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.

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.

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

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

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.

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 …’

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

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

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

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

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.

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.

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?

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.

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.

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.
(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?

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?

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’.

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

L486-489: To my understanding, the change in the land component does not feedback to 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.

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