Response to Reviews of “Assimilation of snow water equivalent from AMSR2 and IMS satellite data utilizing the local ensemble transform Kalman filter” by Joonlee lee, Myong-In Lee, Sunlae Tak, Eunkyo Seo, and Yong-Keun Lee. ([Geoscientific Model Development](https://www.geoscientific-model-development.net/): #gmd-2023-221)

We would like to thank the reviewers for their valuable feedback. Their insightful comments helped improve the quality of this paper. After examining the reviewers' comments, we have corrected and modified our manuscript. Our responses to the individual comments are provided below in blue.

**Reply to the Reviewer (#3)’s Comments :**

**Review of “Assimilation of snow water equivalent from AMSR2 and IMS satellite data utilizing the local ensemble transform Kalman filter”**

**Summary**

**This work assimilates the snow retrieval from AMSR2 (and the snow cover from IMS, albeit indirectly) into the JULES model using LETKF. The data assimilation (DA) framework offers an objective way to optimally combine the two imperfect dataset: the JULES model which has larger uncertainty in the transitional region, and the satellite retrieval which on the other hand exhibits greater uncertainty in the deep snow region. It is shown that the DA simulation is able to provide better initial conditions and forecast for snow, compared to the one without DA and other existing methods.**

**Overall, the DA approach and the experiment setup are carefully designed, the analyses are done well, and the results hold promise. However, there are concerns about the coherence in the current manuscript, especially in the introduction, making it difficult for the readers to follow and to understand the significance of this work. Therefore, I suggest a major revision in this iteration.**

**Comments**

**L70-117: Different snow states products derived using in-situ observation, remote-sensing retrievals, and using numerical models are summarized in these three paragraphs. However, these paragraphs appear disconnected. The coherence could be improved by trimming some unnecessary details, and emphasizing more on, e.g, (1) advantage/limitations of each dataset (2) the exactly snow state (i.e., SWE, SD, SCF, etc) that each dataset provides. Following these paragraphs, e.g., a comparison/summary paragraph for these dataset could be presented, which can lead to the explanation why data assimilation or other data fusion methods are considered necessary/beneficial for constructing snow states.**

Response) Thank you for your comment. As suggested by the reviewer’s comment, we have revised these paragraphs related to different snow states products derived using in-situ observation, remote-sensing retrievals, and using numerical models

Revision) (L85-L125) Snow states, i.e., snow water equivalent (SWE) used directly for hydrological analysis and initial states of the model (Li et al., 2019; Gan et al., 2021), are generally provided from in-situ observations data, remote-sensing retrievals from satellites, or numerical models such as the land surface model (LSM) operated based on the observed atmospheric variables. For the in-situ data snow depth (SD) measurements prevail, largely attributed to the challenges associated with acquiring precise SWE data (Takala et al., 2011; De Rosnay et al., 2014). Surface synoptic observations (SYNOP) serve as the principal source for SD measurements. The in-situ measurements offer the most dependable snow information, yet they are characterized by relatively coarse temporal and spatial resolutions, particularly within limited areas, due to the spatial heterogeneity inherent in snow distribution. (Helmert et al., 2018; Meyal et al., 2020). Satellite-derived observations using conical scanning microwave instruments may provide spatially consistent data coverage across the globe. Cho et al. (2017) showed the SWE retrieval results from two passive microwave sensors, the advanced microwave scanning radiometer 2 (AMSR2) and the special sensor microwave imager sounder (SSMIS). However, the algorithms for SWE retrieval exhibit a degree of sensitivity to a variety of parameters such as snow liquid water content and snow grain size distribution (De Rosnay et al., 2014). Hence, satellite-based SWE data still have limitations in accuracy, especially under deep snow conditions due to the limited penetration depth (Gan et al., 2021). On the other hand, satellite retrieval can estimate snow cover accurately under clear sky conditions (Brubaker et al., 2009). Model simulations obtained from LSMs and simple snow models can cover complete spatiotemporal resolution but involve potentially large uncertainties due to the deficiencies in the physical parameterizations and meteorological forcing data (Dirmeyer et al., 2006; Seo et al., 2021).

