Response to Reviewer Comments

Dear Editor,

Thank you for providing valuable feedback from the reviewers on our manuscript "High-Resolution Snow Water Equivalent Estimation: A Data-Driven Method for Localized Downscaling of Climate Data." We have carefully addressed all of the comments and suggestions to improve the clarity and overall quality of the paper. Below, we provide a point-by-point response to the reviewers' comments.

Reviewer 2

1. Comment: This study by Zakeri et al. presents a method for downscaling Snow Water Equivalent (SWE) to 500 m, from a low-resolution SWE dataset and low-resolution climate reanalysis data. The model is trained using a high-resolution SWE dataset (SWE reanalysis from UCLA) and low-resolution climate data. The downscaling algorithm uses a K-nearest neighbors' method, for which parameters are determined through sensitivity analysis and optimization. Results are shown in two mountainous regions of the Western United States, in California and Colorado, and compared to other SWE spatial datasets.

The paper is interesting for the snow and hydrology community as it offers a new method to produce useful spatial SWE datasets over large areas, without using physical modelling of the snowpack which can be computationally expensive. The method is quite clearly exposed.

However, the paper generally lacks a solid discussion of the results. Results and metrics of comparison are exposed in the result section but are not further discussed since the Discussion and Conclusion section is more a summary. A dedicated Discussion section would be welcome, in particular to convince the reader of the quality of the evaluated method against other methods, provide more physically based explanations of differences (e.g. can the chosen method explain certain biases?), provide a critical point of view on the benefits and limitations of the method, etc.

1. Response: We would like to thank the reviewer for their constructive feedback. To address the reviewer's concern we have added a new Section (6. Discussion) to include a dedicated discussion. This section now provides an in-depth analysis of the results, a comparison with different downscaling methodologies, an exploration of physical explanations, and an evaluation of the method's strengths and limitations.

Lines 530-580:

6. Discussion

In general, using the 'cnrm-esm2-1' model as an estimator results in better accuracy in Colorado at both 100 km and 9 km resolutions compared to other models. For instance, in Colorado, the use of the 'cnrm-esm2-1' model at a 9 km resolution demonstrated close agreement with observed SWE, with an average RMSE of 0.06 meters. This performance highlights the model's strong compatibility with the climatic and geographical complexities of Colorado. Conversely, in California, the 'ec-earth3-veg' model excels at a 9 km resolution, providing the most accurate results with an average RMSE of 0.13 meters compared to the reference datasets. This suggests that its higher resolution better captures the region's complex environmental and topographical variations.

It also appears that a finer resolution of 9 km provides slightly better accuracy than a 100 km resolution across all models, although the difference is not substantial. This underscores the importance of selecting the appropriate climate model for SWE estimation, which can have a more significant impact than merely choosing a higher-resolution model. Moreover, CMIP6 models are designed for long-term climate projections and capture broad climate trends rather than predicting specific weather events. Despite this, the downscaled SWE using the proposed approach based on CMIP6 is comparable to that of WRF-CMIP6, which dynamically downscales CMIP6 data by incorporating ERA5 reanalysis data. This is largely because the proposed methodology relies on long-term climate data through the use of far and near temporal intervals, and CMIP6 effectively captures broad climatic trends and seasonality, including changes in temperature and precipitation patterns.

Accordingly, achieving accurate HR-SWE estimation relies significantly on the choice and accuracy of the climate model inputs, such as precipitation and temperature data, which can introduce biases into the SWE estimates. For example, precipitation biases are a dominant factor influencing SWE estimation errors, while temperature biases become more significant during transitional periods, such as the spring melt season.

The following comparison provides a broader perspective on how our proposed method compares with other statistical downscaling techniques. BCSD methods are effective in reducing uncertainties in climate model outputs by adjusting model biases using high-resolution observations. These methods are particularly valuable for ensuring that model outputs align with observed climatology and capture local variability. However, they depend heavily on the availability of high-quality in-situ data, which limits their application in remote or data-sparse regions. In contrast, our method excels in areas with sparse data, as it uses low-resolution climate data without requiring ground observations, making it adaptable to a broader range of conditions.

