## Referee #3

## Overall evaluation:

'A preliminary study on a synergistic assimilation scheme for multi-band satellite soil moisture data' presents the assimilation, on a global scale, of three soil moisture retrievals from the SMAP, ASCAT and MWRI satellite instruments into the Common Land Model. The three observations differ significantly in terms of the spectral bands used, measurement swathes, resolution and other factors. The study discusses the pros and cons of co-assimilating these products with regard to modelled soil moisture. In the field of geosciences, there is a common debate about the benefits of assimilating complementary or redundant observation datasets.

The results of assimilation experiments involving one, two or three of these observation datasets are carefully compared. The skill of each experiment is evaluated in relation to ERA-5 land reanalysis and in situ global soil moisture observations taken at a depth of 10 cm. From these comparisons, the authors highlight significant regional differences in the experimental results and link them to the distribution of vegetation types, justifying this by the sensitivity of L-, C- and X-bands to dense vegetation, and of C- and X-bands to low-to-moderate vegetation cover and more arid conditions. This evaluation per vegetation type was then used to evaluate the synergies induced by the assimilation of different observations. The authors concluded that the co-assimilation of SMAP+ASCAT offers the best overall improvement and that the addition of MWRI-X-band should only be applied to areas with sparse vegetation to avoid any anti-synergistic effects.

While these conclusions are understandable, there is a major issue with the experimental setup. All experiments were conducted over a consecutive two-month period only. This means that any seasonal effects on vegetation, soil moisture, observation availability and quality could not be considered. Without information on how the analysis performs at other times of the year, the links between regional differences, vegetation types and recommendations for co-assimilating different observation datasets remain unclear.

For this study to be considered for publication, either the simulation period should be extended, or a more thorough investigation into the relationship between localisation, vegetation type and observation availability should be conducted.

Response:

We sincerely thank you for your valuable time and professional guidance. Your comments have greatly improved the quality of this manuscript.

To further enhance the robustness of our conclusions, we conducted additional multi-season experiments. The new results further support our conclusion that, in the assimilation application of X-band products, introducing physical constraints related to vegetation type and optimizing data screening can lead to more stable additive improvements from X-band assimilation. Moreover, through the comparative analysis of multi-season assimilation performance, we found that, in addition to vegetation type, the seasonal variation of vegetation should also be considered when assessing the impact of X-band assimilation. These additional findings further strengthen the scientific value of the manuscript.

Below, we provide a detailed point-by-point response to your comments, and the corresponding revisions in the manuscript have been highlighted in a specific color.

**Major Comments:**

1. l 106-You only selected June to August 2022 as your study period. Why did you choose such a short period? Moreover, 2022 was an unusual year in Europe, with severe heatwaves, droughts and wildfires in the summer.

Response:

Thank you for your suggestions. Following your suggestions, we have extended the assimilation experiments to cover all four seasons of the year (Spring MAM, Summer JJA, Autumn SON, and Winter DJF). Results from other seasons also support our conclusion. The key to achieving positive results with X-band lies in selecting X-band products with smaller observational errors. Indeed, as the reviewer pointed out, seasonal variations affect the selection of X-band data. Through the comparative analysis of multi-season assimilation performance, we found that, in addition to vegetation type, the seasonal variation of vegetation should also be considered when assessing the impact of X-band assimilation.

We have added the relevant analysis to Figures 18 and 19 in Lines 722-766 of the revised manuscript, where Figure 18 shows the seasonal assimilation performance for representative vegetation types and Figure 19 presents the seasonal probability density distributions of the correlation coefficient differences among different assimilation experiments. The revised text is as follows:

To further investigate the differences in assimilation results across seasons, we extended the experiments to include spring (MAM), autumn (SON), and winter (DJF). Figure R1 presents a comparison of the correlation coefficients between the DA_L+C and DA_ALL experiments across the four seasons for different vegetation types. The Non-arctic Grass and Corn regions exhibit more pronounced seasonal differences. In summer (JJA) and winter (DJF), the growth of grasses and crops tends to stabilize, or the vegetation density decreases significantly. As a result, observation errors are relatively stable, making the addition of the X-band more likely to result in positive effects. As shown in the figure, the orange bars are noticeably higher than the blue bars during summer and winter.

