Reviewer 1

This manuscript explores the assimilation of a machine learning-derived Sentinel-1 snow depth product into a NOAH land surface model using a dynamically varying observation error. While the approach is innovative and addresses an important limitation in current snow data assimilation systems, the demonstrated improvements over the static error method are relatively modest/marginal and not consistent across space or time. Given the added complexity of implementing a dynamic error model, I do not fully agree with the authors' conclusion that this approach provides a clear performance advantage. The manuscript has potential, particularly if it reframes the findings to emphasize that the benefits of dynamic error observation methods are highly dependent on the pattern and variability of observation errors. One has minimal leverage on the other, and a more thorough error characterization is essential for selecting an appropriate DA strategy for the problem at hand.

We thank the reviewer for their thoughtful and helpful comments and we believe that our revised manuscript is much improved as a result. Our responses below, are in red, with manuscript text in dark red and *additions to the manuscript in italics.*

Major Comments

Comment 1 - Result:
While the authors claim that the Dvar experiment outperforms $\mathrm{DA_{const}}$ in terms of snow depth and SWE estimation, the practical improvement is marginal at best. For snow depth, the spatial ACC increases only slightly—from 0.72 ($\mathrm{DA_{const}}$) to 0.73 ($\mathrm{DA_{var}}$)—a mere 0.01 gain (Figure 3c), which is unlikely to represent a meaningful enhancement in most applications. The temporal ACC comparison (Figure 3d) shows that just 52% of sites improve with $\mathrm{DA_{var}}$ while nearly half do not, and 11% of sites degrade by more than 0.02.

The improvements in spatial and temporal ACC seem small because the model-only run already does a good job at representing the spatial and temporal snow depth patterns, as the model parameterizations and forcing have been previously tuned for optimal results [Brangers et al., 2024]. Indeed, the OL experiment boasts an average spatial ACC of 0.71. However, we can see from Figure 3c that the improvements of $\mathrm{DA_{var}}$ compared to the OL are more than double those from $\mathrm{DA_{const}}$. We will modify the text in L208-213 to highlight that all experiments well-represent spatial and temporal snow depth patterns in response to the above concern:

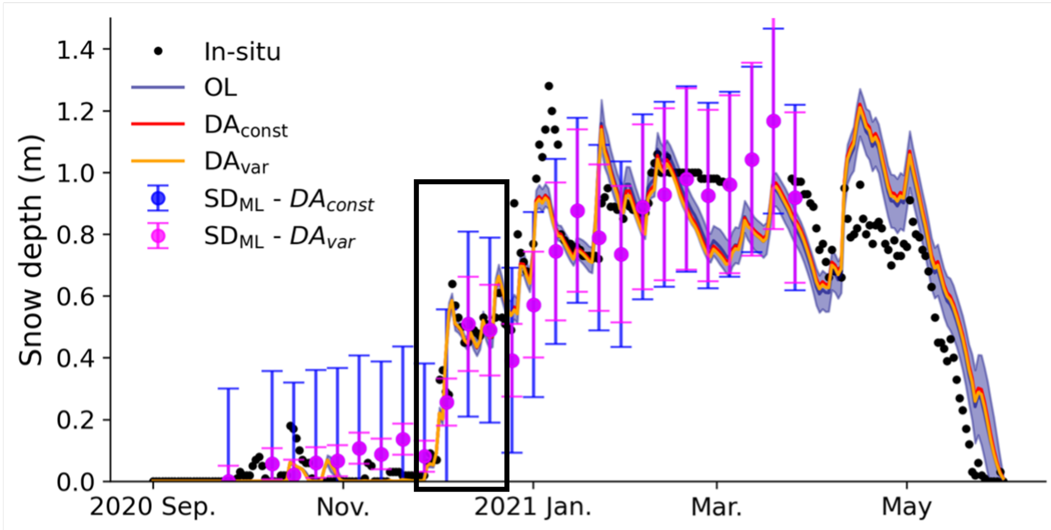
"*While the OL experiment already does a good job at representing spatial snow depth patterns (spatial ACC = 0.71), Figure 3c highlights that, for most of the snow season, the* $\mathrm{DA_{var}}$ *experiment offers slight improvements in the representation of these spatial patterns.* Averaged across the entire year, the spatial ACC increases from 0.71 for the OL experiment to 0.72 for $\mathrm{DA_{const}}$ and to 0.73 for $\mathrm{DA_{var}}$. The greatest improvement in spatial ACC for $\mathrm{DA_{var}}$ occurs during the early snow season (November), with values exceeding those of the OL and $\mathrm{DA_{const}}$

experiments by 0.058 and 0.047, respectively. From December through April, the spatial ACC for $\mathrm{DA_{var}}$ remains approximately 0.021 greater than that of the OL experiment. By mid-April, all three experiments exhibit similar performance in capturing spatial snow depth patterns. *Additionally, both* $\mathrm{DA_{const}}$ *and* $\mathrm{DA_{var}}$ *well-capture temporal snow depth patterns, with average temporal ACC values of 0.68 and 0.72, respectively.* The improvement in temporal ACC for $\mathrm{DA_{var}}$ from both the OL and $\mathrm{DA_{const}}$ is statistically significant ($p < 0.01$, Fig. 3d). Across the 948 sites evaluated, 491 sites (52%) have an improved temporal ACC in $\mathrm{DA_{var}}$ ($> +0.02$ compared to $\mathrm{DA_{const}}$), while only 103 sites (11%) experience a deterioration in temporal ACC ($<$ -0.02 compared to $\mathrm{DA_{const}}$)."

Further, while temporal and spatial ACC are useful metrics for understanding how well the OL and DA experiments capture spatial and temporal snow depth patterns, from a water resource perspective, MAE (or RMSE) and bias are more meaningful statistics. For this reason, most of our Results section focuses on these error and bias metrics. We will further address reviewer concerns regarding MAE and bias improvements in response to the reviewer comments below.

