# Comment on Diggle, Moyeed and Tawn

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The authors are to be congratulated on a most stimulating paper on combining geostatistics with the flexibility of generalized linear models, as well as on the efficient implementation of their method through the techniques of Bayesian computation.

A crucial question for the statistician when analyzing spatial data is whether to model the full probability distribution of the phenomenon or only to model statistical moments of low order. Kriging prediction is based on specified parametric forms for the mean and covariance (or variogram) functions only. In comparison, the authors go further and specify a wide class of parametric models for the underlying probability distribution of the data. This approach is neccessary if the aim is to analyse extremes or excursion sets of the process.

Alternatively, the Kriging approach of modelling mean and covariance parametrically may be extended to a wide class by modeling these moments nonparametrically. This approach may be preferred in data-rich applications when the purpose is spatial prediction and assessment of prediction errors. In Høst (1996) a flexible framework for prediction of a spatial process with unknown trend and correlated residuals is presented. For an example in 1-D, consider a continuous random process $y(s)$, where $s$ is a location on the real line. Let $y(s)$ have the decomposition

$$y(s) = f(s) + v(s),$$

where $f(s)$ is a smooth trend function and $v(s)$ is a zero-mean, second-order stationary residual process.

In applications where the trend is unknown, it may be unrealistic to specify it parametrically. In particular, the Kriging predictor will be biased under the model given above. Consequently, I suggest a local parametric approximation to the trend function $f$ within a window of radius $h$ and I derive an optimal predictor for this local model. The global properties of the predictor will be governed by $h$ and a kernel function, and a framework is obtained in which both local polynomial regression estimation (Hastie and Loader 1993; Fan and Gijbels 1996) and Kriging prediction can be described. In particular, I give an expression for the prediction error which includes also a bias term.

Figure 1 shows simulated data from a process of the type described above, and Figure 2 shows the estimated 95% prediction intervals for a local linear predictor and a linear trend Kriging predictor. The bandwidth $h$ in the proposed predictor was chosen by cross-validation. Figure 2 indicates that Kriging has smaller prediction errors than the local polynomial predictor. However, cross-validation shows that the proposed method has both smaller prediction errors and more realistic estimates of these errors than Kriging. This is due to bias effects and to confounding of trend and residual structure in the Kriging approach.

Future extensions of this approach may include nonparametric modelling of the spatial covariance function, possibly along the lines of Sampson & Guttorp (1992).

# References

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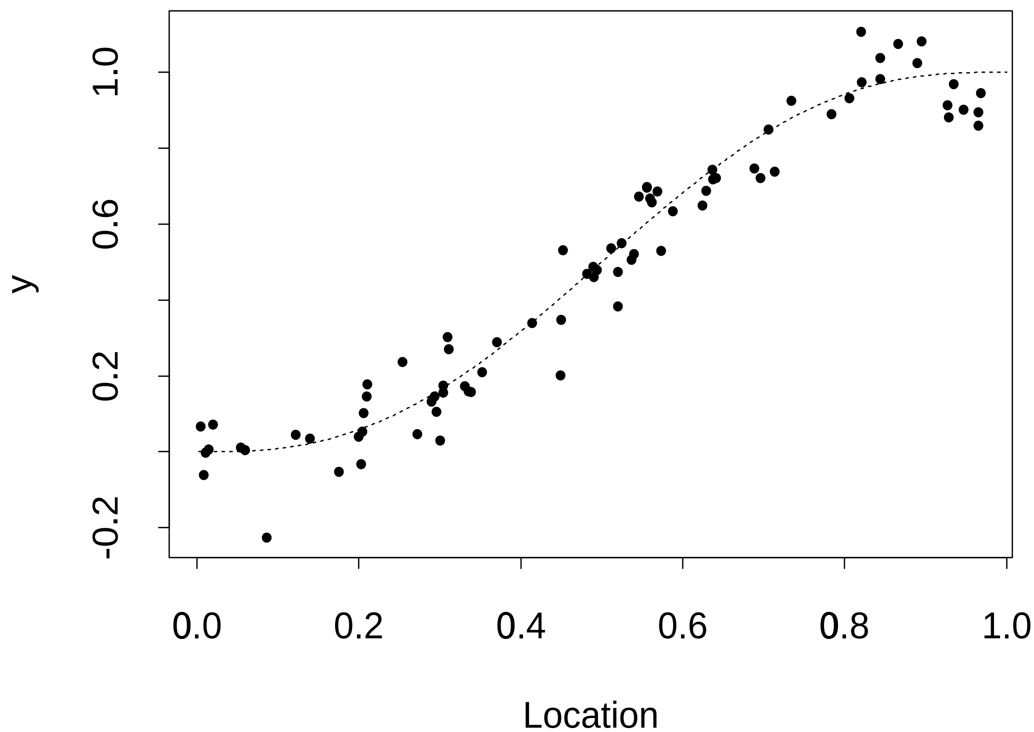


