Response to reviewers' comments

Dear Associate Editor:

My co-authors and I would like to thank the reviewers for their time and valuable feedback, which we have addressed in the revised manuscript. We have enhanced the overall clarity of the document, with all revisions marked in red text for ease of identification. Below, we provide comprehensive responses to each reviewer's comments. We appreciate your consideration and look forward to your feedback.

Regards,

Yonghwan Kwon and co-authors

Reviewer #1:

This study provided an insightful analysis of the pros and cons of multi-sensor soil moisture data assimilation source on a global and regional basis. Using multi-sensor soil moisture remote sensing seems like a valuable and generally more robust approach based on the results provided in the study. The authors also clearly outlined the limitations of the multi-sensor approach and ways to improve it in the future. The findings are interesting because they avoid relying on blended soil moisture datasets, also allowing for a more precise evaluation of each individual soil moisture product.

I found the paper well-structured and informative, though the frequent use of acronyms made it a bit harder to follow at times. That said, it's understandable given the models and datasets that were used. My review focuses primarily on how certain results are framed and interpreted in relation to the study's overarching theme. I also included a few line-specific comments aimed at improving the clarity of specific passages.

General comments

1. The study presents the robustness of SG_AT and SG_SP in the TCA section, but MT_ATSP was excluded due to the restrictions of TCA. However, the added value of multi-sensor DA being the main theme of the study, this makes it difficult to fully interpret the TCA results in the broader context of the study. The TCA results, particularly in Figure 3, are valuable and suggest that SG_SP is generally the more robust option for single-sensor DA. Still, the authors should clarify how these results relate to the overall narrative of the study, given that MT_ATSP is the preferred DA method despite its absence from the TCA.

Response) Evaluating soil moisture improvements through multi-sensor soil moisture DA is indeed important, as the reviewer pointed out. However, global-scale soil moisture evaluations are inherently challenging due to limited reference data. Although we employed the TCA method as an alternative evaluation approach, it has limitations, particularly in constructing TCA triplets without violating underlying assumptions. Because the primary objective of this study is to improve atmospheric forecasts by assimilating soil moisture data from multiple sources, we placed greater emphasis on assessing the added value of multi-sensor DA for atmospheric variables. Although soil moisture evaluation results were presented only for the single-sensor DA experiments, the overall benefit of assimilating both sensors simultaneously can be inferred from the single-sensor results and the atmospheric evaluation. Nevertheless, we acknowledge the reviewer's concern. Accordingly, we revised the last paragraph of Section 7.1 (Lines 714–722 in the revised manuscript) for clarity, and added new sentences in the conclusion (Lines 1002–1011 in the revised manuscript) to highlight the limitation of our study regarding the evaluation of soil moisture estimates from multi-sensor DA.

*Lines 714–722 (Section 7.1):

> "As shown in Figure 2, soil moisture performance gains and losses by each single-sensor soil moisture DA are locally dependent. Thus, some previous studies (e.g., Draper et al., 2012; Kolassa et al., 2017) have shown that simultaneously assimilating soil moisture retrievals from both passive and active sensors achieves higher model soil moisture accuracy than assimilating a single product. However, because soil moisture triplets that fully satisfy the TCA assumptions (see Section 6.1) are difficult to obtain over the global domain for the multi-sensor soil moisture DA experiment, the combined effects of ASCAT and SMAP DA are discussed only in terms of atmospheric variables, which are the ultimate objective of this study, in the subsequent sections."

*Lines 1002–1011 (Section 9, Conclusions):

> "It should be noted that although this study employs the TCA method as an alternative global-scale soil moisture evaluation approach, it has limitations, particularly in constructing TCA triplets for the multi-sensor soil moisture DA experiment without violating underlying assumptions. Therefore, we applied TCA only to the single-sensor DA experiments, and the overall benefit of assimilating both sensors simultaneously can only be inferred from the single-sensor results and the atmospheric evaluation. Future studies should address this limitation to enable a more complete and robust assessment of the impact of multi-sensor soil moisture DA by implementing instrumental variable (IV)-based methods for estimating cross-correlated soil moisture errors, which require only two independent soil moisture datasets (Dong et al., 2020)."

2. The effect of SM DA on precipitation forecast skill is not clearly explained, which makes it difficult to understand the reasoning behind evaluating precipitation forecast. To improve coherence, the authors should clarify how SM DA is expected to influence precipitation forecasts and why these metrics are relevant to assessing the performance of the assimilation methods.

Response) Thank you for your comment. In response, we have added the following paragraph to the revised manuscript (Lines 587–605).

> "Local variations in soil moisture modify boundary-layer heat and moisture fluxes, thereby altering water–energy budgets and influencing convective triggering (Findell and Eltahir, 2003; Pal and Eltahir, 2003) and subsequently influence large-scale dynamics (Cook et al., 2006; Pal and Eltahir, 2003), both of which play key roles in determining precipitation processes. A number of studies have investigated the complex interaction mechanisms between soil moisture and precipitation,

referred to as the ‘soil moisture-precipitation feedback’, using observational analyses (e.g., Catalano et al., 2016; Yang et al., 2018) and computational modeling systems (e.g., Beljaars et al., 1996; Bosilovich and Sun, 1999; Hohenegger et al., 2009; Lin et al., 2023; Pal and Eltahir, 2003). Although these studies generally agree on a predominant positive feedback, the sign and strength vary depending on modeling systems and spatiotemporal scales (Hohenegger et al., 2009; Lin et al., 2023). Differences in the sign of soil moisture-precipitation feedback can be attributed to the complexity of representing the soil moisture-evapotranspiration relationship (Yang et al., 2018) and convective development (Hohenegger et al., 2009). Considerable debate and uncertainty remain regarding the physical mechanisms determining the sign of the feedback (Hohenegger et al., 2009). Nevertheless, there is no doubt that soil moisture and precipitation are reciprocally linked, implying that better characterization of soil moisture conditions through soil moisture DA can enhance precipitation forecasts in land-atmosphere coupled systems.”

***References**

Beljaars, A.C.M., Viterbo, P., Miller, M.J., Betts, A. K., 1996. The anomalous rainfall over the United States during July1993: Sensitivity to land surface parameterization and soil moisture anomalies. Mon. Weather Rev. 124, 362–383. https://doi.org/10.1175/1520-0493(1996)124<0362:TAROTU>2.0.CO;2.

Bosilovich, M.G., Sun, W.-Y., 1999 Numerical simulation of the 1993 Midwestern flood: Land–atmosphere interactions. J. Climate 12, 1490–1505. https://doi.org/10.1175/1520-0442(1999)012<1490:NSOTMF>2.0.CO;2.

Catalano, F., Alessandri, A., De Felice, M., Zhu, Z., Myneni, R.B., 2016. Observationally based analysis of land–atmosphere coupling. Earth Syst. Dynam. 7, 251–266. https://doi.org/10.5194/esd-7-251-2016.

Cook, B.I., Bonan, G.B., Levis, S., 2006. Soil moisture feedbacks to precipitation in southern Africa. J. Climate 19, 4198–4206. https://doi.org/10.1175/JCLI3856.1.

Dong, J., Wei, L., Chen, X., Duan, Z., Lu, Y., 2020. An instrument variable based algorithm for estimating cross-correlated hydrological remote sensing errors. J. Hydrol. 581, 124413. https://doi.org/10.1016/j.jhydrol.2019.124413.

Findell, K.L., Eltahir, E.A.B., 2003. Atmospheric controls on soil moisture–boundary layer interactions. Part I: Framework development. J. Hydrometeor. 4, 552–569. https://doi.org/10.1175/1525-7541(2003)004<0552:ACOSML>2.0.CO;2.

Hohenegger, C., Brockhaus, P., Bretherton, C.S., Schär, C., 2009. The soil moisture–precipitation feedback in simulations with explicit and parameterized convection. J. Climate 22, 5003–5020. https://doi.org/10.1175/2009JCLI2604.1.

Lin, X., Huang, S., Li, J., Huang, Q., Shi, H., She, D., Leng, G., Wei, X., Guo, W., Liu, Y., Luo, J., 2023. Feedback dynamics between precipitation, temperature, and soil moisture in China and their possible driving mechanisms under a changing environment. Atmos. Res. 294, 106983. https://doi.org/10.1016/j.atmosres.2023.106983.

Pal, J.S., Eltahir, E.A.B., 2003. A feedback mechanism between soil-moisture distribution and storm tracks. Q. J. Roy. Meteor. Soc. 129, 2279–2297. https://doi.org/10.1256/qj.01.201.

