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Discussion of “Statistical Modeling of Spatial Extremes” by A. C. Davison, S. A. Padoan and M. Ribatet

Benjamin Shaby and Brian J. Reich

The review paper on spatial extremes by Davison, Padoan and Ribatet is a most welcome contribution. The authors cover quite a lot of ground, making connections between different approaches while highlighting important differences. In particular, we applaud their careful attention to model checking, which can be difficult in general but particularly so for spatial extreme value models.

1. PREDICTION AND MODEL VALIDATION

With its extensive set of diagnostics for evaluating model fit, this paper provides a nice template for practitioners to follow. However, perhaps the most important feature of spatial models is their ability to predict at unobserved sites. The account presented here does not address the prediction problem, which is both a critical task in its own right and a tool for comparing models. More traditional spatial analyses typically include various performance metrics to evaluate prediction at a withheld test set of observation locations. While spatial prediction is difficult for the max-stable process models described in the paper, computational tools to accomplish this task do exist (Wang and Stoev, 2011). Spatial prediction for copula models is considerably more straightforward.

However, we note that even with predictions at holdout locations in hand, evaluating model skill at reproducing extremal quantities requires some care. Clearly, the metrics used in traditional geostatistical analysis such as mean squared prediction error are unsatisfying for block-maximum data. Rather, we recommend the quantile score and the Brier score for threshold exceedences, as discussed and justified by Gneiting and Raftery (2007). These metrics are specifically tailored to evaluate the tail of the predictive distribution and therefore seem more appropriate in this context.

2. TOWARD HIERARCHICAL BAYESIAN MAX-STABLE MODELS

In their discussions of the relative merits of various approaches, the authors highlight the ability of hierarchical Bayesian models to represent richly flexible structures for underlying marginal parameters. As they point out, however, the conditional independence assumption made in the Bayesian analyses they discuss hamstrings the model's ability to produce spatial association in process realizations. Indeed, others have also shown that failing to properly account for spatial dependence can lead to dramatic underestimation of uncertainty, and thus undercoverage of posterior intervals, for the GEV parameters and return levels (Fuentes, Henry and Reich, 2011).

The authors correspondingly laud the ability of max-stable processes to capture joint behavior across spatial locations, but lament the restriction to relatively simple underlying structures that pairwise likelihood fitting of max-stable process models imposes. The trade-off between flexible marginal modeling and realistic spatial dependence modeling is almost treated as an inherent conundrum, almost analogous to a Heisenberg's uncertainty principle for spatial extremes. But we want to have it both ways!

The authors rightly note that the unavailability of joint likelihoods for max-stable process models appears to render their inclusion in hierarchical Bayesian models problematic. We view surmounting this obstacle as a welcome challenge! As they note, progress has already been made. For example, Ribatet, Cooley and Davison (2012) specifies such a hierarchical model, but replaces the joint likelihood with a pairwise likelihood and modifies the resultant MCMC sampler using an asymptotic argument. The resultant sample from the “posterior” distribution appears to have desirable frequentist properties. While this approach may not be

Benjamin A. Shaby is Postdoctoral Researcher, Department of Statistics, University of California, Berkeley, USA (e-mail: bshaby@stat.berkeley.edu). Brian J. Reich is Assistant Professor, Department of Statistics, North Carolina State University (e-mail: brian_reich@ncsu.edu).