Figure 1: *Simulated data (dots) and underlying trend function (broken line) for model with exponential covariance function with range 0.054,* $\sigma = 0.1$ *and* $f(s) = 10s^3 - 15s^4 + 6s^5$

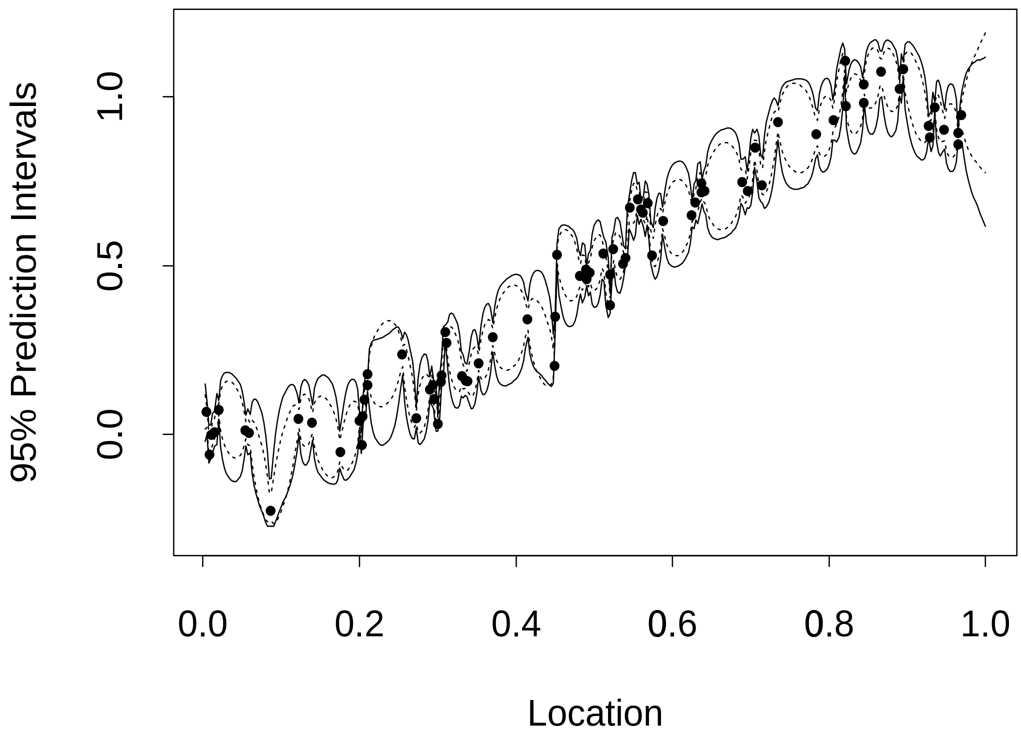


Figure 2: *Prediction intervals from local polynomial Kriging (full line) and universal Kriging for the data of Figure 1*