Response to Reviewer #3.

We would like to thank the Brahma Dutt Vishwakarma 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.

Summary: The manuscript improves assimilation of satellite-derived TWS and SSM products into a hydrological model. They explore various data assimilation strategies, including univariate and multi-variate, to obtain better representation of water storage dynamics over the Brahmaputra River basin. They claim to improve TWS, groundwater, and soil moisture representation in the model. The manuscript is well written and addresses a significant challenge/problem in the field.

Reply: We want to thank the reviewer for the encouraging comments.

Major comments:

1. From a methodological development point of view, the manuscript tries to add information from TWS and SSM in a multivariate DA setting., which is an advance over usual two step DA schemes. The authors also discuss a potential challenge in their approach, which is deciding the weightage given to one variable relative to the other. They discuss tunning approaches and propose observation space mixed localization as a solution. The idea seems interesting. However, see the next point.

Reply: Thanks for acknowledging the methodological advancement.

2. They fix a smaller region of influence for SSM while a larger for TWS. This appears to be driven by data resolution. However, it would be nice to have some discussion and possibly analysis based on spatial wavelengths of processes responsible for changes in SSM or TWS. Groundwater has a larger wavelength than SSM but the current space localization scheme have these wavelengths at least an order of magnitude higher and I believe it could be two order of magnitudes for the time scale at which the assimilation is done, i.e. daily. Around line 270, the arguments presented are again appearing to be motivated by data resolution rather than from process spatial variability.

Reply: We acknowledge that the criteria followed to select the localization radii could use some more details in the manuscript. We agree with the reviewer that in general SSM should have a smaller localization radius than groundwater storage due to its stronger spatial variability. A spatial semivariogram of the OL SSM estimates suggest that daily model SSM estimates become decorrelated at around 4 degrees of distance (Fig. R1). This large spatial coherence likely occurs due to the smoothness of the model parameters, as well as the large spatial coherence of precipitation occurrence in tropical areas (in the order of 100 km, Moron et al., 2007). However, it is likely that satellite-based SSM observations can reflect spatial heterogeneities that are not reflected in the model parameters. To allow the DA process to introduce these heterogeneities, a shorter localization radius needs to be selected. Therefore, and following previous works (Girotto et al., 2019), a half-radius of 0.5 degrees was selected.

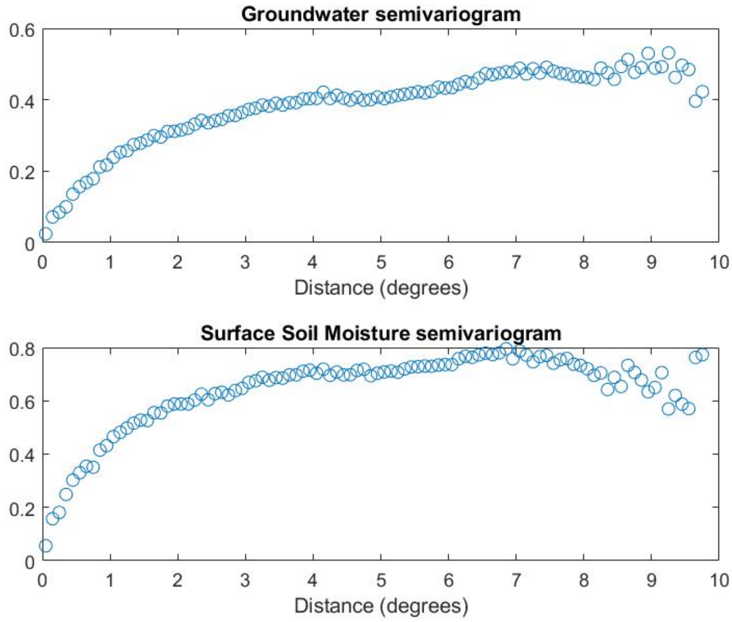

Figure R1. Semivariogram of groundwater and SSM variability in the study area.

As far as groundwater storage is concerned, due to the horizontal independence of model grid cells in the W3RA model, groundwater is found to have a similar semivariogram to that of SSM (Fig. R1). However, the use of small localization radii (3-4 degrees) for groundwater storage was found to lead to very sharp groundwater updates, which degraded the distributed groundwater estimates and reduce the realism of the results (see also Retegui-Schiettekatte et al., 2025). Therefore, from a practical standpoint, a larger localization radius was finally used for the groundwater storage localization (10 degrees).