Conversely, during the transitional phases of spring (MAM) and autumn (SON), the orange bars are lower than the blue bars, indicating that the inclusion of X-band data degrades the overall assimilation performance. This is likely because vegetation undergoes rapid growth or senescence during spring and autumn, accompanied by drastic changes in morphological structure and water content. As a result, X-band observations, which are more sensitive to vegetation effects, are more strongly influenced under these conditions. When vegetation dynamics are not adequately represented, soil moisture retrievals may exhibit increased variability and occasional anomalous estimates, thereby increasing observation errors (Dash and Sinha, 2019; Stradiotti et al., 2025). This elevated error uncertainty causes the assimilation of X-band data to be prone to negative impacts.

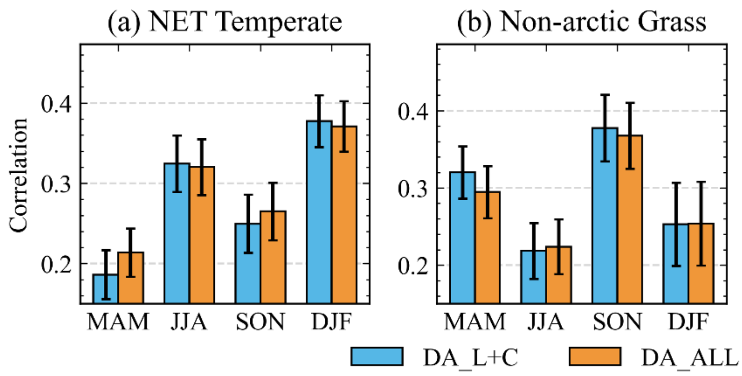


**Figure R1: Comparison of assimilation performance for representative vegetation types across different seasons. The figure shows the correlation coefficients between simulated soil moisture and station observations for (a) NET Temperate, (b) Non-arctic Grass, and (c) Corn across the four seasons. The blue and orange bars represent the DA_L+C and DA_ALL experiments, respectively. Error bars indicate the 95% confidence intervals.**

Based on the above analysis, the winter settings follow those of summer, where X-band data is excluded only in dense vegetation areas. In spring and autumn, X-band data is not introduced in Corn and Non-arctic Grass. This is because Cron and Non-arctic Grass are undergoing rapid growth or senescence during the transitional phases of spring and autumn. The resulting substantial changes in vegetation morphology and water content are prone to enhancing X-band scattering noise and increasing observation uncertainty.

Figure R2 displays the PDF of the differences in correlation coefficients between the three sets of assimilation experiments and the control experiment based on in situ observations. As shown in Figure R2, the differences for all assimilation experiments are primarily distributed in the range greater than zero, indicating that assimilating satellite data produces a positive effect. The probability distribution of these differences reveals that improvements are more likely to occur during spring and autumn, where the probability of a correlation coefficient increment exceeding 0.5 is higher than in the other two seasons. In contrast, the assimilation improvement in winter is relatively small, with the magnitude of correlation coefficient increments mainly concentrated around 0.1.

Comparing the improvement effects of different assimilation experiments, it is evident that the DA_NEW experiment reduces the probability of negative effects across all seasons, shifting the overall probability density distribution toward the positive effect interval. Compared with the DA_ALL experiment, the improvements of the new scheme in spring, summer, and autumn are more concentrated around 0.3, while in winter, they are concentrated around 0.1. Furthermore, the mean correlation coefficients for each season indicate that the DA_NEW experiment produces higher average values than both the DA_L+C and DA_ALL experiments in every season. This demonstrates that the new scheme, by dynamically adjusting the combination of multi-source data, better integrates the advantages of multi-source observations, thereby improving global land surface assimilation performance.