Yang, L., Sun, G., Zhi, L., Zhao, J., 2018. Negative soil moisture-precipitation feedback in dry and wet regions. Sci. Rep. 8, 4026. https://doi.org/10.1038/s41598-018-22394-7.

3. There appears to be a slight disconnect between the presentation of results in Sections 7.1–7.2 and Section 7.3. While the earlier sections highlight the relative performance of SM DA methods compared to the control scenario, the precipitation results are presented in absolute terms, which makes it harder to assess the added value of each method. In Figure 7, the relative performance has to be inferred visually rather than being directly quantified. Is it more important here to show the absolute forecast metrics, or to compare them against the control baseline? Presenting ΔFB and ΔETS scores could make these comparisons clearer and more consistent with the rest of the paper. Boxplots similar to those in Figure 3 might be a good way to present these results more intuitively.

Response) Following the reviewer's suggestion, we replaced Figure 7 with ΔFB and ΔETS scores, and moved the original figure to the supplementary material (Figure S2). Section 7.3 has been revised accordingly, as shown below (Lines 821–882).

"**7.3. Precipitation**

The potential added value of multi-sensor soil moisture DA for precipitation forecasts is assessed using categorical skill score metrics, including the FB and ETS, as detailed in Section 6.3. Daily precipitation rates (mm day^{-1}) are computed from the KIM forecasts at 0-24 h, 24-48 h, and 48-72 h lead times, and compared against reference data using seven conventional thresholds (0.5, 1.0, 5.0, 10.0, 15.0, 20.0, and 25.0 mm day^{-1}). The numbers of model grid points classified as *Hits*, *FalseAlarms*, *Misses*, and *CorrectNegatives* in the contingency table (Table 4) are then counted, and FB and ETS are calculated for six domains (i.e., global domain, Northern Hemisphere, Southern Hemisphere, Asia, Europe, and tropical area). Figure S2 presents the FB and ETS of daily precipitation forecasts from KIM, averaged over the three lead times, for CTL and the three soil moisture DA experiments (SG_AT, SG_SP, and MT_ATSP) during the 00 UTC cycle in July 2022. The corresponding differences ($\Delta\text{FB} = |\text{FB}_{\text{EXP}} - 1| - |\text{FB}_{\text{CTL}} - 1|$, $\Delta\text{ETS} = \text{ETS}_{\text{EXP}} - \text{ETS}_{\text{CTL}}$) are shown in Figure 7.

In the global domain, CTL (without soil moisture DA) tends to overestimate precipitation frequency (FB > 1.0), simulating excessive precipitation events, except for the precipitation threshold of 25.0 mm day^{-1} (Figure S2a). The model significantly overestimates precipitation at the 5.0 mm day^{-1} threshold and exhibits an FB close to 1 for heavier precipitation events (20.0 and 25.0 mm day^{-1}) (Figure S2a), with regional variations (Figures S2b to S2f). Both the smallest FB (close to 1.0) and the largest FB (> 2.5) are observed in the Southern Hemisphere for the lightest (0.5 mm day^{-1}) and heaviest (25.0 mm day^{-1}) precipitation events, respectively (Figure S2c).

Unlike FB, ETS is higher (indicating better skill in predicting precipitation events) at lower precipitation thresholds while ETS decreases as the precipitation intensity thresholds increase in the global domain (Figure S2g) and in the Northern Hemisphere (Figure S2h), including Asia (Figure S2j), Europe (Figure S2k), and tropical areas (Figure S2l). In the Southern Hemisphere, CTL shows the highest ETS skill at the precipitation threshold of 10.0 mm day^{-1} and the lowest at 1.0 mm day^{-1} (Figure S2i). The different model performance patterns (in both FB and ETS) between the Northern and Southern Hemispheres across the range of precipitation intensity thresholds may be attributed to different weather regimes associated with cyclones and monsoons (Dare and Ebert, 2017), along with additional impacts from seasonal variations.

Overall, soil moisture DA improves the prediction of precipitation events (i.e., better ETS; Figure 7g) while its contribution to precipitation frequency (FB) remains neutral (Figure 7a). MT_ATSP demonstrates higher ETS skill than CTL (by up to 1.8%) and single-sensor soil moisture DA (by up to 2.4% and 0.6% relative to SG_AT and SG_SP, respectively) (Figure 7g). The impacts of MT_ATSP on the global FB are marginal, showing negligible improvements at the 0.5, 1.0, 5.0, and 25.0 mm day^{-1} thresholds and slight overpredictions at the 10.0, 15.0, and 20.0 mm day^{-1} thresholds (Figure 7a, Figure S2a). Similar soil moisture DA performance patterns are observed in the Northern Hemisphere (Figures 7b and 7h) and Asia (Figures 7d and 7j). In the Southern Hemisphere, MT_ATSP slightly improves FB for heavy precipitation events (precipitation thresholds ≥ 15.0 mm day^{-1}) while relatively obvious improvements in ETS by MT_ATSP are witnessed at lower thresholds (≤ 1.0 mm day^{-1}) (Figures 7c and 7i). Compared to CTL and SG_AT, multi-sensor soil moisture DA enhances ETS across precipitation thresholds in tropical areas, although it is slightly less effective than SG_SP at thresholds ≤ 5.0 mm day^{-1} (Figure 7l). For FB, MT_ATSP shows improvements over CTL and SG_AT in tropical areas, except at thresholds of 5.0 and 10.0 mm day^{-1}, where SG_SP performs better (Figure 7f). In contrast, MT_ATSP is generally ineffective in Europe (Figures 7e and 7k), except for ETS at precipitation thresholds of 5.0 mm day^{-1} or lower. The overprediction of precipitation in Europe (Figure 7e, Figure S2e), especially for heavy precipitation events (≥ 15.0 mm day^{-1}), may lead to a decrease in ETS (Figure 7k, Figure S2k).”