Similarly, the MAE reduction from $\mathrm{DA_{const}}$ to $\mathrm{DA_{var}}$ occurs at only $\sim$51% of sites, with 12% worsening. These statistics reveal that the advantage of $\mathrm{DA_{var}}$ is not robust or generalizable. The pattern is echoed in the SWE evaluation, where only 56% of sites see improvement in MAE under $\mathrm{DA_{var}}$ compared to $\mathrm{DA_{const}}$. In other words, nearly half the sites experience no benefit or deterioration, which raises questions about the reliability of the variable uncertainty approach. This is consistent with SDD and SCF evaluation (Figures 7 and 8).

First, a 51% improvement vs. a 12% deterioration at sites is convincing considering the representativeness error of in-situ sites in general. Further, while the improvements seem small at individual in-situ sites, these changes may be amplified when applied across the whole European Alps domain. Previous work has demonstrated that small improvements in SD or SWE lead to further improvements in simulated river discharge [Brangers et al., 2024, De Lannoy et al., 2024]. Regarding sites that experience a deterioration: snow depth retrieved from the Sentinel-1 satellite (either through the conceptual snow depth retrieval algorithm of Lievens et al. [2022], or through the ML-based retrieval of Dunmire et al. [2024] (SD_{ML}), is not uniformly robust or necessarily generalizable across all time and space. Many papers have previously demonstrated the limitations of these SAR-based snow depth retrievals [Broxton et al., 2024, Hoppinen et al., 2024, Dunmire et al., 2024]. C-band SAR further appears to be sensitive to snow stratigraphy [Brangers et al., 2024], thus the intensity of snow layering can influence the retrieved snow depth at sites with otherwise similar in-situ snow depth. Given these limitations, there will likely always be locations where the assimilation of a SAR-based snow product deteriorates the simulated snow depth. The $\mathrm{DA_{var}}$ experiment is generally more influenced by the observational information than $\mathrm{DA_{const}}$ and as such, the performance will be deteriorated in locations where the observations are more inaccurate than the OL experiment. Figure 3b in the manuscript demonstrates that this occurs for a minority of sites. While we have accounted for some of the known limitations of the ML-based snow depth retrieval by not assimilating the SD_{ML} product over glaciers or forested terrain, it is impossible to consider every single grid cell where the S1 retrievals may be unreliable. Thus, there remains a relatively small number of sites that experience a deterioration in the $\mathrm{DA_{var}}$



Review Figure 1: Snow depth estimates and independent in-situ measurements from an example site. The dark blue shading represents ±1 standard deviation of the OL ensemble snow depth. The magenta dots represent the assimilated SD_{ML} retrievals, with error bars for the assumed observation error standard deviation from the $\mathrm{DA_{const}}$ experiment. Assumed observation error standard deviation from $\mathrm{DA_{var}}$ is indicated by the blue error bars.

experiment.

The reviewer also points out that many sites experience no benefit in the $\mathrm{DA_{var}}$ experiment. This happens in locations where the DA increments are small, either because the assimilated observations are not substantially different from the prior state, or the uncertainty of the observations is much larger than that of the prior state. For example, we can see in Review Figure 1 that observations in December (black box) are very similar to the simulated snow depth. Additionally, throughout the entire timeseries, σ_{obs} from both $\mathrm{DA_{const}}$ (blue error bars) and $\mathrm{DA_{var}}$ (pink error bars) is substantially larger than the modeled forecast ensemble standard deviation at this site (dark blue shading) which leads to minimal changes in either experiment.

A deterioration in some locations resulting from the DA is perhaps in contrast to the assimilation of lidar data, which are generally more accurate observational products and will lead to more robust and generalizable improvements. However, as demonstrated, assimilating S1-based snow depth observations can still provide benefit, especially as these observations are freely available, and offer frequent, global coverage, qualities which no other snow depth products can offer.

It is also surprising that RMSE was not reported, as it is a standard metric in snow modeling and data assimilation evaluations, and helps better in error magnitude in snow depth and SWE.

MAE is also a standard metric in snow modeling and data assimilation evaluation and both RMSE and MAE are error metrics that indicate how far the predictions are from actual values. We chose to report the MAE instead of RMSE because it gives equal weight to all errors, is more interpretable, and is better for understanding the average error magnitude. In the revised manuscript we will additionally include RMSE values in lines 241-245, and in Figure 5.

"Across the 588 in-situ snow depth measurement sites used for evaluation, the corrections applied in $\mathrm{DA}_{\mathrm{var}}$ result in snow depth estimates that align more closely with in-situ observations (Fig. 3). The OL experiment yields a site-average MAE of 0.244 m, a *RMSE of 0.300 m*, a bias of 0.113 m, and a Pearson correlation coefficient of 0.75. Both the $\mathrm{DA}_{\mathrm{const}}$ and $\mathrm{DA}_{\mathrm{var}}$ experiments show improved performance, with site-average MAE values of 0.237 m and 0.215 m, *RMSE values of 0.292 m and 0.268 m*, and biases of 0.106 m and 0.055 m, respectively."

Despite the narrative of statistical significance (e.g., $p < 0.001$), these results suggest that the magnitude of improvement is small, the spatial consistency is weak, and the operational gain may not justify the added complexity. The authors should contextualize these findings more carefully, perhaps by comparing the computational cost or exploring why improvements are minimal across the full domain.

First, the model-only experiments and atmospheric forcing used here have been previously tuned for optimal performance (in Brangers et al. [2024]) and as such the OL experiment performs reasonably well. If this previous tuning had not been applied, the improvements from the data assimilation would be relatively larger. Nonetheless, the improvements that are presented here are generally larger than other work which assimilates SAR-based snow depth retrievals over the Alps. For instance, Brangers et al. [2024] assimilated the SD_{S1} product over the Western European Alps. They demonstrate that SWE MAE decreases from 134 mm in the OL experiment to 121 mm with DA, a 9.7% reduction in MAE (Figure 4c/f in Brangers et al. [2024]). In our work (which includes substantial additional SWE measurement sites), the SWE MAE decreases from 152 mm in $\mathrm{DA}_{\mathrm{const}}$ to 132 mm in $\mathrm{DA}_{\mathrm{var}}$, a 13.2% reduction. In fact, this improvement is comparable to reduction in MAE resulting from the DA in general, as SWE MAE reduces from 176 mm to 152 mm in $\mathrm{DA}_{\mathrm{const}}$ (-13.6%), indicating that the implementation of $\mathrm{DA}_{\mathrm{var}}$ can double the error reduction from DA.