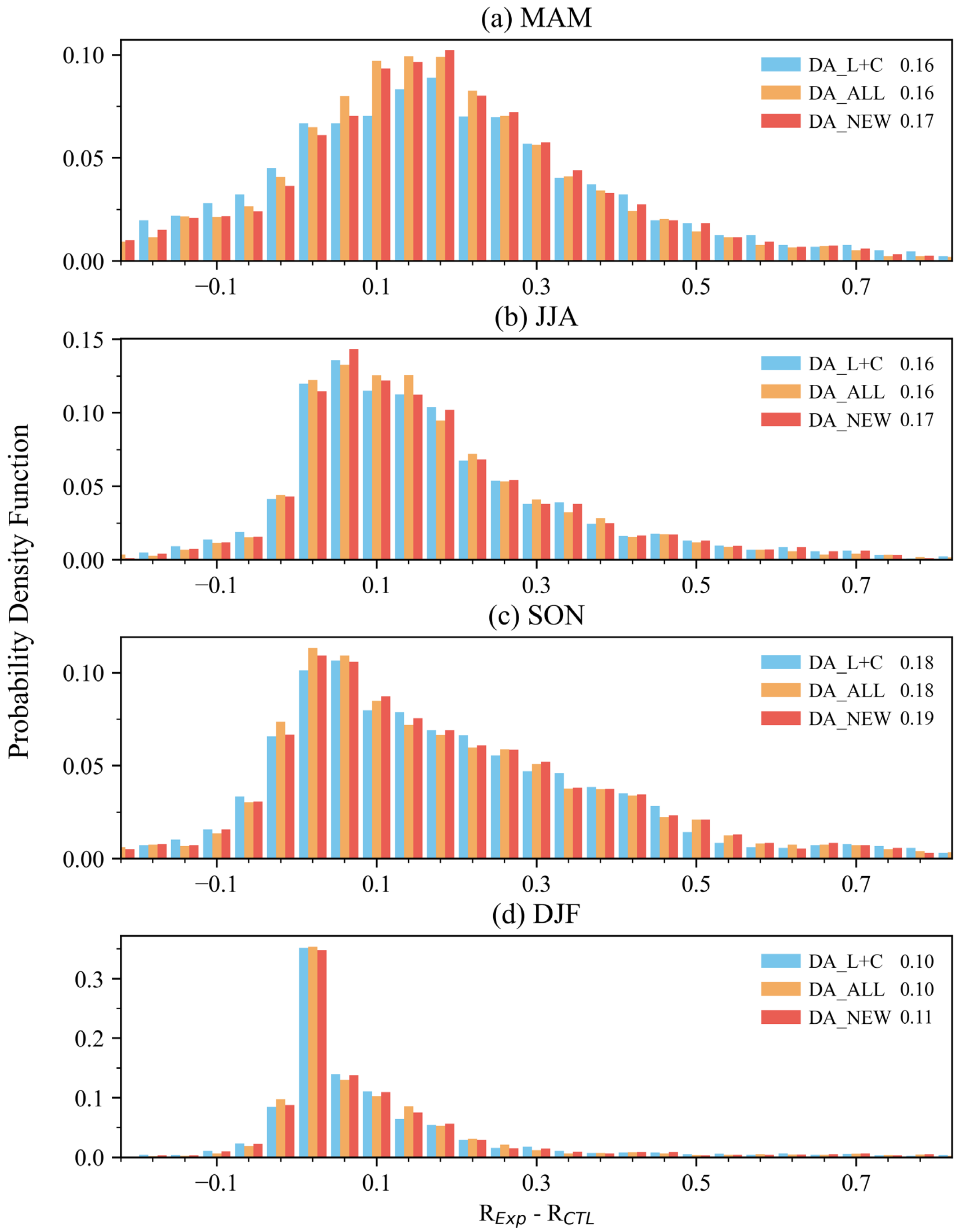


**Figure R2: Seasonal variations in the probability density functions of the correlation coefficient differences between the assimilation experiments (DA_L+C, DA_ALL, and DA_NEW) and the control experiment based on station observations. (a) Spring (MAM), (b) Summer (JJA), (c) Autumn (SON), and (d) Winter (DJF). The numbers in the upper-right corner indicate the mean values.**