Similarly, analog-type statistical downscaling approaches offer a relatively simple and computationally efficient way to project high-resolution data based on historical relationships between large-scale climate patterns and local climate variables. These methods are useful in regions where historical climate patterns are stable and well-documented. Our method introduces several key improvements over traditional analog-type downscaling techniques. First, the adaptation of the k-nn approach through the incorporation of far and near temporal intervals of climate data enhances its ability to handle dynamic variables, such as snow, which are subject to significant changes due to climate variability. Unlike conventional analog methods, which constrain analog candidates to a specific temporal window near the query date, our method eliminates such restrictions.

This is important for three main reasons: (1) the inclusion of far and near temporal intervals allows the selection of the most suitable candidates across a broader temporal range, making narrow constraints unnecessary; (2) it helps in preserving extreme events, as restricting candidates to a narrow temporal window may risk excluding matches that represent rare but important extreme events; and (3) it facilitates downscaling for future periods where no exact analogs exist in the historical record within a specific date range. Instead, suitable analogs may still be found in historical data but during different periods. For instance, as climate change progresses, a future day in winter may no longer have a match on the same calendar day in the past but might find an analog on another calendar day, for example, in a warmer season such as fall or spring.

In terms of computational efficiency, our method is highly effective. By using very low-resolution climate data as input, it reduces both memory requirements and computation time compared to physical snow models, which require high-resolution climate data as input to estimate HR-SWE information. This efficiency enables the generation of HR-SWE estimates over large spatial domains with reduced computational overhead. This is particularly beneficial when applying the method to large areas, long temporal scales, or ensembles of climate data.

2. Comment: Bales et al. (2006) is cited three times (l. 33), more references (particularly more recent ones) could be used in the beginning of the introduction. You could also provide a few more references about physically-based snow models (l. 34).

2. Response: To address this comment, the Introduction is now revised to include recent references, and additional references on physically based snow models to provide a more balanced, and comprehensive context, as follows: Introduction Section, lines 30–48:

Therefore, accurate and detailed information on Snow Water Equivalent (SWE) with high temporal and spatial resolution is crucial for effective water resource management and decision-making (Siirila-Woodburn et al., 2021; Bales et al., 2006; Fiddes et al., 2019).

Although ground stations are valuable for collecting SWE data, their limited presence in certain regions affects their representativeness. Moreover, variations in topography, land cover, and environmental conditions in mountainous areas make point-scale data insufficient for capturing the overall spatial characteristics of a watershed (Bales et al., 2006; Alonso-González et al., 2023). To address this lack of data, physically based snow models utilize an energy balance approach to estimate snowmelt. These models range in complexity, with more advanced models integrating detailed processes such as wind-induced snow transport, interactions with topography, and vegetation impacts. While complex models, such as those incorporating advection-diffusion equations or three-dimensional wind fields, provide more accurate representations of snow properties, they often require extensive input data, which may not always be available (Liston and Sturm, 1998; Lehning et al., 2006; Vionnet et al., 2014). Simpler models, on the other hand, may fail to capture critical aspects of snow dynamics (Bair et al., 2016; Clow et al., 2012). Moreover, to achieve high-resolution SWE (HR-SWE) estimates using these models, it is necessary to use meteorological and land cover-related data that matches the desired output resolution of the SWE. However, obtaining high-resolution data in mountainous regions remains challenging (Wundram and Löffler, 2008). Although generating HR-SWE with physical models can be time-consuming, it is worth noting that recent studies have focused on reducing this computational burden. For instance, advances in SWE modelling have been achieved by implementing parallelized versions of snow models. The approach maintains the integrity of physical processes while utilizing parallelization to manage the computational demands of fine-resolution datasets over large domains (Mower et al., 2024).

3. Comment: l. 61: specify "spatial snow patterns" (or do you also mean temporal patterns?)

3. Response: We have clarified the text to specify that it refers exclusively to spatiotemporal snow patterns that are repeatable between days with similar climatological data.