Despite small improvements to SD or SWE, Brangers et al. [2024] and De Lannoy et al. [2024] demonstrate that these changes further impact river discharge; thus, seemingly marginal improvements can have a large downstream (pun intended) impact in the land surface model. Additionally, these small, localized improvements will be meaningful when an entire basin or mountain range is considered.

We agree that a stronger contextualization of the results is needed within the discussion. We will incorporate the following paragraph into the Discussion section:

"*While* $\mathrm{DA}_{\mathrm{var}}$ *improves performance at most snow depth and SWE measurement sites, some locations see little benefit, or even a deterioration in performance (approximately 12% of snow depth sites and 20% of SWE sites). These degradations are more likely to occur where the*

SD_{ML} product is less accurate than the OL experiment. To account for known limitations of SAR-based snow depth retrievals, we did not assimilate the SD_{ML} product over dense forests or glaciers, and after March 31. Nevertheless, SD_{ML} remains inaccurate in some places, leading to localized deteriorations when these observations are assimilated. Locations with minimal differences between $\mathrm{DA_{const}}$ *and* $\mathrm{DA_{var}}$ *typically occur where the observations already agree well with the OL, or where $\sigma_{obs} >> \sigma_f$, thus the DA increments are small, and the model receives limited benefit from the observational information. Despite these spatial inconsistencies,* $\mathrm{DA_{var}}$ *nearly doubles the improvement in absolute SWE error compared to* $\mathrm{DA_{const}}$*. For instance, the SWE MAE decreases from 152 mm in* $\mathrm{DA_{const}}$ *to 132 mm in* $\mathrm{DA_{var}}$ *(-13.2%), while the overall impact of* $\mathrm{DA_{const}}$ *relative to the OL is a 13.6% reduction (176 mm in the OL to 152 mm in* $\mathrm{DA_{const}}$*). Importantly, previous studies have demonstrated that even modest improvements in snow depth or SWE from DA propagate to further improvements in streamflow [Brangers et al., 2024, De Lannoy et al., 2024].*

...

Finally, in $\mathrm{DA_{var}}$, Equation 2 ($\sigma_{obs} = m * SD_{ML}$, $m = 0.3$) is used to adapt the standard deviation of the observation error in space and time based on the assimilated snow depth. This relationship is a first-order approximation that assumes that the observation error increases linearly with the observation magnitude; however, σ_{obs} could be defined to vary in more complex ways. Future work could explore applying relationships where σ_{obs} varies non-linearly with the assimilated snow depth observation, or statistical parameterizations of σ_{obs} depending on other conditions such as elevation, or forest cover. Furthermore, σ_{obs} could be directly linked to the SD_{ML} retrieval quality which could be obtained e.g. through error propagation. The effectiveness of a dynamic observation error also depends on the magnitude of the forecast error, as the Kalman gain matrix, which determines the strength of the corrections, depends on both forecast and observation error. To maximize benefits, the observation error, whether static or dynamic, should be properly tuned in relation to forecast error. *While most operational systems do not currently include options to dynamically vary the observation error, this functionality is not complicated to incorporate, and the snow-specific MuSA (Multiple Snow Data Assimilation System) system does already provide an option for a user-defined observation error that can vary dynamically [Alonso-González et al., 2022].*"

Comment 2 - Discussion:
The discussion attempts to cover many important aspects of the study. However, it overemphasizes statistical significance while underplaying the marginal and spatially inconsistent nature of the improvements. Standard metrics like RMSE are missing to give a clear picture.

Please see our responses to the above concerns for a discussion on the nature of the improvements, an explanation of how we will better contextualize the results within the discussion, and for our inclusion of RMSE metrics.

Key ideas like bias treatment and dynamic observation error comparison with SD_{S1} are introduced without prior mention or clear connection to the results or existing literature.

We discuss bias because it is a known issue in EnKF DA approaches, and thus the concerns of a biased DA system are important to address here. We will move this discussion into a new a subsection of the Discussion that focuses on these limitations of a bias-blind DA system: ***4.1 Limitations of bias-blind DA systems***

In response to a suggestion from Reviewer 2, we will introduce the comparison with the $\mathrm{DA}_{\mathrm{S1}}$ experiment in the Materials and Methodology section:

2.4.4 Comparison to SD_{S1} DA

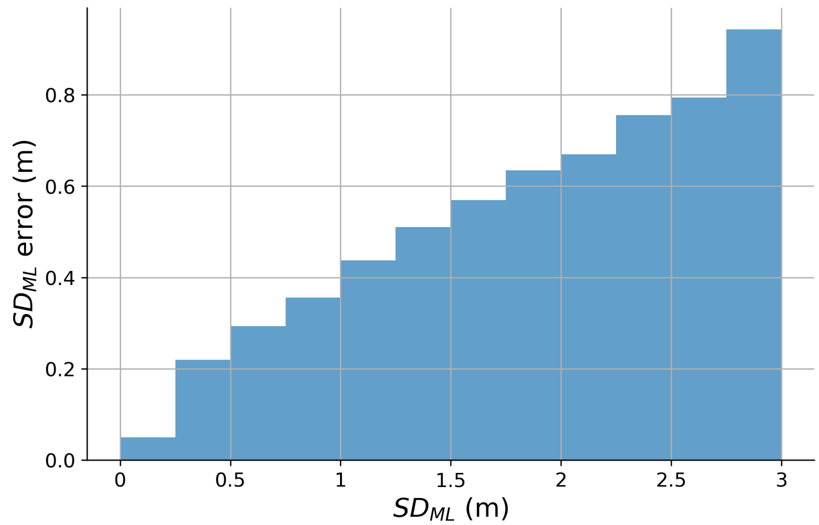
To compare with previous work that assimilates snow depth retrievals from the S1 change detection algorithm (SD_{S1}; Lievens et al. [2022]), we compared output from our two DA experiments with DA output from De Lannoy et al. [2024] (experiment $\mathrm{DA}_{\mathrm{S1}}$). This $\mathrm{DA}_{\mathrm{S1}}$ experiment utilized the same DA setup as in $\mathrm{DA}_{\mathrm{const}}$, with a static observation uncertainty (σ_{obs} = 0.3 m), but assimilates SD_{S1} retrievals instead of SD_{ML}. Here, we utilized 4548 manual SWE measurements collected within the Po River basin (the study domain of De Lannoy et al. [2024]) to compare SWE MAE between the $\mathrm{DA}_{\mathrm{const}}$, $\mathrm{DA}_{\mathrm{var}}$, and $\mathrm{DA}_{\mathrm{S1}}$ experiments.

