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 1

1. Comment: The manuscript is generally well-structured, with a clear flow from the introduction to the methodology, results, and discussion. However, some sections could benefit from further clarification, particularly where the methodology is complex.

Consider adding a diagram or flowchart in the methodology section to visually represent the steps of the proposed downscaling algorithm. This would help readers better understand the process.

1. Response: We would like to thank the reviewer for their constructive feedback. We agree and have reviewed the methodology section, making several adjustments to enhance clarity. Additionally, we have included a flowchart in the methodology section (Section 2.3) to visually represent the steps of the downscaling algorithm, as suggested.

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.

Lines 211-213:

In this study, the k-nn algorithm is applied to downscale low-resolution climate data to HR-SWE estimates by selecting learning days with similar climate conditions. The flowchart (Fig. 2) illustrates the proposed downscaling method for estimating HR-SWE, and the "steps" are as follows:

1. Gather the input variables, including the far and near intervals of temperature, precipitation, shortwave radiation, and the LR-SWE for both the target date and the training dates.
2. Calculate the similarity or distance between the input vector of the target date and the input vectors of the training dates.
3. Select the K-nearest training dates based on their proximity to the target date in the input space.
4. Retrieve the corresponding HR-SWE images associated with the selected K-nearest training dates.
5. Aggregate the retrieved HR-SWE images to estimate $\widehat{SWE}$ for the target date.