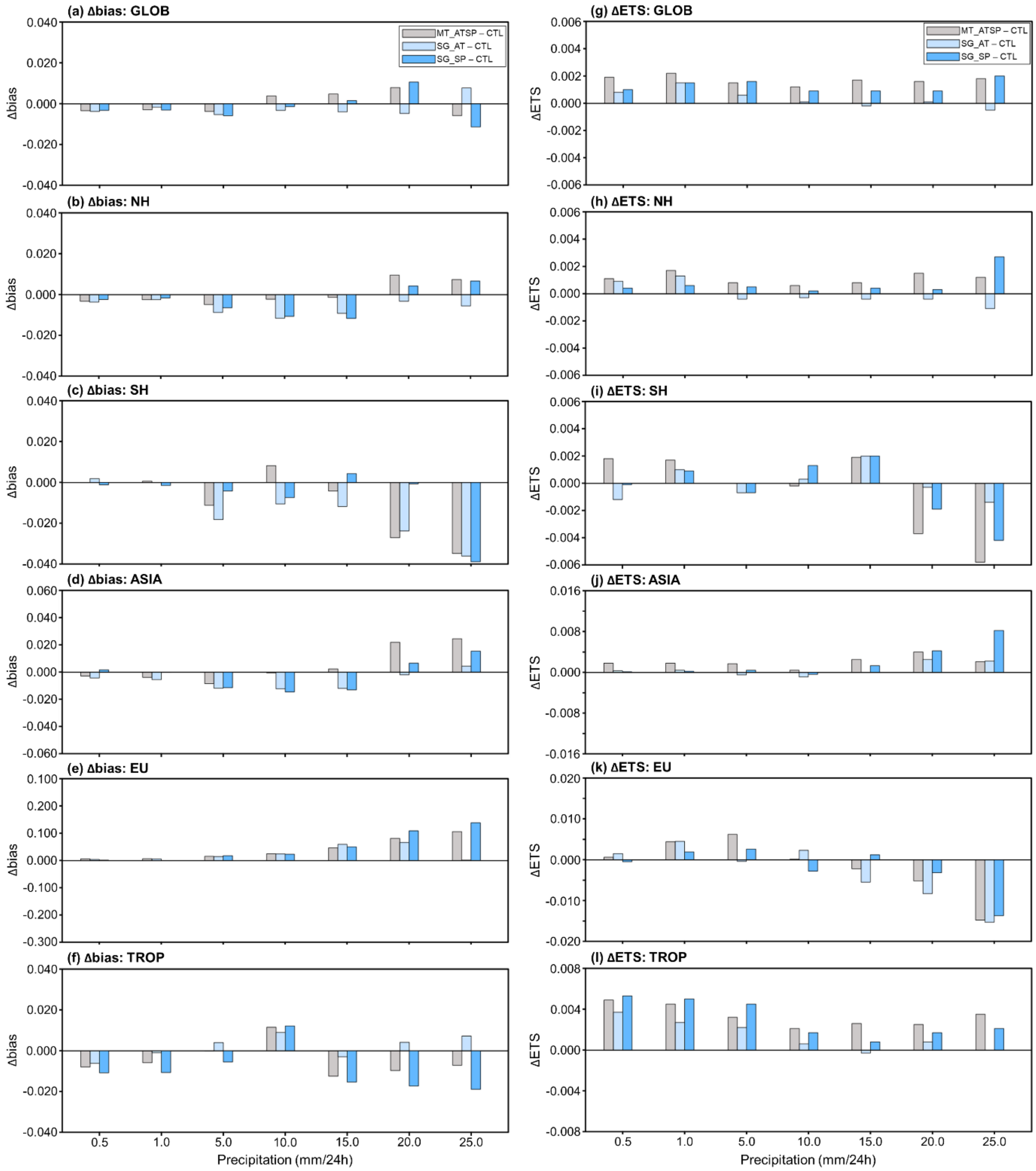

Figure 7. Differences in frequency bias ($\Delta FB = |FB_{EXP} - 1| - |FB_{CTL} - 1|$; a to f) and equitable threat score ($\Delta ETS = ETS_{EXP} - ETS_{CTL}$; g to l) between EXP (MT_ATSP, SG_AT, and SG_SP) and CTL, averaged over 24-72 h precipitation forecasts from the 00 UTC cycle in July 2022, for six domains [i.e., global domain (GLOB; a and g), Northern Hemisphere (NH; b and h), Southern Hemisphere (SH; c and i), Asia (ASIA; d and j), Europe (EU; e and k), and tropical area (TROP; f and l)]. The skill metrics are computed for seven conventional thresholds (i.e., 0.5, 1.0, 5.0, 10.0, 15.0, 20.0, and 25.0 mm day^{-1}). Negative ΔFB and positive ΔETS values indicate improvements from soil moisture DA.

4. In the conclusion, the authors should reiterate that a strength of the study is its use of multiple independent SM datasets, rather than relying on blended products, and briefly explain why it matters.

Response) In accordance with the reviewer's suggestion, we have included the following sentences in the conclusion section of the revised manuscript (Lines 1046–1053).

> "To conclude, a key aspect of this study is the joint assimilation of individual radar- and radiometer-based soil moisture products. Compared to assimilating pre-blended soil moisture data, this approach is advantageous because (1) it accounts for the relative uncertainties of both sensors, which vary across space and time; (2) it provides a flexible framework for incorporating various combinations of soil moisture data sources within DA systems; and (3) it is more suitable for near-real time operational forecast systems, the focus of this study, since soil moisture data blending processes may increase latency and thereby reduce data availability for operational use."

Specific comments

1. Line 164: a proper minus sign should be used to prevent the line break with the following number (this applies to the instances afterwards as well).

Response) A proper minus sign has been used consistently throughout the revised manuscript.

2. Line 166: unclear what "and restart files at 0 h" means, could you clarify?

Response) The phrase 'and restart files at 0 h' indicates that LIS generates a restart file at 0 h in the current UTC cycle. A restart file contains the full set of model state variables at that time, allowing the model to be seamlessly restarted from that point. In our case, the restart file created at 0 h is used to initialize LIS-LSM in the next UTC cycle.

To improve clarity, we have modified the related sentences in the revised manuscript (Lines 201–206; Lines 213–215) as follows:

> **[Original]** "This sequential EnKF procedure (i.e., SM forecast and analysis) is performed from −6 h to 0 h in the current UTC cycle, and LIS writes land outputs every 3 hours (i.e., −3 h and 0 h) and restart files at 0 h."
>
> **[Revised]** "This sequential EnKF procedure (i.e., soil moisture forecast and analysis) is performed from −6 h to 0 h in the current UTC cycle. LIS writes land outputs every 3 hours (i.e., at −3 h and 0 h) and generates a restart file at 0 h. The restart file contains the complete set of model state variables at that time, enabling LIS-LSM to be consistently re-initialized in the subsequent UTC cycle."

> **[Original]** "KIM is further run without DA until +9 h, and the KIM analysis/forecasts from 0 h to +6 h and the LIS-LSM restart file at 0 h in the current UTC cycle are then used for the next UTC cycle LIS implementation."

[Revised] “KIM is further run without DA until +9 h, and the KIM analysis/forecasts from 0 h to +6 h in the current UTC cycle are then used for the next UTC cycle LIS implementation.”

3. Line 179: what are the advantages of the KIM-LIS coupled system mentioned here?

Response) We modified the sentence (Lines 219–222 in the revised manuscript) to provide clearer information regarding the reviewer’s question, as follows:

“In addition, the KIM-LIS coupled system, which employs the LIS-based land DA, has several advantages: (1) it can readily leverage the existing land DA functions of LIS, and (2) it allows straightforward implementation of new land DA developments due to LIS’s extensible framework.”

4. Line 227: please state the specific DA assumption being cited.

Response) The specific DA assumption has already been briefly described at the beginning of the paragraph (Lines 269–270 in the revised manuscript), as shown below:

“Typical DA algorithms are designed to correct random errors under the assumption of unbiased state estimates between models and observations (Dee and da Silva, 1998).”

However, to enhance clarity, we have revised the sentence noted by the reviewer as follows (Lines 274–277 in the revised manuscript):

“Therefore, soil moisture DA systems essentially employ appropriate bias correction strategies to remove these systematic biases prior to assimilation, and thus to comply with the DA assumption of unbiased models and observations (Kolassa et al., 2017; Reichle and Koster, 2004)”

5. Line 232: I think that the reasoning for using different bias correction methods for the two SM datasets should be clearly stated here.

Response) Following the reviewer’s suggestion, we have added the following sentences to the revised manuscript (Lines 281–287) to clarify the application of different bias correction methods for ASCAT and SMAP.

“The use of the anomaly correction method for SMAP follows our previous investigations (Kwon et al., 2022, 2024) aiming to minimize the loss of useful information from the original data through bias correction. In contrast, traditional CDF matching is applied to ASCAT, since the anomaly correction method is not applicable due to difference in soil moisture data type between ASCAT (soil wetness index) and the model (volumetric soil moisture in m^3 m^{-3}). Further details are provided in the following two paragraphs.”

6. Line 409: please change to "March 1st 2022" or an equivalent format.

Response) Based on the reviewer's suggestion, "1 March 2022" has been changed to "March 1, 2022" (Line 473 in the revised manuscript), and the same change has been applied consistently throughout the manuscript.

7. Line 458: I think the formulation for $fMSE_k$ should be presented the same way as equations 2 to 4 for consistency.

Response) The equation for $fMSE_k$ has been modified to ensure consistency with other equations. Accordingly, the associated sentences have been revised in the manuscript (Lines 522–528) as follows:

> "In this study, the fractional mean-square error ($fMSE_k$, Draper et al., 2013), ranging from 0 (free-of-noise soil moisture data) to 1 (no meaningful soil moisture signal), is computed using Equation (5). This metric is employed as a TCA-based global soil moisture evaluation measure, following procedures implemented by Kim et al. (2020 and 2021a) and Kwon et al. (2024).
>
> $$fMSE_k = \frac{\sigma_{\varepsilon_k}^2}{\sigma_k^2} \quad (5)$$"

8. Lines 488-492: more information to justify the timestep of the LSM outputs that were used would improve clarity.

Response) To enhance clarity, the following sentences have been added to the revised manuscript (Lines 563–568).

> "We select model outputs at the approximate midpoint time (e.g., 04:00) between the overpass times of two other satellite-based soil moisture triplet components (e.g., 01:30 AMSR2 and 06:00 SMOS) for a fair comparison. While some errors may still arise due to sampling-time mismatches between the triplet components, we assume these errors are acceptable since the same sampling time was applied to both CTL and DA experimental outputs to evaluate their relative performance."

9. Line 616: "RMSD difference" is used here, but later, in tables 5 and 6, ΔRMSD is used. Please choose one for consistency.

Response) For consistency, we have revised the title of Table 5 as follows:

> "**Table 5.** Domain-averaged RMSD differences ($\Delta RMSD = RMSD_{EXP} - RMSD_{CTL}$) for the 2-m specific humidity and air temperature analyses and (5-day) forecasts across six domains …"

10. Lines 628–632: the statement that MT_ATSP results in a more “balanced improvement” than single-sensor DA methods needs clarification. What does it mean in this context?