Recognizing the potential for snow spatiotemporal patterns to repeat on days with similar climatological characteristics.

4. Comment: l. 85-86: "physical models are computationally expensive". This assertion is not true by itself, see several recent publications where physical snow models are being applied over large domains, e.g. Mower et al. (2024). Please specify in a few words what makes them too computationally expensive for the application (domain, resolution, solved processes...?), or what computational benefit your method offers.

4. Response:

As suggested, we have modified the introduction to include a mention of recent studies that focus on reducing computational burdens, including the approach taken by Mower et al. (2024). Additionally, we have added details about what makes physical models computationally expensive and the benefits of the proposed methodology in the Introduction, as follows:

Introduction lines 45-53:

Although generating HR-SWE with physical models can be time-consuming, it is worth noting that recent studies have focused on reducing this computational burden. For instance, advances in SWE modeling have been achieved by implementing parallelized versions of snow models. This approach maintains the integrity of physical processes while utilizing parallelization to manage the computational demands of fine-resolution datasets over large domains (Mower et al., 2024). However, it is important to clarify that the computational expense becomes significant when operating at high spatial and temporal resolutions, particularly in an ensemble context, which is often required for robust climate predictions. Moreover, high-resolution simulations over large-scale domains require substantial computational resources. Additionally, generating high-resolution snow data using physical models typically necessitates high-resolution climate inputs, such as temperature and precipitation fields, to ensure the quality of the downscaled outputs.

And Introduction lines 133-138:

Finally, our method does not require high-resolution climate input data. This substantially reduces computational demands while maintaining the high quality of the downscaled SWE data, as demonstrated in the results Section. By reducing the resolution requirements for input data and employing a computationally efficient data-driven approach, our method offers significant computational advantages for practical, high-resolution applications, particularly compared to most physical models. These advantages are especially evident when snow data are needed for large areas, over long time periods, or when applied to ensembles of climate data.

5. Comment: l. 92: “climatic variables”. Perhaps rather say “meteorological variables”.

5. Response: We agree and have revised the manuscript to replace 'climatic variables' with 'meteorological variables' for greater clarity.

6. Comment: l. 94-95: “not subject to significant temporal variations within the specified regions”. Note that terrain shading depends on the sun position, so varies throughout the year.

6. Response: We have revised the text to acknowledge the variation in terrain shading throughout the year due to the sun's position.

Lines 173-176:

Although the position of the sun, and therefore terrain shading, changes throughout the year, the K-nearest SWE candidates are chosen based on similar climate conditions, resulting in the nearest candidates being selected within similar months across different years. This minimizes variability in effects like terrain shading, allowing us to assume that these effects are consistent.

7. Comment: l. 97: “SWE is also affected by conditions in the preceding periods”. This sentence is a bit unclear: do you mean SWE conditions? Meteorological conditions? Please clarify "preceding periods" too.

7. Response: We have clarified the sentence in the text:

Lines 178-180:

SWE is also affected by preceding meteorological conditions, such as the temperature and precipitation patterns of previous days. For instance, the amount of SWE today may vary depending on the conditions experienced in the preceding days.

8. Comment: l. 98-99: “These intervals consider climate variables such as minimum temperature, maximum temperature, precipitation, and surface downwelling shortwave radiation”. The use of “such as” makes it unclear whether it is an exhaustive list of considered variables. This section needs more justification of why and how these specific variables were chosen, and why other meteorological variables were discarded.

8. Response: We have revised the manuscript to clearly indicate that this is an exhaustive list of considered variables. Additionally, we have provided justification for the selection of these variables and explained why others were not included.

Lines 256-275:

Details on the experiments conducted to identify the most effective meteorological predictors within these datasets are available in the Supplementary (Table S1 and Fig. S1).

Table S1. A summary of the selected features in each scenario.