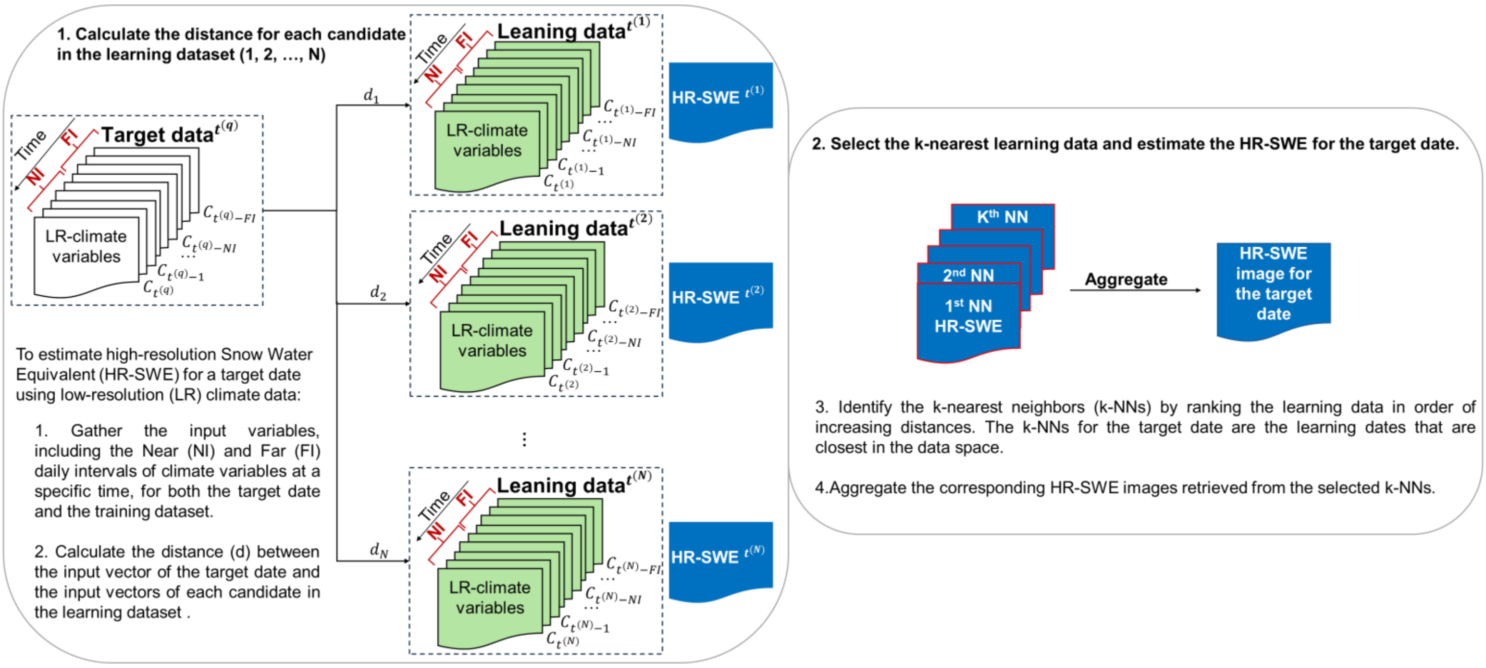

Fig. 2. Visual representation of the proposed downscaling algorithm process.

Lines 219-222:

Unlike the Euclidean distance, which calculates the shortest straight-line distance, the Manhattan distance computes the sum of the absolute differences between variables. This makes it more robust against outliers and better suited for high-dimensional datasets, such as those containing multiple climate variables. In our method, this distance is used to rank the training dates based on their similarity to the target date.

2. Comment: The novelty of the approach is well articulated, but a more explicit statement of how this method advances the field compared to existing approaches would strengthen the introduction.

2. Response: We agree with this suggestion and have now explicitly highlighted how our method advances existing approaches, as follows:

Lines 75-110:

One of the statistical downscaling methods is bias-correction spatial disaggregation (BCSD) (Wood et al., 2004), which effectively reduces uncertainties in climate model outputs by adjusting biases based on high-resolution observational data. These methods excel in capturing local variability while correcting large-scale model biases, making them particularly valuable for hydrological applications. However, their reliance on high-quality and extensive in-situ data restricts their applicability, particularly in remote or data-scarce regions, including areas with complex terrain where reliable climatological observations are limited. In contrast, our method overcomes these limitations by utilizing low-resolution climate data without requiring ground-based observations, making it well-suited for a wider range of conditions, including regions with limited data availability.

Another widely used statistical downscaling method in climatology is based on a pattern known as the analog method (Zorita and Von Storch, 1999). These methods identify patterns in historical data that closely match the patterns simulated by atmosphere-ocean general circulation models. The observed surface climate conditions corresponding to these historical matches are then used as downscaled predictions. Analog methods have seen extensive application, as highlighted in studies such as those by Abatzoglou and Brown (2012), who demonstrated their effectiveness in wildfire assessments through the multivariate adapted constructed analog, which outperformed traditional spatial downscaling methods. Similarly, Pons et al. (2010) utilized analog-based downscaling to analyze snow trends in Northern Spain, successfully replicating observed variability and trends, highlighting its utility for seasonal and climate change projections. The study by Caillouet et al. (2016) demonstrated the utility of probabilistic downscaling in reconstructing high-resolution precipitation and temperature fields over France, effectively addressing seasonal biases. The AtmoSwing software by Horton (2019) highlights the flexibility of analog methods for operational forecasting and climate impact studies.

Additionally, an analog-type method named nearest neighbor resampling, also used by Lall and Sharma (1996), relies on identifying patterns in historical point-based time series data and resampling them using a nearest-neighbor approach to preserve the serial dependence structure of the data. The k-nearest neighbors (k-nn) algorithm is a simple, non-parametric machine learning technique commonly used for classification and regression (Cover and Hart, 1967). It works by identifying the 'k' most similar data points (neighbors) to a target data point based on a chosen distance metric, such as the Manhattan distance. Building on this concept, Rajagopalan and Lall (1999) extended the methodology to multivariate weather simulations, incorporating variables such as precipitation, temperature, and wind speed to simulate daily weather sequences. Later, Yates et al. (2003) used an adapted version of these methods to generate daily weather sequences and alternative climate scenarios. k-nn downscaling by Gangopadhyay et al. (2005) extends the analog method by weighting several similar historical analogs to create predictive ensembles, adding further flexibility to this approach. They used the k-nn approach to derive localized precipitation and temperature forecasts from large-scale atmospheric model outputs. The method integrates global-scale predictors with local-scale station observations to produce downscaled forecasts at individual station locations. In the weather generator models based on k-nn, in general, the day directly succeeding the identified analog day is selected as the next day in the generated sequence, and this process continues iteratively (Gangopadhyay et al., 2005). Similarly, recent advancements, such as the study by Yiou and Déandréis (2019), have extended analog methods to ensemble-based probabilistic forecasts, demonstrating skill in predicting variables like the NAO index and temperatures at European stations. These innovations highlight the adaptability and growing utility of analog-based and k-nn approaches in climate and environmental modeling.