The following references have been added to the reference part of the revised manuscript:


Dash, S. K. and Sinha, R.: A Comprehensive Evaluation of Gridded L-, C-, and X-Band

Microwave Soil Moisture Product over the CZO in the Central Ganga Plains, India, Remote Sensing, 14, 1629, https://doi.org/10.3390/rs14071629, 2019.
Stradiotti, P., Gruber, A., Preimesberger, W., and Dorigo, W.: Accounting for seasonal retrieval errors in the merging of multi-sensor satellite soil moisture products, Science of Remote Sensing, 12, 100242, https://doi.org/10.1016/j.srs.2025.100242, 2025.

2. l 121-These satellites are in a sun-synchronous orbit. How do you schedule assimilation with the SEKF all over the globe? You say that you assimilate all observations at 00:00 UTC daily. Do you only consider observations available at that specific hour, or do you move all observations from throughout the day to 00:00? If so, can you justify that this has no significant impact on the soil moisture diurnal cycle?

Response:

Thanks for your suggestions. Our analysis is not based on satellite observations acquired exactly at 00:00 UTC. Instead, all valid observations collected within 12 hours are aggregated and assimilated simultaneously in a single SEKF update at 00:00 UTC. This approach was adopted primarily because the goal of this study is daily soil moisture estimation.

To assess the effect of this temporal alignment, we performed an additional analysis of soil moisture diurnal variability. As shown in Figure R3, the relative diurnal variation intensity, defined as the ratio of diurnal amplitude to the daily mean, is below 8% over most of the globe. Based on the global average, the 24-hour soil moisture amplitude is approximately 0.0006 $m^3/m^3$, which is smaller than the uncertainty of current mainstream satellite soil moisture products such as SMAP (ubRMSE ≈ 0.04 $m^3/m^3$). This comparison indicates that the timing error introduced by mapping intraday observations to 00:00 UTC is negligible and does not significantly impact the analysis increments. Additionally, employing a daily batch update mitigates the risk of additional model oscillations that could arise from overly frequent local corrections.

Accordingly, we have added the following clarification to the experimental design section of the revised manuscript (Lines 383–386), and Figure R3 has been included in the Supplement as Figure S1:

As shown in Figure S1, the global mean diurnal variation in soil moisture is about 0.0006 $m^3/m^3$, much smaller than the typical satellite retrieval uncertainty of about 0.04 $m^3/m^3$. This approximation is therefore adequate for the temporal scale of this study and has little effect on the global soil moisture estimates.

