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: #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 (#1)'s Comments:

I appreciate the authors' substantial effort to revise the manuscript and address the issues raised in the previous review. The manuscript has been improved, especially in the introduction, which now better highlights the value and the significance of the work. I have only a few very minor questions/suggestions, which I believe won't significantly affect the quality of the paper. Therefore, I consider the manuscript in good shape for publication.

L108: I suggest revise it as "Considering that each snow observation dataset has its respective strengths…"

Response) Corrected as suggested.

L342-345: This sentence is long. I suggest break it into several shorter sentences.

Response) Modified as suggested.

Revision) (L342-L345) In addition, the analysis state of this method is calculated based on the IMS snow cover fraction as follows (Fig. 1). If the SCF from IMS is zero, the snow analysis is set to 0; otherwise, it is derived through data assimilation.

L450: I suggest add "for SWE" after "the Kalman gain" to be more specific

Response) Modified as suggested.

L462-464: a few comments

(1) In SFig.4, does the x-axis refer to the ensemble perturbation of SWE (i.e., SWE of each

ensemble member minus SWE ensemble mean), instead of the SWE? Can SWE be negative?

Response) As the reviewer correctly pointed out, the SWE in SFig.4 represents the ensemble perturbations, with the ensemble mean removed from each ensemble member. To prevent any misunderstanding, we have revised the caption accordingly.

Revision) **Supplementary Fig. 4** Probability density function (PDF) of the standardized SWE ensemble perturbation, with the ensemble mean removed from each ensemble member, at each grid point. The PDF is averaged globally (blue line) and for the transition region (red line) for April from 2013 to 2020. The black line represents the standardized Gaussian function N(0,1).

(2) It is not clear to me whether the distribution look like Gaussian at all.

Response) We agree with the reviewer's comments. We have recalculated the standardized ensemble spread at each grid point and created a new figure accordingly. Consequently, we have revised the relevant text in the manuscript.

Revision) (L462-464) Moreover, the standardized distribution of SWE among the ensemble members exhibits a quasi-Gaussian distribution centered around zero, with the transition region showing a closer resemblance to a standardized Gaussian distribution (SFig. 4).

(3) The Gaussian assumption in LETKF requires that, at each grid, the distribution of the uncertainty (in this study, this is sampled by 25 ensemble member at each grid point) is Gaussian. It seems to me SFig.4 is the distribution mixing all the ensemble states at all grid points(?!). If so, the distribution in SFig.4 will possibly not be Gaussian, but instead, a Gaussian-mixture. This is because the standard deviation of the ensemble distribution is probably different at different grid point.

Response) Given that the standard deviation of the ensemble distribution varies at each grid point, we have recalculated the standardized ensemble spread for each grid point and created a new figure accordingly.