Considering that snow observation datasets have their respective strengths as well as limitations, data assimilation or other data fusion methods can prove to be beneficial for constructing snow states such as reanalysis data (e.g., Brasnett, 1999; Dee et al., 2011; Meng et al., 2012; Pullen et al., 2011; De Rosnay et al., 2014). For example, the snow analysis for the Canadian Meteorological Center (CMC) utilizes a 2-dimensional optimal interpolation (2D-OI) scheme with in-situ observations and the outputs from a simple snow model (Brown et al., 2003). The National Centers for Environmental Prediction (NCEP) climate forecast system reanalysis (CFSR) combines a multi-satellite-based interactive multi-sensor snow and ice mapping system (IMS) as satellite-based snow cover retrieval and the outputs from the global snow model of the Air Force Weather Agency (Meng et al., 2012). At the European Center for Medium Weather Forecast (ECMWF), the ECMWF reanalysis (ERA)-Interim and ERA5 for the snow analysis employ a Cressman interpolation and 2D-OI, respectively, with the IMS, in-situ observation, and the results from a land surface model (Dee et al. 2011; De Rosnay et al., 2014). The Japanese 55-year Reanalysis (JRA55) also utilizes the 2D-OI with in-situ observation, satellite-based snow cover from SSMIS, and the results from an LSM (Kobayashi et al., 2015). Given that the majority of the reanalysis datasets rely on snow depth measurements, the SWE estimation is likely to introduce potential accuracy concerns when the snow depth information is combined with the sow density calculations.

**L103-117: These methods (e.g., optimal interpolation) are similar to using data assimilation in the sense that they both combine the model simulation with the observations. You might want to emphasize why your DA system is a better method compared to these existing methods.**

Response) We have revised the manuscript to highlight the reasons why our data assimilation system outperforms existing methods.

Revision) (L154-L179) However, most previous studies have focused on targeted regions with limited ground-based observations. Snow initialization in global coverage using satellite-derived SWE remains a persistently challenging task.

Therefore, this study developed an advanced SWE data assimilation framework with satellite remote-sensing data using the local ensemble transform Kalman filter (LETKF) and the Joint U.K. Land Environment Simulator (JULES) land model. This constitutes a novel approach that has not been previously attempted, and it offers an objective way to optimally combine two imperfect data sources: the satellite SWE from the Advanced Microwave Scanning Radiometer 2 (AMSR2) and the dynamically-balanced SWE from the JULES land model forced by observed atmospheric fields. The estimated SWE data exhibit better consistence by additionally using snow cover data from the IMS data. This assimilation framework also enables the assessment of improvement as it provides insights into the reasons behind the performance improvement based on the Kalman gain analysis that measures the relative significance of the input data between the satellite and the land model during the data assimilation cycle. The satellite data have demonstrated high reliability in the transition regions of climatologically-shallow snow conditions (Gan et al., 2021), and these regions are known as "hot spots" of strong atmosphere-land coupling through snow melting and associated surface energy and water balance changes (Koster et al., 2004; Dirmeyer, 2011; Huning and AghaKouchak, 2020). From these perspectives, it would be important to evaluate the impact of satellites on the transition regions as well as on the deep accumulation regions where accurate satellite retrievals are challenging. Furthermore, the benefits of assimilating satellite retrievals in extremely high-temperature events, such as the case in April 2020 over Eurasia, can be elucidated. In this regard, we expect that this snow data assimilation framework with satellite-derived SWE can be significant in providing optimal snow initial states for improving the S2S prediction by global climate models.

(L299-L324) The snow assimilation is conducted based on the LETKF (e.g., Hunt et al., 2007), which is utilized to combine remotely sensed retrievals with the LSM model outputs (a.k.a. backgrounds) to produce a snow analysis. Unlike variational data assimilation methods, non-variational approaches (i.e., ensemble-based filters) characterize a probabilistic representation with the spread of the ensemble serving as an estimate of forecast uncertainty. LETKF has several advantages over other data assimilation methods. First, LETKF can efficiently handle large datasets and high-dimensional state variables by localizing the covariance matrix. This offers efficiency in parallel computing, making it suitable for real-time forecasting and high-resolution data assimilation. In this study, the horizontal local patch size and the localization length scale parameters are defined as 150 km and 30 km (Table 1), respectively. This approach involves the weight function for the covariance localization within the local patch centered at the analysis grid (e.g., Houtekamer and Mitchell, 2001; Hamill et al., 2001). This function assigns larger errors to observations located farther away from the center of the local patch, as proposed by Miyoshi and Yamane (2007), depending on the Gaussian function. Secondly, the method utilizes model simulation ensembles to capture the uncertainty in the initial states and background errors, which allows for a better representation of the flow-dependent probability distribution of the state variables that vary in time and space. Third, the LETKF employs an inflation parameter to adjust the ensemble spread, ensuring realistic uncertainty estimation by accounting for background errors. The underestimation of the analysis error covariance is typically issued by spatially and temporally constant boundary conditions and observation errors and limited ensemble members. Based on the standardized LETKF, this study applies a multiplicative covariance inflation of 20% of the spread of 24 member ensembles for each data assimilation cycle. Furthermore, the Kalman gain analysis (Seo et al., 2021), which quantifies the ratio of the background error to the total error (equivalent to the sum of the background and the observation error), is conducted. This analysis serves to determine the weights assigned to assimilated observations in the analysis update processes of the LETKF

**L135: The connection between this and the previous paragraph is unclear.**

Response) We have made revisions to ensure clarity and coherence between the preceding and subsequent paragraphs.

