RC2: 'Comment on tc-2021-225', Anonymous Referee #2, 27 Sep 2021

The authors would like to thank the reviewer for his accute review asking for more clarity in the description of the procedure. Sec. 2 was considerable adjusted to fit with these requirements, and we believe that new Fig. 3 will really help understand our assimilation methods. Note that some slight changes were also made in the manuscript in order to improve its clarity, and are visible in the track changes. In the following, the reviewer initial comments are written in black, our answer in blue and the corrections in the paper are highlighted in red.

Major comments

In the paper titled "Propagating information from snow observations with CrocO ensemble data assimilation system: a 10-years case study over a snow depth observation network" Bertrand Cluzet et al. assimilated snow depth observations from an in-situ network of 295 stations covering the French Alps, Pyrenees, and Andorra over the period 2009–2019. They attempted to demonstrate how in-situ observations of snow depth can help contain intermediate and large-scale modeling errors by means of data assimilation. However, while the results of snow depth data assimilation are closer to observations than the non-operational open-loop counterpart (open-loop), which does not use data assimilation, they are not as good as the operational deterministic snow cover modeling system (oper). It is natural that the results of snow depth data assimilation are better than those of open-loop, but it is necessary to show that snow data assimilation outperforms oper. Moreover, I believe that snow depth data assimilation not only improves the reproducibility of the same snow depth but also affects other parameters of the snow model such as snow water equivalent, snow density, snow surface temperature, and water and energy balances above the snow; hence, I would like to see the discussion on the impact and verification of these factors. The procedure of the data assimilation method is difficult to understand, especially the need to clarify the control variables and the analysis variables. Overall, the paper is not accepted in the current form and needs to be revised in accordance with the following comments. My main concerns are as follows:

(1) Although the method of data assimilation has already been published in papers such as Cluzet et al. (2020, 2021), I feel that it is necessary to describe the flowchart of data assimilation and to clarify what the control variables and analysis values are, so that the data assimilation method can be understood to some extent from this study independently. I feel that since there is a limit to the extent of explanation that can be expressed only in text, I would really like to see a flowchart of data assimilation. I think that data assimilation can be corrected for other elements of the model using cross-covariance and error covariance with snow depth. It should be clarified whether snow depth is the only control variable. Furthermore, the authors conducted two types of experiments for data assimilation using particle filters, but I did not understand the difference between rlocal and klocal. Please explain this in detail

The authors want to thank the reviewer for this detailed question. We believe that the resulting adjustments will really improve the quality and clarity of the manuscript. We identify several elements in this question, and answer it point by point.

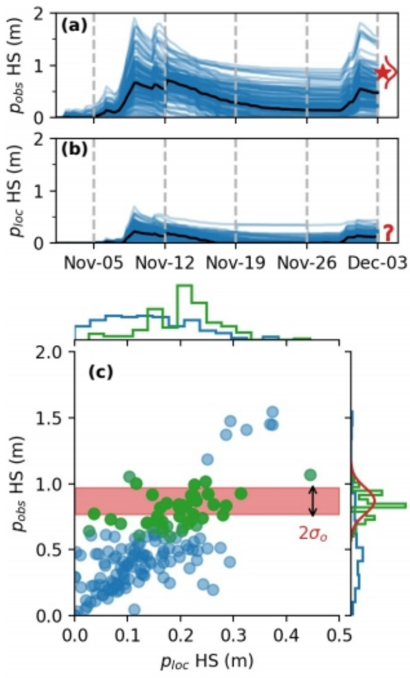
(a) need for a flowchart describing the control/analysis variables:

A new Section (2.2.4) was added, with a new figure (Fig. 3 of the revised manuscript), showing a simplified example of localized data assimilation with two points. Beyond the reference to Cluzet et al., (2021), we believe that this example can illustrate the fact that we use a 160 member ensemble, the sequential weekly assimilation procedure, and show how non-local observations can constrain the ensemble locally.