Scenarios	Features
1st scenario	Minimum and maximum temperatures, precipitation, downwelling shortwave radiation
2nd scenario	Minimum and maximum temperatures, precipitation, downwelling shortwave radiation, LR-SWE
3rd scenario	Minimum and maximum temperatures, precipitation, LR-SWE, MODIS snow cover
4th scenario	Minimum and maximum temperatures, precipitation, LR-SWE, MODIS snow cover, monthly terrain shadow
5th scenario	Minimum and maximum temperatures, precipitation, LR-SWE, downwelling shortwave radiation, MODIS snow cover
6th scenario	Minimum and maximum temperatures, precipitation, LR-SWE, downwelling shortwave radiation, MODIS snow cover, monthly terrain shadow

To evaluate the efficacy of the chosen features, we synthesize SWE images of Colorado for six consecutive years (2005–2010) using ERA5-Land climate data, MODIS snow cover, and monthly terrain shadow with different combinations as explained in Table S1. We analyze the months of January, February, March, April, November, and December across these years. The sum of the RMSE, (1-correlation), and Mean Difference is determined using cross-validation, and the average is calculated to identify which parameters consistently outperform the others (Fig. S1). As shown in Fig. S1, the second scenario generally demonstrates superior performance.

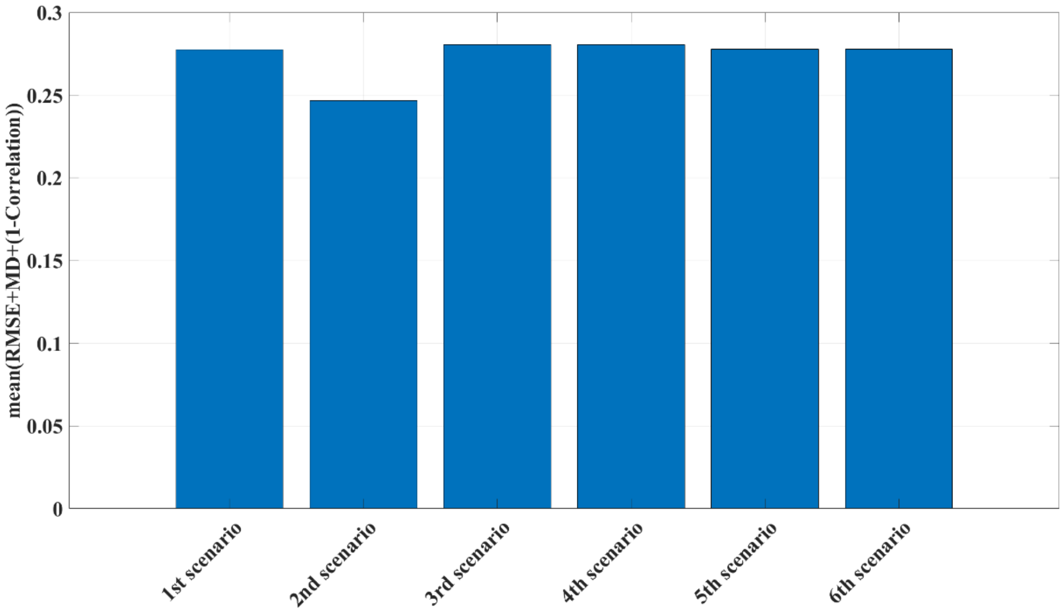


Fig. S1. The average error for the scenarios presented in Table S1.

9. Comment: L. 143: The reference HR-SWE is not an actual "observation", so please simply use reference instead of observation.