Revision) (L134-L144) However, in regions where ground observations are unavailable, large errors may exist in the snow model outputs due to uncertainties in atmospheric forcing and imperfect model parameterization (Boone et al., 2004; Essery et al., 2009). Often, the snow processes parameterized in LSMs rely on observed properties sampled in limited areas (Lim et al., 2022). In addition, as IMS snow cover only identifies the presence of snow, the data assimilation with the satellite snow cover only is not sufficient and inappropriate in constraining water and energy conservation. Alternative methods that consider the physical quantity of snow are required for the snow initialization.

One approach to mitigate the spatial discontinuity of ground observations is to use satellite-derived SWE with wide spatial coverage and frequent temporal resolution.

**L143-146, 149-151: You may want to emphasize the unique contribution of this work compared to previous studies mentioned in these lines.**

Response) We have revised the sentences to emphasize the unique contributions of our study compared to previous research.

Revision) (L154-L179) However, most previous studies have focused on targeted regions with limited ground-based observations. Snow initialization in global coverage using satellite-derived SWE remains a persistently challenging task.

Therefore, this study developed an advanced SWE data assimilation framework with satellite remote-sensing data using the local ensemble transform Kalman filter (LETKF) and the Joint U.K. Land Environment Simulator (JULES) land model. This constitutes a novel approach that has not been previously attempted, and it offers an objective way to optimally combine two imperfect data sources: the satellite SWE from the Advanced Microwave Scanning Radiometer 2 (AMSR2) and the dynamically-balanced SWE from the JULES land model forced by observed atmospheric fields. The estimated SWE data exhibit better consistence by additionally using snow cover data from the IMS data. This assimilation framework also enables the assessment of improvement as it provides insights into the reasons behind the performance improvement based on the Kalman gain analysis that measures the relative significance of the input data between the satellite and the land model during the data assimilation cycle. The satellite data have demonstrated high reliability in the transition regions of climatologically-shallow snow conditions (Gan et al., 2021), and these regions are known as "hot spots" of strong atmosphere-land coupling through snow melting and associated surface energy and water balance changes (Koster et al., 2004; Dirmeyer, 2011; Huning and AghaKouchak, 2020). From these perspectives, it would be important to evaluate the impact of satellites on the transition regions as well as on the deep accumulation regions where accurate satellite retrievals are challenging. Furthermore, the benefits of assimilating satellite retrievals in extremely high-temperature events, such as the case in April 2020 over Eurasia, can be elucidated. In this regard, we expect that this snow data assimilation framework with satellite-derived SWE can be significant in providing optimal snow initial states for improving the S2S prediction by global climate models.

**L162-163: “model error” -> I recommend change to “background error” (also in other places). Also, the Kalman gain measures the ratio of the background error to the sum of the background and the observation error.**

Response) As the point well taken, we corrected it.

**L218-220: it’s unclear how SCF is used based on the statement. You do explain it later in the text, but I suggest add something like ‘this will be detailed later in Section …’**

Response) Thank you for your comment. We have added a sentence indicating that further explanations will be provided later in the manuscript, as per the reviewer's comment.

Revision) (L205-L207) In this study, the application of the assimilation process is determined based on IMS-based SCF, renowned for its superior reliability (e.g., Brown et al., 2014). Further details will be described in Section 3.3.

**L251: I suggest change “due to randomness” -> “to account for the uncertainties in these variables”**

Response) As the point well taken, we corrected it.

**L265-267: This sentence is unclear. The bias/mean of what?**

Response) The sentence has been revised to provide a clear explanation, aiming to enhance understanding.

Revision) (L275-L278) The discrepancy in SWE between remote sensing and LSMs often arises due to uncertainties in the model physics and forcing data and satellite retrievals. These uncertainties can lead to a significant discrepancy in SWE between model simulations and satellite remote-sensing retrievals, potentially degrading performance.

**L293: ‘true probability distribution’ -> ‘flow-dependent probability distribution’**

Response) As the point well taken, we corrected it.

**L294: ‘LETKF applies an adaptive inflation scheme’ -> ‘LETKF is able to adopt an adaptive inflation scheme’.**

Response) As the point well taken, we corrected it.

