arizona U.: Huang|
| U. of Toledo                  | Oregon State U.: Jones   |
| Western Kentucky U.           | Southern Illinois U.: Oyana, Wang |
|                              | SUNY/Buffalo: Yoo        |
|                              | Temple U.: Henry         |
|                              | The Graduate Center/CUNY: Maroko |
|                              | The Ohio State U.: Liu   |
|                              | The Pennsylvania State U.: Cervone |
|                              | U. of Connecticut: Li    |
|                              | U. of Idaho: Dezzani, Liao|
|                              | U. of Louisville: Gaughan|
|                              | U. of Missouri/Columbia: Blodgett |
|                              | U. of Nebraska/Lincoln: Lin|
|                              | U. of Nevada/Reno: Heaton|
|                              | U. of Southern California: Franklin |
|                              | U. of Texas at Dallas: Chun, Griffith |

Source: Ref. (11) by AAG (2013).
always should be accompanied by a prediction error map. In order to be successful in a modern curriculum, an introductory spatial statistics course requires: experience with real-world and simulated spatial data, and an appropriate use of geospatial and statistical technology (e.g. GIS, GeoDa, R, SAS) to support data analyses. Given this context, a spatial statistics course must have some prerequisites.

Second, the educational training and experience necessary to teach an introductory spatial statistics course include: (1) completion of a basic spatial statistics course; and (2) a deep knowledge of statistics via at least several statistical methods courses that include content knowledge of spatial data collection methods, study design, multivariate statistics, and statistical inference; experience with spatial data analysis beyond material taught in an introductory class; and, familiarity with the data-driven techniques used in modern statistics courses. In other words, an introductory spatial statistics course instructor needs more than an elementary background in statistics.

Finally, although spatial statistics builds on a foundation of mathematics, important differences exist between spatial statistical thinking and mathematical thinking. Spatial statistics uses mathematical concepts in an essential way, and certainly can involve narrowly defined problems, and theorems and proofs. Whereas students are accustomed to calculating a single, definitive correct answer that can be boxed and then compared with an answer in the back of their textbooks in mathematics courses, in spatial statistics courses, students need to construct sampling distributions (more than one answer to a question; sampling error), evaluate assumptions (e.g. absence of spatial dependency; specification error), assess location and attribute error (e.g. measurement error), and quantify uncertainty (e.g. prediction error). Furthermore, although students are accustomed to working deductively via theorems and proofs in mathematics courses, in spatial statistics courses, students need to differentiate between spatial situations having random components and being merely observational, to generate/collect spatial data in a meaningful way, and to distinguish between spatial and non-spatial dimensions of data; this supports inductive work. In other words, a spatial statistics course can forgo the formalism of a mathematics course by building upon sophisticated simulation experiments.

These preceding three guidelines promote the effective teaching of an introductory spatial statistics course. Their execution would help prepare a student for a job as a spatial statistician (see http://www.justinholman.com/2012/04/26/spatial-career-guide-spatial-statistician/). Prerequisites for a spatial statistics course should include introductory descriptive and inferential statistics, through bivariate regression analysis and multivariate statistics. Such courses suggest that a spatial statistics course should be at the graduate level. Accordingly, a student specializing in spatial statistics should expect to complete a graduate degree program. In doing so, a student most likely will need to do a number of independent studies and reading courses because most educational programs lack sufficient depth to offer a degree program in spatial statistics. In addition, a student needs to be proficient in a computer language such as SAS, R, SPSS, and especially with geographic information systems (GISs). A student also needs to perfect his/her communications skills, both written and oral; presenting the results of a spatial statistical analysis requires effective communication. Finally, a student needs considerable collection, cleaning/editing, and analysis experience with georeferenced data.

4. Selected course offerings
Table 3 summarizes the sequence of topics covered in the original Oregon State University course (34). This set of topics includes two subjects that are common to many existing introductory spatial statistics courses, namely,
measures of spatial autocorrelation and spatial auto-
models, especially the auto-normal probability model.

North Carolina State University offers an applied spa-
tial statistics course (http://www.stat.ncsu.edu/~reich/
st733/). Textbooks for this course are written by Kitanidis
(35) and Cressie (9), whereas the software used is R. Data
for analysis include environmental (i.e. fine particulate
matter) that are point location based, geographic (i.e.
Cressie’s NC data), and space-time (i.e. MN snow depth)
that are polygonal location based. This course treats point
pattern analysis and spatial scan statistics, the Moran
coefficient for measuring spatial autocorrelation, the CAR
and SAR auto-normal models, geostatistics, Bayesian
map analysis, and simulation.

Purdue University offers a similarly titled course
(http://www.stat.purdue.edu/~zhanghao/appliedspatial.
html). Rather than a textbook, it is accompanied by a set
of reference books about geostatistics. Half of its listed
topics concern geostatistics, with some emphasis on
assumption assessment (e.g. stationarity). The course
content also includes treatment of the CAR auto-
model, and spatial point pattern analysis. Its programming lan-
guage is R. Georeferenced data for analysis include
ozone measures from monitoring stations and individual
incidents of plant–human disease that are point based,
and US county statistics that are polygon based.