Minor Comments

Comment 1 - Introduction:
Since this paper focuses on evaluating different data assimilation (DA) approaches, it would strengthen the manuscript to include a more thorough overview of existing DA algorithm literature, for context and completeness. I recommend adding this near Lines 44–51, where the background on DA methods is introduced.

Agreed. We will provide a more thorough overview of existing DA algorithm literature in this paragraph as follows:

"*One method for assimilating observations into a physical model is via direct insertion, whereby the model's state variables are directly replaced with observations without any statistical blending or error weighting [Rodell and Houser, 2004, Toure et al., 2018]. Increasing in sophistication, optimal interpolation methods, which consider model and observational uncertainty to blend the model and observations using statistically optimal weights [Liston and Hiemstra, 2008], are commonly used at operational centers [Helmert et al., 2018]. Also common among operational centers [Helmert et al., 2018], and one of the most-used DA techniques within the land surface modeling community is the Ensemble Kalman Filter (EnKF; Reichle et al. [2002]).* With an EnKF, the background-error covariance is not explicitly computed, but instead estimated using an ensemble of model trajectories. While this ensemble approach is advantageous for high-dimensional, nonlinear systems where an exact computation of the background-error covariance is impractical, the assumption of unbiased, normally distributed model-state errors is often violated for cumulative state variables like snow depth. Despite its reliance on Gaussian assumptions, the EnKF has been extensively used in previous snow data assimilation work [Slater and Clark, 2006, Durand and Margulis, 2006, De Lannoy et al., 2012, Huang et al., 2017, Pflug et al., 2024]. *An alternative solution that is commonly used in snow DA, particle batch filters and smoothers are capable of handling non-Gaussian noise*



Review Figure 2: *(Supplemental Figure 1 of revised manuscript) Actual observation error per bin of assimilated snow depth (SD_{ML}). The error is computed using 588 independent in-situ measurement sites.*

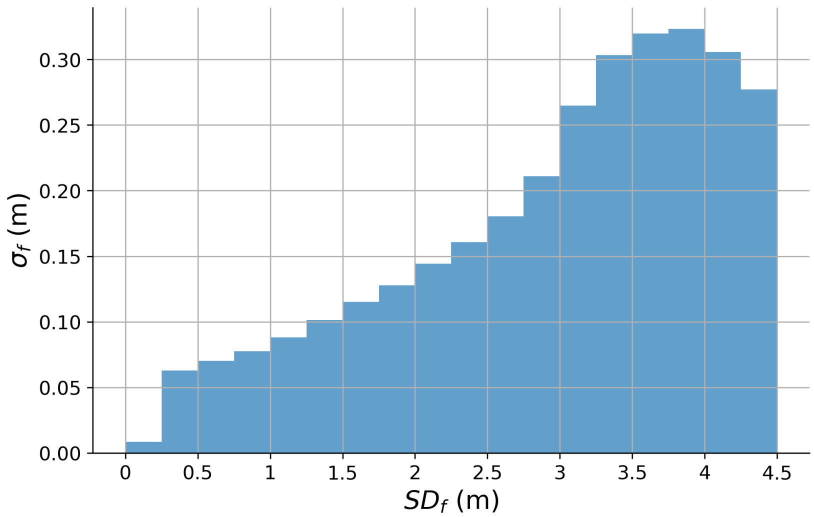
and complex posterior distributions. In particular, particle batch smoothers have been commonly applied to create snow reconstructions [Margulis et al., 2015, Baldo and Margulis, 2018, Girotto et al., 2024]."

Comment 1 - Methods/Results:
Justify the use of 0.05 to 1.05 bounds and increasing error with time. It would be helpful to include spatial and temporal figures (e.g., from representative sites) comparing the input observations against independent validation data. This could illustrate the spatial and temporal variability of observation errors and help justify the bounds selected for dynamic error modeling (0.05 to 1.05). For instance, do errors vary systematically with snow depth, such as being lower in shallow snow and higher in deeper snow? As noted by Alonso-González et al. (2024), no data assimilation algorithm is universally superior; performance depends on the data and task at hand. Thus, this figure can further support the choice of the Ensemble Kalman Filter (EnKF) and observation error technique.

To justify the use of an observation error that varies with snow depth we will include Review Figure 2 in the supplementary material, demonstrating how the SD_{ML} error varies with snow depth at our 588 independent measurement sites:

We will also modify the following text to provide this justification, and to justify of our 0.05 and 1.05 lower and upper threshold on the observation error

"... We defined m experimentally by selecting the optimal value when comparing modeled snow depth with in-situ observations in a subset region (6-8 °E, 45-46 °N). Here, we used $m = 0.3$. *Equation 2 assumes that σ_{obs} varies linearly as a function of assimilated snow depth. Supplemental Figure 1 demonstrates that this assumption is valid at independent in-*



Review Figure 3: *(Supplemental Figure 2 of revised manuscript) Standard deviation of the forecast error (σ_f) per bin of forecast snow depth (SD_f). σ_f is computed as the standard deviation of the ensembles for the OL.*

situ measurement sites. For SD_{ML} below 0.25 m, the average error of the SD_{ML} product compared to in-situ measurements is 0.05 (Supplemental Figure 1), and as such we chose this as a minimum threshold value for σ_{obs} (Equation 2). Setting this minimum threshold also avoids issues when $SD_{ML}(i,t) = 0$ m. We can see from Supplemental Figure 1 that there are no assimilated snow depths above 3 m at these in-situ measurement sites, making it difficult to characterize the observation error for deeper assimilated snow depths. As such, we also defined an upper threshold for σ_{obs} of 1.05 m, corresponding to an assimilated snow depth of 3.5 m (Equation 2). This value was also chosen as an upper threshold because we observed that σ_f, which represents the uncertainty in the model-only (OL) simulated snow depth, given by the standard deviation of the model ensembles, levels off above 3.5 m snow depth (Supplemental Figure 2). We chose to reflect this feature of the forecast error in our characterization of the observation error."

