Response to reviewers' comments

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.

Dear Reviewer #1:

My co-authors and I would like to thank you for your 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 your comments. We appreciate your consideration and look forward to your feedback.

Regards,

Yonghwan Kwon and co-authors

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**

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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.

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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 ($\Delta\mathrm{FB} = |\mathrm{FB}_{\mathrm{EXP}} - 1| - |\mathrm{FB}_{\mathrm{CTL}} - 1|$, $\Delta\mathrm{ETS} = \mathrm{ETS}_{\mathrm{EXP}} - \mathrm{ETS}_{\mathrm{CTL}}$) are shown in Figure 7.

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)."

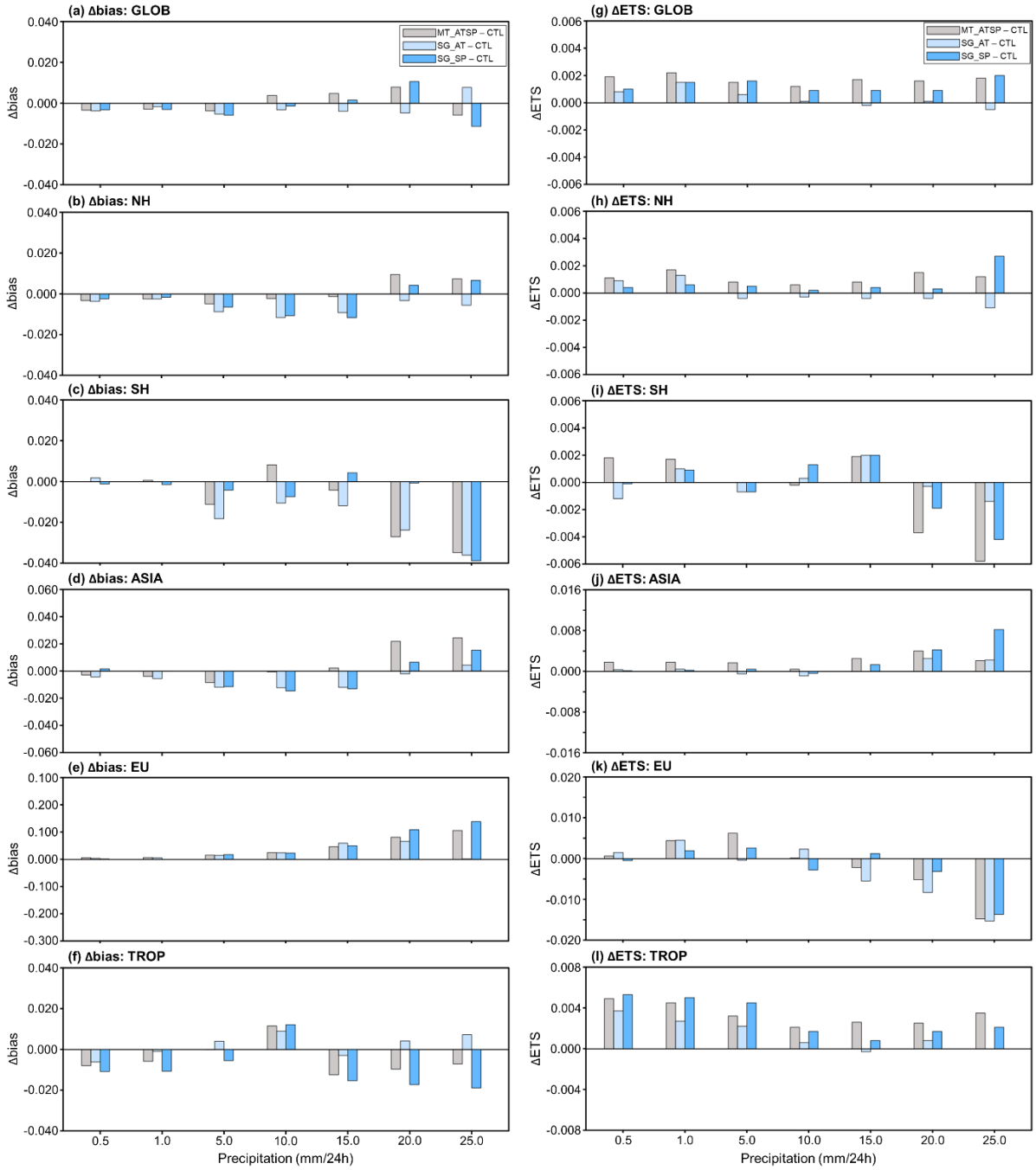

Figure 7. Differences in frequency bias ($\Delta FB = |FB_{EXP} - 1| - |FB_{CTL} - 1|$; a to f) and equitable threat score ($\Delta ETS = ETS_{EXP} - ETS_{CTL}$; g to l) between EXP (MT_ATSP, SG_AT, and SG_SP) and CTL, averaged over 24-72 h precipitation forecasts from the 00 UTC cycle in July 2022, 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).
>
> $$fMSE_k = \frac{\sigma^2_{\varepsilon_k}}{\sigma^2_k} \quad (5)$$"

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)]."