Response to Reviewer #1.

We would like to thank Reviewer #1 for the insightful comments provided. We believe that the various suggestions provided have helped to improve the quality of the study and the manuscript. In what follows, our replies to the comments are presented point by point.

Comment 1: Retegui-Schietekatte et al. address the problem of observation localization in multivariate ensemble data assimilation. The application here is integration of both GRACE TWSA maps and satellite SSM maps in hydrological modelling for the Brahmaputra basin.

The Brahmaputra basin (BB here) represents a hydrologically complex region with significant long-term changes due to warming climate in the Himalayas, above-average sea level rise with increased river blocking and salinization, and socio-economic processes such as land use change, population pressure and water diversion, but also with frequent large-scale flooding caused by cyclone landfall. Since the hydrological ground infrastructure is sparse, improved understanding of hydrological processes with the aid of satellite data is welcome. The manuscript addresses thus an important topic with broad relevance.

Reply: Thanks for the acknowledging the significance of the study.

GRACE data assimilation has been often evaluated with sparse surface soil moisture data, and only few papers address joint assimilation. As most frameworks nowadays seem to rely on some localization technique, a systematic study such as provided here is welcome. The proposed model space mixed localization appears new to me in this context. The results are interesting and support the new idea. This would certainly warrant publication. The authors may want to elaborate somewhat more on the reason for the need for localization, is it due to spurious model ensemble correlations and if yes why, is it due to the observation error characteristics or is it both?

Reply: We agree that additional contextual information on the purpose and advantages of covariance localization would be beneficial. <u>The following paragraph will be added to the Introduction section:</u>

> Covariance localization is widely used in hydrological DA, as well as in other geoscientific disciplines, to mitigate spurious ensemble correlations or sampling errors arising from limited ensemble sizes and inherent constraints in ensemble-perturbation methods. Especially, distance-based localization helps to confine the influence of observations to relevant spatial domains, thereby increasing their impact on the relevant model variables (Houtekamer et al., 1998; Hamill et al., 2001).

Additionally, one of the conclusions of our study is that localization provides additional benefits in multivariate DA applications, such as regulating the relative contribution of different observation types and reducing cross-component influences. This is discussed in the Conclusions section of the original manuscript (lines 670-684). That part of the text will be reformulated to better highlight this conclusion.

Comment 2: However, the manuscript in present form suffers from two major drawbacks, in my view: (1) The hydrological model is not well motivated and described, and it is thus not clear at all what the baseline for the data assimilation is. (2) The evaluation of results appears not very thorough. Here are more details:

The hydrological model that is used in this study is neither mentioned in the abstract nor in the introduction, which raises a red flag. The BB hydrology is really complex and the choice of a model should be motivated by the study purpose; are we interested in river discharge forecasting, in flood potential monitoring on timescales of days of weeks, in agricultural forecast, in water management at which level, water resources, or in climate change assessment on decadal timescales? The authors need to clarify this and explain why their model is fit for purpose, and how it compares to other global or regional models that have been used to describe the BB hydrology.

Reply: We acknowledge that this study design choice should be clarified. The objective of the study is to generate improved *water storage* estimates in the sub-seasonal to decadal timescale for the Brahmaputra River basin, with the aim of supporting future investigations concerning the water storage variability and availability (in the inter-annual to decadal timescale) as well as the role of land water in flood generation mechanisms (in sub-seasonal to inter-annual timescale). A sentence will be added in the Introduction section to specify this.

Given this study purpose, the W3RA model was chosen based on previous works suggesting its good performance at representing water storage variability when compared to other state-of-the-art models (Mehrnegar et al., 2020). In addition, the result evaluations performed in this study also suggest a reasonable agreement between the model and satellite observations prior to DA in terms of water storage. GRACE and modelled TWS present a similar seasonality and interannual variability in terms of timing and magnitude, and mainly differ in the decadal variability and trend, which is a feature that many hydrological models fail to represent accurately (Scanlon et al., 2018; Fig. 3a of original manuscript). Regarding SSM, model estimates and satellite observations show similar dynamics from the sub-seasonal to the inter-annual timescale, when averaged over the basin (Fig. 3e of original manuscript). This suggests that the W3RA provides a reasonable representation of the large-scale water storage variability in the Brahmaputra River basin and constitutes a strong baseline for the DA experiments. We acknowledge that this information was missing in the paper and it will be added in the section “Data and Model”. Additionally, we will also mention the use of W3RA both in the Abstract as well as in the Introduction.