Lines 118-149:

This method provides several key advancements over existing statistical downscaling techniques. First, the adaptation made to the k-nn downscaling method, specifically by introducing far and near temporal intervals of climate data, is highly adaptable to dynamic variables undergoing significant changes due to climate variability. Second, unlike most analog methods that restrict analog candidates to a specific temporal window near the query date, this approach does not impose such limitations. This flexibility is crucial for three reasons: (1) the inclusion of far and near temporal intervals makes such restrictions unnecessary, as the most suitable candidates are selected based on their match within the temporal window; (2) it contributes to preserving extreme events, as restricting candidates to a narrow date range risks losing matches that represent rare but important extreme events; and (3) it enables downscaling for future periods where exact analogs may not exist in the historical record within a specific date range. However, suitable analogs may still be found in historical observations but on different dates. For example, with climate change, a specific snow day in winter may no longer match the query day, but an analog might be found in another season, such as fall or spring, under warmer climatic conditions.

Moreover, unlike physical SWE data generation models, this method can reconstruct HR-SWE data for historical periods where only low-resolution climate data are available, providing valuable insights into past snow conditions. Additionally, the method excels at capturing fine-scale SWE patterns in complex terrains, such as mountainous regions, significantly improving upon traditional statistical models that often struggle in such environments. 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.

3. Comment: The methodology is thorough, but some sections are densely packed with technical details, making it challenging to follow. The description of the Manhattan distance metric, in particular, could be expanded to enhance reader understanding. Explain how the Manhattan distance operates within the context of your downscaling approach. This will help make the concept more accessible, especially for readers less familiar with the metric.

3. Response: We have expanded the explanation of the Manhattan distance metric in Section 2.3 to provide greater clarity. Specifically, we explain how this metric is used to rank dates in the training dataset and why it is preferred over the Euclidean distance for this specific problem. We also added more details and made several adjustments to enhance clarity (please refer to Response 1).

4. Comment: The choice of parameters (e.g., FI and NI intervals) is justified through sensitivity analysis, which is appropriate. However, the manuscript could benefit from a brief discussion on the potential limitations or assumptions made in the parameter selection process.

4. Response: We have added a discussion in Section 2.4.1 to highlight potential limitations related to the choice of parameters, as follows:

Lines 250-256:

While the parameters are selected through a sensitivity analysis to minimize ε, it is worth mentioning that the selected parameters may not represent a global optimum. This means that while they perform well in the studied regions, they may not generalize as effectively to other locations or climatic conditions. Therefore, we recommend performing a sensitivity analysis for each region. Additionally, the sensitivity analysis assumes that the influence of these intervals is consistent across different temporal scales, which may not always hold true, particularly in regions with highly variable climate patterns. Despite these assumptions, the chosen parameters strike a balance between computational efficiency and accuracy for the downscaling task. Moreover, the subsequent weight optimization further mitigates the impact of non-global optimal parameter selection.

5. Comment: The results are comprehensive and well-presented with relevant figures and tables. However, the discussion on the comparison between different models and resolutions could be expanded to provide more insights into why certain models perform better in specific regions.