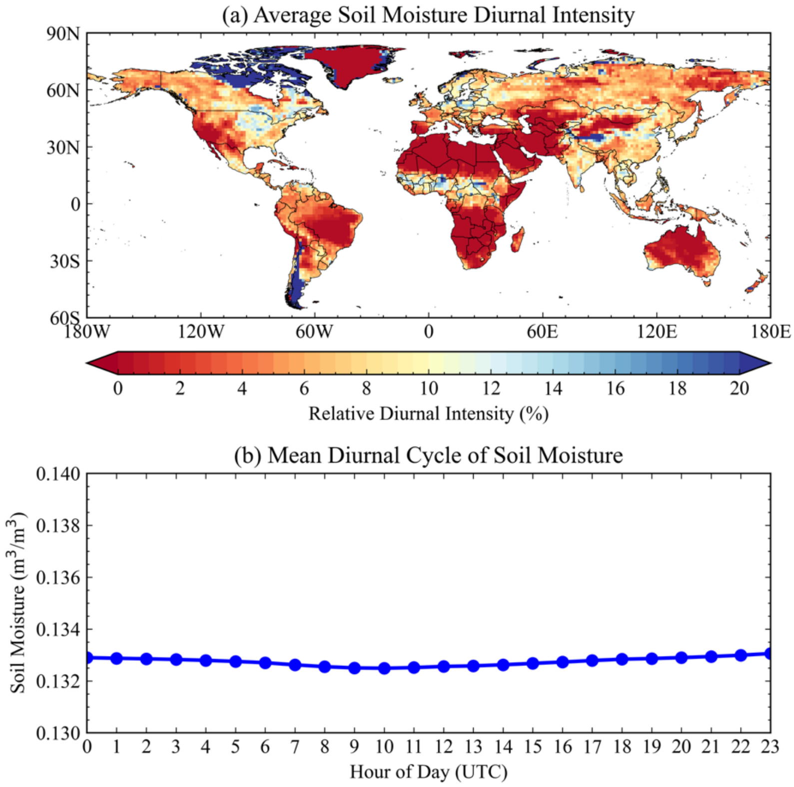


**Figure R3: Analysis of the global soil moisture diurnal variability. (a) Spatial distribution of the Relative Diurnal Intensity, defined as the ratio of the daily amplitude (max-min) to the daily mean soil moisture; (b) The global mean diurnal cycle of soil moisture over a 24-hour UTC period.**

3. 1 131-Please justify the depth taken for this study.

Response:

Thanks for your suggestions. In this study, we use 10 cm as the main validation depth for two practical reasons. The first is the physical focus of the work. Our assimilation framework is designed for near-surface soil moisture retrieval using multi-band microwave observations, and the sensing depths of the L-, C-, and X-bands are mainly limited to the upper soil layers. Since the proposed vegetation-adaptive scheme is intended to improve the assimilation of near-surface soil moisture by adjusting the relative weights of different microwave bands, shallow soil moisture is the most relevant target for evaluation.

The second reason is data availability. In the CMA automatic station network, 10 cm is the shallowest standard soil moisture observation depth. Using this layer allows us to retain the largest number of valid stations for evaluation and therefore provides better spatial coverage and more robust statistics. To ensure consistency between the model output and the in-situ measurements, we calculated the soil moisture for the 0–10 cm layer by summing the simulated soil moisture across the layers within this depth range before comparison.

Following your suggestion, we have added this clarification to the revised manuscript (Lines 260-264):

In this study, the 10 cm soil depth was used for primary validation to bridge the gap between satellite sensing and in-situ monitoring. Since L-, C-, and X-band microwave observations mainly reflect near-surface soil moisture, and 10 cm is the shallowest standardized measurement depth also has the fewest missing values across the CMA station network. To better align with the research objectives and ensure a sufficient number of validation data points, we focus on evaluating the impact of land data assimilation on 10-cm soil moisture.

4. l 150-Could you clarify whether your LAI is prognostic (modelled) or forced? If it is forced, which climatology database or observation product are you using?

Response:

Thanks for your suggestions. In our CoLM setup, LAI is prescribed as an external forcing rather than predicted prognostically by the model. We use a monthly climatological LAI dataset reprocessed from MODIS and provided by Beijing Normal University. Following Yuan et al. (2011), this dataset was designed to reduce noise and temporal discontinuities in the original MODIS product, so that seasonal vegetation dynamics are represented more realistically. We have added a description of the LAI dataset to the revised manuscript (Lines 289-292) as follows:

In this study, the Leaf Area Index (LAI) is prescribed from the monthly reprocessed MODIS LAI dataset, which was generated following the approach of Yuan et al. (2011). This prescribed LAI drives the two-big-leaf canopy scheme in CoLM to partition the canopy into sunlit and shaded leaves and to compute canopy-scale radiation absorption, photosynthesis, stomatal conductance, and transpiration.

The following references have been added to the reference part of the revised manuscript:

Yuan, H., Dai, Y., Xiao, Z., Ji, D., and Shangguan, W.: Reprocessing the MODIS Leaf Area Index products for land surface and climate modelling, Remote Sensing of Environment, 115, 1171–1187, https://doi.org/10.1016/j.rse.2011.01.001, 2011.