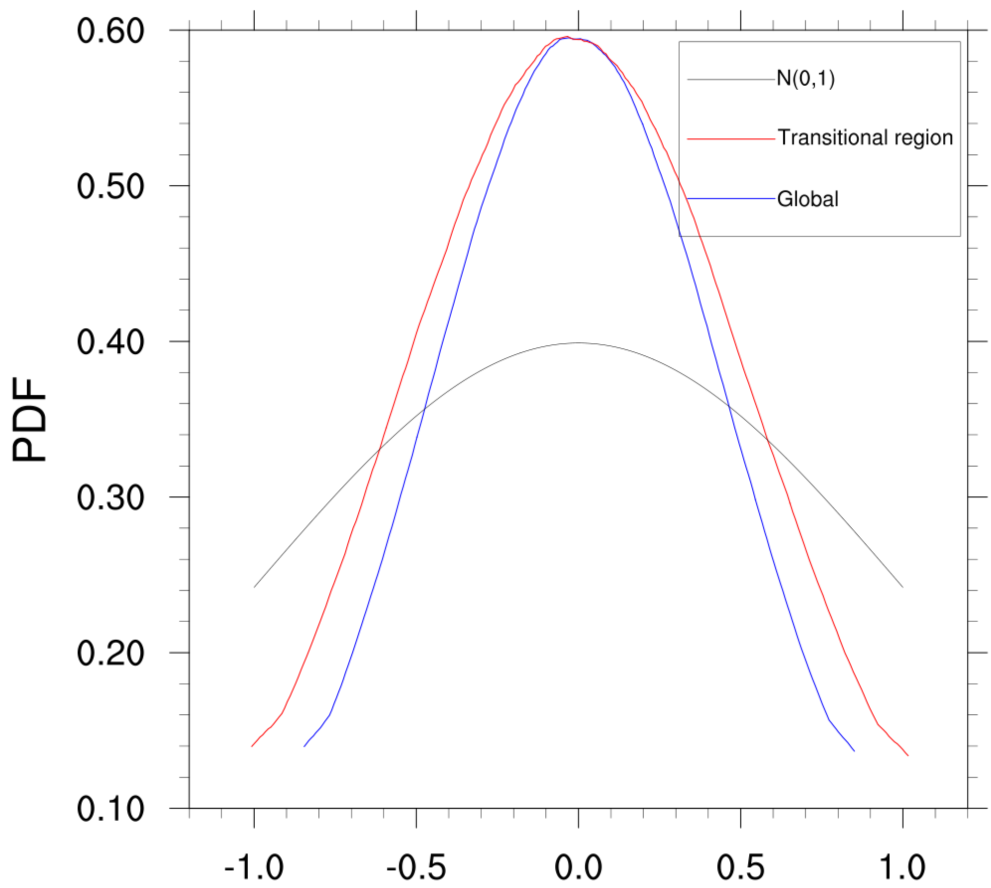
(4) I don't insist doing the following analysis (as it won't add much to the paper), but here is one possible way to verify the Gaussian assumption.

-(a) Normalize the ensemble perturbation at each grid point respectively

-(b) Plot the histogram of all the normalized ensemble perturbation at all grid points (or the grid points within the transitional region)

-(c) Compare the histogram in (b) to a standard Gaussian N(0,1)

Response) Based on the reviewer's suggestion, we have plotted the standardized PDF at each grid point instead of the histogram and added the standard Gaussian N(0,1) for comparison. As shown in SFig.4, the standardized PDF of SWE among the ensemble members appears to follow a symmetric quasi-Gaussian distribution for both the global and transition regions.



Supplementary Fig. 4 Probability density function (PDF) of the standardized SWE ensemble perturbation, with the ensemble mean removed from each ensemble member, at each grid point. The PDF is averaged globally (blue line) and for the transition region (red line) for April from 2013 to 2020. The black line represents the standardized Gaussian function N(0,1).

Reply to the Reviewer (#2)′s Comments :

I think this version of the manuscript addresses the concerns of the previous reviewers. I have just a few minor suggestions:

1) 26 'Snow Water Equivalent (SWE), as one of the land initial conditions, ' -> Initial or boundary conditions

Response) Modified as suggested.

2) 33 'This constitutes a novel approach that has not been previously attempted'

: This is not totally correct. There are quite a few papers on snow depth or snow water equivalent assimilation. A search in Google Scholar under the search field 'snow water equivalent assimilation' yields several pages of papers since 2020, which are not cited or discussed in the introduction. Perhaps the authors would want to place their study in the context of those papers

Response) As the reviewer pointed out, while there are existing studies on SWE data assimilation (e.g., Oaida et al., 2019; Smyth et al., 2020; Luojus et al., 2021), the use of passive microwave observations based on the LETKF in this context is relatively rare (e.g., Girotto et al., 2020). Specifically, the approach of optimally combining AMSR2 and IMS satellite data with the JULES LSM model for data assimilation, as done in this study, represents a first attempt and provides a distinctive contribution. In agreement with the reviewer's comment, we have removed the term "novel" from the sentence and revised the sentence accordingly. Additionally, we have included references to existing SWE data assimilation studies in the manuscript.

