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Upskilling predictions from physical process models by using statistical spatial-temporal models

Abstract:

Many environmental models have been developed based on physical processes and become highly valuable for environmental predictions. However, these models can be subject to errors, and improvements to the predictions may be needed for practical applications. Statistical post-processing of model outputs is a cost-effective way to produce more accurate predictions. In this talk, I will introduce a recently developed method to post-process dimensionally high spatial-temporal model outputs by combining empirical orthogonal function (EOF) analysis and regression. The EOF analysis is to reduce the high-dimensional spatial-temporal data to time series of a small number of reduced variables. These reduced variables then become the target for improvement through statistical calibration. Finally, a reverse application of the EOF analysis to the improved predictions of the reduced variables leads to post-processed, and expectantly improved, predictions of the original high-dimensional variables in a spatial field.

I will demonstrate the effectiveness of the method through two applications. One application is to improve precipitation forecasts from numerical weather prediction models. With our new method, we post-process forecasts for all grid-cells in a large field at once, directly embedding spatial structures in the produced ensembles. This method contrasts with the commonly used approach of post-processing grid-cell by grid-cell, followed by spatially connecting the ensemble members of individual grid-cells - a problem yet to be satisfactorily resolved.

A second application is to improve flood inundation simulations of low-fidelity hydrodynamic models. The use of low-fidelity models is to reduce model run time for real-time deployment, as high-fidelity hydrodynamic models are generally computationally too intensive, especially for ensemble runs. However, low-fidelity model simulations need to be made more accurate before use. With our new method, we post-process simulations from the low-fidelity models to accurately emulate high-fidelity hydrodynamic models, while in total using only a fraction of the time needed to run the latter. It then becomes feasible to produce ensemble forecasts of the evolution of flood inundation ahead of events.