5. l 185-Please describe the values sets in B and R error covariance matrices.

Response:

Thanks for your suggestions. In the revised manuscript, we have expanded this part in Section 3.3 (Lines 347–355) and added Figure R4 to the revised manuscript as Figure 4 to illustrate the spatial distributions of observation errors and background errors. The added text is as follows:

For areas without station observations, errors are characterized by the RMSE against the ERA5-Land product. In station-covered regions, observation and background errors are estimated via Triple Collocation (TC) using CoLM simulations, in-situ data, and satellite retrievals as independent inputs. These TC estimates were scaled to match RMSE magnitudes to ensure consistency. Spatial patterns of these errors are shown in Figure R4. Based on these estimated errors, and following de Rosnay et al. (2013), we specified both the background and observation error covariance matrices as diagonal, with their diagonal entries derived from the errors.

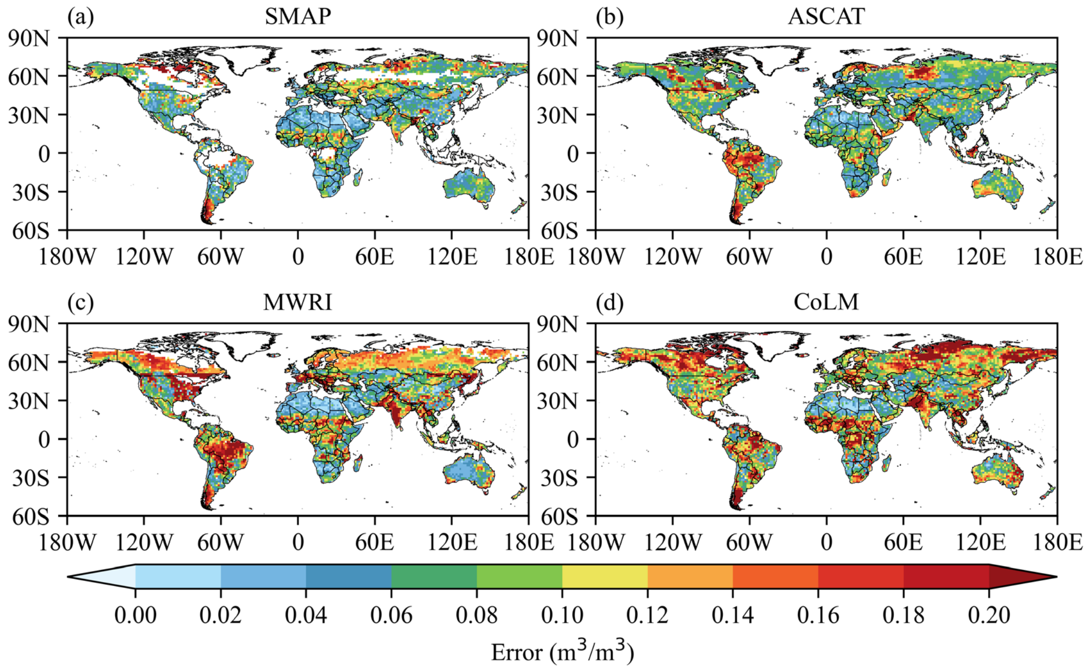


**Figure R4: Spatial distributions of observation and background errors for different satellites. (a) SMAP observation error; (b) ASCAT observation error; (c) MWRI observation error; and (d) CoLM background error.**

6. Figure 3-Could you show the bias maps averaged over your assimilation period using ERA5-Land instead? That is what you are describing in the text. This would make it easier to read.

Response:

Thanks for your suggestions. Following your suggestions, we have revised the Figure 3. ERA5-Land soil moisture is now shown as the reference field, while the other three panels display the differences between each assimilation experiment and ERA5-Land. Variable labels and units have also been added to the color bars.