Revision) (L315-L317) Third, the LETKF employs an inflation parameter to adjust the ensemble spread, ensuring realistic uncertainty estimation by accounting for background errors.

**L294-296:** **In most adaptive inflation schemes (for adjusting the ensemble spread), they are used to address to issues of insufficient ensemble spread, which mainly comes from the insufficient ensemble size (i.e., sampling errors) and model errors that are not properly accounted for. I suggest rephrase the sentence and delete the observational error. In addition, since the adaptive inflation scheme (to adjust the ensemble spread) is not used in this work, maybe you could just remove it as it doesn’t add much here.**

Response) The sentence has been revised in accordance with the reviewer's comment.

Revision) (L315-L321) Third, the LETKF employs an inflation parameter to adjust the ensemble spread, ensuring realistic uncertainty estimation by accounting for background errors. The underestimation of the analysis error covariance is typically issued by spatially and temporally constant boundary conditions and observation errors and limited ensemble members. Based on the standardized LETKF, this study applies a multiplicative covariance inflation of 20% of the spread of 24 member ensembles for each data assimilation cycle.

**L296-320: This paragraph needs to be rewritten. There are many details in the equations that are not explained. Since these equations are quite standard for LETKF, I would recommend trim down some details, and use plain language to briefly explain what LETKF is and how it works. Also, you might want to introduce and define Kalman gain here as it is discussed in Section 4.2.**

Response) Thank you for your comment. In response to the reviewer's comment, we have streamlined and provided a concise explanation of some details regarding LETKF. Additionally, we have included the definition of Kalman gain in this section.

Revision) (L299-L324) The snow assimilation is conducted based on the LETKF (e.g., Hunt et al., 2007), which is utilized to combine remotely sensed retrievals with the LSM model outputs (a.k.a. backgrounds) to produce a snow analysis. Unlike variational data assimilation methods, non-variational approaches (i.e., ensemble-based filters) characterize a probabilistic representation with the spread of the ensemble serving as an estimate of forecast uncertainty. LETKF has several advantages over other data assimilation methods. First, LETKF can efficiently handle large datasets and high-dimensional state variables by localizing the covariance matrix. This offers efficiency in parallel computing, making it suitable for real-time forecasting and high-resolution data assimilation. In this study, the horizontal local patch size and the localization length scale parameters are defined as 150 km and 30 km (Table 1), respectively. This approach involves the weight function for the covariance localization within the local patch centered at the analysis grid (e.g., Houtekamer and Mitchell, 2001; Hamill et al., 2001). This function assigns larger errors to observations located farther away from the center of the local patch, as proposed by Miyoshi and Yamane (2007), depending on the Gaussian function. Secondly, the method utilizes model simulation ensembles to capture the uncertainty in the initial states and background errors, which allows for a better representation of the flow-dependent probability distribution of the state variables that vary in time and space. Third, the LETKF employs an inflation parameter to adjust the ensemble spread, ensuring realistic uncertainty estimation by accounting for background errors. The underestimation of the analysis error covariance is typically issued by spatially and temporally constant boundary conditions and observation errors and limited ensemble members. Based on the standardized LETKF, this study applies a multiplicative covariance inflation of 20% of the spread of 24 member ensembles for each data assimilation cycle. Furthermore, the Kalman gain analysis (Seo et al., 2021), which quantifies the ratio of the background error to the total error (equivalent to the sum of the background and the observation error), is conducted. This analysis serves to determine the weights assigned to assimilated observations in the analysis update processes of the LETKF.

**L317-318: You mentioned the adaptive inflation scheme, but here you apply a fixed inflation scheme. Have you tried using any adaptive inflation scheme to adjust the ensemble spread?**

Response) In this study, we employ an inflation parameter based on a previous study (e.g., Seo et al., 2021), instead of utilizing the adaptive inflation scheme. The ensemble spread in this study demonstrates a sufficiently valid magnitude in comparison with the RMSE, as illustrated in SFig. 1, indicating that it is well estimated.

Revision) (L315-L321) Third, the LETKF employs an inflation parameter to adjust the ensemble spread, ensuring realistic uncertainty estimation by accounting for background errors. The underestimation of the analysis error covariance is typically issued by spatially and temporally constant boundary conditions and observation errors and limited ensemble members. Based on the standardized LETKF, this study applies a multiplicative covariance inflation of 20% of the spread of 24 member ensembles for each data assimilation cycle.

**L321: You may want to add a few sentences to** **briefly explain what the localization is(and also why) here, before introducing the weight function.**

Response) Thank you for your comment. We have added a brief explanation about localization in accordance with the reviewer's comment.

