We would like to thank the Referee #2 for his insightful and thorough review of the paper. The comments are addressed in the following response.

Referee #2: The paper is, in general, technically sound. However, the motivations for using the ensemble Kalman filter in this case are not clearly stated. Generally, the Kalman filter includes the full system state, whereby all state variables in the model are updated based on few measurements according to the uncertainties in model and measurements and the correlation between measurements and system states. However, in the present implementation only the reservoir levels, which are measured, are included in the state vector. In this case the benefit of using the Kalman filter is not clear. Why not just do a direct insertion of the measured reservoir levels in the model or apply a relaxation approach taking measurement uncertainties into account. This is much easier and computationally much more efficient.

Reply: The Kalman filter is used here to update the states of the river network mass balance model (Mike basin). The rainfall-runoff model states are not updated. Runoff is considered as a stochastic forcing term for the river network mass balance model. The statistics of the runoff are determined by running an ensemble of 50 rainfall-runoff models. We use the Kalman filter because we want to take the uncertainty of both the model and the measurements into account.

It is correct that the model uncertainty is typically significantly larger than the measurement uncertainty; however, simple insertion of the measurements would ignore any information contained in the model runs.

It is also correct that we assume that a measurement of one model state (water level in one of the reservoirs) does not tell us anything about the water level in the other reservoirs. We basically assume that H in equation 8 is an identity matrix. We think this assumption is a reasonable starting point, because the system is highly regulated. However, this assumption could be modified in future work. There are numerous altimetry targets on river cross sections available for the Syr Darya. In a modified Kalman filtering approach, they could be used useful for real-time modeling.

Computational efficiency: The Kalman filter itself does not take much CPU time in our case. The bulk of the simulation time is taken for the computation of the runoff ensembles. Computing the runoff ensembles would be necessary for any approach that uses both model and measurement uncertainty, thus also for a relaxation approach.

To summarize: Yes, this is a very simple application of the Kalman filter. We decided to use EnKF because it is an efficient method for combining data and models and because it provides the flexibility to extend our approach in the future. The discussion of the approach will be extended in a revised version of the manuscript.
Referee # 2: p. 8354. It is not clearly described how the NAM parameter settings given in Table 1 will affect the modelling. The settings of TOF and TIF will practically result in no overland flow and interflow being generated, and in this case the parameters CQOF, CKIF and CK12 are insensitive. With the parameter settings base flow is the only runoff component. However, looking at the calibrated time constants of the upper groundwater reservoir in Table 5, one could question if one should include an interflow component to describe this response.

Reply: Table 1 is presented to show how we enforced the rainfall-runoff model structure presented in section 3.1 in NAM. Section 3.1 contains all hydrological processes and equations that are active in the rainfall-runoff model. It is correct that overland flow and interflow are effectively switched off by this choice of parameters. Instead of working with two groundwater reservoirs (as we decided to do), one could probably have obtained an equally good fit with an interflow component and one groundwater reservoir. However, given the large size of the subcatchments, we decided to represent all runoff processes by linear reservoirs.

Referee # 2: p. 8356. Notation in Eq. (6) is not consistent with notation above.

Reply: We are sorry for this mistake. It will be fixed. GS_shallow should be GS and GS_deep should be DG.

Referee # 2: p. 8357, l. 13. Which losses are included?

Reply: Only evaporation losses are included. This will be stated explicitly in the revised manuscript.

Referee # 2: p. 8358, l. 14. Parameter ns is not defined. $\mathbf{X}_{\mathbf{E} \mathbf{E} \mathbf{f}}$ should be a matrix containing state vectors of each ensemble member.

Reply: ns is the number of model states (in our case the number of reservoirs). We formulate equation 8 for one ensemble member $x_{i \mathbf{E} \mathbf{f}}$, which is not entirely consistent with our notation in equation 7. The notation in this section will be checked for consistency.

Referee # 2: p. 8358. In this case where all states are measured Eqs. (8)-(9) can be simplified.

Reply: There are several reservoirs in the system, where we don’t have altimetry data, i.e. not all states are measured. Moreover, not all states are measured simultaneously, i.e. measurements over the reservoirs are not necessarily available in coincident time steps.

Referee # 2: p. 8359. How is the uncertainty in the rainfall product described? Which distribution is assumed?

Reply: The rainfall product comes with a pixel-by-pixel error estimate. We assumed a normal distribution with a standard deviation equal to the error estimate.

Referee # 2: p. 8359. Why is a log-normal distribution chosen for describing the uncertainty of the model parameters? I would think a normal distribution would be a more natural choice.

Reply: At least for the linear reservoir time constants, the log-normal distribution is the natural choice, as they are related to aquifer transmissivities. For the size of the storage compartments U and L, in the absence of field data, it is not clear whether normal or log-normal distribution is more appropriate. The log-normal distribution has the advantage of guaranteed non-negativity.

Referee # 2: p. 8362-8363. The presentation of the results is very condensed. This section could be elaborated.

Reply: The section will be expanded in the revised version of the manuscript.

Referee # 2: p. 8363. As I understand the data assimilation, altimeter data are assimilated every 35 days. This means that in between assimilation times the model will drift due to different error sources. To avoid that the model drifts too far between assimilation times one could distribute the innovation (difference between model forecast and measurement) in a time window around the time of observation and assimilate into the
model.

Reply: This is a very interesting idea, which we will explore in follow-up work on assimilation of altimetry data.

Referee # 2: Table 4. The content of this table is not explained. Line with units should be shifted. The table caption indicates that data have been bias-corrected. Is a bias correction included in the assimilation?

Reply: We are sorry for the misalignment of the units. This will be corrected. RMSE is the root mean square deviation between simulated and observed reservoir level. Level range and volume range are the typical seasonal water level and volume variations in the reservoirs (derived from historical records). Residence time is the mean residence time in the reservoir. No bias correction has been performed. The table caption will be modified to avoid misunderstandings.

Referee # 2: Table 5. Explain RÊE2.

Reply: This is the coefficient of determination of the rainfall-runoff models in the different subcatchments. This explanation will be added to the revised manuscript.

Referee # 2: Table 6. Unit missing.

Reply: We are sorry for the missing unit. All numbers are in meters. The unit will be added to the revised manuscript.

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., 7, 8347, 2010.