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Developments in non-linear Kalman Ensemble and Particle Filtering techniques for hydrological data assimilation

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Quantifying large-scale (basin/global) water storage changes is essential to understand the Earth's hydrological water cycle. Hydrological models have usually been used to simulate variations in storage compartments resulting from changes in water fluxes (i.e. precipitation, evapotranspiration and runoff) considering physical or conceptual frameworks. Models however represent limited skills in accurately simulating the storage compartments that could be the result of e.g., the uncertainty of forcing parameters, model structure, etc. In this regards, data assimilation provides a great chance to combine observational data with a prior forecast state to improve both the accuracy of model parameters and to improve the estimation of model states at the same time.

Various methods exist that can be used to perform data assimilation into hydrological models. The one more frequently used particle-based algorithms suitable for non-linear systems high-dimensional systems is the Ensemble Kalman Filtering (EnKF). Despite efficiency and simplicity (especially in EnKF), this method indicate some drawbacks. To implement EnKF, one should use the sample covariance of observations and model state variables to update a priori estimates of the state variables. The sample covariance can be suboptimal as a result of small ensemble size, model errors, model nonlinearity, and other factors. Small ensemble can also lead to the development of correlations between state components that are at a significant distance from one another where there is no physical relation. To investigate the under-sampling issue raise by EnKF, covariance inflation technique in conjunction with localization was implemented.

In this study, a comparison between latest methods used in the data assimilation framework, to overcome the mentioned problem, is performed. For this, in addition to implementing EnKF, we introduce and apply the Local Ensemble Kalman Filter (LEnKF) utilizing covariance localization to remove long range spurious correlations and increase the effective ensemble size. To evaluate and compare the mentioned data assimilation methods and study their performance, numerical experiments are generated using assimilation of Gravity Recovery and Climate Experiment (GRACE) observations into AWRA (Australian Water Resource Assessment) model. Fundamental issues regarding the assimilation of water storage observations into the spatially extended chaotic system are addressed.