Yale University also offers a similarly titled course
(http://reuningscherer.net/fes781/). It treats point pro-
tesses and geostatistics, and primarily uses Diggle and
Riberio’s Model-Based Geostatistics (36) because this
book is a free Yale University electronic resource. Eight
other books also are listed, and the softwares used are R
and ArcGIS. More specific course topics include spatial
sampling, visualizing spatial data, quantifying spatial
association and autocorrelation, interpolation methods,
fitting variograms, kriging, and related modeling tech-
niques for spatially correlated data. Application examples
are drawn from ecology, sociology, public health, and
subjects proposed by students. Students are required to
have a data-set comprising at least 20 observations and
at least three variables, and are allowed to analyze a sin-
gle data-set in groups of 2–3.

Stanford University offers a course simply entitled
“spatial statistics” (http://statweb.stanford.edu/~jtaylo/
courses/stats352/). This course uses Cressie’s book,
employs R, and focuses on geostatistics, Markov random
fields, and point pattern analysis. It has a stronger mathe-
matical dimension, having stochastic processes and math-
ematical statistics as its prerequisites. It also treats
assumptions assessment.

Texas A&M University offers a similarly titled course
(http://www.stat.tamu.edu/~huiyan/syllabus647-
HS.pdf), one very similar to the preceding ones. It uses
the R package, has Schabenberger and Gotway (37) for
its textbook, and covers the full range of topics, from
autocorrelation and Bayesian spatial statistics, through
point processes and spatial autoregression, to variograms.

Meanwhile, my spatial statistics course at the Univer-
sity of Texas at Dallas is more conceptual in nature,
mostly covering geostatistics and spatial autoregression, addressing point pattern analysis only in terms of spatial sampling, and treating the following topics: spatial autocorrelation, spatial sampling, spatial configurations, eigenfunction theory, spatially adjusted regression (e.g. spatial autoregression), local statistics, spatial variance and covariance, spatial interpolation and imputation, spatial error, Bayesian spatial analysis, simulation experiments, and space-time data. Its textbook is Chun and Griffith (38), and the software used includes R, SAS, ArcGIS, and GeoDa.

Table 4 enumerates a number of other US educational institutions that offer a spatial statistics course, with many being housed in a Statistics Department. This list reveals that such a course is offered across the various tiers of US schools, and is offered in graduate programs. Although several dozens of schools offer some type of spatial statistics course, this is not much considering that the US has 4599 accredited colleges and universities whose students are eligible for federal student financial aid; nor is it many when compared to the 1024 Carnegie Classification schools with graduate programs.

5. Valuable web and other resources

Free web resources exist to support the teaching of spatial statistics. Obvious ones are for GeoDa (http://geodacenter.asu.edu/) and for the R spdep library (http://cran.r-project.org/web/packages/spdep/index.html). Pace compiled links to a number of other pages (http://www.spatial-statistics.com/). GSLIB furnishes a support page for geostatistics (http://www.gslib.com/), as does GEOEAS (http://www.epa.gov/ada/csmos/models/geoeas.html). LeSage provides a spatial econometrics toolbox (http://www.spatial-econometrics.com/). SatScan furnishes a page (http://www.satscan.org/) for spatial temporal, and space-time scan statistics. CrimeStat can be accessed via the ICPSR (https://www.icpsr.umich.edu/CrimeStat/download.html). Finally, GRASS GIS furnishes a free downloadable GIS package (http://grass.osgeo.org/download/).

Commercial software also is available. Foremost are ArcGIS, IDRISI, S+; and SAS. Other licensed software is expanding into this area, including Mathematica, beginning with version 7.0, which has acquired GIS capabilities. Other commercial softwares, such as MINITAB (39), also can be used to implement spatial statistics.

6. A model spatial statistics course: GISC 7361, the University of Texas at Dallas

This graduate-level course covers spatial statistical analysis in a data analytic way, building upon the standard linear regression model and visualizing with a geographic information system. Mathematical ideas are illustrated with data and numerical examples employing commercial software. Students are introduced to elementary spatial statistics and data handling, a conceptual overview of the theory of spatial statistics, areal unit configuration and locational information, reformulating classical linear statistical models and semivariogram modeling, spatial autocorrelation and spectral analysis, missing data on a two-dimensional surface and kriging, and error propagation analysis. Each student is required to perform analyses on a georeferenced data-set of her/his choice. Computer softwares used include SAS, R, Mathematica, GeoDa, and ArcGIS.