This section presents an illustrative example for the propagation of information with the localised PF. On December 3rd, 2009, we perform an analysis at an unobserved point p_{loc} (2135 \unit{m.a.s.l}) using an observation from a nearby point p_{obs} (2293 \unit{m.a.s.l}, 7 \unit{km} away). The top panel of Fig. \ref{fig:example} shows the HS simulated by the 160 ensemble members at the two locations until the considered assimilation date. The observed HS at p_{obs} is 0.87 \unit{m}, above the ensemble median at this location (about 0.5 \unit{m}). The PF will likely select the particles that have above average HS at p_{obs}. The bottom panel of Fig. \ref{fig:example} shows the particles' HS values at p_{obs} as a function of their value at p_{loc}. A correlation can be noted: the particles predicting the highest HS at p_{loc} usually also predict higher than average HS at p_{obs}. It means that the ensemble that we constructed (see Sec. \ref{sec:assim_setup}) considers that the modelling errors are linked: if there is an underestimated snowfall in early December at p_{obs}, it's likely that this is also the case at p_{loc}.\\

The localised PF performs an analysis for p_{loc} by comparing the values modelled at p_{obs} with the available observation, thereby selecting the 'best' particles at p_{obs}, (bottom panel, in green). The marginal distribution of the ensemble at p_{obs} (right of the bottom panel, in green) is significantly sharpened compared to the background, and is much closer to the observation. At p_{loc}, the distribution of the HS values of these particles is also sharper, and exhibits higher HS than before the analysis.\\

This example shows how the localised PF has used the non-local observation at p_{obs} to infer information about the local unobserved point p_{loc}. This example can be generalized to the situation where multiple observations are assimilated simultaneously as done in this study. It also highlights the implicit importance of ensemble correlations with distant locations: in the absence of correlation, no information can be transferred. In such a situation, the klocal algorithm would discard the observations from the least areas, while the rlocal would keep them. Finally, note that if the ensemble correlation is dramatically wrong, (i.e. positive correlation instead of negative correlation), the analysis will degrade the ensemble performance.\\



(b) The method should be understood to some extent from this study independently.

Sec. 2.2.3 has been completely re handled, in order to give more details and explanations on the data assimilation flowchart.

The Particle Filter used in this work is based on the version described in \citet{cluzet2021croco}. Only a brief description of the procedure is given here. The ensemble is updated sequentially with the PF on each assimilation date and propagated forward until the following assimilation date. The PF is localised: each point receives a different analysis. Based on the comparison of neighbouring simulations of HS with their corresponding HS observations, the PF selects a sample of the best ensemble members. The idea is that if a particle is performing well against nearby observations, it should also be efficient locally \citep{farchi2018comparison}. Different localisation radius are tested in this study ranging from 17 \unit{km} to 300 \unit{km}. Note that when a particle is selected by the PF, the full local state vector is copied: the local physical consistency of the variables is preserved.\\

Particle Filter degeneracy (see Sec. \ref{sec:intro}) may arise even with a reduced local domain size, and approaches to increase the PF tolerance may be required to overcome it. The localisation is complemented here by two different strategies described in \citet{cluzet2021croco}, inflation and k-localisation, leading to the 'rlocal' and 'klocal' algorithms, respectively. If the initial analysis is degenerated (i.e. the effective sample size N_{eff} is inferior to a target N_{eff}^*), the rlocal and klocal iteratively modify the assimilation settings to make it more tolerant, so that the PF analysis reaches a sample size of N_{eff}^*. The rlocal algorithm performs an inflation of observation errors inspired by \citet{larue2018assimilation}. The klocal algorithm discards observations coming from locations exhibiting the lower ensemble correlations with the considered location. It is important to note that inside a localisation radius, the rlocal method assimilates all available observation stations whereas the klocal method only selects a subset of observations from locations where the ensemble members are sufficiently correlated with the simulation members of the considered point.\\

(c) I think that data assimilation can be corrected for other elements of the model using cross-covariance and error covariance with snow depth.

With the answer to (b), it should be clear now that in the PF, the full local state vector is replicated, not only HS. Therefore no statistical assumption is made to update other state variables from HS.

(d) It should be clarified whether snow depth is the only control variable.

