

## REVIEWER # 1

### General Comments:

#### COMMENT # 1.1

*The authors present a very interesting and promising study about spatial snow data assimilation for high-resolution simulations. The study shows how information from sparse snow depth observations can be used to improve spatially complete simulations obtained using a physically-based snow model at very high spatial resolution. The manuscript is easy to read and well-written, the results are clearly shown and discussed in depth. Overall, the paper is a strong contribution to existing literature on snow data assimilation since few studies have addressed the problem of propagating information from sites with observations to locations lacking measurements. My comments on the manuscript are only minor, and listed below.*

#### Reply:

We appreciate the reviewer's positive comments and are very grateful for the constructive suggestions that have helped us to improve this study. The following provides a point-by-point response to the reviewer's comments.

#### Specific comments:

#### COMMENT # 1.2

*Abstract: The study would benefit from a shorter and more concise abstract.*

#### Reply:

Thanks for the suggestion, we have reduced the abstract by removing the first sentences as also suggested by Reviewer 2.

#### Changes:

~~Monitoring the snowpack remains challenging in part due to the limited availability of observations. On the one hand, the deployment of dense ground-based monitoring networks is hampered by logistical hurdles. On the other hand, satellite-based remote sensing products provide only partial information about the snowpack, often limited to snow-covered area or surface temperature. Numerical models are a valuable tool to help fill the gaps in snowpack monitoring. Model performance is nonetheless contingent upon the quality of meteorological forcing, which is often highly uncertain~~

~~especially in complex terrain. To address these limitations, data~~ [Data](#) assimilation techniques that integrate available...

COMMENT # 1.3

*L 150-152: The sentence is difficult to read. Please reformulate.*

**Reply:**

We have reformulated this sentence as follows.

**Changes:**

MuSA is an open-source snow data assimilation toolbox. [It is](#) designed to assimilate ~~various observations of the snowpack into an ensemble of snowpack observations~~ [into](#) simulations generated by the energy and mass balance model the Flexible Snow Model (FSM2 [1](#)), [or other snow models.](#)

COMMENT # 1.4

*L 173: Is optimal interpolation only occasionally used in operational data assimilation? Is not many very important weather forecasting models using this method, such as ECMWF? ECMWF: IFS Documentation CY45R1 – Part II: Data assimilation, in: IFS Documentation CY45R1, IFS Documentation, ECMWF, <https://www.ecmwf.int/en/elibrary/80893-ifs-documentation-cy45r1-part-ii-data-assimilation> (last access: 16 November 2022), 2018.*

**Reply:**

We would like to thank the reviewer for this thoughtful comment which has made it clear to us that these OI methods are still widely used operationally, including at ECMWF. We have thus modified the text accordingly and added a more up to date reference, namely [\(2\)](#), on the use of OI (and other) methods in operational DA.

**Changes:**

Indeed, ensemble Kalman methods are closely related to many spatial modeling techniques, including kriging [\(3; 4\)](#) methods in geostatistics [\(5; 6\)](#) and the nearly equivalent Optimal Interpolation [\(7; 8\)](#) methods that ~~were widely (and are still occasionally)~~ [are widely](#) used in operational DA ~~[\(9\)](#)~~[\(9: 2\)](#).

COMMENT # 1.5

*Data and methods: How were the snowpack layers in FSM2 updated during the assimilation experiments? If the assimilation step adjusts the total depth of the snowpack, also the number of modelled snow layers may change. How was this handled? Please clarify.*

**Reply:**

Unlike how data assimilation is typically implemented in the numerical weather prediction community, we do not directly update the model states in the assimilation step. Indeed, updating the snow layers of the simulation would introduce many problems, such as dealing with different numbers of layers in each ensemble member (the number of layers changes dynamically depending on the snow depth up to a maximum of 3) or the need to assume a composition of the layers (their ice and water content) at the time of the analysis, in order not to make the model unstable. Instead, we directly infer model parameters, in this case meteorological forcing correction parameters, for each water year and we let the dynamical model consistently solve for the updated state of the snowpack. This is explained on L197 and in more detail in (10). This method is not unique to our work and has been called the forcing formulation of the Bayesian data assimilation problem (11). We have now clarified this further in the text around L197.