It should be noted that the methods explored in this paper can be applied to any hydrological model. A sentence noting this will be added to the Conclusions section.

Comment 3: The authors mention some limitations of W3RA, e.g. the model has not been calibrated over the BB region, they use ERA5/ERA5 land forcing but there seems no bias-correction.

Reply: Thank you for this comment. The main reason for not applying model calibration or precipitation bias correction is that we expect the DA process to address possible limitations of model parameters and forcing data. A sentence will be added to specify this in the “Data and Model” section.

Comment 4: Even if the authors must rely on this model due to the assimilation framework, they should compare the open-loop total water storage, surface soil moisture and river discharge to the results from some published global models such as GLDAS, WaterGAP, PCR-GLOBWB in the BB.

Reply: We agree that addition of such comparison would be interesting. However, we think that the realism of the water storage representation within the W3RA is well justified based on the arguments provided in the answer to Comment 3. We consider that an inter-comparison of the OL model performance with other available models is out of scope of this article.

Comment 5: Since TWSA and SSM are assimilated, the authors should also explain the W3RA parameterization of processes relevant to these observables such as crops, water demand and anthropogenic water withdrawal, groundwater, surface water storage beyond river storage (lakes, floodplanes, reservoirs), and soils (which soil maps are used). How is evapotranspiration computed in W3RA? There will be severe limitations in the W3RA representation of these processes, as it is for other models, but whether assimilation is useful depends on our understanding of such error sources.

Reply: We agree that the manuscript could benefit from more details on the representation of various water balance processes in the W3RA model, which would also help interpret the results. A detailed description of the model representation of processes affecting TWS and SSM variables will be added in the “Data and model” section, and possible uncertainty sources coming from the model structure will be discussed.

Comment 6: Put in other words, if the baseline model is poor then the assimilation will almost always successed in „bringing the model closer to reality“ (page 25).

Reply: We absolutely agree with the statement of the of the reviewer, as DA in a poorly performing model will almost always lead to an improvement. However, we do not think that the W3RA constitutes a poor baseline: at the contrary, we think the model water storage estimates are realistic when compared to observations and other models, as exposed in the answer to Comment 2. We believe that the inclusion of more details in the manuscript concerning the general performance of W3RA compared to other models (see comment 2), the similarity of its estimates with the satellite observations (see comment 2), and the parameterization and structure of the W3RA model (see comment 5) will help clarify the baseline from which this study departs and convince the reader of its adequacy.

Comment 7: Validation in the BB is challenging, as the authors are aware. This raises the question why the study did not focus on Australia where the model was calibrated and the monitoring infrastructure appears much more complete, or some other region like the US.

Reply: We acknowledge that alternative study regions such as the United States or Australia could have facilitated a more comprehensive validation of our results due to the availability of extensive open-access hydrological datasets. However, these regions have already been widely investigated in the context of TWS DA and multivariate DA frameworks (Australia: Tian et al., 2017; Khaki et al., 2019, 2020; Tangdamrongsub et al., 2020; U.S.: Girotto et al., 2019; Khaki et al., 2019, 2020).

Our selection of the Brahmaputra River basin was motivated by two primary considerations. First, we sought to evaluate multivariate data assimilation techniques in a hydrological environment that differs substantially from those examined in previous studies. Second, the basin exhibits a pronounced hydrological variability which is difficult to track precisely due to the lack of abundant in situ observations, leading to significant challenges for water resources management and hydrological risk mitigation. As such, this region stands to benefit from refined and more accurate hydrological water storage estimates. Despite the limited availability of ground-based hydrological observations, we were able to collect in-situ groundwater and river water level measurements for portions of the basin. These datasets provide a foundation for validating a subset of our model outputs.

We will add a paragraph to the Introduction to clearly articulate the rationale behind the selection of the study area.

Comment 8: Comparison against the SPEI appears doubtful to me – W3RA also uses precipitation and radiation input and computes evapotranspiration and I wonder why then the simple SPEI could be considered as a „truth“ for groundwater change?

Reply: We thank the reviewer for this comment and we acknowledge that SPEI relies on a model and uncertain input data, and therefore is affected by its own uncertainties. Comparison against SPEI in this study is not meant as a validation, but rather as a consistency check in sub-basins where no other data is available. In regions where in-situ groundwater data was available, validation was performed against in-situ data. A sentence will be added to clarify this at the stage where the SPEI comparison is described.