Line to Line Comments

1) Lines 17–29 would be more effective as a single cohesive paragraph. The current break into two paragraphs disrupts the logical flow and makes the message harder to follow.

We will merge these two paragraphs into a single paragraph.

2) Lines 30-43 discuss various SWE estimation methods, but some other approaches such as spaceborne laser altimetry (e.g., ICESat/ICESat-2), Sentinel-2, and MODIS, are missing and should be acknowledged for completeness. Additionally, the paragraph uses SWE and snow depth somewhat interchangeably (line 42). It would strengthen the clarity to note

explicitly that snow density is required to convert snow depth into SWE.

We will update the text in this paragraph to mention other satellite-based SWE estimation methods:

"Snow depth has also been retrieved using satellite observations, which have the benefit of providing frequent, global coverage [Lievens et al., 2019]. *One approach estimates snow depth by comparing digital elevation models (DEMs) from snow-on and snow-off conditions. These DEMs can be generated from satellite laser altimetry such as ICESat-2 [Enderlin et al., 2022, Deschamps-Berger et al., 2023, Besso et al., 2024] or from very-high-resolution stereoscopic satellite imagery via photogrammetric methods [Marti et al., 2016, Shaw et al., 2020, Deschamps-Berger et al., 2020]. Globally, passive microwave and synthetic aperture radar (SAR) observations are more commonly used to estimate snow depth.* [Kelly et al., 2019, Luojus et al., 2021, Lievens et al., 2022]. However, passive microwave imagery has a coarse spatial resolution…"

We will also clarify the distinction between snow depth and SWE at the beginning of the paragraph:

"Despite the importance of snow within Earth's climate and as a natural resource, accurately quantifying snow mass (or snow water equivalent, SWE) in mountainous, complex terrain remains a challenge. *Because SWE is difficult and costly to directly quantify [Dozier et al., 2016], measurements and retrieval algorithms more commonly focus on snow depth, which is related to SWE via the snow density.*"

3) Line 58-59: particle batch filters and smoothers. can be more computationally expensive given the large number of particles required." While this is generally true for particle filters, it is not necessarily the case for particle batch smoothers (PBS). For example, Alonso-González et al. (2024) showed that PBS was less computationally expensive than EnKF and other particle-based methods across multiple particle counts (100, 200, 300). The authors should either revise the statement to reflect this variability or cite relevant studies to justify the statement.

We will modify the paragraph that contains lines 58-59 in accordance with this reviewer's first minor comment. Our modifications will provide more background details for other various DA methods used in the snow community. In our modification, we will also remove the comment that particle batch filters and smoothers can be more computationally expensive given the number of particles required.

4) Line 67/86: Report the accuracy metrics from Lievens et al. compared to those from Dunmire et al. (2024). Additionally, please clarify that higher accuracy was achieved when evaluated over the European Alps only, as this distinction is crucial for understanding the geographic limitations of these methods.

Following L67, we will add the following sentence to provide metrics for the conceptual [Lievens et al., 2022] and ML-based [Dunmire et al., 2024] models: "*For instance, compared* *to 798 Alps-wide in-situ measurement sites, the ML model has an average site mean absolute error (MAE) of 0.18 m and an average site bias of -8 mm, compared to an MAE of 0.22 m and a bias of -99 mm for the conceptual model, respectively.*" We will also clarify that that these metrics are valid over the European Alps specifically.

Following L86, we will add the following text to provide metrics for the superiority of ERA5 forcing on modeled snow depth accuracy and bias: "*From Brangers et al. [2024], the ERA5, MERRA-2, and M2CORR atmospheric forcing led to average modeled snow depth MAEs of 0.367 m, 0.404 m, and 0.434 m, and average snow depth biases of -0.07 m, +0.138 m, and -0.363 m, respectively, compared to in-situ measurement stations in the Western European Alps (Figure 10, Brangers et al. [2024]).*"

5) Line 62-73: Clarify that the primary goal of this work is to assess the utility of incorporating dynamic observation errors versus static ones, because there are studies that have compared the performance of different algorithms already.

We will clarify that the primary goal of this work is to assess the utility of incorporating dynamic observation error versus static ones.

6) Line 101-102: specify the reported accuracy metrics (same as 67 and 86). What does better mean?

We will modify the sentence in L102 as follows to include accuracy metrics: "When compared to in-situ snow depth stations and airborne photogrammetry snow depth maps, SD_{ML} is shown to reduce MAE and improve bias compared to SD_{S1} *(MAE reduction from 0.22 m for* SD_{S1} *to 0.18 m for* SD_{ML}*, bias improvement from -99 mm for* SD_{S1} *to -8 mm for* SD_{ML}*).*"

7) Line 173-184: The evaluation section introduces Snow Disappearance Date (SDD) and Snow Cover Fraction (SCF) without prior mention or justification in the earlier sections of the manuscript. To improve clarity and coherence, it would be helpful to introduce these variables earlier in the manuscript, explain their relevance to the study objectives.

Snow Disappearance Date and Snow Cover Fraction are relevant to the study objectives in that they are used to **evaluate the DA experiments**. Therefore, we believe that it is most appropriate to introduce these concepts in the Evaluation subsection of Materials and Methodology. We have restructured this section (2.4 Evaluation) to better introduce these concepts and the materials used for this evaluation by adding further subsections. This revised structure will be as follows:

2.4 Evaluation

For each of our three experiments (OL, $\mathrm{DA}_{\mathrm{const}}$*,* $\mathrm{DA}_{\mathrm{var}}$*), we utilized a variety of in-situ and satellite-based products to evaluate 1) snow depth, 2) SWE, and 3) snow cover fraction (SCF) and snow disappearance date (SDD).*

2.4.1 Snow depth evaluation

...

2.4.2 SWE evaluation

...

2.4.3 SCF and SDD evaluation

8) Figure 2:

- Why were these two sites chosen? State reason (representativeness, topography, etc) either in the figure description or the result section.

  We will add the following text to the figure caption: "These two sites were chosen because a continuous time series of in-situ data was available, and these sites are generally representative of locations where the DA removes and adds snow."