Revision) (L304-L312) First, LETKF can efficiently handle large datasets and high-dimensional state variables by localizing the covariance matrix. This offers efficiency in parallel computing, making it suitable for real-time forecasting and high-resolution data assimilation. In this study, the horizontal local patch size and the localization length scale parameters are defined as 150 km and 30 km (Table 1), respectively. This approach involves the weight function for the covariance localization within the local patch centered at the analysis grid (e.g., Houtekamer and Mitchell, 2001; Hamill et al., 2001). This function assigns larger errors to observations located farther away from the center of the local patch, as proposed by Miyoshi and Yamane (2007), depending on the Gaussian function.

**L342-345: The assignment of the observation error seems to be a little arbitrary here. Are there any studies trying to estimate the observation error (e.g., using Desroziers et al. 2005) for this retrieval? I suggest elaborate more on the observation error as it is an important part of the DA system.** **Desroziers, G., Berre, L., Chapnik, B. and Poli, P. (2005), Diagnosis of observation, background and analysis-error statistics in observation space. Q.J.R. Meteorol. Soc., 131: 3385-3396.**

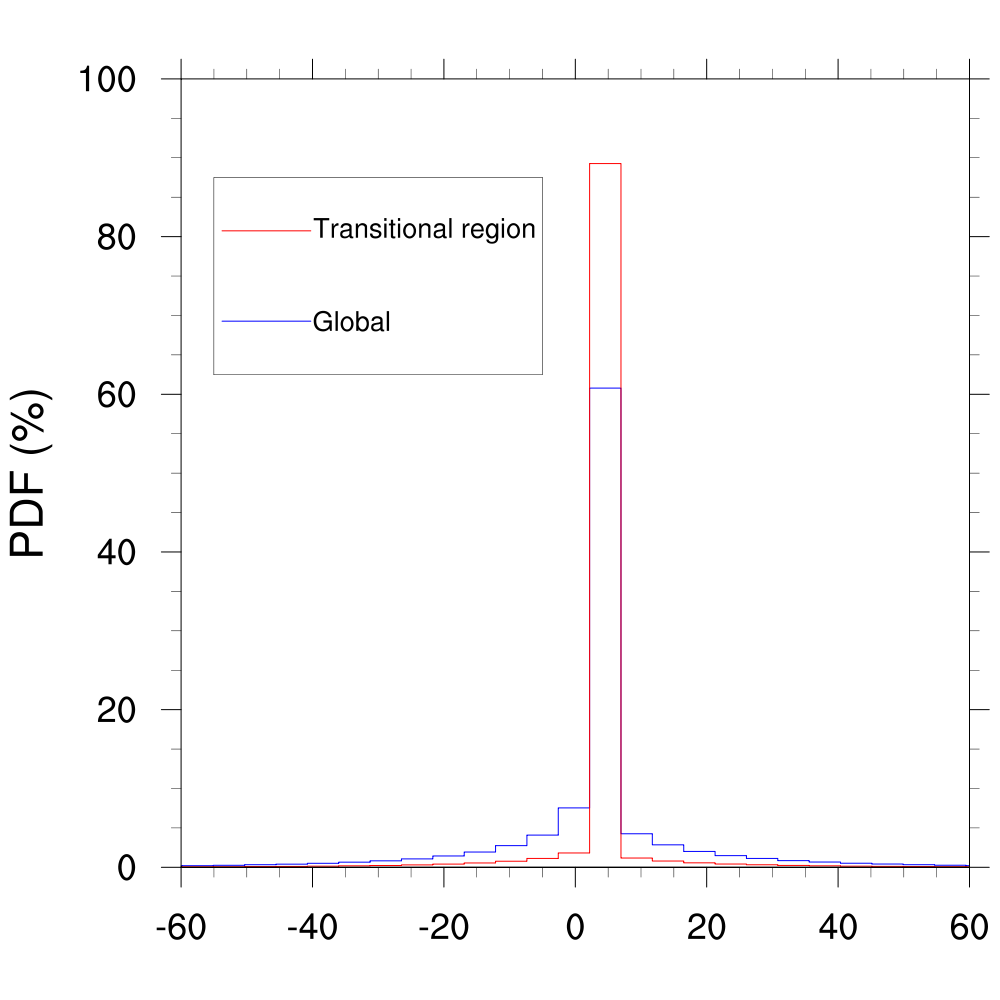
Response) As mentioned by reviewers, observational error in data assimilation is a crucial aspect within the context. Regrettably, there is a lack of previous studies addressing the accurate observational errors pertaining to AMSR2 SWE. Therefore, the observation error in this study is conservatively prescribed as 10% of AMSR2 SWE for each grid compared to the previous study utilizing AMSR2 SWE data (Lee et al., 2015), considering the general increase in the errors during the snow accumulation period with the development of deep snowpack. It has been revised as follows:

Revision) (L335-L339) Due to the absence of precise error estimates for AMSR2 SWE retrievals, the observation error is conservatively prescribed as 10% of AMSR2 SWE for each grid compared to the previous study utilizing AMSR2 SWE data (Lee et al., 2015), considering the general increase in the errors during the snow accumulation period with the development of deep snowpack (Foster et al., 2005; Cho et al., 2017).