**Changes:**

The parameters are updated with the ensemble Kalman analysis step in the transformed (Gaussian) space but fed through the forward model in the physical (untransformed) space (10). [As such, we adopt a forcing formulation of the data assimilation problem \(11\) where model parameters are directly updated leading to indirectly but dynamically consistent updates in the model states.](#)

COMMENT # 1.6

*Data and methods: Please specify the total computation time of running one assimilation experiment, and also add information about the computer resources that were used. This is interesting for potential applications of the methods developed in this study.*

**Reply:**

We have added the following estimation around L332.

**Changes:**

The experiments developed in this work were launched in the supercomputing facilities of the Centre National d'Études Spatiales. As a reference, 30 nodes were used, with 10 processors each. The experiments took around 5 hours, but this estimate should be taken with caution. As the operation is I/O intensive, depending on the configuration of the simulations, the computing scheme and the spatial density of observations, the computational cost can vary tremendously even for the same domain and spatial resolution.

COMMENT # 1.7

*Table 1: Would it be possible and more visually appealing to show these metrics as time series plots?*

**Reply:**

We would like to thank the reviewer for this constructive suggestion. At the same time, based on our experience with the snow data assimilation literature, it is normal to summarize the performance of experiments using multiple evaluation metrics in a table as we have done here. Generating discrete time series plots with these metrics is not straightforward given that the timing of the drone acquisitions is irregularly distributed. Such a modification would also require a relatively large figure with separate panels for each of these metrics since they vary considerably in terms of both their units and dynamic range. In summary, although a discrete time series may be more visually appealing, the use of a table such as this is a more compressed representation of the results.

**Technical comments:**

COMMENT # 1.8

*L 119: A space is missing before the reference.*

**Reply:**

Corrected.

COMMENT # 1.9

*L190: Error in spelling. "Spare" to "sparse".*

**Reply:**

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Corrected.

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COMMENT # 1.10

L405: *Is the sentence correct? (“which shows is nearly flat”)*

**Reply:**

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Thanks for spotting this typographic error, it has now been corrected.

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COMMENT # 1.11

L 518: *“e.g.” misplaced.*

**Reply:**

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Corrected.

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## REFERENCES

- [1] R. Essery, “A factorial snowpack model (FSM 1.0),” *Geosci. Model Dev.*, 2015.
- [2] P. de Rosnay, G. Balsamo, C. Albergel, J. Muñoz-Sabater, and L. Isaksen, “Initialisation of Land Surface Variables for Numerical Weather Prediction,” *Surveys in Geophysics*, vol. 35, pp. 607–621, 2014.
- [3] D. Krige, “A statistical approach to some basic mine valuation problems on the Witwatersrand,” *Journal of the Southern African Institute of Mining and Metallurgy*, 1951.
- [4] G. Matheron, “Principles of geostatistics,” *Economic Geology*, 1963.
- [5] L. Bertino, G. Evensen, and H. Wackernagel, “Sequential Data Assimilation Techniques in Oceanography,” *International Statistical Review*, 2003.
- [6] J. Chilès and P. Delfiner, *Geostatistics: Modeling Spatial Uncertainty*. Wiley, 2012. 2nd Edition.
- [7] A. Eliassen, “Provisional report on calculation of spatial covariance and autocorrelation of the pressure field,” in *Dynamic Meteorology: Data Assimilation Methods (1981)* (L. Bengtsson, M. Ghil, and E. Källén, eds.), pp. 319–330, Springer, 1954. Reprinted from Videnskaps-Akademiets Institutt for Vær-Og Klimaforskning, Oslo, Norway.

- [8] L. Gandin, "Objective analysis of meteorological fields," 1963. Gridromet. Izd. Leningrad (Russian).
- [9] O. Talagrand, "Assimilation of observations, an introduction," *Journal of the Meteorological Society of Japan*, pp. 191–209, 1997.
- [10] E. Alonso-González, K. Aalstad, M. W. Baba, J. Revuelto, J. I. López-Moreno, J. Fiddes, R. Essery, and S. Gascoin, "The Multiple Snow Data Assimilation System (MuSA v1.0)," *Geosci. Model Dev.*, 2022.
- [11] G. Evensen, F. C. Vossepoel, and P. J. van Leeuwen, "Data Assimilation Fundamentals: A Unified Formulation of the State and Parameter Estimation Problem," *Springer International Publishing*, 2022.