- Axis can be shared for better readability (general comment for all figures).

  We will share and simplify the x-axis of the graph for better readability (see Review Figure 4)

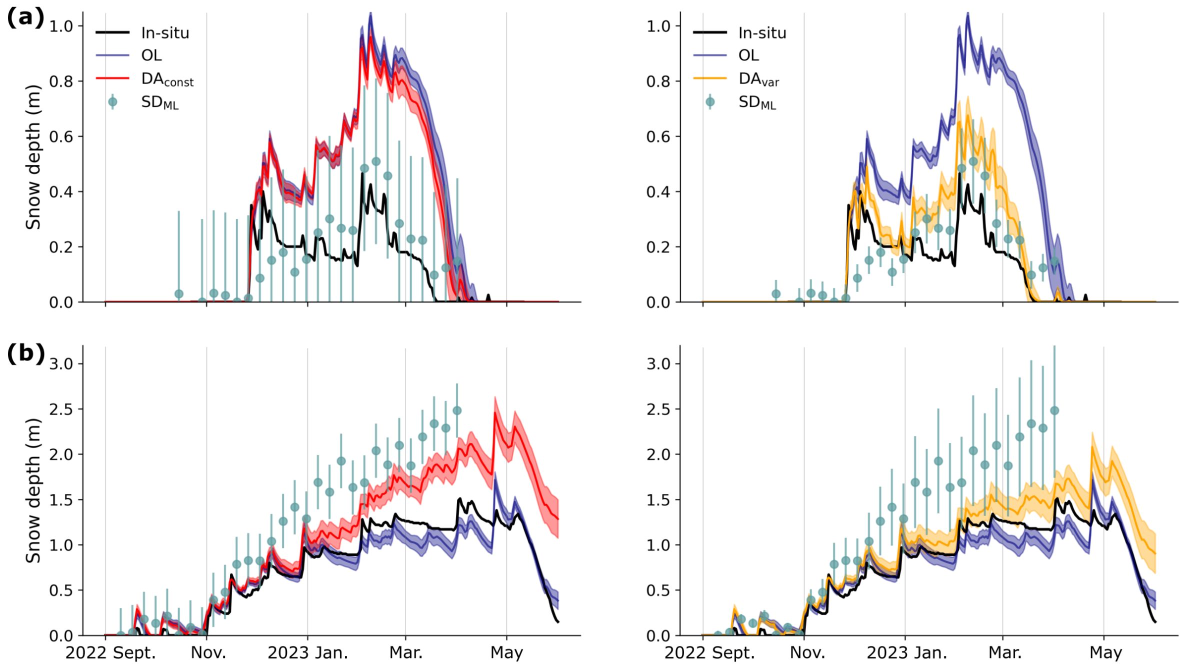
Line 240-243: State the bias-corrected numbers for the constant as well and compare them to the variable. "Both $\mathrm{DA_{const}}$ and $\mathrm{DA_{var}}$ also substantially improve the Pearson correlation coefficient..." report numbers.

We will incorporate in-text numbers as suggested for the $\mathrm{DA_{const}}$ bias and the Pearson correlation coefficients:

"As a result, the overall average SWE bias decreases from +81 mm in the OL to +18 mm in $\mathrm{DA_{var}}$. This bias reduction is significantly greater than that for $\mathrm{DA_{const}}$ *(+76 mm bias)*, which only marginally corrects the high bias for low observed SWE, due to minimal model adjustments for shallow assimilated snow depths (e.g., Fig. 5a). Both $\mathrm{DA_{const}}$ and $\mathrm{DA_{var}}$ also substantially improve the Pearson correlation coefficient *(R = 0.60 for OL, R = 0.72 for* $\mathrm{DA_{const}}$*, R = 0.71 for* $\mathrm{DA_{var}}$*)*, indicating a stronger correlation with measured SWE."

9) Line 325: The claim that dynamic observation error estimation "had not yet been explored" overlooks prior work that has implemented such approaches (e.g., Alonso-González et al., 2022). While these studies may not compare dynamic and constant errors directly, they do demonstrate prior use of dynamic error treatment in snow science. I suggest rephrasing to acknowledge existing efforts and clarify this study's specific novelty.

We assume that the Alonso-González et al (2022) reference here is referring to the MuSA paper in Geoscientific Model Development. According to this manuscript, a dynamic observation error was not implemented. In Section 2.3, the authors state: "A temporally and spatially static constant scalar corresponding to the assumed observation error variance must



Review Figure 4: (Figure 2 in the Manuscript) Snow depth estimates and independent in-situ measurements at two example sites. (a) Snow depth from DA_{const} (red, left) and DA_{var} (orange, right) compared with the OL (navy) from a measurement station in Austria (13.6228 °E, 47.0944 °N, 1050 m elevation). The shading represents ±1 standard deviation in the model ensembles. The sage green dots represent the assimilated SD_{ML} retrievals, with error bars for the assumed observation error standard deviation (σ_{obs} , Equation 2). (b) Same as (a), but for a different measurement station in Switzerland (7.7836 °E, 45.9872 °N, 2948 m elevation). *These two sites were chosen due to a lack of gaps in the in-situ measurements and their general representativeness of locations where the DA removes and adds snow.*

be provided for each type of observation that is to be assimilated." [Alonso-González et al., 2022]. In fact, options for a dynamic observation error in MuSA were not incorporated until to v2.1, which was released on May 8, 2024.

However, there does exist other prior work that has utilized dynamic observation errors and as such we will modify this statement accordingly: "While the specification of observation uncertainty substantially influences DA performance, in snow DA systems, this uncertainty is often prescribed as a constant value [Helmert et al., 2018]. *Some previous studies have incorporated dynamic observations errors (e.g., Magnusson et al. [2017], Oberrauch et al. [2024]); however, the utility of dynamic observation errors, relative to an assumed static observation error, in snow DA has not yet been explored prior to this work.*"

References

Esteban Alonso-González, Kristoffer Aalstad, Mohamed Wassim Baba, Jesús Revuelto, Juan Ignacio López-Moreno, Joel Fiddes, Richard Essery, and Simon Gascoin. The Multiple Snow Data Assimilation System (MuSA v1.0). *Geoscientific Model Development*, 15 (24):9127–9155, 12 2022. ISSN 1991-9603. doi: 10.5194/gmd-15-9127-2022.