Comment 9: Many studies have shown that accumulated precipitation (minus evapotranspiration) corresponds well to TWSA but this does not prove anything about groundwater, in a region where surface water dynamics plays a BIG role.

Reply: We completely agree with the reviewer and acknowledge that surface water has a large contribution to TWS variability in the Brahmaputra River basin (see, e.g., Retegui-Schiettekatte et al., 2025). More specifically, river water level observations suggest that, while no significant decadal trend is observed in river water storage, it can be affected by a strong inter-annual variability. To account for this factor, in the revised manuscript the SPEI will be compared to modelled TWS rather than modelled groundwater. Additionally, the glacier trends will also be included in this comparison, since glacier mass changes can also be equated to precipitation minus evapotranspiration dynamics. The following subsection will be added in the Results section:

> We first compare the sub-basin averaged TWS results with the SPEI-12 index, which reflects hydrological wetness and dryness based on precipitation and evapotranspiration data. As the SPEI-12 is based on a hydrological balance model and is affected by its own uncertainties, this comparison is aimed as a consistency check rather than a validation. SPEI-12 is aggregated over a 12-month window, and therefore we apply the same treatment to the model TWS time series.

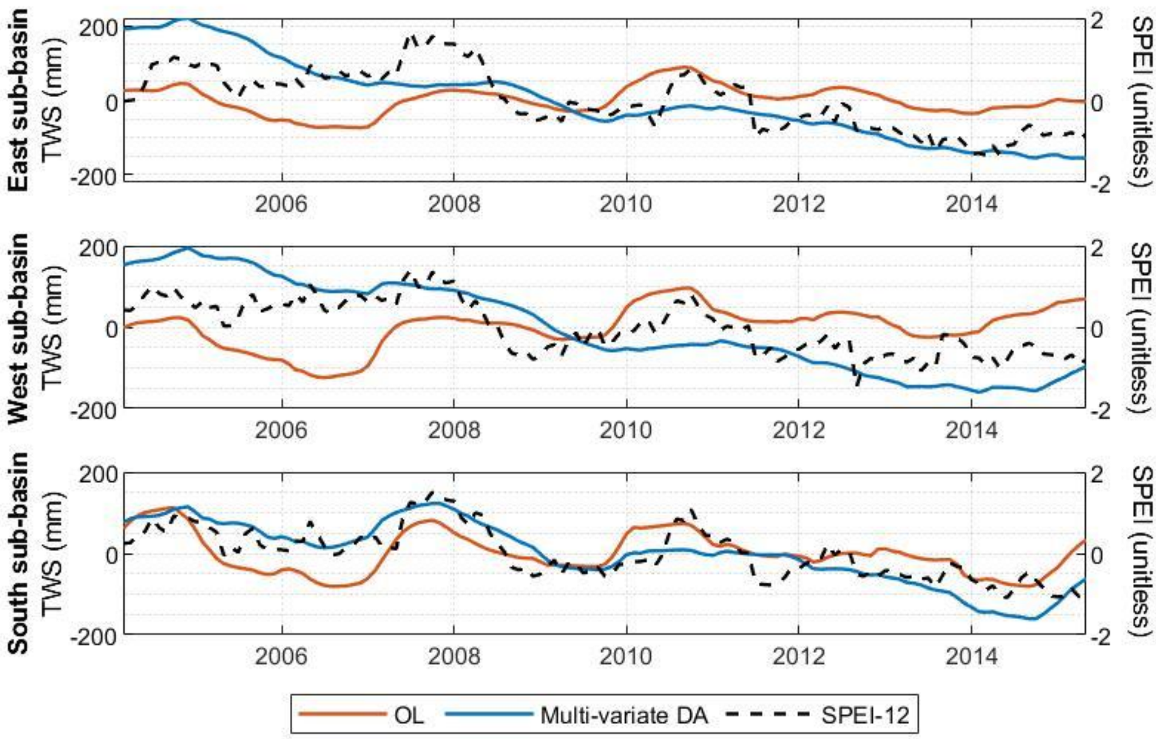

Figure 1. Inter-annual TWS variability of OL and multi-variate DA for the three sub-basins; SPEI time series are plotted in the right axis.

