Response to reviewers' comments

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:

Dear Reviewer #2:

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

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."

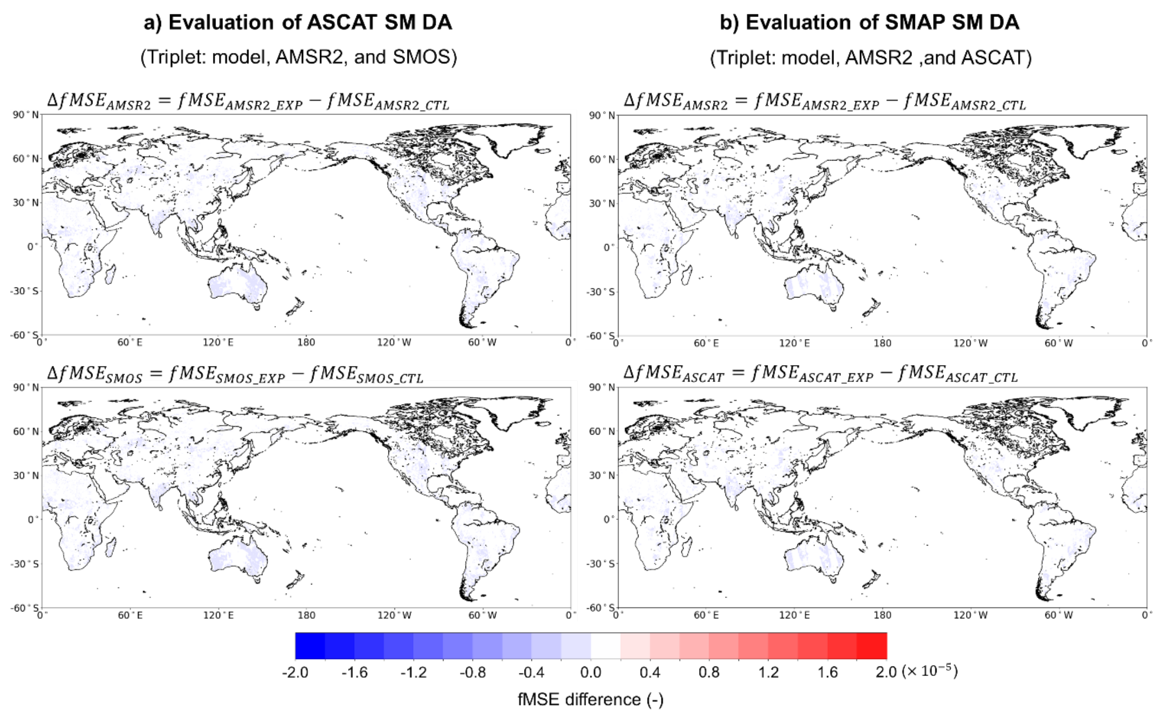

Figure S1. fMSE differences of AMSR2, SMOS, and ASCAT soil moisture data between DA and CTL experiments when used as triplet components to evaluate (a) ASCAT DA (SG_AT) and (b) SMAP DA (SG_SP).

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."

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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."

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*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."

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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 ($\Delta RMSD = RMSD_{EXP} - RMSD_{CTL}$) 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).