Response) To improve clarity, we have revised the sentence as follows (Lines 738–742 in the revised manuscript):

> “Although MT_ATSP exhibits somewhat reduced performance in the air temperature (Figure 5c) and specific humidity analyses (Figure 5b) compared to SG_AT and SG_SP, respectively, it achieves a more balanced improvement, meaning that neither variable is degraded while both show moderate gains compared to CTL, by assimilating radar- and radiometer-based soil moisture data together.”

11. Line 713: I assume that the FB and ETS were computed for the 00 UTC cycles for all the days in July? The methodology to compute the precipitation amounts is a bit unclear.

Response) To enhance clarity, we revised the following paragraph (Lines 824–834 in the revised manuscript).

> “Daily precipitation rates (mm day^{-1}) are computed from the KIM forecasts at 0-24 h, 24-48 h, and 48-72 h lead times, and compared against reference data using seven conventional thresholds (0.5, 1.0, 5.0, 10.0, 15.0, 20.0, and 25.0 mm day^{-1}). The numbers of model grid points classified as *Hits*, *FalseAlarms*, *Misses*, and *CorrectNegatives* in the contingency table (Table 4) are then counted, and FB and ETS are calculated for six domains (i.e., global domain, Northern Hemisphere, Southern Hemisphere, Asia, Europe, and tropical area). Figure S2 presents the FB and ETS of daily precipitation forecasts from KIM, averaged over the three lead times, for CTL and the three soil moisture DA experiments (SG_AT, SG_SP, and MT_ATSP) during the 00 UTC cycle in July 2022. The corresponding differences ($\Delta\mathrm{FB} = |\mathrm{FB}_{\mathrm{EXP}} - 1| - |\mathrm{FB}_{\mathrm{CTL}} - 1|,\ \Delta\mathrm{ETS} = \mathrm{ETS}_{\mathrm{EXP}} - \mathrm{ETS}_{\mathrm{CTL}}$) are shown in Figure 7.”

12. Line 820: Please clarify if Figures S4 and S1c come from Kim et al. (2025) as well.

Response) To avoid confusion regarding the figure sources, we have revised the sentence as follows (Lines 951–953):

> “… and croplands in South Asia (Figure S6) [see Figure S3c for the land-cover type map generated in this study using the MODIS-IGBP global land-cover classification (Friedl et al., 2002)].”

Reviewer #2:

This manuscript evaluates the impact of assimilating ASCAT and SMAP soil moisture retrievals, both individually and simultaneously, within the KIM-LIS weakly coupled land-atmosphere data assimilation system. The aim is to assess the potential synergistic effects on global soil moisture analysis and numerical weather prediction skill. This work has significant prospects for application on related platforms and systems. The efforts made in this work are highly commendable. However, the validity of the evaluation methodology and the significance of the marginal improvements achieved are called into question. My suggestions are as follows:

Major comments:

1. The methodology used to quantify the improvement in accuracy from data assimilation (reported as 4.0% and 10.5% for ASCAT and SMAP, respectively) raises serious concerns. The approach of comparing TC-derived error estimates from two different triplets—specifically, comparing the error of CTL in the [AMSR2, SMOS, CTL] triplet with the error of the DA experiment (e.g., SG_AT) in the [AMSR2, SMOS, SG_AT] triplet—may not be fully justified. Since TC computes errors relative to the entire triplet in which a dataset is embedded, replacing one member (CTL with SG_AT) changes the reference framework and can lead to a re-balancing of the error estimates for all three components. This means the error estimates for CTL and the DA experiment may not be directly comparable across these two separate TC configurations. Therefore, the reported percentage improvements could be influenced by methodological artifacts rather than reflecting a true measure of performance.

Response) We agree with the reviewer's concern. Based on your comment, we conducted additional analyses and found that the fMSE calculation using different triplets does not significantly alter the results. This is because the replaced model-based triplet members (i.e., SG_AT, SG_SP, and CTL) are generated by the same land surface modeling system and share identical spatial grids, meteorological forcing, and climatology. In other words, each DA experiment and its corresponding CTL case differ only in the assimilated satellite-based soil moisture data, while the reference satellite products in each triplet (AMSR2-SMOS for SG_AT and AMSR2-ASCAT for SG_SP) remain the same. Consequently, the large-scale statistical relationships between the model-based and satellite-based soil moisture datasets are preserved, and replacing the CTL member with its DA counterpart (SG_AT or SG_SP) does not meaningfully alter the inter-dataset covariance structure or the fMSE estimates, as shown in Figure S1. Therefore, the impact of triplet replacement on the TCA-based fMSE results is negligible and does not affect the overall statistical conclusions or our main findings. We have added the following sentence in the revised manuscript (Lines 659–667) and provided Figure S1 in the supplementary material.

> "Note that we use identical first and second triplet components for DA and CTL (Table 3), replacing only the CTL soil moisture estimates with those from the DA experiments (SG_AT and SG_SP) to assess the relative performance gain from soil moisture DA. This approach (i.e., replacing one triplet member) may alter the fMSE calculation of the other two triplet components and thus influence the comparison results between DA and CTL. However, because the soil moisture estimates from DA and CTL share the same spatial and temporal coverage and

climatology, as they are generated from the identical modeling system, the impact of replacing the model-based triplet member is negligible, as shown in Figure S1. Therefore, the fMSE comparison results (Figure 2) can be considered reliable."

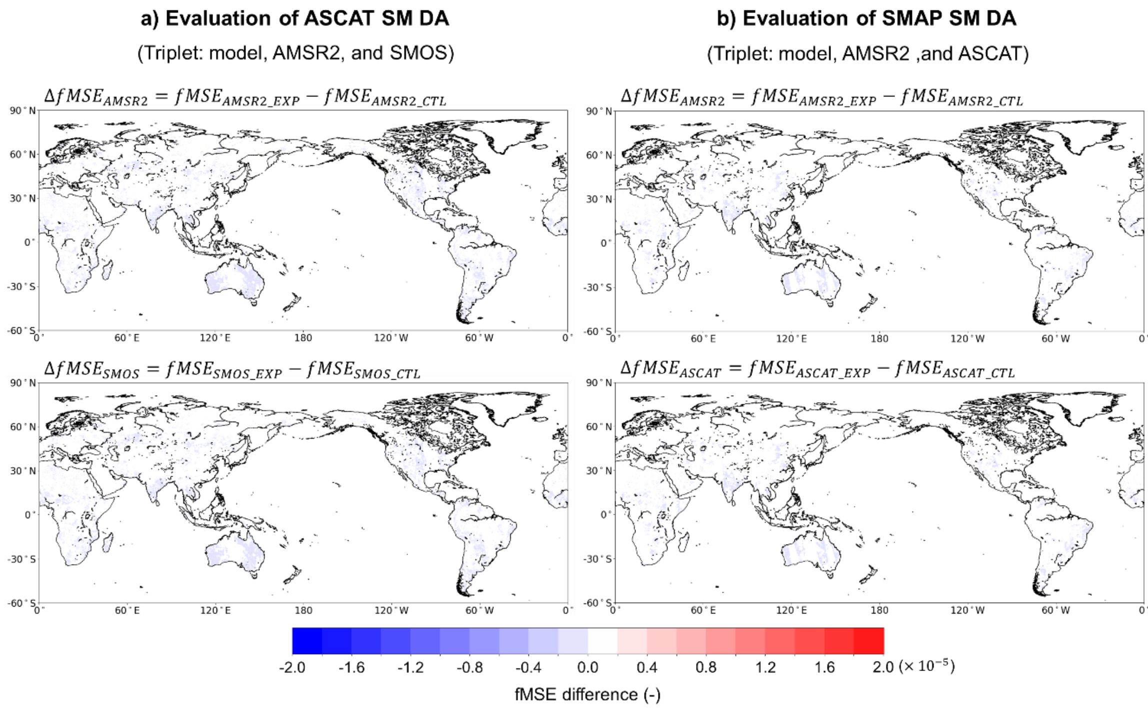

Figure S1. fMSE differences of AMSR2, SMOS, and ASCAT soil moisture data between DA and CTL experiments when used as triplet components to evaluate (a) ASCAT DA (SG_AT) and (b) SMAP DA (SG_SP).