9. Response: We have revised the text to replace 'observation' with 'reference', as suggested.

10. Comment: l. 147: please provide the units (days?).

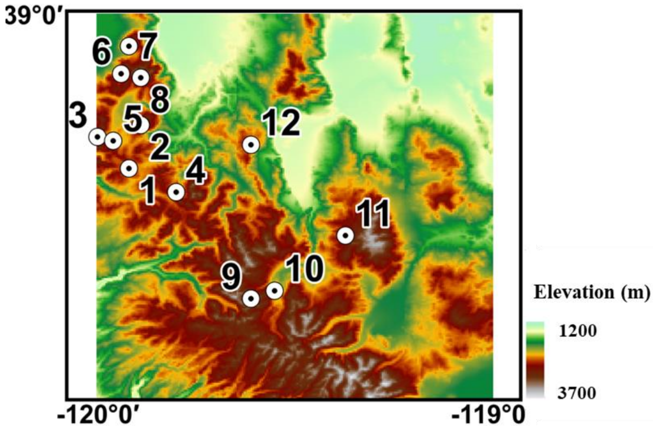
10. Response: We have specified the units as 'days' in the revised manuscript.

Line 239:

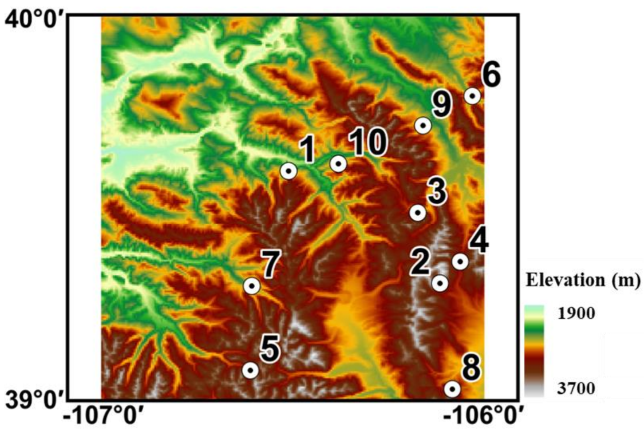
we conduct a sensitivity analysis within predefined ranges, set by $NI \in [1,7]$ days and $FI \in [1,90]$ days, aiming to minimize ε.

11. Comment: Fig. 2: Maybe a better colour than blue can be chosen for visibility of the numbers on the map.

11. Response: Thank you for this suggestion. We have revised Fig. 2 and updated the color scheme to improve the visibility of the numbers on the map. A contrasting color was selected to enhance clarity for the readers.



(b) California



(c) Colorado

12. Comment: Section 3.1: you could add a few words on the snow climatology of these two regions.

12. Response: We have added a brief description of the snow climatology for the California and Colorado regions in Section 3.1 as follows:

To demonstrate the context of snow climatology in these regions, it is important to note that the California Sierra Nevada snowpack plays a critical role in water resource management, contributing approximately 30% of the state's water supply through snowmelt. However, its sensitivity to warming temperatures is evident, with the 2015 SWE on April 1 dropping to just 5% of historical averages. This dramatic decline underscores the combined effects of reduced precipitation and higher temperatures, which amplify drought severity and alter the timing of water availability (Belmecheri et al., 2016).

In the Upper Colorado River Basin, snowmelt accounts for 70–90% of annual streamflow, making snowpack dynamics essential for hydrology and water management. Heldmyer et al. (2023) identify three distinct snow drought types: "warm", "dry", and "warm-and-dry", which differentially impact SWE and streamflow timing. Warm droughts tend to reduce SWE at lower elevations, while dry conditions cause uniform SWE reductions across elevations. These droughts advance peak streamflow timing by 7–13 days, emphasizing the region's sensitivity to climatic changes in temperature and precipitation (Heldmyer et al., 2023).

13. Comment: l. 175: A bit more details (one or two sentences) on what this dataset is based would be appreciated for the reader's understanding.

13. Response: We agree and have expanded the description of the dataset to include details on its basis, as outlined in lines 288–293:

It combines high-resolution remotely sensed data with a Bayesian data assimilation (Margulis et al., 2019; Margulis et al., 2015; Margulis et al., 2016) framework. The dataset is derived from Landsat-based fractional snow-covered area observations, updated daily, and incorporates a land surface model to estimate SWE and snow depth. This approach enables spatially and temporally continuous SWE estimates, which are verified against in situ and lidar-derived SWE measurements for accuracy.