A paragraph explaining this will be added to the section Model run and DA. For conciseness, the figure with the variograms will be omitted in the manuscript.

3. Equation 4, suggests independence between TWS and SSM, while it is known to be strongly correlated with the TWS budget equation defining causality. Would it be better to not have off diagonals as zero. This issue also haunts the framework, where TWS and SSM are ingested while information from SSM is a subset of TWS, although at different spatial resolution. A philosophical as well as analytical explanation would help a lot.

Reply: We agree that this point requires further clarification. As noted by the reviewer, correlations between TWS and SSM are expected within the hydrological system. These physical correlations are represented in the off-diagonal elements of the model error covariance matrix $C(X_k^-)$ in Eq. (2).

In contrast, the covariances contained in the observation error covariance matrix Σ_{y^0} (Eq. 4) do **not** describe correlations between hydrological variables. Instead, they represent possible correlations between the *empirical errors* of the GRACE TWS observations and satellite-derived SSM observations. Such empirical observation errors arise from factors including, but not limited to, instrumental noise, GRACE orbit determination uncertainties, and post-processing errors. Given the fundamentally different measurement principles and processing chains underlying TWS and SSM products, it is theoretically unlikely that correlated empirical observation errors would exist between the two.

From a practical standpoint, there is no evidence that incorporating cross-correlations between these observational errors would improve the performance of the DA system. Moreover, estimating the magnitude of such cross-covariances would be highly challenging. For these reasons, and consistent with previous studies (e.g., Wongchuig et al., 2024), the off-diagonal elements of the observation error covariance matrix were set to zero. <u>A more detailed explanation will be added to the main manuscript to make this point clearer</u>.

4. The validation could be improved a lot. SPEI-12 is very smooth. With simulations and DA done at daily scale, SPEI-3 itself is good enough. Majority of drought studies use either SPEI-6 or 3.

Reply: We thank the reviewer for this comment. A comparison of water storage changes (smoothed at scales of 3 and 6 months) with SPEI-3 and SPEI-6 is represented in Figs. 1 and 2, respectively (see below). The results show that DA improves the model performance in terms of correlation coefficient in both timescales. However, SPEI-3 and SPEI-6 seem to respond very strongly to sub-seasonal anomalies and does not always capture the seasonality reflected in water storage estimates (see, e.g., beginning 2012 or 2010), leading to overall lower correlation coefficient with both the OL and DA. In contrast, SPEI-12 presents much smoother dynamics and overall higher correlation coefficients with both OL and DA (Fig. 3).

These results are consistent with those obtained in previous studies, where a higher correlation between water storage and SPEI or SPI (Standardized Precipitation Index) was found at timescales of 12 months rather than 3 or 6 months (Zhang et al., 2018; Cammalleri et al., 2019; Satish Kumar et al., 2019). This can be explained by the fact that the SPEI represents anomalies in water fluxes (precipitation minus evapotranspiration, has no memory of past anomalies), while water storage is a time integration of these flux anomalies (has a memory of past states). The strong temporal smoothing applied to SPEI-12 effectively works as a temporal integration and therefore makes it mode adequate for comparison with water storage estimates (Camalleri et al., 2019).

Based on the results observed and the theoretical background explaining the poor agreement at the 3- and 6-months timescales, we will keep the comparison with SPEI-12. <u>For conciseness, the comparison with SPEI-3 and SPEI-6 will not be explicitly included in the manuscript, but a few sentences will be added in the results section to justify the comparison with SPEI-12 and briefly report the results obtained in the comparisons with SPEI-6 and SPEI-3.</u>

