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Interactive Comment

Interactive comment on "Data assimilation in integrated hydrological modeling using ensemble Kalman filtering: evaluating the effect of ensemble size and localization on filter performance" *by* J. Rasmussen et al.

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Thank you for your comments which we have tried to address point-by-point.

- Comment: The paper describes only twin experiments with generated measurements. I agree with the authors that this is the best way to obtain quantitative insight into the data assimilation methodology. With respect to the performance indicators described in Section 2.8 the role of the third one is not clear to me. Why not focus on the first two indicators: The head and discharge RMSE?

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Response: As a joint state updating and parameter estimation approach is used in the paper, we find it relevant to show how well the filter estimates the parameters. Furthermore, the head and discharge RMSE in certain cases depends on the estimation of the parameters, and the connection between RMSE and parameter estimation means that relevant information is left out if the parameter estimation is not presented.

Modifications: None.

- Comment: The paper is rather self-contained and provides a very brief overview of the various components of the methodology. For the technical details the reader has to study the various references mentioned. I only missed a general discussion about Ensemble Kalman filtering algorithms. At the beginning of Section 2.3 without any introduction the Ensemble Transform Kalman filter is described. There are many Ensemble Kalman filter algorithms available. Why is this implementation used?

Response: We agree that the paper will benefit from a short discussion of filter algorithms, but would also like to keep the focus of the paper on other issues than the filter algorithm as we believe that the conclusions of the study would be the same regardless of the filter used.

Modifications: Section 2.3 (titled “Data Assimilation) has been added the following:

“A number of algorithms exist that may be used for data assimilation. In hydrological data assimilation, the Ensemble Kalman Filter (EnKF) and variations and extensions thereof are primarily used, and have been shown to perform well. The variations of the EnKF have primarily been made to improve the computational efficiency of the filtering or to relax some of the assumptions made in the EnKF about model and parameter error.

This study uses the Ensemble Transform Kalman Filter (ETKF) (Bishop et al., 2001), which is a computationally efficient implementation of the EnKF. The ETKF is also deterministic and does not require a full error covariance matrix to be generated, which makes it computationally less demanding. Furthermore, adaptive localization is particularly easy in the ETKF, as will be shown in section 2.3.4, due to the implementation which updates the states variable by variable, rather than updating the entire state vector. This makes the ETKF a natural choice of filter for this study."

- Comment: Page 2286 Fig. 1 should be Fig. 6.

Modifications: Changed - Comment: page 2287 Fig. 7 should be Fig. 8.

Modifications: Changed.

- Comment: The quality of the Figures 6 and 8 is not good. It is quite a puzzle to reconstruct the results from these figures. Increasing the size and/or less lines per Figure might help here.

Modifications: The figures have been redesigned to improve the readability.

- Comment: The fact that in a few experiments the RMSE increases with the ensemble size is worrying (Fig. 6 bottom). The explanation in the paper (page 2286, lines 23-27) is not very convincing. And what would be the RMSE for ensemble sizes larger then 200 in these cases?

Response: We agree that it seems problematic that the RMSE increases with ensemble size, but the error can in many cases be attributed to spurious correlation, which is random by nature and highly dependent on the sampling of both parameters and forcing noise. As such, the RMSE of scenarios where spurious correlation is a dominant source of error is to some extent random, and so an increase is not unusual.

Modifications: The following is added to the section in question (page 2286, lines 27): "The presence of spurious correlations depends strongly on the sampling of both parameters and model forcing noise and is by nature random. As such, a clear trend in RMSE as a function of ensemble size cannot always be expected when spurious correlation is s significant source of error".

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., 12, 2267, 2015.