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Hydrology and Earth System Sciences
Discussions

Interactive comment on "Data assimilation of GRACE terrestrial water storage estimates into a regional hydrological model of the Rhine River basin" *by* N. Tangdamrongsub et al.

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We firstly would like to acknowledge the insightful comments and suggestions provided by Referee 1. Followings are the responses (A) based on the comments (Q):

Q1: Page 11841: You cite Güntner et al. (2008) for satellite altimetry. However, this paper is not really about altimetry and quite significant progress has been made in recent years regarding the accuracy of radar altimetry and its applicability to inland surface water bodies. I therefore suggest to reference a more recent state of the art publication on this topic.

A1: We agree with the referee and have updated the references to Phan et al. (2012); Schwatke et al. (2013), Kleinherenbrink et al. (2014) and these will be added in the revised manuscript.

Q2: Page 11847, lines 17ff: It is not entirely clear to me what the impact of GLDAS is here. If you use soil moisture from GLDAS to determine groundwater variations from the measurements, is this really an independent observation of groundwater? How meaningful is this observation after mixing it with GLDAS? Or do you rather validate against the soil moisture compartment of GLDAS? Please discuss this issue with a bit more detail.

A2: In order to validate our estimated GW, we need to express the variations in piezometric head in terms of a change in storage in order to compare them to the GW (UZ+LZ) estimates from the model simulation. Previous literatures have shown that GW storage can be computed by GRACE minus GLDAS SM. Therefore, we adopt a similar idea by using the relationship between GRACE minus GLDAS SM and the observed head to scale the observed head. Ideally, we would prefer to use in-situ soil moisture data, but they are not available at the well locations, and the nearest station from ISMN (Dorigo et al., 2011) does not have data covering the GRACE observation period. We did not use estimates of soil moisture from remote sensing because the penetration depth depends on frequency and would not be the same as that in OpenStreams-wflow. It is emphasized here that we only used the relationship between GRACE-GLDAS_{SM} and the observed head to determine the parameters a and b in Eq. (2)). These parameters are used to scale the observed head, so it can be compared with the estimated GW from the model. Note that we do not use GRACE-GLDAS_{SM} directly. Discussion of this will be added to the revised manuscript for clarity.

Q3: Chapter 4.1: How did you set up your ensemble Kalman filter procedure? Did you use an available software package (such as, for example, DART)? Or did you implement the procedure individually?

A3: We did not make use of any external software package of the EnKF, instead using our own implementation coded in Matlab based on Evensen (2003), Eq. (44) - Eq (54). The descriptions of the EnKF and its implementation will be clearly stated in the revised manuscript Sect. 4.1 and 4.2.

Q4: Chapter 4.2: It does not become clear to me how you use the GRACE observations. Do you use them as a basin mean averaged over the Rhine catchment? Or did you calculate the GRACE TWS values on some grid?

A4: GRACE TWS is calculated and assimilated at the model grid (1km). This will be stated clearly in the revised manuscript.

Q5: Page 11849, lines 14ff: I do not really understand how the vertical distribution of the GRACE information into the soil moisture (SM) and the groundwater compartments (LZ and UZ) works. If I understand correctly, SM is adjusted first and if this storage reaches its upper or lower limit, the rest of the increment is applied to LZ and UZ (?). However, I would assume that the information about the distribution of the increment among the different model compartments can be obtained directly from the Kalman filter itself? Should this information (given a reasonable ensemble model covariance matrix, see also my question regarding Chapter 4.3 below) not be provided by the Kalman gain matrix? Please give some more details on this and why you chose to carry out the vertical distribution the way you do.

A5: The information about the distribution of the increment among the different model compartments could be obtained directly from the Kalman filter itself if SM, UZ and LZ were the states in the state vector. The state vector includes TWS (i.e. SM+UZ+LZ), rather than the individual constituents. We chose to carry out the vertical distribution the way we do due to the way that the stores are parameterized in the OpenStreams-wflow model. While the SM and LZ stores have upper bounds determined by model parameters, UZ does not. As a result, allowing it to update freely in the EnKF runs the risk that it becomes excessively large, which would also have a detrimental effect on

run-off. Instead, we adopted the approach described in the manuscript. The referee is correct. SM is adjusted first and if this storage reaches its upper or lower limit, the rest of the increment is applied to LZ and the remainder (after LZ reaches its limit) to UZ. The order in which the stores are filled is based on their relative contributions to TWS as illustrated in Figure 1. This discussion will be stated clearly in the revised manuscript.