HS is unambiguously the only assimilated variable (in the submitted manuscript, l. 4-5, 10-12, 16-18, 53-55, 89-97). This ambiguity should be raised with the answers to points (a) and (b).

(c) explain in detail the difference between the rlocal and the klocal approaches. The difference between the two algorithms were described in l.158-164 of the manuscript (Sec. 2.2.3). This paragraph was rewritten in order to improve its clarity and details were added.

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the rlocal method assimilates all available observation stations whereas the klocal method only selects a subset of observations from locations where the ensemble members are sufficiently correlated with the simulation members of the considered point.\\

(2) I would like to see an explanation of the difference between Oper and open-loop as a reference.

The distinction between oper and openlop was briefly given at the beginning of Sec. 3 (l. 161-164 of the submitted manuscript). This paragraph was updated to improve its clarity:

This work aims at assessing the potential transfer of information between points in an HS observation network by means of localized data assimilation, and more specifically to address the questions presented in the end of Sec. \ref{sec:intro}. To demonstrate that, the data assimilation system must over-perform its ensemble counterpart with the assimilation switched off (open-loop) and the state-of-the-art operational deterministic snow cover modelling system from Météo-France (oper), which consists in a default Crocus version forced by the unperturbed SAFRAN meteorological forcing \citep{vernay2021meteorological}.

I would also like to see a more detailed explanation of the SAFRAN massif, with expanded abbreviation, and the convincing data provided by SAFRAN to the snow model.

Details on SAFRAN massifs were given in Sec. 2.2.2. We aknowledge that this lacked some clarity, and thank the reviewer for pointing this out. The first paragraph of this section was expanded, insisting in particular on how SAFRAN analysis is performed over each massif, and then interpolated at the stations of the study:

Meteorological forcings are taken from SAFRAN (Système D'Analyse Fournissant des Renseignements Adaptés à la Neige, \citet{durand1993}) reanalysis over the Alps and Pyrenees. SAFRAN is a surface meteorological analysis system adjusting backgrounds from NWP model ARPEGE \citep{courtier1991} with local meteorological observations (air temperature, pressure, precipitation, humidity) within so-called massifs of about 1000 \unit{km^2} (see Fig. \ref{fig:meth_obs_density_massif}) and further downscaled to the stations of our study. Over the considered period of time, 438 observation sites provided precipitation observations to SAFRAN between November and April. These stations are mostly located at lower elevations (below 1500 m) as presented in Fig.4 of \citet{vernay2021meteorological}. Among them, 164 of these sites correspond to locations with snow depth observations included in the present study. SAFRAN analysis is issued separately for each massif in a semi-distributed geometry, i.e within 300 \unit{m} elevation bands, aspect and slopes, the main topographic parameters controlling the snow cover evolution. This analysis is subsequently downscaled into the specific topographic conditions (i.e. elevation, slope, aspect and local topographic mask) of the simulated station \citep{vionnet2016}. This means that a same analysis is applied to all the points within a same massif, and interpolated consistently with their topographic parameters, while analyses for neighbouring stations located in distinct massifs will be different.\\

(3) Advantage of data assimilation is that by assimilating snow depth data, the information is correlated to other factors such as snow water content and precipitation, which will improve the accuracy of model estimation other than direct snow depth improvement. If you have observational data on snow density, snow surface temperature and snow water content, please add a discussion on whether the assimilation of snow depth affects other model parameters.

Such data is unfortunately unavailable at the studied stations. We agree that this would have been a valuable source of information for this study.

(4) I feel that there is a lack of literature in the introduction. As a pioneering work in satellite data assimilation, I feel it is necessary to mention the data assimilation study of MODIS snow cover and AMSR-E snow water content by Andreadis and Lettenmaier (2006).

We agree that this pioneering work should have been cited in the introduction. The sentence corresponding to l. 38-41 was adapted to include this reference:

Andreadis, K. M.; Lettenmaier, D. P. Assimilating remotely sensed snow observations into a macroscale hydrology model. Adv. Water Resour. 2006, 29, 872–886.