Although SPEI is standardized and is not suitable for validating the magnitude of TWS variability, it reveals clear negative trends for the three sub-basins in the period 2004-2014 (Fig. 1). These trends, absent in the OL simulations, emerge distinctly through the multi-variate DA. Regarding the sub-decadal variability, multi-variate DA preserves the inter-annual variability of OL, although it also excessively smooths certain anomalies (e.g., 2007 and 2010), possibly due to GRACE TWS resolution or interference with the decadal trends. In general, the correlation with SPEI is significantly improved through DA from 0.13/-0.25/0.55 (OL) to 0.74/0.79/0.82 (DA) for the East, West, and South sub-basins, respectively (Table 1). An especially large improvement is observed in the West sub-basin, where the OL estimates suggest a positive TWS trend as opposed to the DA TWS and SPEI data.

Correlation coefficient	OL	DA
East sub-basin	0.13	0.74
West sub-basin	-0.25	0.79
South sub-basin	0.55	0.82

Table 1. Correlation coefficient between modelled TWS and SPEI. All correlations are significant with p-value < 0.01.

Comment 10: In this reviewer's opinion, the authors need to validate groundwater change against quality-controlled well data with documented specific yield information (it wasn't clear to this reviewer whether this was available for the wells in Fig. 7). Or they validate against specific groundwater 3D modelling that has been calibrated against wells. If this is not possible, this kind of validation cannot be performed.

Reply: We agree that groundwater validation is a critical part of this study and should be well supported with quality controlled data and specific yield information. The groundwater level data used to validate the results have been quality controlled by the collecting institution (the Bangladesh Water Development Board) and curated by Shamsudduha et al. (2022). A sentence will be added in the "Data and Model" section of the manuscript to clarify this.

In the original manuscript, no specific yield data was used to perform the groundwater validation. Following the reviewer's suggestion, specific yield data has now been used to convert groundwater levels to groundwater storage. The distributed specific yield information was originally obtained from around 200 pumping tests and interpolated using ground lithology maps by Shamsudduha et al. (2011). The specific yield values range from 1% to 20% with a mean value of 6%. The groundwater storage changes were computed by multiplying groundwater level change (Δh) with the specific yield (S_y), $\Delta S_{GW} = \Delta h \times S_y$. This information will be added in the "Data and Model" section of the manuscript.

The use of specific yield data allowed to evaluate the magnitude of model groundwater variability. The results are described in what follows and will be added to the manuscript.

Groundwater validation

Model groundwater estimates in the South sub-basin can be validated against groundwater storage changes derived from in situ groundwater level observations, which are available for the Bangladesh area (Shamsudduha et al., 2011, 2012, 2019).

Spatially distributed specific yield data from Shamsudduha et al. (2011) was used for a first comparison (see Section Data and Model for more information). The results show a significant scale difference between the modelled and observed groundwater variability, both in the seasonal timescale (STD of 182 and 140 mm for OL and DA respectively, and 65 mm for observations, Fig. 2a) and the inter-annual timescale (STD of 35/50/14 mm for OL, DA and observations respectively, Fig. 2c).

Various reasons could be behind this discrepancy in magnitude, which concern both the groundwater level observations and the model. On the observation side, the groundwater wells used for validation in this study measure water levels in shallow aquifers (mean depth of 30 m, Shamsudduha et al., 2012), while the model and GRACE water storage changes reflect water mass variations at all ground levels including deep aquifers, and can therefore be expected to present a larger variability as observed (see, e.g., Qu et al., 2024). The specific yield values used to convert observed groundwater levels to groundwater storage values can also be affected by biases and uncertainties (Rodell et al., 2007): factors in the measurement of the specific yield, such as an insufficient duration of the pumping test or the assumption of partial penetration, can lead to an underestimation of the specific yield, consequently leading to an underestimation of groundwater storage variability. The spatial interpolation of specific yield data, which was performed based on ground lithology maps (Shamsudduha et al., 2011), can additionally contribute to their uncertainty.

On the model side, an inadequate partitioning of the soil profile in its different layers could result in attributing part of the soil water storage variability to the groundwater component (Sun et al., 2010; Shamsudduha et al., 2012). In theory, general model limitations to represent water storage variability could also contribute to this discrepancy, although this possibility is here considered less likely due to the good agreement found between W3RA and GRACE water storage variability.