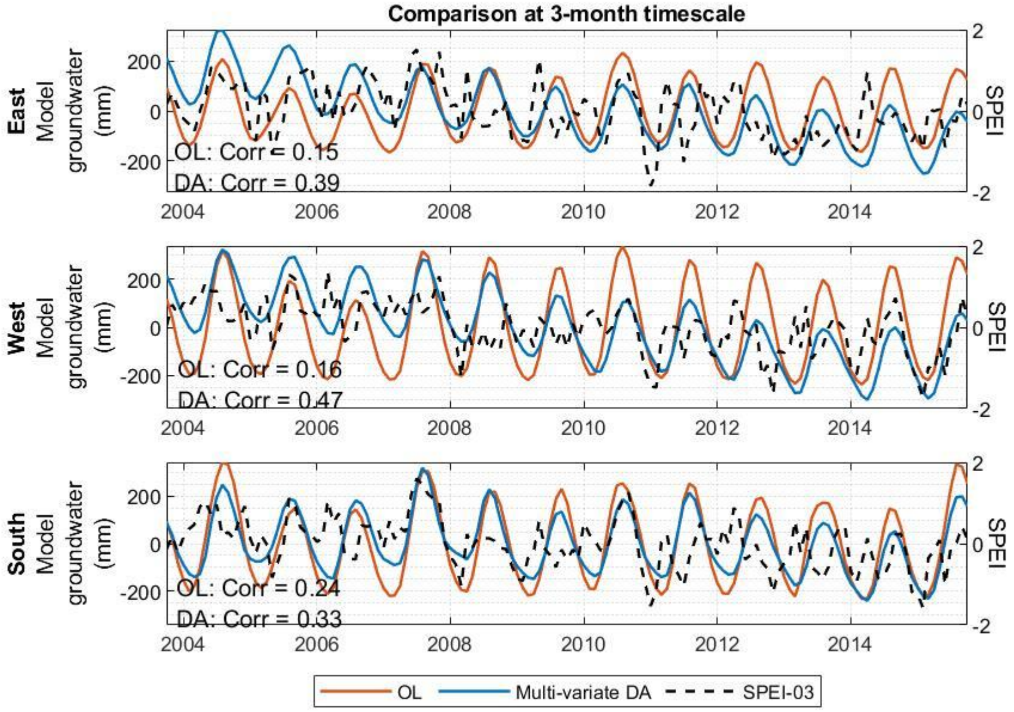

Figure 1. Comparison of OL and multivariate DA groundwater estimates with SPEI at a **3-month** timescale.

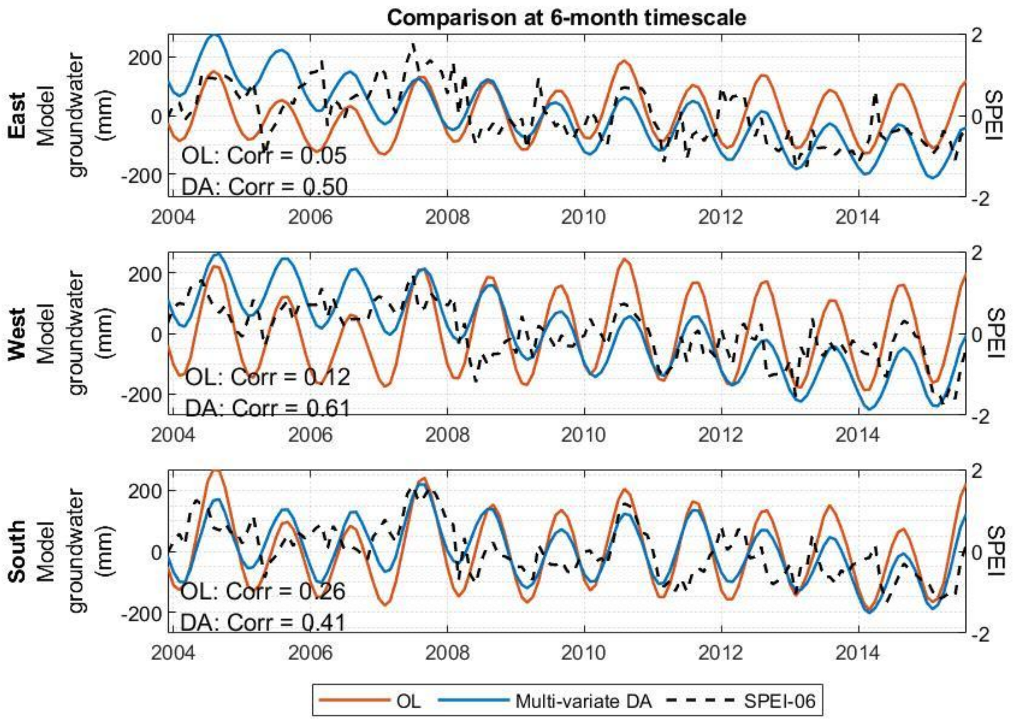

Figure 2. Comparison of OL and multivariate DA groundwater estimates with SPEI at a **6-month** timescale.

