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Keywords: data assimilation, ensemble optimal interpolation, parameter bias

Introduction

Uncertainties in the input data, model structure and model parameters among others render the hydrological predictions imprecise¹⁾. Data assimilation algorithms such as the ensemble Kalman filter (EnKF) which provide a framework to represent and subsequently reduce these uncertainties by merging observations into the model continue to receive significant attention in the field of hydrological forecasting. While the evidence of the effectiveness of EnKF is abundant in the literature, its use in operational forecasting may be limited by its high computational demand as it requires multiple runs of the model to characterize the uncertainties. On the other hand, the ensemble optimal interpolation (EnOI) algorithm, unlike the EnKF, contains a single model run akin to the deterministic simulation except for the correction from the observations. While it does not provide any information about the uncertainty in the model predictions, the reduced computational cost of this approach makes it an attractive option for real-time implementation. However, the efficacy of the EnOI in hydrological data assimilation is not yet completely understood and as such, this study aims to investigate the suitability of this computationally inexpensive assimilation algorithm in reducing the parameter bias present in a distributed hydrological model. The experiments conducted are of synthetic in nature and are applied to a small-scale river basin in Japan.

Synthetic observation generation and EnKF implementation

True water level data were first obtained by feeding an assumed true precipitation input to the rainfall-runoff-inundation model²⁾ characterized by a spatially uniform true model parameter set. These “true” water stages were then perturbed by a predefined noise model to generate the synthetic water level observations. Uncertainty in the model was limited to the model parameters and was represented by uniformly distributed samples in the parameter space. The EnKF was able to correctly approximate the two model parameters (i.e. the manning’s roughness coefficient for the river channel and the soil hydraulic conductivity) at the end of the assimilation period as the assimilated variable i.e. the river stage was found to be more sensitive to these two parameters. This tendency was found to be consistent across different initial parameter uncertainty representations and for the two flood events (from 2013 and 2018) tested.

EnOI implementation

While the covariance matrix needed for parameter update is calculated based on the ensemble anomalies in the EnKF, such estimation is not possible in EnOI as only a single model is integrated forward. As such, background ensembles have to be predefined in order to calculate the errors and allow for the updates of the state variables (and/or the parameters) with the EnOI. This study used the background ensembles from different time steps of the EnKF implementation to calculate the covariance matrices and fixed them for the entirety of the assimilation period of the EnOI implementation. At the start of the assimilation, the model parameters were randomly generated which were then subsequently corrected by using the pre-specified background and observation error covariance matrices. Since a single parameter value was generated for each of the model parameters, this was essentially a deterministic model run with the update to the parameters at each assimilation step.

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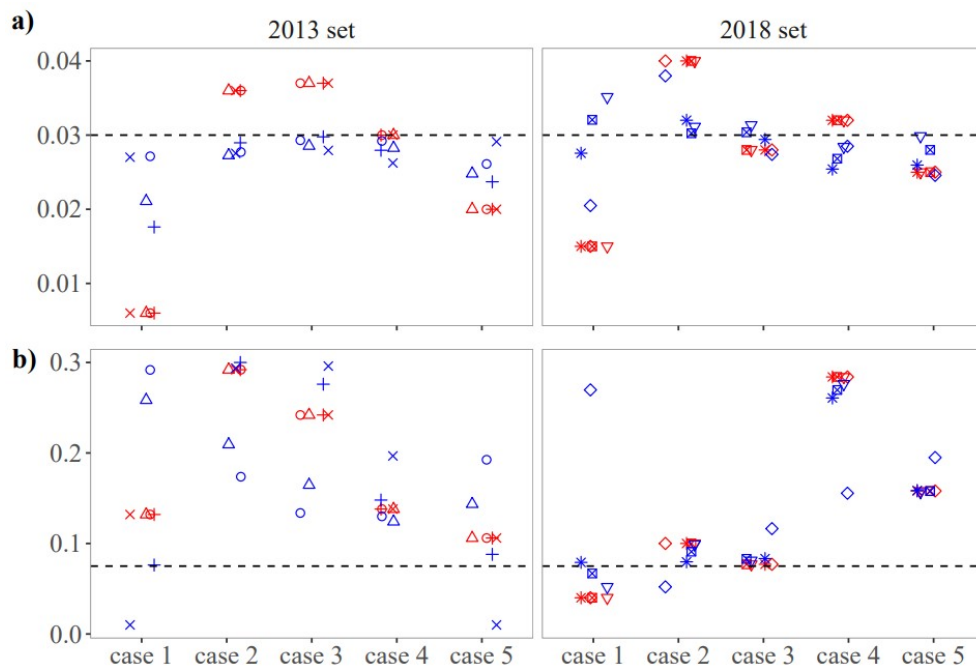


Fig. 1: Model parameters (a) manning's n for river channel and (b) soil hydraulic conductivity (m/s) at the beginning (red) and end (blue) of the assimilation period for the 2018 flood. Dotted lines indicate the true parameter values and the cases represent different initial values of the parameters. Different point shapes represent different covariance matrices (only the results for a select few matrices are shown). The two columns "2013 set" and "2018 set" indicate the flood event from which the covariance matrices are taken.

EnOI was able to reduce the bias in the model parameters to an extent for those matrices which had small covariances between the state variables at the observation locations and the model parameters. When large gains were allowed by the update, parameters became unstable leading to unreasonable water level estimations. In general, EnOI was able to better approximate the channel roughness coefficient (also see Fig. 1) likely because of the high sensitivity of the assimilated variable to this parameter. Encouragingly, covariance matrices from a previous flood event were also found to be effective in a latter flood ("2013 set" in Fig. 1 for 2018 flood). Future works will extend the study to other events and model uncertainties including experiments with real data.

Conclusions

This study investigated the efficacy of a computationally inexpensive assimilation algorithm i.e. the ensemble optimal interpolation in reducing the biases in the model parameters by using synthetic river stage observations for assimilation. Ensemble Kalman filter was first applied to two flood events to yield a set of covariance matrices (both background and observation error) which were then utilized to update the model parameters of the deterministic model runs. While large magnitudes of covariances led to oscillations in the parameters, gradual nudging through small gains led the parameters - especially the manning's n for river - to be close to the truth at the end of the assimilation period.

References

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