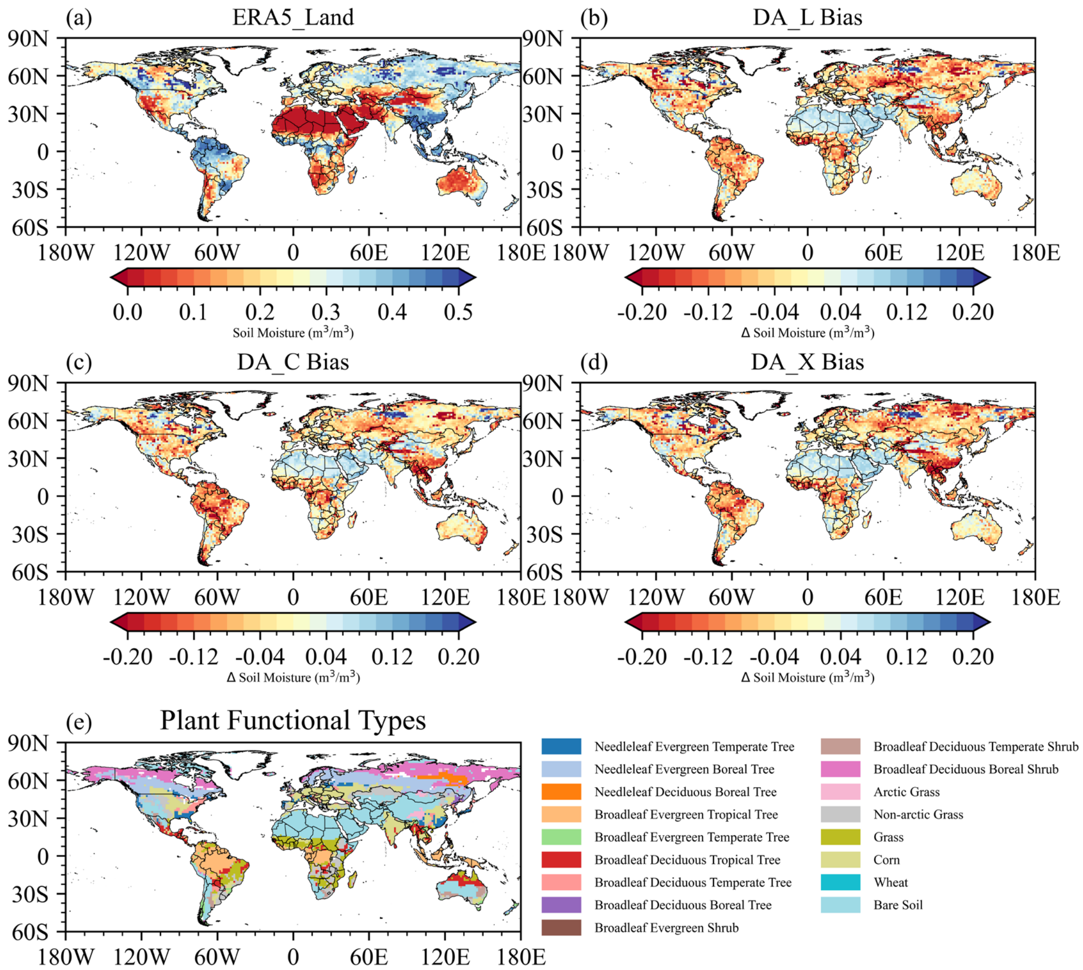


**Figure R5: Spatial distribution of mean soil moisture in the top layer (0-7 cm) during 2 June to 3 July 2022. (a) shows the soil moisture from the ERA5_Land product. (b)–(d) show the soil moisture differences of the analysis fields from the DA_L, DA_C, and DA_X assimilation experiments relative to ERA5_Land, respectively (i.e., DA experiment minus ERA5-Land). (e) shows the spatial distribution of vegetation cover.**

## Minor Comments:

1. l 43-... to improving model performance -> to improve forecast skills of the model. The initial conditions do not change the model.

Response:

Thanks for your suggestions. Following your suggestions, we revised the sentence as follows: “Optimizing initial conditions is a crucial method to improve the forecast skill of the model.”