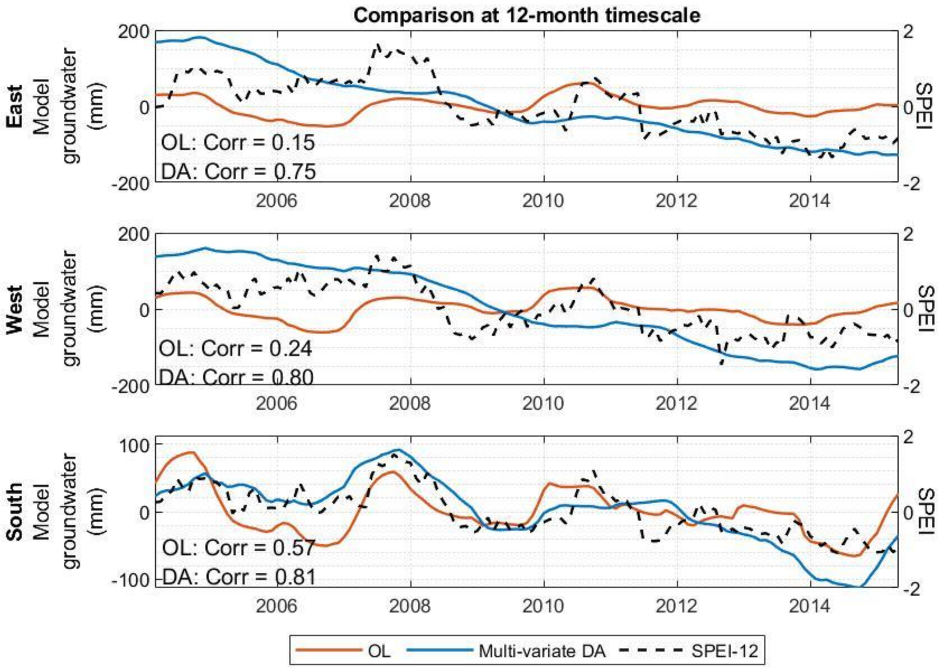

Figure 3. Comparison of OL and multivariate DA groundwater estimates with SPEI at a **12-month** timescale.

Secondly, the well observations are compared in term of their correlation in Figure 7. The GW storage from MV-DA appears to do poorly in comparison to OL in c and f subplots (RMSE). This correlation plot also suggests that groundwater spatial-variability is not very large (in line with point 2 above).

Reply: The reviewer suggests that the multivariate DA performs worse than the OL in Fig. 7c and Fig. 7f.

Regarding Fig. 7f, we agree that the multivariate DA underperforms relative to the OL. This outcome is in fact one of the key points highlighted in our analysis. The figure represents the average groundwater time series from a limited number of wells located predominantly along the Brahmaputra River. As discussed in lines 573–578, these locations do not exhibit declining groundwater trends, likely due to continuous river-induced groundwater recharge. When the negative TWS trend is assimilated in the multivariate DA experiment, a corresponding negative trend is introduced at these sites, which degrades the correlation with the reference groundwater measurements. To clarify this, we will add an explanatory note to the figure caption.

However, for the remaining sites shown in Fig. 7c, we believe it is not accurate to conclude that the multivariate DA performs poorly relative to the OL. At these locations, groundwater levels show a pronounced declining trend that the OL fails to capture but the multivariate DA successfully introduces. Certain short-term anomalies, such as the positive anomaly in 2010–2012, may appear better represented in the OL solution, posing a need for further investigation in future studies, particularly to assess potential links to sub-decadal glacier- or snow-related anomalies. Conversely, other anomalies, such as the 2007–2009 event, are more accurately reproduced by the multivariate DA.

To improve clarity, additional explanatory lines will be incorporated into the manuscript. Furthermore, a table reporting RMSE values computed over standardized time series will be added to Appendix E.

5. SSM relation with TWS is tricky in irrigated regions. For example, in rainy season, a change in TWS is positively correlated with SSM but when groundwater irrigation is done, SSM is anti-correlated to TWS change. This has a significant impact on water budget also, which can lead to phase shifts tin ET (for example, see Goswami et al., 2025). How is the assimilation approach able to deal with such scenarios?