**Minor comments for the DA setup:**

**(1) LETKF is optimal when the background error is Gaussian distributed. I suspect that in the transitional region, the ensemble distribution of SWE might not be Gaussian (e.g., when some ensemble members have snow while others do not). It might be interesting to have a look at the background and analysis ensemble at these grids.**

Response) Thank you for your comment. Unlike soil moisture, SWE presents varying characteristics in the CDF distribution across different regions, such as between high and low latitudes or when some regions have snow while others do not, thus requiring the estimation of distribution at each grid point. However, the SWE distribution among ensemble members consistently exhibited a Gaussian distribution (Additional\_Fig.1). Particularly, a distinct Gaussian distribution was evident in transitional regions, indicating its association with performance enhancement through data assimilation with optimized background error distribution. In response to this aspect, the following content has been incorporated into the manuscript.

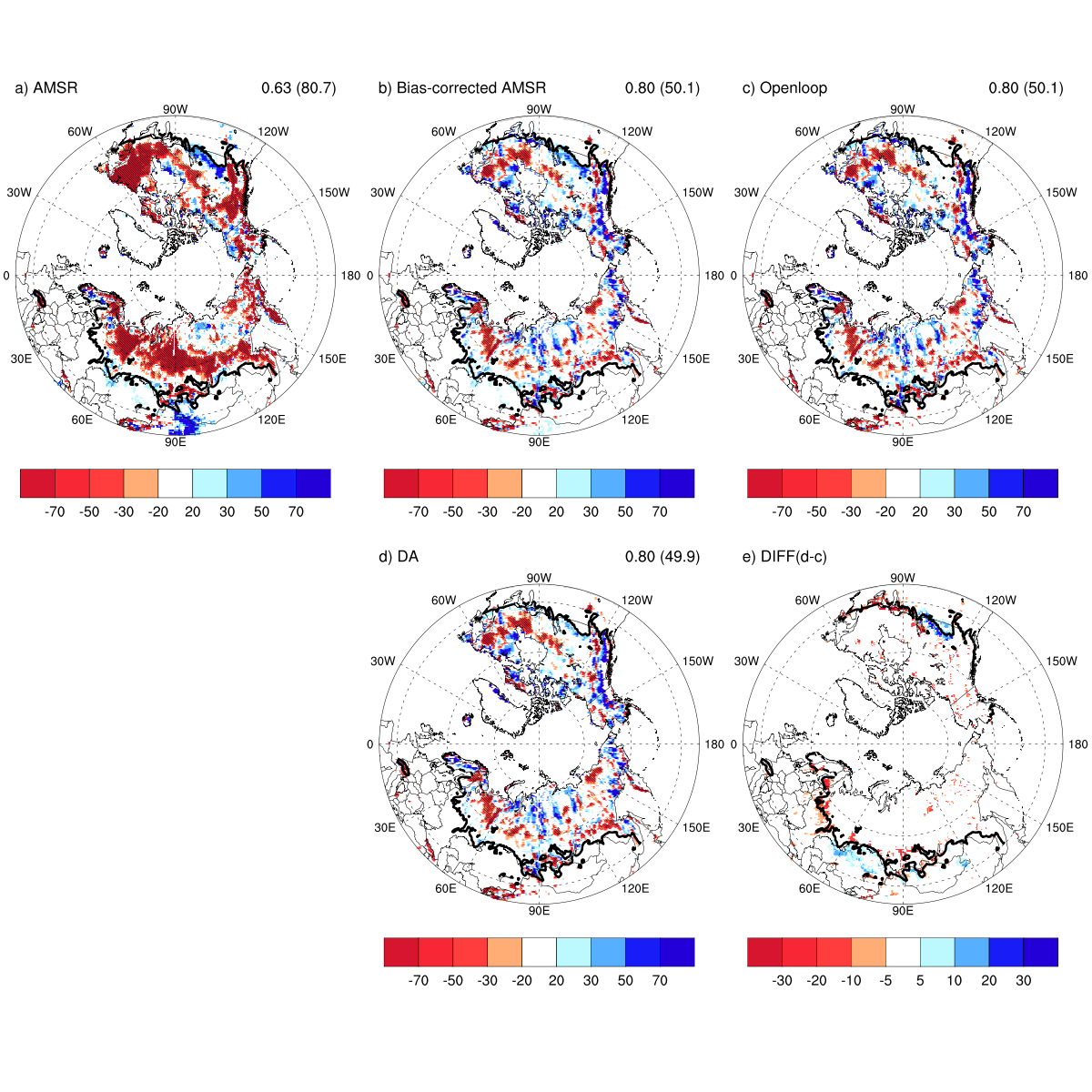


Additional\_Figure1 (Supplementary Fig. 4). Probability Density Function (PDF) of ensemble distribution for Snow Water Equivalent (SWE) over Global (red line) and Transitional Region (red line) for April during 2013-2020.

Revision) (L460-L463) The ensemble spread in this study demonstrates a sufficiently valid magnitude in comparison with the RMSE, as illustrated in SFig. 1, indicating that it is well estimated. Moreover, the SWE distribution among ensemble members consistently exhibited a Gaussian distribution, with a distinct this distribution particularly evident in transitional regions (SFig. 4).

**(2) The observation error standard deviation is assigned to be proportional to the observed value. With this situation-dependent observation error, it is easier for DA to decrease the model SWE (when model > obs) as opposed to increase SWE (when model < obs). I am curious if this leads to negative biases in the SWE?**

Response) Thank you for your comment. In Figure 8, similar to observational errors (Fig. 8a), it is apparent that the background error exhibits considerable variation depending on the quantity of snow (Fig. 8b). Also, due to standard normal deviation scaling as bias correction applied to the satellite data utilized in data assimilation (Additional \_Fig.2b), no discernible structural negative bias in the data assimilation results is evident (Additional \_Fig.2d). Through additional figures, we can observe that the areas where bias is improved via data assimilation are predominantly transitional regions (Additional \_Fig.2e).

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Additional\_Figure2. Mean bias of SWE from CMC for AMSR2 (a), bias-corrected AMSR (b), Openloop (c), and DA (d), and difference (e: d-c) for April during 2013-2020. The black line represents the boundary of the transition region, defined as the climatological-mean SWE of less than 16mm. Each value on the top right is the pattern correlation with CMC for 26482 pixels over 40N and the root-mean-squared difference (unit: kg/m2) from CMC (parenthesis) for 15323 pixels over 40-60N. Negative values in red shades are indicated with a diagonal line.