14. Comment: l. 180: Please don't use "such as" if it is the exhaustive list of considered variables.

14. Response: We have revised the text to remove 'such as' and explicitly state that the listed variables are included.

15. Comment: l. 227-228: it would be interesting to discuss the relative weights of each variables from a physical perspective.

15. Response: We have added a discussion in lines 345-350 about the relative weights of each variable, including an analysis of their physical significance and contribution to the downscaling process as follows:

From a physical perspective, this weighting aligns with the processes governing SWE distribution and dynamics. Minimum temperature ($T_{min,LR}^{NI}$) significantly influences freezing and melting thresholds, which are critical for snowpack accumulation or melting. Precipitation variables, both near and far intervals (P_{LR}^{NI}, P_{LR}^{FI}), directly contribute to SWE through their impact on the volume of snowfall. Meanwhile, the inclusion of SWE_{LR} as a highly weighted variable highlights its role as a baseline indicator of existing snowpack conditions.

16. Comment: l. 240: Please stick to mm as SWE unit, which corresponds to the standard unit kg/m2. Potentially m for high values, but cm introduces confusion.

16. Response: We have updated the manuscript to consistently use millimeters (mm) as the standard unit for low SWE values. For exceptionally high values, meters (m) are used to maintain clarity and avoid confusion.

17. Comment: l. 246-250, Table 3: It is probably unnecessary to define very common metrics like mean difference, correlation and RMSE.

17. Response: We agree with this comment and have moved Table 3 to the Supplementary.

18. Comment: Why aren't in-situ SNOTEL SWE measurements not shown? Metrics of comparison to these point measurements could be presented and compared to metrics of the other products.

18. Response: In our study, we utilized the spatial locations of in-situ SNOTEL SWE measurement sites for pixel-based evaluations, comparing our downscaled SWE estimates with well-established SWE datasets in the United States, including the UCLA SWE dataset, SNODAS, Daymet, and the University of Arizona dataset. This approach demonstrates that the proposed downscaling method effectively preserves SWE information at the pixel level while analyzing the values of each pixel over multiple years.

It is worth noting that the UCLA SWE dataset has been previously validated against in-situ observations, including SNOTEL SWE measurements, establishing its robustness as a state-of-the-art dataset for SWE estimation in the Western United States (Fang et al., 2022). Moreover, the snow reanalysis framework has been successfully utilized in the past to generate datasets for the Sierra Nevada (Margulis et al., 2016).

Additionally, the UCLA SWE dataset has been widely adopted in subsequent studies as a benchmark for SWE validation. For instance:

Ma et al. (2023) used the UCLA SWE dataset as a ground truth reference to evaluate machine learning approaches for spatiotemporal SWE estimation.

Fang et al. (2023) employed the UCLA SWE dataset as a baseline reference to quantify snow water storage uncertainty in the midlatitude American Cordillera.

By utilizing this extensively validated reanalysis dataset and incorporating SNOTEL site locations for pixel-based assessments, we ensured a rigorous evaluation of our methodology. The manuscript has been revised to emphasize these points and improve clarity, as follows in lines 364-370:

It is important to emphasize that while the SNOTEL network provided the spatial locations for these comparisons, we did not use direct in-situ SNOTEL SWE measurements in this analysis. The UCLA SWE dataset has been previously validated against in-situ observations, including SNOTEL SWE measurements, and has been widely recognized as a benchmark for SWE validation in subsequent studies. For example, Ma et al. (2023) used the UCLA SWE dataset as a reference to assess the performance of machine learning approaches for estimating spatiotemporally continuous SWE. Similarly, Fang et al. (2023) employed the UCLA SWE dataset as a baseline for evaluating snow water storage uncertainty. These applications highlight the dataset's reliability and its critical role in advancing snow hydrology research.

19. Comment: See the general comment about a more in-depth discussion of the results.

19. Response: We have addressed the general comment. Please refer to our response to Comment 1.

We hope these revisions address all of your concerns, and we thank you once again for your valuable feedback.

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