The general learning objectives of the course are as follows:

- explain the meaning of spatial autocorrelation.
- detect spatial autocorrelation in georeferenced data.
- account for the effects of spatial autocorrelation in georeferenced data.
- differentiate between global and local statistics.
- differentiate between spatial autoregressive and semivariogram modeling.
- implement spatial autoregressive models.
- implement semivariogram models.
- implement spatial filter models.
- estimate data values for unobserved locations.

| Lecture No. | Course |
|-------------|--------|
| 1           | Background review: what is spatial autocorrelation? (Ch. 2) |
| 2           | Spatial sampling (Ch. 3) |
| 3           | Spatial composition and configuration (Ch. 4) |
| 4           | Eigenfunction theory relevant to spatial statistics |
| 5           | Spatially adjusted regression and related spatial econometrics (Ch. 5) |
| 6           | Class presentation of data analyses |
| 7           | Local statistics: hot and cold spots (Ch. 6) |
| 8           | Analyzing spatial variance and covariance with geostatistics and related techniques (Ch.7) |
| 9           | Methods for spatial interpolation in two-dimensions (Ch. 8) |
| 10          | Concluding comments: intermediate topics in spatial statistics (Ch. 9) |
| 11          | USEPA atrazine assessment: a special application of spatial statistics |
| 12          | Learning GeoDa (http://geodacenter.asu.edu/): “deliberate practice” learning |
| 13          | Group presentation demonstrating GeoDa |
| 14          | Class presentation of data analyses |
• know how to undertake Bayesian map analysis.
• know how to undertake frequentist random effects analysis.
• know how to read and interpret spatial statistical papers.

These goals emphasize many of the subjects of the previously discussed spatial statistics courses.

The textbook for this course is written by Chun and Griffith (38). Two of its advantages are: (1) an affiliated supporting web page (http://www.sagepub.com/chun_griffith/study/default.htm); and (2) an inexpensive soft cover version. Material supplementing the content of this book comes from a number of different sources. For example, spatial sampling discussion is augmented with materials from Müller (40), and Mateu and Müller (41). Spatial econometrics themes are complemented with materials from Anselin (16), Arbia (42), and LeSage and Pace (30). The Moran eigenvector spatial filtering (ESF) presentation is enhanced with materials from Griffith (43). Treatment of space-time analysis is supplemented with materials from Cressie and Wikle (32). Finally, the course begins with the SASIM computer game (44), which now is implemented in R.

Table 5 enumerates the sequence of lecture topics, indexed to the relevant chapters of Chun and Griffith (38). The course includes exposure to both R code and GeoDa so that a student acquires spatial statistical experience with non-commercial software.

7. Conclusions

One can ask what we know today about the teaching of spatial statistics in the US. The answer is multifaceted. Spatial statistics courses are taught at all tiers of US universities, but in graduate programs, and in only a few dozens of the thousands of possible educational institutions. Spatial statistics content also is found in spatial analysis and quantitative geography courses. Spatial statistics cannot be taught without GIS support. Increasingly, more general software programs are acquiring spatial statistics capabilities. Some emphases in spatial statistics are turning from point pattern analysis to the treatment of space-time analysis. Finally, spatial statistics is shifting part of its focus to space-time statistics.

Meanwhile, a survey of the job market (http://www.indeed.com/q-Spatial-Statistics-jobs.html) reveals that spatial statistics skills are in demand (on 13 May 2014) not only in academics (e.g. California State University/Fullerton, Michigan Technological University, and University of Maryland/Baltimore County), but also by the government (e.g. National Geospatial-Intelligence Agency, Springfield, VA), and by industry (e.g. American Legacy Foundation, Washington, DC; AT&T, Bedminster, NJ; DeepStream, Addison, TX; MaxPoint, Austin, TX; and, Monsanto, St. Louis, MO).

Finally, while spatial statistics has evolved from a preoccupation with point pattern analysis to the treatment of non-normal RVs and Bayesian map analysis, it also faces new frontiers. One is ESF, which supports non-normal georeferenced random variable usage, and Bayesian and spatially varying coefficients model specifications. This new spatial statistical methodology already has been implemented in R, as SpatialFiltering within the spdep library, and is in the process of being made widely available by LIESMARS (Wuhan University) as a cloud service.

Notes

1. See http://www.sagepub.com/chun_griffith/study/default.htm.
2. See http://en.wikipedia.org/wiki/Higher_education_in_the_United_States.
3. See http://en.wikipedia.org/wiki/Carnegie_Classification_of_Institutions_of_Higher_Education.

Note on contributor

Daniel A. Griffith is an Ashbel Smith professor of Geospatial Information Sciences, the current International Spatial Accuracy Research Association (ISARA) Steering Committee chair, an IGU Commission on Modeling Geographical Systems Steering Committee member, an International Collaborative Center for Geo-computation Studies (ICCGS), Wuhan University, Advisory Committee member, an elected Regional Science Association International (RSAI) councilor, a Fulbright Senior specialist, and a fellow of the Spatial Econometrics Association and the RSAI.

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