We appreciate the reviewer’s valuable comments which have been very helpful in improving the quality of the manuscript. We have provided point-by-point responses to the reviewer’s comments and carefully revised the manuscript accordingly.

This manuscript contributes to model improvement in snow cover fraction parameterization. The manuscript is suitable for the journal. The topic is interesting and the potential achievements are expected to have prospects for numerical simulation and forecasting over the Tibetan Plateau region or even the globe. However, there is still large space to improve the manuscript for final publication, including descriptions and verification of technical methods, investigations and discussions. Therefore, a major revision is suggested. My comments are listed in the following.

1. Section 2.4, Please clarify which data is used for these selections.

Reply: Thank you for your comment. The snow depth data used for event selection were obtained from the daily 0.05° snow depth dataset over the Tibetan Plateau (2000–2021), which was introduced in Section 2.1. In the revised manuscript, we have added a clarification in Section 2.4.

2. Please add the resolution/size of sub regions in Figure 2, A, B, C, D and A1, A2......, other wise may confuse the readers, confused with grid resolution/size.

Reply: Thank you for your comment. In Figure 2, the spatial resolution of the eight subregions (A, B, C, D, E, F, G, and H) is 1° × 1°, while the spatial resolution of the individual panels (e.g., A1, A2, A3, and A4) is 0.5° × 0.5°. We have added a clarification regarding the spatial resolutions of the subregions and panels in the revised manuscript.

3. Add units in proper places, such as the tables, introduction text of variables in each

equation.

Reply: Thanks. Added.

4. Section 3.2, Please clarify which snow depth and SCF data is used for optimization.

Reply: Thank you for your comment. For the analysis in Section 3.2, we used a daily cloud-free MODIS SCF dataset (2000–2015) with a spatial resolution of 500 m, which was generated using a cloud-removal algorithm based on cubic spline interpolation (Tang et al., 2013). We also used a daily 0.05° snow depth dataset (2000–2021), which was developed based on a sub-pixel spatiotemporal downscaling algorithm and the fusion of a snow cover probability dataset with the long-term snow depth dataset over China (Yan et al., 2022). In the revised manuscript, we have clarified the information regarding the snow depth and SCF datasets used in this study.

5. Line 135, Better to introduce W_snow and W_max, and how to derive the two.

Reply: Thanks for your comment. W_{snow} represents the snow water equivalent, while $W_{\max}$ denotes the maximum snow water equivalent.

W_{snow} is directly calculated in CLM5 and can also be obtained from observations. In CLM5, $W_{\max}$ is determined by integrating snowfall amounts into snow water equivalent during snowfall events and is subsequently derived from the snow depletion curve. In other words, $W_{\max}$ is a diagnostic variable introduced to ensure consistency between the updated snow cover fraction and the total snow water equivalent. During the estimation of the optimal N_{melt} value, the maximum snow water equivalent among the 100 selected snowmelt events is defined as the $W_{\max}$, because these snowmelt events are sequentially treated as a continuous snow depletion process. To improve clarity, we have added explanations of W_{snow} and W_{max} in the revised manuscript.

6. Line 166: ‘Through judging the smallest RMSE between observed SCF and the fitted value’: ‘using the least square fitting method’ maybe better.