2. l 93-97-You discuss the complementarity of the observations used according to their vegetation sensitivities, stating that you will capitalise on this to engender synergistic improvements. However, as will be seen later in the article, complementarity between observations does not always lead to synergistic improvements. 'Complementary' does not mean 'in agreement with each other'. What you are discussing here is the necessity of a screening step to select the observations to assimilate to avoid anti-synergistic behaviour. The terms 'to engender' synergistic improvements feels awkward, you should only expect them to occur.

Response:

Thanks for your suggestions. Following your suggestions, we have revised the description in Lines 162-167 to emphasize that the framework screens observations to avoid anti-synergistic behavior. The specific modifications are as follows:

Therefore, this study explicitly incorporates X-band data and quantifies the vegetation-type-dependent heterogeneity in the assimilation efficacy of diverse satellite retrievals, thereby delineating the relative advantages associated with each spectral band. Based on this insight, a vegetation-aware multi-satellite data-assimilation framework is formulated to effectively screen and select observations with complementary potential under different vegetation conditions. This design aims to **reduce anti-synergistic behavior** arising from observational conflicts and improve forecast skills of the model.

3. l 105-Precise the frequency of the product (daily, 10-days,...).

Response:

Thanks for your suggestions. Following your suggestions, we have clarified that although the soil moisture retrievals are derived from the SMAP, ASCAT, and MWRI products, all observations were aggregated to the daily timescale before assimilation. The corresponding description has been added to the revised manuscript at Line 177, as follows:

Informed by the complementary strengths of active and passive microwave sensing at divergent frequencies, this study assimilates soil-moisture retrievals from three mainstream sensors: the U.S. Soil Moisture Active Passive (SMAP), the European Advanced Scatterometer (ASCAT), and China's Microwave Radiation Imager (MWRI). The data period covers June to August 2022, **and the observations were aggregated to a daily timescale before assimilation.**

4. 1 119-Please detail the retrieval model you used for MWRI or cite it.

Response:

Thanks for your suggestions. Following your suggestions, we added a description that includes the data period, operating frequency bands, spatial resolution, revisit time, temporal resolution of the product, and retrieval algorithm. The added text can be found in Lines 201–207 of the revised manuscript, as follows:

The MWRI soil moisture dataset was developed by the National Satellite Meteorological Center (NSMC) of the China Meteorological Administration (CMA). The FY-3D afternoon satellite was successfully launched in November 2017, with its MWRI data record officially available since early 2018. The dataset is derived from global passive microwave brightness temperature observations acquired by the MWRI instrument onboard FY-3D, which has equatorial crossing times of approximately 2:00 AM (descending orbit) and 2:00 PM (ascending orbit), providing a global revisit time of 1–2 days. Surface soil moisture is primarily retrieved from the X-band (10.65 GHz) dual-polarized brightness temperatures using a **parameterized $Q_p$ emission model** that accounts for vegetation scattering, optical depth, and soil surface roughness effects (Kang et al., 2020). This daily product combines ascending and descending overpasses and is provided on a 25 km Equal-Area Scalable Earth (EASE-Grid) projection.

The following references are cited here and were already included in the original manuscript:

Kang, C. S., Zhao, T., Shi, J., Cosh, M. H., Chen, Y., Starks, P. J., Collins, C. H., Wu, S., Sun, R., and Zheng, J.: Global Soil Moisture Retrievals from the Chinese FY-3D Microwave Radiation Imager, IEEE Trans. Geosci. Remote Sens., 59, 4018–4032, https://doi.org/10.1109/TGRS.2020.3019408, 2020.

5. Figures-units please

Response:

Thanks for your suggestions. We checked all relevant figures throughout the manuscript and added the missing physical units and colorbar labels (e.g., the soil moisture unit, $m^3/m^3$). We also reviewed the numerical ranges and tick labels of the colorbars to ensure that the variables and their units are presented clearly and consistently across the figures. These revisions have been made in Figures 1, 2, 4, 5, 6, 7, 9, 12, and 13.