

Geostatistical prediction of spatial extremes and their extent

Noel Cressie

Jim Zhang

Peter F. Craigmile

The Ohio State University

Abstract

Suppose we are interested in making inference on the spatial process $\{Z(\mathbf{s}): \mathbf{s} \in D \subset \mathbb{R}^d\}$ based on a sample $\mathbf{Z} \equiv (Z(\mathbf{s}_1), \dots, Z(\mathbf{s}_n))'$ taken at locations $\{\mathbf{s}_1, \dots, \mathbf{s}_n\}$. It is well known that optimal linear prediction of linear functionals of Z (e.g., $Z(\mathbf{s}_0)$ at a known point \mathbf{s}_0 or $Z(B) \equiv \int_B Z(\mathbf{u})d\mathbf{u}/|B|$ over a given block B in D) is obtained through (universal) kriging. When the functional of Z is nonlinear, such as the α -th spatial quantile in D , $Z_\alpha(D) \equiv \inf\{z: \int_D I(Z(\mathbf{u}) \leq z)d\mathbf{u}/|D| \geq \alpha\}$; α near 1, a plug-in kriging predictor is highly biased. The reason is that kriging is based on a squared error loss function that results in “oversmoothing”; that is, the peaks of Z are rounded and the valleys of Z are filled in. One way to deal with this is to add a constraint that matches certain variances and covariances of the predictor to that of Z : covariance-matching constrained kriging (CMCK). The other way is to change the loss function to put more emphasis on the peaks (and valleys): integrated weighted quantile squared error loss (IWQSEL) prediction. Craigmile et al. (2004) have shown that IWQSEL prediction can target a given value of α and accurately predict extremes and their extent associated with that α . In this paper, we compare CMCK to the IWQSEL-prediction standard for a given α , using a dataset of TCDD-contaminated soil.