hess-2015-54: Authors' response (in *blue italics*) to comments by Dr. Ming Pan (in black)

The work titled "Operational aspects of asynchronous filtering for hydrological forecasting" by O. Rakovec et al. presented a data assimilation study for river discharge simulations using the Asynchronous Ensemble Kalman Filter (AEnKF). The experiments are mainly focused on testing the effects of two procedures: lumped filter updates against observations from multiple time steps and partial updating of the model states. The study is very carefully designed and carried out and the paper is well organized and well written. In general, the study and presentation is of fairly good scientific quality. I recommend its publication after minor revisions.

Authors' response: We appreciate that Referee Dr. Ming Pan finds our manuscript well written, carefully designed and well organized. We discuss and answer his comments in detail below.

Here are my main concerns:

First of all, the AEnKF procedure needs some more justification and clarification. The authors described the AEnKF as a "state augmentation". It is not exactly the case because it only updates the current state x_k and none of the previous ones from x_{k-1} to x_{k-W}. (Of course, that probably shouldn't matter much if we only care about the forecasts.) Sakov et al. 2010 claimed that AEnKF is "formally equivalent to EnKS solution." This statement is only true if the dynamic system is strictly linear (see Equation 17 in Sakov et al. 2010). If the dynamic system is not linear, the step-by-step updates will make a big difference w.r.t. the lumped updates because the nonlinearity errors will accumulate during continuous and unconstrained model integration. Is the river routing scheme (kinematic wave) linear? Is the hydrological model linear? I guess not because otherwise the ensemble method wouldn't be used.

Authors' response: We describe the AEnKF approach as augmentation of the state matrix with past forecasted observations (P 3177 L 9-13 and Eq. 13). The Referee is correct that x_{k-1} to x_{k-W} are not included in the augmented state matrix, but we do not state that in the manuscript. If past model states would have been included in the analysis, we should have spoken rather about a smoother than a filter. Additionally, we will acknowledge in the revised manuscript that both the kinematic wave model for the routing, and the hydrological model exhibit nonlinear behavior. Additionally, we already mention on P 3172 L 15-18 that although "the Kalman-type of assimilation methods was developed for an idealized modeling framework with perfect linear problems with Gaussian statistics, it has been demonstrated to work well for a large number of different nonlinear dynamical models (Evensen, 2009)".

Given that, we can say the longer the update window W is, the more nonlinearity errors to accumulate. However, longer windows will bring more information to the updates. If the nonlinearity is not a problem, then the window should be as long as necessary. Pan and Wood 2013 experimented a river discharge assimilation approach that resorts to a full and explicit state augmentation over the longest necessary window, i.e., across the maximum streamflow travel time of the river basin involved. (Their study only works with a fully linear river routing scheme thus is free of nonlinearity errors.)

Authors' response: We thank the Referee for mentioning the interesting study by Pan and Wood (2013). We will include a note on their results into the revised version of our manuscript.

It is not clear whether the discharge observations at one gauge station are used to update all the grid cells in the entire basin or just those within the subcatchment that flows down to that gauge station. This is an important issue because the discharge from one gauge does not contain any information about the grid cells outside (i.e. downstream) of its own drainage area. Also, are the discharge data from all 6 river gauges assimilated altogether simultaneously, or one gauge at a time? The discharge from 6 gauges contain information of different lag times with respect to different grid cells. See Pan and Wood 2013 for a fully explicit handling of such lags in time and space.

Authors' response: We assimilated all discharge gauges simultaneously in the case study, when four gauges (1,3,5,6) were assimilated. This is the same as was presented by Rakovec et al (2012). This means that we did not apply any localization method here. We will make this clearer in the revised manuscript. The difference between forecast and analysis of individual model states is shown in a spatial manner in Figure 5 for one time instant (see also Figure 4). These results illustrate the effect of W and spatially distributed discharge observations on spatially distributed innovations. Note that two other gauges (2 and 4) were left out from the analysis for validation.

Another major concern I have is the very short length of the study period. All we can see is just one winter event. It is really too short. We can't even see a robust model validation. We can't see how the DA behaves under other conditions (like low flows). This really limits the significance and robustness of any conclusion you can draw here. If extension is impossible, the conclusions have too be very carefully constrained.

Authors' response: Although the exemplary Figures 6 and 8 present results for a single flood event, the overall results presented in Figure 7 include all eight flood events presented in Table 1, which is also written on P 3184 L 20-22 and in the caption of Figure 7. The Referee is right however that our analysis can be generalized only for high flows and not directly for low flow conditions. Therefore, we will include a note in the revised manuscript that analysis of low flow conditions was beyond the scope of the presented study. Additionally, we will change the title as follows: Operational aspects of asynchronous filtering for flood forecasting.

I suggest the authors calculate the auto-correlation function of the innovation time series. That's the best way answer Referee 1's concerns on systematic errors. The EnKF types of methods are supposed to correct dynamic errors (i.e. time-random), persisting biases are considered static (time-invariant) errors, and they should be corrected using static methods.

Authors' response: We thank the Referee Dr. Ming Pan for his suggestions, but we do not *consider calculating the innovation auto-correlations. However, Figure 7 shows the RMSE (so +/- corrections disappear) of many forecasts over many events. It is impossible to deduce on the basis of Figure 7 that there is a constant bias. That the forecast accuracy is decaying with leadtime is common to all DA studies, as the model slowly returns to the model climatology.*

Figure 6: I can't distinguish between the lines of different shades of red (different lead times). I can't even count how many lines there are on the plots. This has to be redone.

Authors' response: We agree, we will improve quality and readability of Figure 6 in the revised manuscript.

References:

Evensen, G.: Data Assimilation: The Ensemble Kalman Filter, Springer, doi:10.1007/978-3-642-03711-5, 2009.

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