To account for possible uncertainties in the specific yield data, a second comparison was performed by considering a uniform specific yield of 15 % for all the groundwater wells, which is close to values of 10% used by Shamsudduha et al. (2012) for Bangladesh or average values of 14% reported by Rodell et al. (2007) for the US in previous studies. This significantly increases the magnitude of the observed groundwater variability (STD of 171 mm in the seasonal timescale and 40 mm in the inter-annual timescale, Fig. 2b and 2d), increasing the agreement with the modelled groundwater. The new comparison suggests that the RMSD between modelled and observed groundwater is reduced from 95 mm to 88 mm after DA. Especially, the DA results display a high agreement with observed data during the wet periods, as also reported by Shamsudduha et al. (2012) for the period 2004-2007, although the DA results seem to slightly underestimate the seasonal amplitude when compared to the OL. In the inter-annual timescale, DA reduces the RMSD from 40 mm to 36 mm (Fig. 2d).

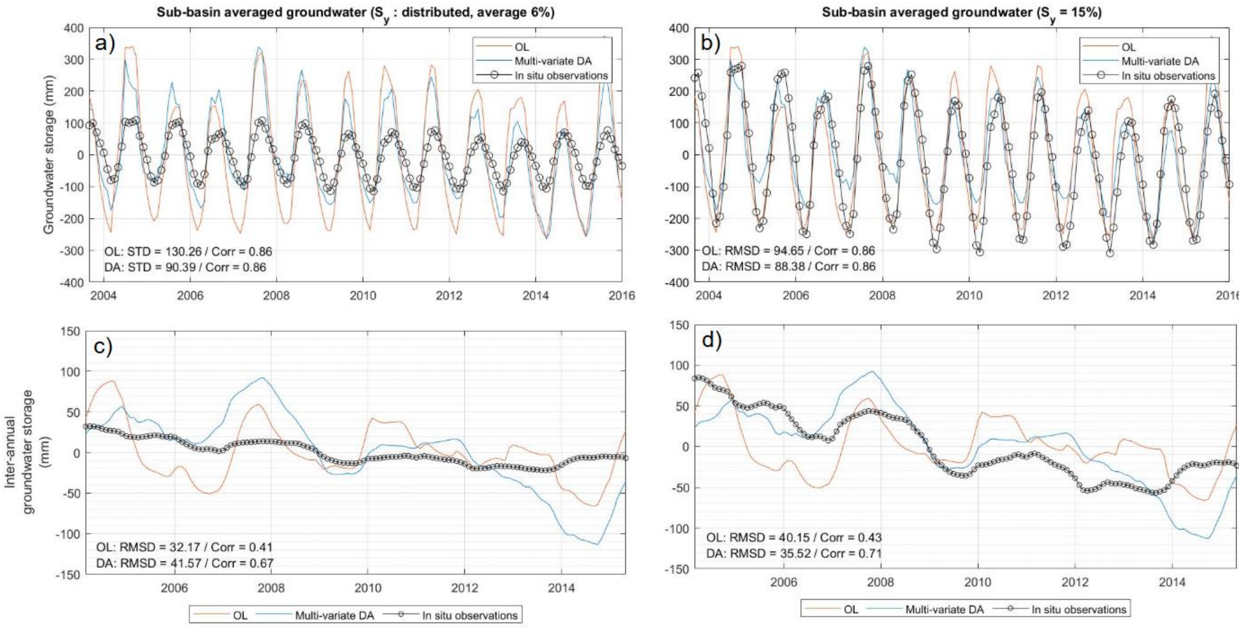

Figure 2. Inter-annual groundwater storage variability derived from OL, multi-variate DA and in-situ groundwater level observations. a and b represent the time series, with their inter-annual variability component represented in c and d. In a and c, the observed groundwater storage was computed using distributed yield values computed by Shamsudduha et al. (2011). In b and d, a uniform specific yield value of 15% was used.

To ensure that the obtained results are not an artifact of the chosen specific yield, the comparison is repeated in terms of Peason correlation coefficient, a metric that is scale invariant. When the seasonality is included in the validation (Fig. 2b), both the OL and DA lead to similar correlation coefficients (0.86 for both), likely because the time series are dominated by the seasonal signal, which both solutions represent similarly well. In contrast, in the inter-annual timescale (Fig. 2d), the correlation with observed groundwater storage is increased from 0.43 to 0.71 after DA. Especially, the groundwater storage derived from DA presents a negative trend for the period 2004-2014, with higher levels in 2005–2008 than in 2013–2014, which is clearly featured in the observed data and not reflected in the OL model estimates. DA also displays realistic sub-decadal variability, capturing key anomalies such as the 2007 peak and the wet period of 2010–2011, which remain distinguishable despite the overarching negative trend.