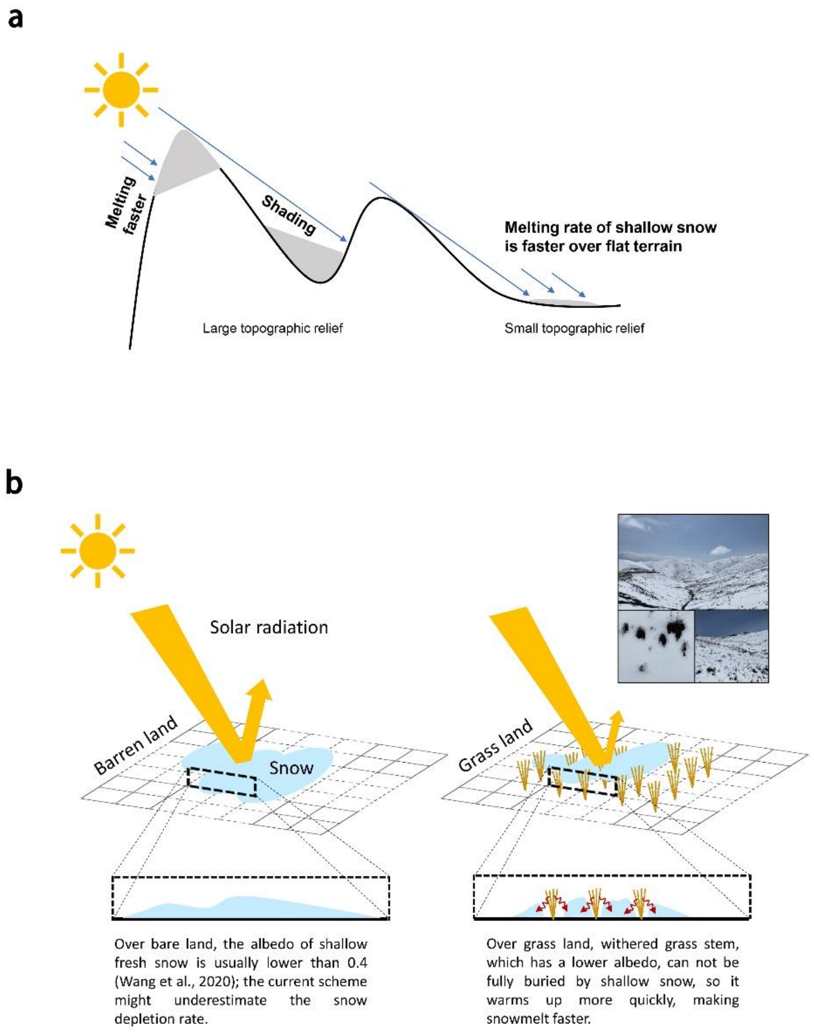
Reply: Thanks for your comment. In this study, we retained the functional relationship between SCF and snow depth described by Eq. (2), and then estimated the optimal values of k_{accum} by minimizing the RMSE between the observed SCF and the SCF fitted using Eq. (2). In other words, the optimal k_{accum} value corresponds to the fitted SCF that is closest to the observations. This approach is conceptually similar to the principle of the least-squares fitting method. To improve clarity, we have added an explanation in the revised manuscript regarding the rationale for adopting this method instead of directly applying the least-squares fitting method.

7. Is K_accum and N_melt depends more on σ _topo or SAI for grass land? I suggest to do some analysis. For example, calculate the coefficients of K_accum/N_melt between the two.

Reply: Thank you for your comment and suggestion. Over the Tibetan Plateau (TP), snow cover distribution and snowmelt processes are strongly influenced by both complex terrain and short vegetation (i.e., withered grass stems). The effects of topographic relief are twofold. On the one hand, shallow snow over relatively flat terrain (small topographic relief) tends to melt faster because the albedo of shallow fresh snow is generally lower than 0.4 (Wang et al., 2020). On the other hand, in regions with large topographic relief, terrain shading promotes snow persistence and slows snowmelt. Therefore, the influence of terrain on snow cover is bidirectional (Figure R1).

Over barren land, where the influence of short vegetation is absent, topographic relief (σ_{topo}) is the dominant factor controlling snow probability distribution (k_{accum}) and snow melt (N_{melt}). Over grassland, both k_{accum} and N_{melt} are jointly affected by σ_{topo} and withered grass stems (SAI).

To support these physically based relationships, correlations of k_{accum} and N_{melt} with σ_{topo} and SAI were analyzed (Figure 4 and 6). In the revised manuscript, we have added more detailed physical explanations for the parameterizations of k_{accum} and N_{melt}.



Over bare land, the albedo of shallow fresh snow is usually lower than 0.4 (Wang et al., 2020); the current scheme might underestimate the snow depletion rate.

Over grass land, withered grass stem, which has a lower albedo, can not be fully buried by shallow snow, so it warms up more quickly, making snowmelt faster.

Figure R1. Schematic diagram of (**a**) effects of topographic relief and (**b**) short vegetation (i.e., withered grass stems) on snow cover.

8. Is the optimized scheme resolution dependent? I suggest to added some analysis is better, or at least some associate discussions.

Reply: Thank you for your comment and suggestion. The physical processes and principles underlying the optimized scheme are not expected to depend on spatial resolution. However, the coefficients in Eq. (6) and Eq. (10) (e.g., 1.15, −0.55, -5×10^{-4}, 0.18, 3.3, 9.5, 0.49, and −0.004) may vary slightly with spatial resolution because the sample values differ somewhat across resolutions. More details on this issue are provided in our response to Comment 10. In the revised manuscript, we have added further analysis and discussion regarding this aspect.

9. How the form of each equation for K_accum and F is chosen. For example, Eq.5, Bare land the form of eq. Is: a*X**b, while for grass land is: a*X1*X2+b. Why the two are different? I suggest to add some explanations.