5. Response: We agree and have now referenced Kouki et al. (2022), who analyzed CMIP6 models and found significant variations in model performance based on regional climatic and geographical conditions. Additionally, we have expanded the discussion to include the contributions of temperature and precipitation to SWE biases. Specifically, we emphasize that precipitation plays a dominant role in winter SWE biases, while temperature becomes more influential during the spring snowmelt season. These insights have been added to Section 5 to highlight important factors that affect model performance, although they were not the central focus of this study.

Lines 246-256:

In comparing the performance of different models across regions, several factors contribute to why certain models outperform others in specific locations. While a detailed comparison between model performances across various regions is beyond the scope of this study, other studies have explored this area. For example, Kouki et al. (2022) evaluated the ability of CMIP6 models to estimate SWE across the Northern Hemisphere and found that different models perform better in specific regions based on their capacity to simulate particular climatic and geographical conditions. In terms of the contribution of temperature and precipitation to SWE biases, precipitation plays a more dominant role, especially in winter. However, temperature becomes more significant during spring, when snowmelt occurs, particularly in regions with more temperate climates, such as the southern parts of North America and Europe. In regions where temperatures are closer to 0°C, biases in temperature can substantially affect snowmelt. This highlights the importance of accounting for both temperature and precipitation biases when evaluating model performance across different regions.

Discussion Section, Lines 548-551:

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.

6. Comment: Consider including a more detailed comparison of the proposed method with existing downscaling techniques. This could be done in the discussion section, where you could highlight the strengths and limitations of your approach relative to others.

6. Response: We agree and have now added more detail in the Discussion section, lines 553–581, as follows:

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.

7. Comment: The conclusion could be more definitive in summarizing the key findings and contributions of the study. The main quantities results should be added in the conclusion.

7. Response: We have now divided the conclusion and discussion section into two separate sections: Section 6, Discussion, which includes more detailed analysis, and Section 7, Conclusion, to more definitively summarize the key findings and contributions of the study.

Below, we provide a portion focused on the results.

6. Discussion, Lines 531-551

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.

Additional details have also been incorporated into this Section, as highlighted in Response 5, Discussion Section, Lines 548–551.

7. Conclusion, Lines 600-604:

Overall, the 'cnrm-esm2-1' model tends to provide higher accuracy in Colorado when used as an estimator, outperforming other models at both 100 km and 9 km resolutions. In contrast, the 'ec-earth3-veg' model performs best in California at a 9 km resolution. A finer resolution (9 km) generally offers slightly better accuracy than a 100 km resolution across models, though the difference is modest, emphasizing the importance of selecting the right climate model over simply increasing resolution.

8. Comment: Given the limitations of ground observations in data-scarce high mountain regions, to what extent do you believe that the method used in your study can provide accurate and comprehensive insights into SWE? Are there any potential sources of uncertainty or bias that need to be addressed?

8. Response: The proposed methodology does not use ground observation data as input. Instead, it focuses on downscaling low-resolution climate data to generate high-resolution SWE information. However, we have now added more details to Section 6, Discussion, and Section 7, Conclusion, addressing potential sources of uncertainty. Specifically, we discuss how the choice and accuracy of climate model inputs may introduce biases into the SWE estimates (please refer to Response 7).

9. Comment: Abstract (Lines 1-20): The abstract is informative but could be condensed to focus more on the results and implications rather than the background. The key findings should be more prominently highlighted.