Revision) (L33-36) This approach constitutes an objective method that optimally combines two previously unattempted incomplete data sources: the satellite SWE retrieval from the Advanced Microwave Scanning Radiometer 2 (AMSR2) and dynamically-balanced SWE from the JULES land surface model.

(L147-160) In previous studies, various approaches have been attempted to improve SWE product performance, such as combining satellite-derived SWE with ground observations (Pulliainen et al., 2020), different satellite data sets (Gan et al., 2021), simple snow models

(Dziubanski and Franz, 2016), or LSMs (Kwon et al., 2017; Kumar et al., 2019). 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. While there are existing studies on SWE data assimilation (e.g., Oaida et al., 2019; Smyth et al., 2020; Luojus et al., 2021), the use of passive microwave observations based on the LETKF in this context is relatively rare (e.g., Girotto et al., 2020).

Add reference)

Girotto, M., Musselman, K. N., and Essery, R. L. H.: Data Assimilation Improves Estimates of Climate-Sensitive Seasonal Snow, Current Climate Change Reports, 6, 81–94, https://doi.org/10.1007/s40641-020-00159-7, 2020.

Luojus, K., Pulliainen, J., Takala, M., Lemmetyinen, J., Mortimer, C., Derksen, C., Mudryk, L., Moisander, M., Hiltunen, M., Smolander, T., Ikonen, J., Cohen, J., Salminen, M., Norberg, J., Veijola, K., and Venäläinen, P.: GlobSnow v3.0 Northern Hemisphere snow water equivalent dataset, Sci. Data, 8, 163, https://doi.org/10.1038/s41597-021-00939-2, 2021.

Oaida, C. M., Reager, J. T., Andreadis, K. M., David, C. H., Levoe, S. R., Painter, T. H., Bormann, K. J., Trangsrud, A. R., Girotto, M., and Famiglietti, J. S.: A High-Resolution Data Assimilation Framework for Snow Water Equivalent Estimation across the Western United States and Validation with the Airborne Snow Observatory, J. Hydrometeorol., 20, 357–378, https://doi.org/10.1175/JHM-D-18-0009.1, 2019.

Smyth, E. J., Raleigh, M. S., and Small, E. E.: Improving SWE Estimation With Data Assimilation: The Influence of Snow Depth Observation Timing and Uncertainty, Water Resour. Res., 56, e2019WR026853, https://doi.org/10.1029/2019WR026853, 2020.

3) 41 'superior performance in high-latitude regions' : superior is not the right word here. Why not use just better ?

Response) Modified as suggested.

4) 52 'This assimilation framework is anticipated to contribute to a more precise prediction of atmospheric conditions by realistically capturing the interaction between

the atmosphere and land, given the substantial influence of SWE on energy and water balance at the interface of the atmosphere and land'

: This paragraph does not fit in the abstract. It is not informative, and, as I mentioned in a previous point, there are many other SWE assimilation schemes.

Response) We agree with the reviewer's comment and have deleted the corresponding sentence from the abstract.

5) The methods section and, I believe, the manuscript as a whole do not indicate that the assimilation is done at the grid-cell level. This has some consequences for the assumptions of the observational errors, as the observation error-covariance is assumed to be diagonal.

Response) Thank you for your comment. Following the reviewer's comment, to prevent any misunderstanding, we have added the following clarification to the manuscript that data assimilation is performed at each grid point:

Revision) (L282-284) To address this issue, we attempted to apply a simple and effective standard normal deviation scaling to satellite-derived SWE at each grid point, considering its potential use as initial conditions for JULES LSM-based climate models.

(L296-298) 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) at each grid point to produce a snow analysis.

(L325-327) This study conducts the advanced daily cycle snow data assimilation experiment at each gird point using the LETKF based on the satellite data and the JULES LSM model outputs driven by 3-hourly JRA55 reanalysis atmospheric forcing.