Elisabeth Baldo and Steven A. Margulis. Assessment of a multiresolution snow reanalysis framework: a multidecadal reanalysis case over the upper Yampa River basin, Colorado. *Hydrology and Earth System Sciences*, 22(7):3575–3587, 7 2018. ISSN 1607-7938. doi: 10.5194/hess-22-3575-2018.

Hannah Besso, David Shean, and Jessica D. Lundquist. Mountain snow depth retrievals from customized processing of ICESat-2 satellite laser altimetry. *Remote Sensing of Environment*, 300:113843, 1 2024. ISSN 00344257. doi: 10.1016/j.rse.2023.113843.

I. Brangers, H. Lievens, A. Getirana, and G. J. M. De Lannoy. Sentinel-1 Snow Depth Assimilation to Improve River Discharge Estimates in the Western European Alps. *Water Resources Research*, 60(11), 11 2024. ISSN 0043-1397. doi: 10.1029/2023WR035019.

Patrick Broxton, Mohammad Reza Ehsani, and Ali Behrangi. Improving Mountain Snowpack Estimation Using Machine Learning With Sentinel-1, the Airborne Snow Observatory, and University of Arizona Snowpack Data. *Earth and Space Science*, 11(3), 3 2024. ISSN 2333-5084. doi: 10.1029/2023EA002964.

Gabriëlle J. M. De Lannoy, Rolf H. Reichle, Kristi R. Arsenault, Paul R. Houser, Sujay Kumar, Niko E. C. Verhoest, and Valentijn R. N. Pauwels. Multiscale assimilation of Advanced Microwave Scanning Radiometer–EOS snow water equivalent and Moderate Resolution Imaging Spectroradiometer snow cover fraction observations in northern Colorado. *Water Resources Research*, 48(1), 1 2012. ISSN 0043-1397. doi: 10.1029/2011WR010588.

Gabriëlle J. M. De Lannoy, Michel Bechtold, Louise Busschaert, Zdenko Heyvaert, Sara Modanesi, Devon Dunmire, Hans Lievens, Augusto Getirana, and Christian Massari. Contributions of Irrigation Modeling, Soil Moisture and Snow Data Assimilation to High-Resolution Water Budget Estimates Over the Po Basin: Progress Towards Digital Replicas.

Journal of Advances in Modeling Earth Systems, 16(10), 10 2024. ISSN 1942-2466. doi: 10.1029/2024MS004433.

César Deschamps-Berger, Simon Gascoin, Etienne Berthier, Jeffrey Deems, Ethan Gutmann, Amaury Dehecq, David Shean, and Marie Dumont. Snow depth mapping from stereo satellite imagery in mountainous terrain: evaluation using airborne laser-scanning data. *The Cryosphere*, 14(9):2925–2940, 9 2020. ISSN 1994-0424. doi: 10.5194/tc-14-2925-2020.

César Deschamps-Berger, Simon Gascoin, David Shean, Hannah Besso, Ambroise Guiot, and Juan Ignacio López-Moreno. Evaluation of snow depth retrievals from ICESat-2 using airborne laser-scanning data. *The Cryosphere*, 17(7):2779–2792, 7 2023. ISSN 1994-0424. doi: 10.5194/tc-17-2779-2023.

Jeff Dozier, Edward H. Bair, and Robert E. Davis. Estimating the spatial distribution of snow water equivalent in the world's mountains. *WIREs Water*, 3(3):461–474, 5 2016. ISSN 2049-1948. doi: 10.1002/wat2.1140.

Devon Dunmire, Hans Lievens, Lucas Boeykens, and Gabriëlle J.M. De Lannoy. A machine learning approach for estimating snow depth across the European Alps from Sentinel-1 imagery. *Remote Sensing of Environment*, 314:114369, 12 2024. ISSN 00344257. doi: 10.1016/j.rse.2024.114369.

Michael Durand and Steven A. Margulis. Feasibility Test of Multifrequency Radiometric Data Assimilation to Estimate Snow Water Equivalent. *Journal of Hydrometeorology*, 7(3): 443–457, 6 2006. ISSN 1525-7541. doi: 10.1175/JHM502.1.

Ellyn M. Enderlin, Colten M. Elkin, Madeline Gendreau, H.P. Marshall, Shad O'Neel, Christopher McNeil, Caitlyn Florentine, and Louis Sass. Uncertainty of ICESat-2 ATL06- and ATL08-derived snow depths for glacierized and vegetated mountain regions. *Remote Sensing of Environment*, 283:113307, 12 2022. ISSN 00344257. doi: 10.1016/j.rse.2022.113307.

Manuela Girotto, Giuseppe Formetta, Shima Azimi, Claire Bachand, Marianne Cowherd, Gabrielle De Lannoy, Hans Lievens, Sara Modanesi, Mark S. Raleigh, Riccardo Rigon, and Christian Massari. Identifying snowfall elevation patterns by assimilating satellite-based snow depth retrievals. *Science of The Total Environment*, 906:167312, 1 2024. ISSN 00489697. doi: 10.1016/j.scitotenv.2023.167312.

Jürgen Helmert, Aynur Şensoy Şorman, Rodolfo Alvarado Montero, Carlo De Michele, Patricia de Rosnay, Marie Dumont, David Finger, Martin Lange, Ghislain Picard, Vera Potopová, Samantha Pullen, Dagrun Vikhamar-Schuler, and Ali Arslan. Review of Snow Data Assimilation Methods for Hydrological, Land Surface, Meteorological and Climate Models: Results from a COST HarmoSnow Survey. *Geosciences*, 8(12):489, 12 2018. ISSN 2076-3263. doi: 10.3390/geosciences8120489.

Zachary Hoppinen, Ross T. Palomaki, George Brencher, Devon Dunmire, Eric Gagliano, Adrian Marziliano, Jack Tarricone, and Hans-Peter Marshall. Evaluating snow depth retrievals from Sentinel-1 volume scattering over NASA SnowEx sites. *The Cryosphere*, 18 (11):5407–5430, 11 2024. ISSN 1994-0424. doi: 10.5194/tc-18-5407-2024.