Reply: We definitely acknowledge the reviewer's point. As shown by Goswami et al. (2025), SSM and TWS can be anti-correlated in areas with widespread irrigation practices, such as the Ganges basin. This is likely also the case in some areas of the Brahmaputra with a high presence of irrigation, and should therefore be discussed. The following paragraph will be added in the Discussion section:

Previous studies in multi-variate land DA report that this cross-variable interference can lead to a diminished performance in multi-variate DA due to conflicting constraints or anti-correlated updates induced by the two observation sets (Tian et al., 2017; Girotto et al., 2019). This needs to be especially considered in regions with the presence of irrigation, as is the case of the Brahmaputra River basin, where negative TWS and groundwater trends caused by water pumping can be strongly anti-correlated with increasing SSM values caused by expanding irrigation practices (Goswami et al., 2025). If the influence of TWS DA in the SSM component is not adequately constrained, this can result in the introduction of long term trends in SSM and evapotranspiration, degrading the representation of these variables within the model (Girotto et al., 2017). In a multi-variate DA framework, this could lead to conflicts in the DA updates caused by the TWS and SSM observations.

Other comments:

- Section 2.1: here authors acknowledge groundwater irrigation and thus point 5 above can be discussed.

Reply: indeed, as the reviewer suggests, there is an important presence of irrigation in some parts of the Brahmaputra basin.

- Daily GRACE products are generated using a KF, which introduces a strong autocorrelation in time. How would this impact the quality of assimilation?

Reply: We acknowledge the reviewer's point. The ITSG-Grace2018 daily TWS solution is computed using a Kalman smoother, which can be expected to introduce temporal autocorrelations in the daily to weekly timescale. In the present study, these temporal correlations were not accounted for, for two main reasons. First, our analysis focuses on monthly, seasonal, and inter-annual water storage variability. At these longer timescales, the temporal autocorrelation present in the daily ITSG-18 product is expected to be minimal, or at least not greater than that inherent in standard monthly GRACE TWS products. Therefore, explicitly accounting for these correlations is not essential for the objectives of this study (see, e.g., Zhao and Yang, 2018). Second, no quantitative estimate of the magnitude or temporal structure of these autocorrelations has yet been provided. Deriving such an estimate would require a dedicated methodological effort beyond the scope of this work.

For future DA experiments aimed at improving sub-monthly water storage dynamics, incorporating these temporal correlations could indeed be beneficial. However, further research is needed to characterize the temporal error structure of the ITSG-18 daily product. Moreover, the inclusion of temporally correlated observation errors in DA systems would require more sophisticated assimilation approaches.

To improve clarity, we will add a few lines to the manuscript addressing this aspect.

- Line 170: Well data should also be checked for errors (repeating values, negative values, large gaps, see Kuruva et al., 2025). In South-east Asia, the dataset quality check is necessary sometimes. If that has been done, please mention.

Reply: we appreciate the reviewer's comment. 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.

- Since the covariance localization approach uses damped-spatial correlation based on distance b/w observations and model, do we expect observations to be at a higher spatial resolution than model? If yes, then it must be clarified how a coarse resolution GRACE product was used? Same values for all grids in a sub-basin?

Reply: We thank the reviewer for this comment. In all of the experiments, the TWS observations were assimilated as sub-basin averaged fields, and ensemble-statistics were used to disaggregate the spatially averaged observations into the model grid cells. When observation-space localization was used, the centre of each sub-basin was taken as a reference point to compute localization distances. This approach (i.e., assuming a point location for each TWS observation) has been often used in previous literature, especially for the assimilation of gridded TWS fields (e.g., Girotto et al., 2019; Khaki et al., 2020). We acknowledge that this assumption is not ideal, since TWS observations are smooth fields rather than localized observations, and this is one of the reasons why we propose model space localization: as mentioned in lines 276-279 of the manuscript, model space localization avoids the need to assume a point-location for the observations.

We acknowledge that this aspect is not clearly explained in the manuscript, and we will add an explanation to clarify it.

- L 265: Smooth distant, whould be replaced by smooth distance .

Reply: Thanks, will be applied.

- Line 299 and 303: use comma, not full stop (33.808 -->33,808)

Reply: Thank you for the comment, it will be applied.

- Result section was slightly harder to follow. Maybe improve the writing aspect.

Reply: Thanks for this comment. We will carefully revise the writing of the results section to make the results easier to follow.

Best,

Bramha

Reply: We appreciate the useful and specific comments of the reviewer, and we believe they will contribute to improving the manuscript.

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