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Title: Bayesian space-time gap filling for inference on extreme hot-spots: an application to Red Sea surface temperatures

Abstract:

We develop a method for probabilistic prediction of extreme value hot-spots in a spatio-temporal framework, tailored to big datasets containing important gaps. In this setting, direct calculation of summaries from data, such as the minimum over a space-time domain, is not possible. To obtain predictive distributions for such cluster summaries, we propose a two-step approach. We first model marginal distributions with a focus on accurate modeling of the right tail and then, after transforming the data to a standard Gaussian scale, we estimate a Gaussian space-time dependence model defined locally in the time domain for the space-time subregions where we want to predict.

In the first step, we detrend the mean and standard deviation of the data and fit a spatially resolved generalized Pareto distribution to apply a correction of the upper tail. To ensure spatial smoothness of the estimated trends, we either pool data using nearest-neighbor techniques, or apply generalized additive regression modeling. To cope with high space-time resolution of data, the local Gaussian models use a Markov representation of the Matérn correlation function based on the stochastic partial differential equations (SPDE) approach. In the second step, they are fitted in a Bayesian framework through the integrated nested Laplace approximation implemented in R-INLA. Finally, posterior samples are generated to provide statistical inferences through Monte-Carlo estimation. Motivated by the 2019 Extreme Value Analysis data challenge, we illustrate our approach to predict the distribution of local space-time minima in anomalies of Red Sea surface temperatures, using a gridded dataset (11,315 days, 16,703 pixels) with artificially generated gaps. In particular, we show the improved performance of our two-step approach over a purely Gaussian model without tail transformations.