A comparison of model estimates against distributed groundwater time series provided by individual wells is shown in Fig. 7 [of the original manuscript]. Biases and discrepancies found in the basin averaged assessments is likely to be multiplied when the assessment is performed for specific wells, and therefore this comparison is exclusively performed in terms of correlation coefficient. *[Lines 566-578 and Fig. 7 of the original manuscript would come here, validating spatially distributed groundwater estimates].*

In conclusion, the multivariate DA appears to improve the groundwater storage dynamics in the South sub-basin, especially through the modification of inter-annual groundwater variability and the introduction of a negative trend for the period 2004-2014 that is also reflected in groundwater level observations. It is important to note that the comparisons performed here validate the groundwater dynamics but not magnitude of the trend, due to uncertainties in the scale between the modelled and observed groundwater data. Namely, the magnitude of the DA trend and inter-annual variability could be overestimated due to the over-allocation of surface water or shallow soil variability to the groundwater component in the DA process. The allocation of glacier trends to groundwater is not likely due to the absence of glaciers in the South sub-basin.

Comment 11: And the situation is similar for SSM, the authors need to work with in-situ data from the representative depth range, potentially with models informed by in-situ data. WaterGAP as a conceptual model has known limitations in soil moisture representation, and even disregarding this, comparing soil moisture across different models with differing layers, model physics, data integrated is highly problematic. If there is no ground data, no validation is possible.

Reply: We acknowledge that comparing the data DA results with WaterGAP model outputs does not constitute a rigorous validation, but rather provides a consistency check, similar to the comparison with SPEI. A sentence will be added prior to the comparison to clarify this aspect. Unfortunately, openly accessible in-situ soil moisture observations are not available for the study region. A common approach in previous studies has been to compare the DA results with independent satellite observations (e.g., Soltani et al., 2024). However, the assimilated SSM product (ESA CCI Combined) integrates both passive and active soil moisture satellite retrievals; consequently, any comparison against these satellite datasets would also lack independence. We therefore recognize that the absence of independent SSM validation represents a limitation of this study. A sentence will be added to the manuscript to explicitly disclose this limitation in the Results section and in the Conclusions section.

Comment 12: The authors could still compare their results to measured streamflow. Of course the evaluation should be tailored to the purpose of the study, i.e. looking at either short or long timescales.

Reply: We acknowledge the relevance of this suggestion. The improvement of streamflow is not one of the primary objectives of this study (see reply to Comment 2), but it is true that a comparison against streamflow at the basin outlet would help validate the water storage changes, which would be relevant given the absence of other independent validation data such as in-situ soil moisture observations. However, comparisons against river water levels provided in Section 2.2 of the original manuscript denote a lack of sensitivity of model river water storage estimates to changes in soil and groundwater storage. This lack of sensitivity equally affects streamflow estimates, and therefore a comparison against streamflow would not lead to any conclusive results. A sentence will be added to the manuscript to ensure that this aspect is clearly reflected.

Comment 13: Last, I noticed the authors compared river water storage from the assimilation to gauge observations, this requires an explanation. While stage-discharge (rating curve) relations are typically derived empirically from simultaneous measurements with ADCPs and gauges, it is less clear how the routed model simulation can be mapped to observable water level change as this would require river cross-section assumptions.

Reply: As the reviewer suggests, we acknowledge that river water storage cannot strictly be compared to water levels without assumptions on the river cross section. Due to this reason, model estimates of river water storage were rescaled to match the observed river level data before validation (lines 401-403). In other words, we assume a rectangular cross-section and we set the width of the rectangle to obtain a maximum agreement between observed and modelled water levels. We acknowledge that this approach has many limitations. However, in any case, the final conclusion of the streamflow comparison is the little sensitivity of the model estimates to water storage updates in the seasonal to sub-seasonal timescale. Therefore, the simplified the cross-section assumption does not hinder any of the conclusions. A sentence will be added in Section

4.3.3 to recall the approach adopted to perform the comparison and mention this assumption.

Final reply: We would like to thank the reviewer for the exhaustive and critical comments. We believe that the multiple suggestions made to improve the result evaluation and validation have helped to strengthen our study and the manuscript.

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