Efficient spatio-temporal modelling and interpolation of Global Sea Surface Height

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Research Group: Statistics and Data Science

Project description:

Big environmental data combined with modern data science offer a key opportunity to better understand our environment and address climate change. Yet environmental data poses specific challenges due to spatio-temporal dependence: 1. Modelling. Most models of spatio-temporal dependence are homogenous, which in general is not an accurate description of real-world phenomena. 2. Estimation. More complex parametric models of covariance are often not amenable to estimation via exact likelihood due to computational inefficiency and lack of robustness to model misspecification.

In this project, you will develop new parametric covariance models and estimation methods for the analysis of Sea Surface Height (SSH). The surface height of the oceans is monitored by passing satellites on a global scale. The modelling of SSH is vital to a better understanding of the global climate and to making more accurate interpolation via kriging [1].

Firstly, your research will focus on estimating the parameters of a spatial covariance model of Sea Surface Height. You will pursue recent developments in quasi-likelihood estimation [2, 3, 4, 5, 6] for spatio-temporal data to propose a parametric estimation method that is both computationally and statistically efficient. The idea behind quasi-likelihood estimation is to maximize a computationally efficient approximation to the exact likelihood.

Secondly, you will develop more advanced parametric models of covariance that can incorporate some additional physical phenomena that drive SSH. Possible directions for this part of the project range from relaxing the assumption of spatial homogeneity [7], to modelling temporal dependence and seasonal patterns [8]. These methodological developments can also have an impact in other application areas such as econometrics.

This project will be in collaboration with C. Wortham and J. Early, NorthWest Research Associates, Seattle, USA, who have been granted funding by the NASA to develop mapping software for SSH.

References

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Further information:

How to apply

Entry requirements

Fees and funding