Authors' reply to Short Comment by Yuan Li

We thank Yuan Li for his time in commenting on our paper. For clarity, his comments are given in italics, our response in plain text.

I am afraid that the setup of the Retrospective EnKF (REnKF) is not theoretically correct. The REnKF described in this paper is totally different from that described in the original papers [Pauwels and De Lannoy, 2006; Pauwels and De Lannoy, 2009]. The REnKF should update the model states within t-n to t simultaneously, and then rerun the model from t-n+1 to t+1 for model prediction [Pauwels and De Lannoy, 2009]. However, in this paper, the author update the states at t-n first and run the model from t-n to t to recalculate the flow prediction; and then update the states at t-n+1 using the SAME observation and run the model from t-n+1 to t to recalculate the flow prediction... This process is repeated from t-n to t, which means they are using one observation for n times. The prediction recalculated based on the updated states contains the information from the observation, which violates the basic assumption of EnKF that model prediction error and observation error should be independent. I think the authors may need further check the papers by Pauwels and De Lannoy [2006] and Pauwels and De Lannoy [2009] to make sure the setup of REnKF is correct.

We are very grateful to Yuan Li for bringing to our attention that it was incorrect to state that the set-up of our REnKF was identical to that of Pauwels and De Lannoy (2006). This error occurred due to a misunderstanding between the co-authors, and we will fully correct it in our revised paper to explain the differences between the two methods. To this end, we will rename our method in the revised paper.

Yuan Li correctly understands the method used in our paper, which we aimed to explain clearly so that it was reproduceable. Our method takes the idea from Pauwels and De Lannoy that a flow observation at time t should be used to update all model states between t-n and t, to allow for the natural lag time of the catchment. In the Pauwels and De Lannoy (2009) paper, we note their conclusion that using the HBV hydrological model, only a marginal improvement in results was obtained over a non-assimilating model. The reason given was because the REnKF updated states only up to a number of timesteps (the lag time) before the forecast was required, which allowed model error to accumulate, and override the benefits of the updated initial conditions (from our experiments with different forecast lead times, we know that in our system the benefit of updated initial states also decreases with time). In our implementation, we aimed to address this problem by updating all model states up to the time of the latest observation, as close as possible to the start of the forecast period. As our results show, this method is successful in providing significant improvement over the non-assimilating or EnKF methods at forecast lead times of 0-6 hours. In our revised paper we will also assess the forecast performance at longer lead times. We agree that in our method, there is an indirect effect of the information of the observation onto subsequent flow forecasts, which are themselves updated using the same observation, losing the strict independence between model and observation error. However, we argue that most hydrological implementations of the Kalman Filters are unable to meet the strict conditions for theoretical correctness, for example that model and observed errors can be modelled as Gaussian and without bias and that the standard deviation is known, and that the model update can be linearised, and that (often assumed) observation errors at neighbouring timesteps are independent. However, despite these common assumptions, Ensemble Kalman Filters are valuable tools for hydrological modelling, as demonstrated by many authors as we reference in our paper. Previous authors (e.g. Komma et al, 2008) have also used heuristic approaches to account for the natural lag times of the catchment, in that case using an iterative similarity approach to update model soil moisture states. We are therefore confident that the method we propose is useful, and as we showed produced reliable results in the test catchments.

We agree with Yuan Li that these are important issues, and we will add a section to the paper to state much more clearly the assumptions inherent in the Ensemble Kalman Filter, how those apply to our implementation, and literature that supports the usefulness of Kalman Filter techniques even when strict theoretical conditions for optimality are not met.

[Reference: Komma, J., Bloschl, G., and Reszler, C.: Soil moisture updating by Ensemble Kalman Filtering in real-time flood forecasting, Journal of Hydrology, 357, 228-242, 10.1016/j.jhydrol.2008.05.020, 2008.]