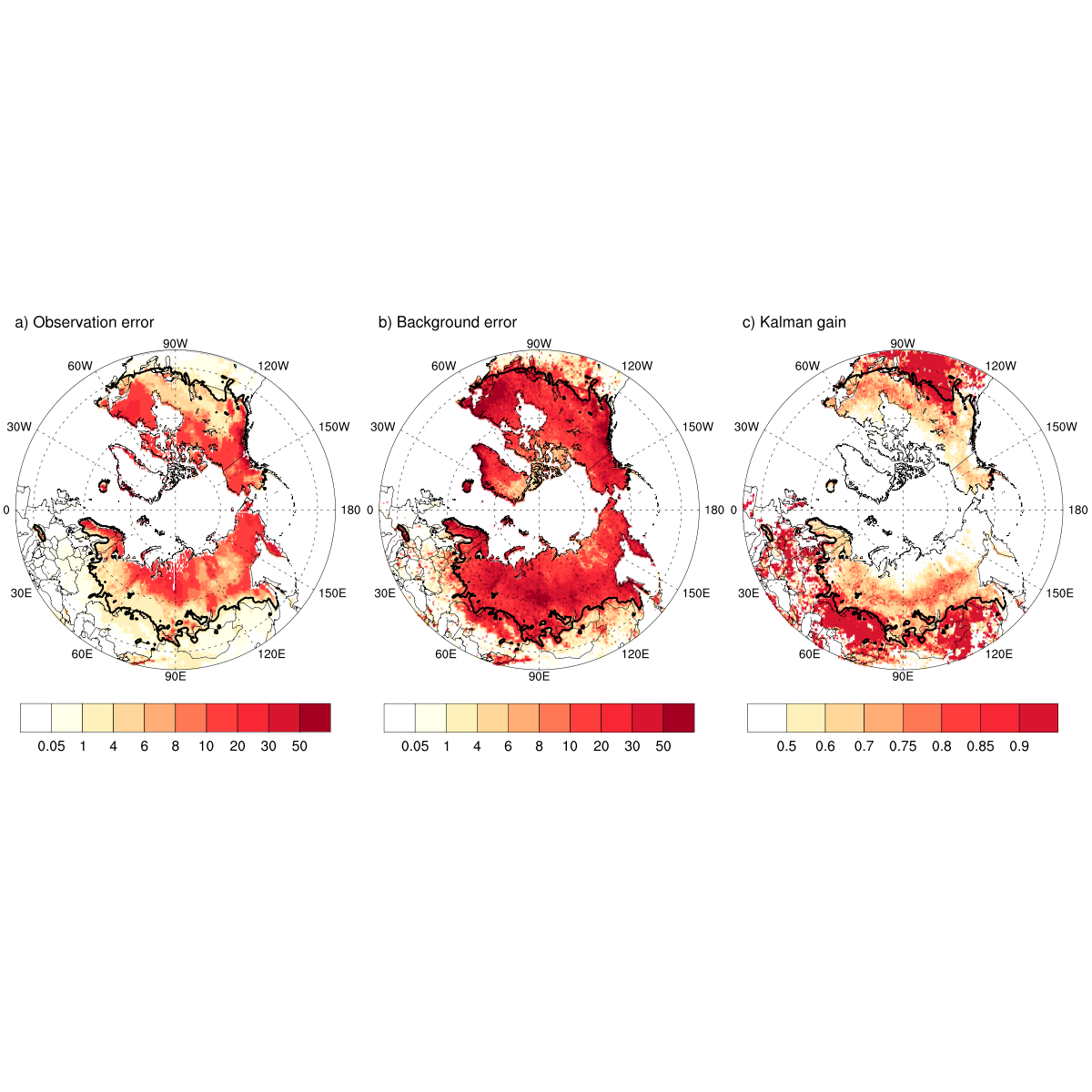


Figure 8. Spatial distribution of observation error (unit: kg/m2), background error (unit: kg/m2), and Kalman gain. The black line represents the boundary of the transition region, defined as the climatological-mean SWE of less than 16mm.

**L433-434 (and Figure 7): Although overall DA is better than DA\_AMSR2, there are more blue patches in DA compared to DA\_AMSR2. DA\_AMSR2 shows improvement almost globally. Do you have any comments on this?**

Response) DA exhibits inferior performance compared to Openloop in certain exceptional cases, which may be attributed to discrepancies in snow identification between the CMC observations used for correlation and the IMS data utilized for data assimilation. Based on the reviewer’s comment, we have modified the sentence as follows:

Revision) (L439-L442) Notably, the skill is enhanced significantly in DA by incorporating the IMS SCF. DA exhibits inferior performance compared to Openloop in certain exceptional cases, which may be attributed to discrepancies in snow identification between the CMC observations used for correlation and the IMS data utilized for data assimilation.

**L455 (and S Figure 1): It’s hard to tell from (c) that the ratios are one especially in the transitional region. Nevertheless, the overall pattern in (a) and (b) looks similar, which is a good sign, suggesting the ensemble system does a decent job in quantifying the uncertainty. I suggest change (b) to ‘ensemble spread’.**

Response) As the point well taken, we corrected it.