2. A critical issue lies in the very limited to negligible improvement in the forecasts of key atmospheric variables. In some cases, negative skill increments are observed. These results significantly undermine the practical justification and operational feasibility of the proposed multi-sensor assimilation approach. Consequently, the study fails to provide readers with quantifiable and meaningfully positive conclusions regarding the benefits of simultaneously assimilating soil moisture retrievals for enhancing numerical weather prediction.

Response) We acknowledge that the overall domain-averaged improvements in atmospheric estimates from multi-sensor soil moisture data assimilation (DA), compared to single-sensor DA, are marginal. Nevertheless, we consider the findings of this study promising for several reasons. First, clear synergistic local skill improvements through multi-sensor DA are evident, particularly in regions and periods where both single-sensor experiments show positive impacts. Second, the magnitude of forecast skill improvements from both single- and multi-sensor soil moisture DA, relative to CTL, is comparable to those achieved in previous studies (e.g., Draper and Reichle, 2019; Lin and Pu, 2019; Muñoz-Sabater et al., 2019; Reichle et al., 2023), with multi-sensor DA yielding slightly better (though not statistically significant) performance. Importantly, although the improvements in near-surface variables are modest, the small but systematic gains in 2-m temperature and humidity directly contribute to better initialization of convective processes and precipitation forecasts. In fact, our results show that precipitation forecast skill was improved by the multi-sensor DA experiment. Finally, as emphasized in the manuscript, simultaneous assimilation of ASCAT and SMAP produces a more balanced improvement across atmospheric variables than single-sensor DA. These results highlight the value of assimilating soil moisture observations from multiple sensors, even though some trade-offs remain for certain variables in specific regions or periods where single-sensor impacts are conflicting.

Meanwhile, the marginal improvements in atmospheric variables, despite relatively significant improvements in soil moisture analysis through satellite-based DA, remain an ongoing issue in land-atmosphere coupled systems. While many processes may contribute, one potential factor is the soil moisture-latent heat flux coupling strength in land surface models, as discussed in several studies (e.g., Crow et al., 2023; Kwon et al., 2024; Lei et al. 2018).

We have revised the conclusion of the manuscript (Lines 1029–1067 in the revised manuscript) to emphasize the promising aspects of this study, acknowledge its limitations, and highlight the need for future studies to address these issues, in addition to our original discussions.

> "This study suggests that simultaneously assimilating the ASCAT and SMAP soil moisture products within the KIM-LIS coupled system can leverage their complementary advantages, as demonstrated for the estimates of specific humidity, air temperature, and precipitation. The findings obtained in this study are promising for three main reasons. First, clear synergistic local skill improvements from multi-sensor DA are evident, particularly in regions and periods where both single-sensor experiments show positive impacts. Second, the magnitude of atmospheric forecast skill improvements from both single- and multi-sensor soil moisture DA, relative to CTL, is comparable to improvements reported in previous studies (e.g., Draper and Reichle, 2019; Lin and Pu, 2019; Muñoz-Sabater et al., 2019; Reichle et al., 2023), with multi-sensor DA yielding slightly better (though not statistically significant) performance. Achieving consistent improvements across the globe remains challenging due to factors discussed in Section 8, which can cause local skill degradations in atmospheric estimates. Finally, as emphasized above, simultaneous assimilation of ASCAT and SMAP produces a more balanced improvement across atmospheric variables than single-sensor DA. These results highlight the value of assimilating soil moisture observations from multiple sensors, even if trade-offs remain for certain variables in regions or periods where single-sensor impacts conflict.
>
> To conclude, a key aspect of this study is the joint assimilation of individual radar- and radiometer-based soil moisture products. Compared to assimilating pre-blended soil moisture data, this approach is advantageous because (1) it accounts for the relative uncertainties of both sensors, which vary across space and time; (2) it provides a flexible framework for incorporating various combinations of soil moisture data sources within DA systems; and (3) it is more suitable for near-real time operational forecast systems, the focus of this study, since soil moisture data blending processes may increase latency and thereby reduce data availability for operational use. However, it is acknowledged that overall domain-averaged improvements in atmospheric estimates through multi-sensor soil moisture DA, relative to single-sensor DA, are still marginal and statistically insignificant. The following issues remain to be addressed in future studies to enhance future performance. First, the impact of subsurface scattering on the quality of the ASCAT soil moisture product under dry soil conditions needs to be considered in

quality control procedures. Second, an alternative soil moisture bias correction method, especially for ASCAT data, should be explored. Lastly, more realistic spatially or spatiotemporally distributed estimates of soil moisture observation errors are required to maximize the benefits of multi-sensor soil moisture DA. In addition, as discussed in several previous studies, addressing biases in the soil moisture-latent heat flux coupling in LSMs (Crow et al., 2023; Kwon et al., 2024; Lei et al. 2018), accounting for the background error covariance between atmospheric and land variables during DA (Kwon et al., 2024), and assimilating screen-level observations (de Rosnay et al., 2013; Lin and Pu, 2020) can improve the positive impacts of soil moisture DA on atmospheric forecast in coupled systems."

***References**

Crow, W.T., Kim, H., Kumar, S., 2023. Systematic modelling errors undermine the application of land data assimilation systems for hydrological and weather forecasting. J. Hydrometeor. 25, 3–26. https://doi.org/10.1175/JHM-D-23-0069.1.

de Rosnay, P., Drusch, M., Vasiljevic, D., Balsamo, G., Albergel, C., Isaksen, L., 2013. A simplified extended Kalman filter for the global operational soil moisture analysis at ECMWF. Q. J. Roy. Meteor. Soc. 139, 1199–1213. https://doi.org/10.1002/qj.2023.

Draper, C., Reichle, R.H., 2019. Assimilation of satellite soil moisture for improved atmospheric reanalyses. Mon. Weather Rev. 147, 2163–2188. https://doi.org/10.1175/MWR-D-18-0393.1.

Kwon, Y., Jun, S., Kim, E., Seol, K.-H., Hong, S., Kwon, I.-H., Kang, J.-H., Kim, H., 2024. Improving weather forecast skill of the Korean Integrated Model by assimilating Soil Moisture Active Passive soil moisture anomalies. Q. J. Roy. Meteor. Soc. 150, 5305–5336. https://doi.org/10.1002/qj.4871.

Lei, F., Crow, W.T., Holmes, T.R.H., Hain, C., Anderson, M.C., 2018. Global investigation of soil moisture and latent heat flux coupling strength. Water Resour. Res. 54, 8196–8215. https://doi.org/10.1029/2018WR023469.

Lin, L.-F., Pu, Z., 2019. Examining the impact of SMAP soil moisture retrievals on short-range weather prediction under weakly and strongly coupled data assimilation with WRF-Noah. Mon. Weather Rev. 147, 4345–4366. https://doi.org/10.1175/MWR-D-19-0017.1.

Lin, L.-F., Pu, Z., 2020. Improving near-surface short-range weather forecasts using strongly coupled land–atmosphere data assimilation with GSI-EnKF. Mon. Weather Rev. 148, 2863–2888. https://doi.org/10.1175/MWR-D-19-0370.1.

Muñoz-Sabater, J., Lawrence, H., Albergel, C., de Rosnay, P., Isaksen, L., Mecklenburg, S. et al., 2019. Assimilation of SMOS brightness temperatures in the ECMWF integrated forecasting system. Q. J. Roy. Meteor. Soc. 145, 2524–2548. https://doi.org/10.1002/QJ.3577.

Reichle, R.H., Zhang, S.Q., Kolassa, J., Liu, Q., Todling, R., 2023. A weakly-coupled land surface analysis with SMAP radiance assimilation improves GEOS medium-range forecasts of near-surface air temperature and humidity. Q. J. Roy. Meteor. Soc. 149, 1867-1889. https://doi.org/10.1002/qj.4486.

3. While the introduction outlines what the study does, it falls short in providing a comprehensive literature review and a compelling justification for why this study is necessary. Specifically, (1) the objective of enhancing soil moisture estimates by integrating satellite data is clear. however, the introduction lacks a critical discussion on the broader landscape of methodologies available to achieve this goal. Notably, it omits any mention of alternative approaches, such as statistical fusion techniques or the rapidly advancing field of machine learning, which have been extensively employed for soil moisture reconstruction, data fusion, and even forecasting. (2) The introduction describes the applicability of data assimilation in general (Lines 36-50), the use of ASCAT and SMAP in data assimilation (Lines 67-80), and the combination of active and passive sensors (Lines 81-93). Yet, it fails to clearly articulate the specific research gap and the novelty of this particular research. The reader is left wondering: What is the unique contribution of this work? Is it the use of the specific KIM-LIS coupled model platform? Is it the simultaneous assimilation of ASCAT and SMAP retrievals? If it is the former, the authors should more clearly articulate what makes the KIM-LIS platform itself a novel or particularly advantageous choice for this specific investigation, beyond merely being the system used. If the latter case, how does this approach differ from and improve upon previous studies that assimilate multi-source data?