Chengcheng Huang, Andrew J. Newman, Martyn P. Clark, Andrew W. Wood, and Xiaogu Zheng. Evaluation of snow data assimilation using the ensemble Kalman filter for seasonal streamflow prediction in the western United States. *Hydrology and Earth System Sciences*, 21(1):635–650, 1 2017. ISSN 1607-7938. doi: 10.5194/hess-21-635-2017.

Richard Kelly, Qinghuan Li, and Nastaran Saberi. 'The AMSR2 Satellite-Based Microwave Snow Algorithm (SMSA): A New Algorithm for Estimating Global Snow Accumulation. In *IGARSS 2019 - 2019 IEEE International Geoscience and Remote Sensing Symposium*, pages 5606–5609. IEEE, 7 2019. ISBN 978-1-5386-9154-0. doi: 10.1109/IGARSS.2019.8898525.

Hans Lievens, Matthias Demuzere, Hans-Peter Marshall, Rolf H. Reichle, Ludovic Brucker, Isis Brangers, Patricia de Rosnay, Marie Dumont, Manuela Girotto, Walter W. Immerzeel, Tobias Jonas, Edward J. Kim, Inka Koch, Christoph Marty, Tuomo Saloranta, Johannes Schöber, and Gabrielle J. M. De Lannoy. Snow depth variability in the Northern Hemisphere mountains observed from space. *Nature Communications*, 10(1):4629, 10 2019. ISSN 2041-1723. doi: 10.1038/s41467-019-12566-y.

Hans Lievens, Isis Brangers, Hans-Peter Marshall, Tobias Jonas, Marc Olefs, and Gabriëlle De Lannoy. Sentinel-1 snow depth retrieval at sub-kilometer resolution over the European Alps. *The Cryosphere*, 16(1):159–177, 1 2022. ISSN 1994-0424. doi: 10.5194/tc-16-159-2022.

Glen E. Liston and Christopher A. Hiemstra. A Simple Data Assimilation System for Complex Snow Distributions (SnowAssim). *Journal of Hydrometeorology*, 9(5):989–1004, 10 2008. ISSN 1525-7541. doi: 10.1175/2008JHM871.1.

Kari Luojus, Jouni Pulliainen, Matias Takala, Juha Lemmetyinen, Colleen Mortimer, Chris Derksen, Lawrence Mudryk, Mikko Moisander, Mwaba Hiltunen, Tuomo Smolander, Jaakko Ikonen, Juval Cohen, Miia Salminen, Johannes Norberg, Katriina Veijola, and Pinja Venäläinen. GlobSnow v3.0 Northern Hemisphere snow water equivalent dataset. *Scientific Data*, 8(1):163, 7 2021. ISSN 2052-4463. doi: 10.1038/s41597-021-00939-2.

Jan Magnusson, Adam Winstral, Andreas S. Stordal, Richard Essery, and Tobias Jonas. Improving physically based snow simulations by assimilating snow depths using the particle filter. *Water Resources Research*, 53(2):1125–1143, 2 2017. ISSN 0043-1397. doi: 10.1002/2016WR019092.

Steven A. Margulis, Manuela Girotto, Gonzalo Cortés, and Michael Durand. A Particle Batch Smoother Approach to Snow Water Equivalent Estimation. *Journal of Hydrometeorology*, 16(4):1752–1772, 8 2015. ISSN 1525-755X. doi: 10.1175/JHM-D-14-0177.1.

R. Marti, S. Gascoin, E. Berthier, M. de Pinel, T. Houet, and D. Laffly. Mapping snow depth in open alpine terrain from stereo satellite imagery. *The Cryosphere*, 10(4):1361–1380, 7 2016. ISSN 1994-0424. doi: 10.5194/tc-10-1361-2016.

Moritz Oberrauch, Bertrand Cluzet, Jan Magnusson, and Tobias Jonas. Improving Fully Distributed Snowpack Simulations by Mapping Perturbations of Meteorological Forcings Inferred From Particle Filter Assimilation of Snow Monitoring Data. *Water Resources Research*, 60(12), 12 2024. ISSN 0043-1397. doi: 10.1029/2023WR036994.

Justin M. Pflug, Melissa L. Wrzesien, Sujay V. Kumar, Eunsang Cho, Kristi R. Arsenault, Paul R. Houser, and Carrie M. Vuyovich. Extending the utility of space-borne snow water equivalent observations over vegetated areas with data assimilation. *Hydrology and Earth System Sciences*, 28(3):631–648, 2 2024. ISSN 1607-7938. doi: 10.5194/hess-28-631-2024.

Rolf H. Reichle, Dennis B. McLaughlin, and Dara Entekhabi. Hydrologic Data Assimilation with the Ensemble Kalman Filter. *Monthly Weather Review*, 130(1):103–114, 1 2002. ISSN 0027-0644. doi: 10.1175/1520-0493(2002)130¡0103:HDAWTE¿2.0.CO;2.

M. Rodell and P. R. Houser. Updating a Land Surface Model with MODIS-Derived Snow Cover. *Journal of Hydrometeorology*, 5(6):1064–1075, 12 2004. ISSN 1525-7541. doi: 10.1175/JHM-395.1.

Thomas E. Shaw, Simon Gascoin, Pablo A. Mendoza, Francesca Pellicciotti, and James McPhee. Snow Depth Patterns in a High Mountain Andean Catchment from Satellite Optical Tristereoscopic Remote Sensing. *Water Resources Research*, 56(2), 2 2020. ISSN 0043-1397. doi: 10.1029/2019WR024880.

Andrew G. Slater and Martyn P. Clark. Snow Data Assimilation via an Ensemble Kalman Filter. *Journal of Hydrometeorology*, 7(3):478–493, 6 2006. ISSN 1525-7541. doi: 10.1175/JHM505.1.

Ally M. Toure, Rolf H. Reichle, Barton A. Forman, Augusto Getirana, and Gabrielle J. M. De Lannoy. Assimilation of MODIS Snow Cover Fraction Observations into the NASA Catchment Land Surface Model. *Remote Sensing*, 10(2):316, 2 2018. ISSN 2072-4292. doi: 10.3390/rs10020316.