**L478-481: I am not sure if I understand the causal relation implied here. Please clarify.**

Response) We have clarified the implied causality in this sentence based on the reviewer's comment.

Revision) (L485-L488) Additionally, it has been revealed that the occurrence of high temperatures in the Siberian region is found to be closely associated with large-scale atmospheric waves in the upper atmosphere over the Eurasian region originating from the Atlantic (De Angelis et al., 2023).

**L486-489: To my understanding, the change in the land component does not feedbackto the atmospheric conditions in your DA setup (e.g., Figure 1). Therefore, I suspect if we can see the mechanism mentioned in L486-489 in your DA experiment. Do you really see the mechanism by comparing DA and OpenLoop, or is L486-489 simply an inference for a hypothetical scenario when a two-way coupled system is used? Please clarify.**

Response) Previous study (Collow et al., 2022) shows the land-atmosphere interaction utilizing a coupled atmosphere-land model. We have modified the potentially misleading sentence to more accurately represent the content of the paper as follows:

Revision) (L493-L497) Substantial snow melt can contribute to record-breaking heatwaves through albedo feedback and changes in the ratio of the latent and sensible heat fluxes from the exposed surface, coupled with favorable atmospheric circulation patterns (Collow et al., 2022). Collow et al. (2022) demonstrated that the exposed surface contributed to up to 20% of the temperature anomaly over Siberia in spring 2020.

**L766 (Figure 1): “OBSERVAIONS” -> “OBSERVATIONS”**

Response) As the point well taken, we corrected it.