Response) To address the reviewer's valuable comments, we have incorporated the following paragraphs into the revised manuscript.

*Lines 57–71:

> "In addition to DA methods, a variety of alternative data fusion techniques have been widely explored to integrate soil moisture information from different sources, including remote sensing products, in-situ measurements, model simulations, and reanalysis datasets. One group of approaches relies on statistical methods (e.g., Min et al., 2022; Wang et al., 2021; Xie et al., 2022), such as unweighted averaging, linear weight fusion, and emergent constraint. Another group leverages machine learning (e.g., Huang et al., 2023; Lamichhane et al., 2025; Long et al., 2019; Zhang et al., 2022, Zeng et al., 2024) and deep learning techniques (e.g., Fuentes et al., 2022; Huang et al., 2022; Jiang et al., 2025; Singh and Gaurav, 2023; van der Schalie et al., 2018). These machine learning and deep learning approaches are rapidly gaining prominence because of their ability to incorporate diverse data sources and to capture complex, nonlinear relationships between datasets (Huang et al, 2022; Zeng et al., 2024). While different fusion approaches have distinct strengths and limitations, this study is devoted to DA methods, with the goal of improving model-based soil moisture estimates that interact with atmospheric processes in operational land-atmosphere coupled systems, thereby enhancing weather forecasts."

***References**

Fuentes, I., Padarian, J., Vervoort, R.W., 2022. Towards near real-time national-scale soil water content monitoring using data fusion as a downscaling alternative. J. Hydrol. 609, 127705. https://doi.org/10.1016/j.jhydrol.2022.127705.

Huang, S., Zhang, X., Wang, C., Chen, N., 2023. Two-step fusion method for generating 1 km seamless multi-layer soil moisture with high accuracy in the Qinghai-Tibet plateau. ISPRS J. Photogramm. 197, 346–363. https://doi.org/10.1016/j. isprsjprs.2023.02.009.

Huang, S., Zhang, X., Chen, N., Ma, H., Fu, P., Dong, J., Gu, X., Nam, W.-H., Xu, L., Rab, G., Niyogi, D., 2022. A novel fusion method for generating surface soil moisture data with

high accuracy, high spatial resolution, and high spatiotemporal continuity. Water Resour. Res. 58, e2021WR030827. https://doi.org/10.1029/2021WR030827.
Jiang, M., Qiu, T., Wang, T., Zeng, C., Zhang, B., Shen, H., 2025. Seamless global daily soil moisture mapping using deep learning based spatiotemporal fusion. Int. J. Appl. Earth Obs. 139, 104517. https://doi.org/10.1016/j.jag.2025.104517.
Lamichhane, M., Mehan, S., Mankin, K.R., 2025. Surface soil moisture prediction using multimodal remote sensing data fusion and machine learning algorithms in semi-arid agricultural region. Sci. Remote Sens. 12, 100255. https://doi.org/10.1016/j.srs.2025.100255.
Long, D., Bai, L., Yan, L., Zhang, C., Yang, W., Lei, H., Quan, J., Meng, X., Shi, C., 2019. Generation of spatially complete and daily continuous surface soil moisture of high spatial resolution. Remote Sens. Environ. 233, 111364. https://doi.org/10.1016/j.rse.2019.111364.
Min, X., Shangguan, Y., Li, D., Shi, Z., 2022. Improving the fusion of global soil moisture datasets from SMAP, SMOS, ASCAT, and MERRA2 by considering the non-zero error covariance. Int. J. Appl. Earth Obs. 113, 103016. https://doi.org/10.1016/j.jag.2022.103016.
Singh, A., Gaurav, K., 2023. Deep learning and data fusion to estimate surface soil moisture from multi-sensor satellite images. Sci. Rep. 13, 2251. https://doi.org/10.1038/s41598-023-28939-9.
van der Schalie, R., de Jeu, R., Rodríguez-Fernández, N., Al-Yaari, A., Kerr, Y., Wigneron, J.-P., Parinussa, R., Drusch, M., 2018. The Effect of three different data fusion approaches on the quality of soil moisture retrievals from multiple passive microwave sensors. Remote Sens. 10, 107. https://doi.org/10.3390/rs10010107.
Wang, Y., Mao, J., Jin, M., Hoffman, F.M., Shi, X., Wullschleger, S.D., Dai, Y., 2021. Development of observation-based global multilayer soil moisture products for 1970 to 2016. Earth Syst. Sci. Data 13, 4385–4405. https://doi.org/10.5194/essd-13-4385-2021.
Xie, Q., Jia, L., Menenti, M., Hu, G., 2022. Global soil moisture data fusion by Triple Collocation Analysis from 2011 to 2018. Sci. Data 9, 687. https://doi.org/10.1038/s41597-022-01772-x.
Zhang, H., Wang, S., Liu, K., Li, X., Li, Z., Zhang, X., Liu, B., 2022. Downscaling of AMSR-E soil moisture over north China using random forest regression. ISPRS Int. J. Geo Inf. 11, 101. https://doi.org/10.3390/ijgi11020101.
Zheng, J., Yuan, X., Ji, P., 2024. The important role of reliable land surface model simulation in high-resolution multi-source soil moisture data fusion by machine learning. J. Hydrol. 630, 130700. https://doi.org/10.1016/j.jhydrol.2024.130700.

*Lines 138–150:

> “While several studies have explored the simultaneous use of radar and radiometer-based soil moisture data in offline land DA systems, mainly to improve soil moisture estimates and associated hydrological processes (e.g., Draper et al., 2012; Khaki and Awange, 2019; Khaki et al., 2019, 2020; Kolassa et al., 2017; Kumar et al., 2019; Nair and Indu, 2019; Renzullo et al., 2014; Seo et al., 2021; Tangdamrongsub et al., 2020), only a few have investigated their impacts on atmospheric forecasts in land-atmosphere coupled NWP systems (e.g., de Rosnay et al., 2022; Draper and Reichle, 2019; Fairbairn et al., 2024). Even among studies

using coupled forecast systems, most assimilate only ASCAT and SMOS together, despite evidence that SMAP provides high-quality soil moisture data (e.g., Bhuiyan et al., 2018; Chan et al., 2018; Colliander et al., 2017) and often outperforms other sensors (Kumar et al., 2018). In this regard, the novelty of this study is the combined use of ASCAT and SMAP soil moisture products in the KIM-LIS-based land-atmosphere coupled DA system, demonstrating their feasibility."

***References**

Bhuiyan, H., McNairn, H., Powers, J., Friesen, M., Pacheco, A., Jackson, T. J., Cosh, M. H., Colliander, A., Berg, A., Rowlandson, T., Bullock, P., Magagi, R., 2018. Assessing SMAP soil moisture scaling and retrieval in the carman (Canada) study site. Vadose Zone J. 17, 180132. https://doi.org/10.2136/vzj2018.07.0132.

Chan, S.K., Bindlish, R., O'Neill, P., Jackson, T., Njoku, E., Dunbar, S. et al., 2018. Development and assessment of the SMAP enhanced passive soil moisture product. Remote Sens. Environ. 204, 931–941. https://doi.org/10.1016/j.rse.2017.08.025.

Colliander, A., Jackson, T.J., Bindlish, R., Chan, S., Das, N., Kim, S. B. et al., 2017. Validation of SMAP surface soil moisture products with core validation sites. Remote Sens. Environ. 191, 215–231. https://doi.org/10.1016/j.rse.2017.01.021.

de Rosnay, P., Browne, P., de Boisséson, E., Fairbairn, D., Hirahara, Y. et al., 2022. Coupled data assimilation at ECMWF: current status, challenges and future developments. Q. J. Roy. Meteor. Soc. 148, 2672–2702. https://doi.org/10.1002/qj.4330.

Draper, C.S., Reichle, R.H., De Lannoy, G.J.M., Liu, Q., 2012. Assimilation of passive and active microwave soil moisture retrievals. Geophys. Res. Lett. 39, L04401. https://doi.org/10.1029/2011GL050655.