9. Response: The abstract has been revised to highlight key results as follows:

Lines 15-21:

To evaluate the performance of our approach, we conduct tests in California's Sierra Nevada and Colorado's Upper Colorado River Basin in the western United States using different low-resolution climate models ('ec-earth3-veg', 'mpi-esm1-2', and 'cnrm-esm2-1') at both 100 km and 9 km scales. A cross-validation analysis is performed, and comparisons are made with commonly used gridded SWE datasets as well as through point-scale time series comparisons. The results demonstrate that our approach enables the generation of downscaled SWE that closely matches observations in reanalysis data in terms of statistical properties. The outputs demonstrate that, for each region, performance depends on the choice and accuracy of the climate model inputs, such as precipitation and temperature data. Overall, the 'cnrm-esm2-1' model demonstrates superior accuracy in Colorado, outperforming other models at both 100 km and 9 km resolutions. Conversely, the 'ec-earth3-veg' model achieves the best performance in California at a 9 km resolution. Across models, a 9 km resolution typically provides slightly better accuracy compared to a 100 km resolution.

10. Comment: Please describe the study regions in the abstract to provide context for where the proposed method was tested. This addition will give readers a better understanding of the geographical relevance of the study, as follows:

10. Response: We have added a brief description of the study regions (California and Colorado) to the abstract to provide context. Please refer to Response 9.

11. Comment: Section 2.3 (Lines 115-130): The explanation of the K-nearest neighbor algorithm could be clarified. Please further illustrate how the algorithm works in the context of downscaling SWE.

11. Response: We have revised the paper to include a more detailed explanation of how the K-nearest neighbor algorithm operates in the context of SWE downscaling (please refer to Response 2). Additionally, we have incorporated more details and made several adjustments to improve clarity (please refer to Response 1).

12. Comment: Ensure consistency in the use of terms such as "high-resolution" and "low-resolution" throughout the manuscript. Some sections use these terms interchangeably with "HR-SWE" and "LR-SWE," which could confuse readers.

12. Response: We have carefully reviewed the manuscript to ensure consistency in the use of the terms "high-resolution SWE" (HR-SWE) and "low-resolution SWE" (LR-SWE).

13. Comment: There seems to be an issue with Table 3, as some information might be missing or incomplete.

13. Response: It is corrected now and also based on the second reviewer's comment that Table 3 contains commonly used metrics, we have moved Table 3 to the Supplementary.

14. Comment: Lines 268-269: The reference to "Evaluation criteria Table 1" appears to be incorrect. Please check this sentence and ensure that the correct table is referenced.

14. Response: This issue has been corrected.

15. Comment: The legend and boxplot in Figure 6 require revision, as they currently do not appear to be properly formatted. Please ensure that the legend is clear and correctly labeled, and that the boxplot is visually consistent with the rest of the figure.

15. Response: We use a combination of color and line style to avoid repetitions.To make it clear, now we have added an explanation in the figure caption as follows:

The average of the UCLA SWE (black dotted line, reference) and the downscaled SWEs ($\hat{SWE}$; blue and green lines) for each area over the six-year period from 2005 to 2010 are shown. The three climate models used in the downscaling are represented by different colors: light blue for 'ec-earth3-veg', green for 'cnrm-esm2-1', and dark blue for 'mpi-esm1-2'. Line styles indicate the spatial resolution of the climate models: solid lines correspond to results based on a 9 km resolution, and dashed lines represent results based on a 100 km resolution. The dotted black line represents the average UCLA SWE, which is the reference.

16. Comment: Figures 9, 11, 13, and supplementary figures: The Y-axis values in Figures 9, 11, 13, and the supplementary figures need to be revised. Please check that the scales are appropriate and clearly labeled to ensure that they accurately represent the data being presented.

16. Response: We have revised the Y-axis values in Figures 9, 11, 13, and the supplementary figures.

17. Comment: Tables and Figures Captions: Please remove the bold formatting from all table and figure captions. The current formatting detracts from the overall appearance of the manuscript. Standardize the captions to match the style used throughout the manuscript.

17. Response: We have removed the bold formatting from all table and figure captions and standardized the style.

18. Comment: There are a few minor grammatical errors and typos that should be corrected. For example, in line 30, "Snow Eater equivalent" should be corrected to "Snow Water Equivalent."

18. Response: We have corrected all identified grammatical errors and typos, including changing "Snow Eater equivalent" to "Snow Water Equivalent."

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

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