Data assimilation of snowpack observations may help address this issue in complement to these observations. Remotely-sensed retrieval of snow bulk properties (e.g. the height of snow (HS, \unit{m}) and the snow water equivalent (SWE, \unit{kg} \unit{m^{-2}})) is a promising wealth of snowpack observations for data assimilation \citep[e.g.][] {margulis2019utility} but it is inherently limited by spatio-temporal gaps \citep{delannoy2012}, or only available at coarse resolutions \citep{andreadis2006assimilating}.

Line 42–43: "Their potential to improve local simulations is unambiguous as demonstrated by many studies." After this sentence, please consider adding references such as Liston and Heimstra (2008) and Suzuki et al. (2015).

Liston, G. E.; Hiemstra, C. A. Simple data assimilation system for complex snow distributions (SnowAssim) *J. Hydrometeorol.* **2008**, *9*, 989–1004.

Suzuki, K.; Liston, G. E.; Matsuo, K. Estimation of continental-basin-scale sublimation in the Lena River Basin, Siberia. *Adv. Meteorol.* **2015**, *2015*.

The authors would like to thank the reviewer for these interesting citations. A reference to Liston et Heimstra (2008), was added in the following sentence, because it was more fair for this citation (which is more ambitions than only improving local simulations)

The potential to transfer information into neighbouring areas is therefore a key question when considering their potential added value for snow cover modelling over large domains \citep[e.g.][]{slater2006snow,liston2008simple,gichamo2019ensemble}

Line 61–62: "These variants are used in a localised framework, in which only observations coming from a certain radius around the considered location are assimilated." After this, please consider adding references such as Zupanski (2021).

Zupanski, M. The Maximum Likelihood Ensemble Filter with State Space Localization. *Mon. Weather Rev.* 2021.

With the corresponding sentence, we wanted to focus on particle filter Particle Filter localization methods that could directly relate to our approach. Even though this brand new method may have similarities with the PF method, we find it a bit off topic (ery theoretical) here.

(5) Line 389: There are two reasons why the operational run could not be beaten by the assimilation in terms of RMSE.

Reworded into:

There are two reasons why the assimilation could not outperform the operational run in terms of RMSE.

Line 454–455: In other words: the assimilation can not beat the open-loop in the most densely observed areas (e.g. in the Northern Alps, 455 where the observation density is similar to the studies of Magnusson et al. (2014) and Winstral et al. (2019)) because the open-loop performance is already high there.

Here, 'beat' was replaced by 'outperform'

In the above two sentences, the verb "beat" is used, but I feel it is not appropriate. I would like to see this correction with more appropriate words.

Line 267–269: The text needs to be revised and made more readable.

Reworded into:

In the following, we will investigate the different factors influencing the skill variability of the assimilation runs. As described in the previous Sec. \ref{sec:res_assim}, there are only small skill differences between the localised radii of 17-50 \unit{km}, and between the rlocal and klocal algorithm. For the sake of illustration, we decided to focus on the assimilation configuration yielding the lowest median RMSE. This configuration, the klocal with a 35 \unit{km} localisation radii, is further referred to as 'klocal' configuration.

(6) The results of data assimilation in Fig. 6 should be shown in the form of Table 1 with numerical values. Moreover, there is no data for oper in RMSE and SS in Fig. 6; please resolve this.

The authors would like to thank the reviewer for suggesting an improvement to this figure. There is actually a flaw, with a missing RMSE plot for th oper. This was corrected in the revised version of the manuscript. However, the ss cannot be computed for the oper (since it is a deterministic run, there is no spread), this is why ss is missing. And we are not sure whether putting all the data in a table would be readable, as there would be five times more data than in Table 1.

Added RMSE values for the open on Fig. 6.

References:

Cluzet, B., Lafaysse, M., Cosme, E., Albergel, C., Meunier, L.-F., and Dumont, M.: CrocO_v1. 0: a particle filter to assimilate snowpack observations in a spatialised framework, Geoscientific Model Development, 14, 1595–1614, https://doi.org/10.5194/gmd-14-1595-2021, 2021.