Draper, C., Reichle, R.H., 2019. Assimilation of satellite soil moisture for improved atmospheric reanalyses. Mon. Weather Rev. 147, 2163–2188. https://doi.org/10.1175/MWR-D-18-0393.1.

Fairbairn, D., de Rosnay, P., Weston, P., 2024. Evaluation of an adaptive soil moisture bias correction approach in the ECMWF land data assimilation system. Remote Sens. 16, 493. https://doi.org/10.3390/rs16030493.

Khaki, M., Awange, J., 2019. The application of multi-mission satellite data assimilation for studying water storage changes over South America. Sci. Total Environ. 647, 1557–1572. https://doi.org/10.1016/j.scitotenv.2018.08.079.

Khaki, M., Hendricks Franssen, H.-J., Han, S.C., 2020. Multi-mission satellite remote sensing data for improving land hydrological models via data assimilation. Sci. Rep. 10, 18791. https://doi.org/10.1038/s41598-020-75710-5.

Khaki, M., Hoteit, I., Kuhn, M., Forootan, E., Awange, J., 2019. Assessing data assimilation frameworks for using multi-mission satellite products in a hydrological context. Sci. Total Environ. 647, 1031–1043. https://doi.org/10.1016/j.scitotenv.2018.08.032.

Kolassa, J., Reichle, R.H., Draper, C.S., 2017. Merging active and passive microwave observations in soil moisture data assimilation. Remote Sens. Environ. 191, 117–130. https://doi.org/10.1016/j.rse.2017.01.015.

Kumar, S.V., Dirmeyer, P.A., Peters-Lidard, C.D., Bindlish, R., Bolten, J., 2018. Information theoretic evaluation of satellite soil moisture retrievals. Remote Sens. Environ. 204, 392–400. https://doi.org/10.1016/j.rse.2017.10.016.

Kumar, S.V., Jasinski, M., Mocko, D.M., Rodell, M., Borak, J., Li, B., Beaudoing, H.K., Peters-Lidard, C.D., 2019. NCA-LDAS land analysis: Development and performance of

a multisensory, multivariate land data assimilation system for the national climate assessment. J. Hydrometeorol. 20, 1571–1593. https://doi.org/10.1175/JHM-D-17-0125.1.
Nair, A.S., Indu, J., 2019. Improvement of land surface model simulations over India via data assimilation of satellite-based soil moisture products. J. Hydrol. 573, 406–421. https://doi.org/10.1016/j.jhydrol.2019.03.088.
Renzullo, L.J., van Dijk, A.I.J.M., Perraud, J.-M., Collins, D., Henderson, B., Jin, H., Smith, A.B., McJannet, D.L., 2014. Continental satellite soil moisture data assimilation improves root-zone moisture analysis for water resources assessment. J. Hydrol. 519, 2747–2762. https://doi.org/10.1016/j.jhydrol.2014.08.008.
Seo, E., Lee, M.-I., Reichle, R.H., 2021. Assimilation of SMAP and ASCAT soil moisture retrievals into the JULES land surface model using the Local Ensemble Transform Kalman Filter. Remote Sens. Environ. 253, 112222. https://doi.org/10.1016/j.rse.2020.112222.
Tangdamrongsub, N., Han, S.-C., Yeo, I.-Y., Dong, J., Steele-Dunne, S.C., Willgoose, G., Walker, J.P., 2020. Multivariate data assimilation of GRACE, SMOS, SMAP measurements for improved regional soil moisture and groundwater storage estimates. Adv. Water Resour. 135, 103477. https://doi.org/10.1016/j.advwatres.2019.103477.

4. The manuscript is overloaded with abbreviations, making it exceedingly difficult to read. This is particularly problematic in the Abstract and Figure Captions, where the pervasive use of undefined acronyms obscures the authors' intended message and hinders comprehension. The authors should prioritize clarity over brevity and significantly reduce the use of non-standard abbreviations to ensure their work is accessible to a broad audience.

Response) The following abbreviations have been replaced with their full names to reduce abbreviation usage in the revised manuscript. While abbreviations are retained for commonly used terminologies, satellite missions and data product names, well-known institutions, and specific systems, models, and algorithms, we have added a list of abbreviations in Appendix A of the revised manuscript.

“SM” → “soil moisture”
“QC” → “quality control”
“KMA” → “Korea Meteorological Administration”
“NRT” → “near-real time”
“SWI” → “soil wetness index”
“CONUS” → “continental United States”
“GVF” → “green vegetation fraction”
“BEC” → “background error covariance”
“GC” → “Gaspari and Cohn”
“RTPP” → “relaxation-to-prior perturbation”
“1-D” → “1-dimensional”
“SW” → “shortwave radiation”
“LW” → “longwave radiation”
“P” → “precipitation”
“ML” → “machine learning”
“T_B” → “brightness temperature”
“H” → “horizontally”

“V” → “vertically”

Appendix A: Abbreviations

AMSR2	Advanced Microwave Scanning Radiometer 2
AMSU-A	Advanced Microwave Sounding Unit-A
AMVs	Atmospheric Motion Vectors
ASCAT	Advanced SCATterometer
ATMS	Advanced Technology Microwave Sounder
CDF	Cumulative distribution function
CDR	Climate Data Record
CPC	Climate Prediction Center
CrIS	Cross-track Infrared Sounder
CTL	Control case serving as a baseline experiment
DA	Data assimilation
DCA	Dual Channel Algorithm
EASE	Equal Area Scalable Earth
ECMWF	European Centre for Medium-Range Weather Forecasts
EnKF	Ensemble Kalman filter
ERA5	Fifth generation of the ECMWF atmospheric reanalysis
ESA CCI	European Space Agency Climate Change Initiative
ESME	Estimated Soil Moisture Error
ETS	Equitable threat score
EUMETSAT	European Organisation for the Exploitation of Meteorological Satellites
FAO	Food and Agriculture Organization
FB	Frequency bias
fMSE	Fractional mean-square error
GLDAS	Global Land Data Assimilation System
GPS-RO	Global Positioning System Radio Occultation
Hybrid 4DEnVar	Hybrid four-dimensional ensemble variational
IASI	Infrared Atmosphere Sounding Interferometer
IFS	Integrated Forecasting System
IGBP	International Geosphere-Biosphere Programme
KIAPS	Korea Institute of Atmospheric Prediction Systems
KIM	Korean Integrated Model
KPOP	KIM Package of Observation Processing
KVAR	KIM VARiational
LETKF	Local ensemble transform Kalman filter
LIS	Land Information System
LPRM	Land Parameter Retrieval Model
LSM	Land surface model
LST	Local solar time
L2	Level 2
MetOp	Meteorological Operational
MHS	Microwave Humidity Sounder

MODIS	Moderate resolution imaging spectroradiometer
MT_ATSP	Multi-sensor soil moisture data assimilation experiment
NASA	National Aeronautics and Space Administration
NCEP	National Centers for Environmental Prediction
NOAA	National Oceanic and Atmospheric Administration
NSIDC	National Snow and Ice Data Center
NWP	Numerical weather prediction
RFI	Radio Frequency Interference
RMSD	Root mean square difference
SG_AT	Single-sensor data assimilation experiment using the ASCAT soil moisture data
SG_SP	Single-sensor data assimilation experiment using the SMAP soil moisture data
SMAP	Soil Moisture Active Passive
SMOS	Soil Moisture and Ocean Salinity
SMOS-IC	SMOS-INRA-CESBIO
SRTM	Shuttle Radar Topography Mission
STATSGO	State Soil Geographic
TCA	Triple collocation analysis
TU Wien	Vienna University of Technology
UTC	Coordinated Universal Time
VV	Vertical transmit vertical receive
WMO	World Meteorological Organization
4DIAU	Four-dimensional incremental analysis update

In addition, we have revised the abstract to reduce abbreviations, and included full names for certain abbreviations in figure and table captions to improve clarity. The revised abstract and captions are shown below.

