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Discussion of “Spatial statistics: Marks, maps and shapes”

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Dr. Possolo has provided us with a stimulating and thorough article on the emerging field of spatial statistics. Starting with lattices and points it moves toward maps and is concluded with the statistical treatment of alpha-shapes. The last topic may be somewhat curious in the context of the remainder of the article, but it provides a nice visualization tool and it is applied in a solid way for spatial and spatiotemporal information. Maybe even more than the theory, the article is thought-provoking by providing a range of important examples: oil wells including the amount of production show a clear economical and energy dimension, folded limestone from the Jurassic coast points to applications in the domain of geology where geo-statistics emerged, toward the recent critical study on observations following the Fukushima disaster. The examples are analyzed with standard R libraries that are devoted to spatial statistics. In this sense, the article is well accessible and complete. As an introductory document there is little to add; recent developments elsewhere and in addition to the above are what I like to introduce in this short discussion note.

The first and foremost issue is the recent development of space–time procedures. It is a straightforward extension of spatial statistics domain, and it has currently received so much attention that its mentioning is important. Space–time point patterns have been addressed by Gabriel and Diggle (2009), whereas space–time geostatistics is the core of Cressie and Wikle (2011). Changing spatial marks have also been addressed. Spatial–temporal statistics were abundantly explored during the recent spatial statistics conference on emerging patterns.

Next, object-based spatial statistics has been developed in addition to and extending point-based spatial statistics. It was already present in the earliest books on geostatistics (e.g., Journel and Huijbregts 1978), and currently it somehow returns in the discussions on big data. In those discussions, identification and classification of objects becomes increasingly important for finding the important information and reducing the amount of the data. We see this, for example, in remote sensing studies, where objects that are internally varying are identified (crop parcels, slum areas, and water quality; Zhao, Stein, and Chen 2011). Typical issues are to study relations between objects when making predictions in space or in space and time (Truong, Heuvelink, and Pebesma 2014).

The third issue concerns identification and modeling of spatial extremes. For this work, much attention is being given to max-stable processes and to copulas. Copulas were developed some 10 years ago and are still developing rapidly toward new forms. They have shown to be powerful in properly dealing with probabilistic prior information. They are also primarily based on spatial studies, but current work has extended them also in the space–time domain. Max-stable processes relate to integrating extreme value distribution functions into the domain of spatial statistics (Schlather 2002).

The fourth issue I like to raise concerns sampling. Spatial statistics has developed various procedures in doing so. Traditionally data collection was based upon classical design theory. Later on, model-based geostatistical methods were developed (Stein and Ettema 2003). A statistical design com-

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monly considers estimating the mean value, whereas model-based sampling optimizes a user-specified criterion. The combination of the two is moving forward.

The final issue that has recently found its place in spatial statistics concerns integrated nested Laplace approximations (INLAs), a relatively new development that has found a place now in spatial statistics. It was developed some 5 to 10 years ago, by the seminal work of Havard Rue and his group (Rue, Martino, and Chopin 2009). There is a long way ahead in this very interesting and developing field of spatial statistics.

Maybe, considering the above, what is an important feature that could have been added to the article is the Bayesian approach toward spatial statistics. With the introduction of Bayesian statistics, and the advent of software packages such as Winbugs and several R routines, the usual computational problems inherent in using Bayesian statistics have been resolved. On the demand side, and there is in fact the main contribution of the current article, is the increasing need to make solid and convincing statements on important problems in nature, the environment, and the economy. Realizing the spatial dimension of these domains gives a large momentum toward further development and application of spatial statistical methods.

I think that this is the major power of the current article, namely, that it provides us with an excellent and timely introduction to the subject and paves the way to include further developments.

About the author

A. Stein is professor of spatial statistics and image analysis at the Faculty of Geo-information Science and Earth Observation of the University of Twente, Enschede, The Netherlands. He holds an M.Sc. in mathematics and computer science and a Ph.D. in agricultural and environmental sciences. He is editor-in-chief of the new scientific journal *Spatial Statistics* that recently received an impact factor. A main focus of his work is on problems in developing countries.

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