Q6: Page 11849 lines 21/22: You apply an observation error of 2cm for your GRACE TWS observations. This appears to be a rather simplistic assumption. First of all this number disregards the recent improvements of GRACE accuracy (Klees et al. 2008 used RL04 data). Furthermore, the Klees et al. refer to this accuracy for river basins above 1 million km2, which is significantly larger than the Rhine. Have you performed any kind of error propagation to test whether this assumption is valid for your test area? Or did you carry out any tests on how different GRACE error estimates would affect your assimilation results?

A6: The 20 mm observation error value was taken from Klees et al (2008), and while the analysis from this paper made use of measurements over larger basins, the results are consistent with other error assessment studies involving RL04 data (Wahr et al., 2006; Schmidt et al., 2008), and is a value adopted for other GRACE DA studies (Zaitchik et al., 2008; Houborg et al., 2012). The RL05 may indeed have better error characteristics (Dahle et al. (2014) mention GFZ RL05 errors of $\sim$15 mm at 330km, although this was obtained from an RMS of the spatial variations, and not validated with independent measurements), but the 20 mm level still serves as a reasonable bound, albeit a conservative one. Nonetheless, the exploration of more sophisticated error models for GRACE, to include potential spatial variations, is a topic of future work. In the preliminary stages of our study, we did test how the GRACE error would affect the result, but this was done primarily to ensure that the code was working correctly. When this was done, the filter performed as expected in that the TWS estimated moved towards the GRACE measurements when the GRACE errors were small, and moved closer to the open-loop solution with larger GRACE errors. This is also why we chose to set the GRACE errors to independently determined values (please also see the response A3 in Referee 2). This explanation will be added in our revised manuscript for clarity.

Q7: Page 11850: lines 5ff: In your "non-calibrated" case, you set each parameter value to its mean value over the whole basin. This way, on average the non-calibrated and the calibrated cases agree. Is this really the case in data sparse regions? I would assume that even the mean value of the non-calibrated parameters might differ quite significantly from the mean value of the calibrated parameters. Therefore, I believe that setting the mean values equal is over-optimistic and not a necessary assumption. I would expect that your results might show the positive impact of GRACE in data sparse regions even better, if you would not assume a "correct" mean value for the parameters.

A7: The model is non-linear, so it is not necessarily the case that the non-calibrated and calibrated cases agree on average. Figures 5, 7, 8, 9 and 10 confirm that they do not agree. We agree with the referee that using parameters further from the “correct” value would result in a more positive impact of GRACE. However, we wanted to make the simulation “realistic” rather than trying to maximize the potential improvement by giving spurious parameter values. Assuming no knowledge at all, one could set the mean parameter value in the non-calibrated case to the mean of the range of values permitted in OpenStreams-wflow. However, even in data sparse regions, something is known about the land cover type, topography, climatology, etc. Figure 3 shows how variable the parameters are across the Rhine basin. Averaging each parameter across the entire Rhine basin is intended merely to reflect this kind of first-order assumption. Please also see the response A1 in Referee 3 for further information.

Q8: Chapter 4.3: How do the model uncertainties enter the Kalman filter algorithm? Do you determine a full empirical ensemble covariance matrix with the dimensions of all of the model grid cells and the three model compartments? Or do you use only the

variances? Please give a few more technical details on your approach.

A8: In this study, we implement a so-called “1D-EnKF” in which each grid cell is updated individually, so the only the variances were used. As shown by De Lannoy et al. (2009), working with a spatially distributed state vector can lead to an improved estimate. Given the coarse resolution of GRACE, we expect that implementing our framework with a 3D-EnKF (De Lannoy et al., 2009) would lead to an improved performance. As discussed in the response A5, the state vector contains TWS (i.e. SM+UZ+LZ) for an individual grid cell. The descriptions of the EnKF and its implementation will be clearly stated in the revised manuscript Sect. 4.1 and 4.2.

Q9: Additional references: Quite recently, there have been additional studies on assimilating GRACE data into hydrological models (see full references below). First of all, Forman and Reichle (2013) discuss the effect of spatial aggregation of GRACE TWS estimates before assimilating them into a hydrological model. And Eicker et al. (2014) discuss the introduction of the full GRACE error structure into the assimilation procedure. (A more detailed treatment of the GRACE error from the product itself is an issue you also mention as topic for future research in your conclusions). I would suggest that you include references to those new studies in your manuscript.

A9: We thank the referee for the suggestion and will add these 2 additional references into our revised conclusion.

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