Abstract: "The combined use of independent soil moisture data from radar and radiometer measurements in data assimilation (DA) systems is expected to yield synergistic performance gains due to their complementary strengths. This study evaluates the impact of simultaneously assimilating soil moisture retrievals from ASCAT (Advanced SCATterometer) and SMAP (Soil Moisture Active Passive) into the Korean Integrated Model (KIM) using a weakly coupled DA framework based on the National Aeronautics and Space Administration's Land Information System (LIS). The Noah land surface model (LSM) within LIS, which is the same as that used in KIM, is used to simulate land surface states and assimilate soil moisture retrievals. The impact of soil moisture DA is evaluated using independent reference datasets, assessing its influence on soil moisture analysis and numerical weather prediction performance. Overall, assimilating ASCAT or SMAP soil moisture data into the LSM improves global soil moisture analysis accuracy by 4.0% and 10.5%, respectively, compared to the control case without soil moisture DA, achieving the most significant enhancements in croplands. Relative to single-sensor soil moisture DA, multi-sensor soil moisture DA yields more balanced skill enhancements for both specific humidity and air temperature analyses and forecasts. The most pronounced synergistic improvements by simultaneously assimilating both soil moisture products are observed in the 2-m air temperature analysis and

forecast, especially when both soil moisture products have a positive impact. The results also demonstrate that precipitation forecast skill, particularly in predicting precipitation events, can be enhanced by constraining the modeled soil moisture with multiple soil moisture retrievals from different sources. This paper discusses remaining issues for future studies to further improve the weather prediction performance of the KIM-LIS multi-sensor soil moisture DA system."

"**Figure 1.** Schematic diagram of the KIM-LIS-based land-atmosphere weakly coupled data assimilation (DA) system. The figure outlines the process flow between KIM and LIS in one UTC cycle that is performed four times (i.e., 00, 06, 12, and 18 UTC cycles) a day. (IAU: incremental analysis update, QC: quality control)"

"**Figure 2.** Global maps of the soil moisture triple collocation analysis (TCA) results for (a) ASCAT (i.e., SG_AT) and (b) SMAP soil moisture data assimilation (i.e., SG_SP). Upper panels show the fractional mean-square error (fMSE) of CTL soil moisture at 04:00 am/pm local solar time (LST) (left panel) and 11:00 am/pm LST (right panel), respectively. Lower panels show the soil moisture fMSE difference between SG_AT and CTL (left panel) and between SG_SP and CTL (right panel) where the negative fMSE difference indicates the improved soil moisture estimates by ASCAT and SMAP soil moisture DA, respectively."

"**Figure 3.** Differences in the soil moisture fractional mean-square error (fMSE) between the single-sensor soil moisture data assimilation (i.e., SG_AT and SG_SP) and control [without soil moisture data assimilation (DA); i.e., CTL] experiments depending on land cover types. A dominant land cover type in each model grid is obtained from the MODIS-IGBP land cover classifications (Friedl et al., 2002). The asterisk symbol (*) indicates statistical significance at $p < 0.05$. Negative values represent the improved soil moisture estimates by soil moisture DA. Results are not plotted for closed shrublands and permanent wetlands because of missing triplet data."

"**Figure 4.** Vertical profile time series of RMSD differences in the specific humidity analysis (left column) and air temperature analysis (right column) between the soil moisture data assimilation (DA) and CTL experiments. The RMSD is calculated using the ECMWF-IFS analysis as reference data. Negative RMSD differences indicate improved estimates of the atmospheric variables by assimilating the soil moisture retrievals."

"**Figure 5.** Vertical profile time series of RMSD differences in the specific humidity analysis (left column) and air temperature analysis (right column) between the multi-sensor soil moisture data assimilation (DA) (MT_ATSP) and single- sensor soil moisture DA [SG_AT (a and c) and SG_SP (b and d)] experiments. The RMSD is calculated using the ECMWF-IFS analysis as reference data. Negative RMSD differences indicate improved estimates of the atmospheric variables by additionally assimilating the SMAP or ASCAT soil moisture retrievals."

"**Figure 6.** Difference in the 2-m atmospheric analysis RMSD [i.e., specific humidity (upper panels) and air temperature (lower panels)] between the soil moisture data assimilation (DA) and CTL experiments. Evaluation results for the 12 UTC cycle from June to July 2022 (a two-month period) are presented with domain-averaged values in parenthesis. The RMSD is calculated using the ECMWF-IFS analysis as reference data. Negative RMSD differences indicate improved estimates of the atmospheric variables by assimilating the soil moisture retrievals."

"**Figure 7.** Differences in frequency bias ($\Delta \mathrm{FB} = |\mathrm{FB}_{\mathrm{EXP}} - 1| - |\mathrm{FB}_{\mathrm{CTL}} - 1|$; a to f) and equitable threat score ($\Delta \mathrm{ETS} = \mathrm{ETS}_{\mathrm{EXP}} - \mathrm{ETS}_{\mathrm{CTL}}$; g to l) between EXP (MT_ATSP, SG_AT, and SG_SP) and CTL, averaged over 24-72 h precipitation forecasts from the 00 UTC cycle in July 2022, for six domains [i.e., global domain (GLOB; a and g), Northern Hemisphere (NH; b and h), Southern Hemisphere (SH; c and i), Asia (ASIA; d and j), Europe (EU; e and k), and tropical area (TROP; f and l)]. The skill metrics are computed for seven conventional thresholds (i.e., 0.5, 1.0, 5.0, 10.0, 15.0, 20.0, and 25.0 mm day^{-1}). Negative ΔFB and positive ΔETS values indicate improvements from soil moisture DA."

"**Figure 8**. ASCAT soil moisture error standard deviations used for ASCAT soil moisture data assimilation (DA) in this study. The spatially distributed ASCAT soil moisture errors (m^3 m^{-3}) are derived by rescaling the constant 10% soil wetness index using the ratio of the standard deviations of the Noah land surface model (LSM) and ASCAT soil moisture time series."

"**Table 1.** Perturbation parameter values used for autoregressive temporal correlation and cross correlations between different variables (SW: shortwave radiation, LW: longwave radiation, P: precipitation, SM1: top layer soil moisture, SM2: second layer soil moisture, SM3: third layer soil moisture, and SM4: bottom layer soil moisture)."

"**Table 2.** Summary of land-atmosphere coupled data assimilation (DA) experiments conducted in this study (SM: soil moisture; see Appendix A for additional abbreviations)."

"**Table 3.** Triple collocation analysis (TCA) triplet composition to quantify the relative improvement in the soil moisture estimates by soil moisture data assimilation (DA) as compared to CTL. The CTL soil moisture estimates are also evaluated using the same satellite-based reference soil moisture products as used for each single-sensor soil moisture DA experiment (EXP: SG_AT and SG_SP)."

"**Table 5.** Domain-averaged RMSD differences ($\Delta \mathrm{RMSD} = \mathrm{RMSD}_{\mathrm{EXP}} - \mathrm{RMSD}_{\mathrm{CTL}}$) for the 2-m specific humidity and air temperature analyses and (5-day) forecasts across six domains [i.e., global domain (GLOB), Northern Hemisphere (NH), Southern Hemisphere (SH), Asia (ASIA), Europe (EU), and tropical area (TROP)]. The RMSD is calculated for the 00 UTC cycle from April to July 2022 (whole experimental period) using the ECMWF-IFS analysis as reference data. Negative ΔRMSD indicates improved estimates of the atmospheric variables by assimilating the soil moisture retrievals."

Minor comments:

1. Line 1: The abstract lacks a clear statement of the research motivation. It should briefly highlight the importance of assimilating multi-sensor soil moisture data for improving numerical weather prediction to better contextualize the study for reader.

Response) Based on the reviewer's comment, the following sentence has been added in the abstract of the revised manuscript (Lines 2–4).

> "The combined use of independent soil moisture data from radar and radiometer measurements in data assimilation (DA) systems is expected to yield synergistic performance gains due to their complementary strengths."

2. Lines 405-412: The choice to use GLDAS for LSM spin-up but ERA5 for model initialization may introduce inconsistencies. Although GLDAS is a land data assimilation system and ERA5 is reanalysis, both of them provide land surface data and atmospheric forcing data. The authors should address whether this discrepancy in forcing data sources could have impacted the results.

Response) We understand the reviewer's concern but we believe that the impact of this discrepancy on the experimental results is negligible for two reasons. First, as noted in the manuscript, although the long-term offline spin-up (2008–2020) of the Noah LSM was driven by GLDAS forcing fields, it was additionally run from 2020 to 2022 using the historical KIM forcing data until March 1, 2022. This minimizes the discrepancy between KIM and LSM. Second, we conducted an additional one-month spin-up (March 1–31, 2022) of the coupled system. Because the atmospheric model does not require a long-term spin-up, this one-month period is sufficient to ensure consistency between KIM and LSM.

3. Lines 421-422: "The four experiments (i.e., CTL, SG_AT, SG_SP, and MT_ATSP) listed in Table 1". The experiments are listed in Table 2.

Response) We appreciate the reviewer's careful reading. We have corrected "Table 1" to "Table 2" in the revised manuscript (Line 451).