Reply: Thanks for your comment and suggestion. The functional forms of the equations for k_{accum} and F were empirically selected based on their statistical relationships with σ_{topo} and SAI. Nevertheless, the choice of each equation can also be physically justified. For barren land, k_{accum} is represented by a power function ($y = a \cdot x^b$) that depends solely on σ_{topo}. Specifically, when σ_{topo} is small (i.e., the ground surface is relatively flat), snowfall is distributed more evenly across the surface, resulting in a relatively high snow cover fraction (Figure R2). In contrast, as σ_{topo} increases (i.e., terrain relief becomes more pronounced), snow tends to accumulate in topographic depressions, leading to a relative decrease in snow cover fraction. However, as terrain complexity continues to increase, the suppressing effect of topography on snow cover fraction gradually weakens. This is because snow cover over the Tibetan Plateau (TP) is generally shallow due to limited snowfall, resulting in only minor changes in snow distribution even under highly complex terrain conditions. For grassland, the probability distribution of snow cover during snowfall is jointly suppressed by both σ_{topo} and SAI. Therefore, k_{accum} is calculated by a linear equation that depends on $\sigma_{topo} \times SAI$ which represents the combined their effects.

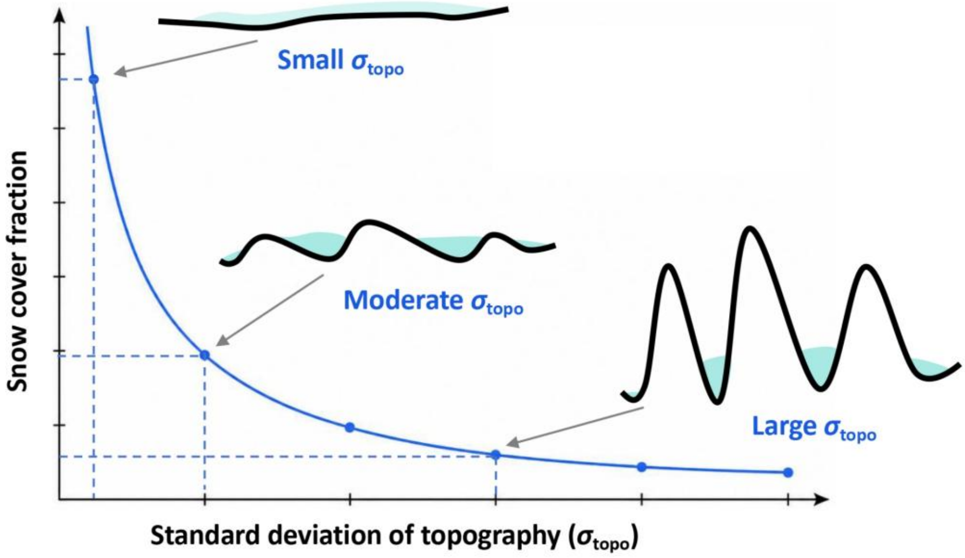


Figure R2. Schematic diagram of the nonlinear variations in snow cover fraction (SCF) under different topographic relief conditions. Topographic relief is represented by the bold black curve, while SCF is illustrated by the light blue shading.

Regarding the functional forms of the equations for a revised factor F, over barren land, F shows a positive relationship with σ_{topo}. In the current scheme, larger σ_{topo} values imply faster snowmelt, which tends to underestimate the snow depletion rate. When σ_{topo} is small, F is also small , allowing a stronger correction to the overestimation bias of SCF. As σ_{topo} increases, however, the terrain shading effect (as shown in Figure R1), which is neglected in the current scheme, partially offsets the enhanced melting effect on sunlit slopes. Consequently, F becomes larger (i.e., F approaches 1, indicating a weaker corrective effect). Therefore, over barren land, F is represented by a linear equation that depends on σ_{topo}. Over grassland, withered grass stems promote snowmelt and constitute the dominant effect. As SAI increases, F decreases (i.e., the corrective effect becomes stronger), indicating a negative relationship between F and SAI. Considering the additional influence of σ_{topo}, we further define a factor SAI^2 / σ_{topo} to represent the combined nonlinear effects of σ_{topo} and SAI. Accordingly, F is calculated using an exponential function that depends on this factor.

10. Why not using all TP region for the optimization but only using 4 small sub regions? Normally, from a statistical perspective, the more samples, the results are more robust. I.e. if another 4 sub regions is selected randomly from the TP for bare land and grass land, are the same equation can be achieved? Qualitatively, by how much (personally, uncertainties within 10% is acceptable, but within more than 50% maybe too large) the fitted coefficients is reliable needs to be answered.

Reply: Thank you for your professional comment. The four subregions selected for barren land and grassland were chosen because they exhibit relatively large snow cover fraction (SCF) biases. In addition, the standard deviation of topography (σ_{topo}) within these subregions is generally smaller than 200, while the panels divided from these subregions show distinct differences in topographic relief (σ_{topo}) and SAI. Therefore, these subregions were selected as representative areas for the analysis.

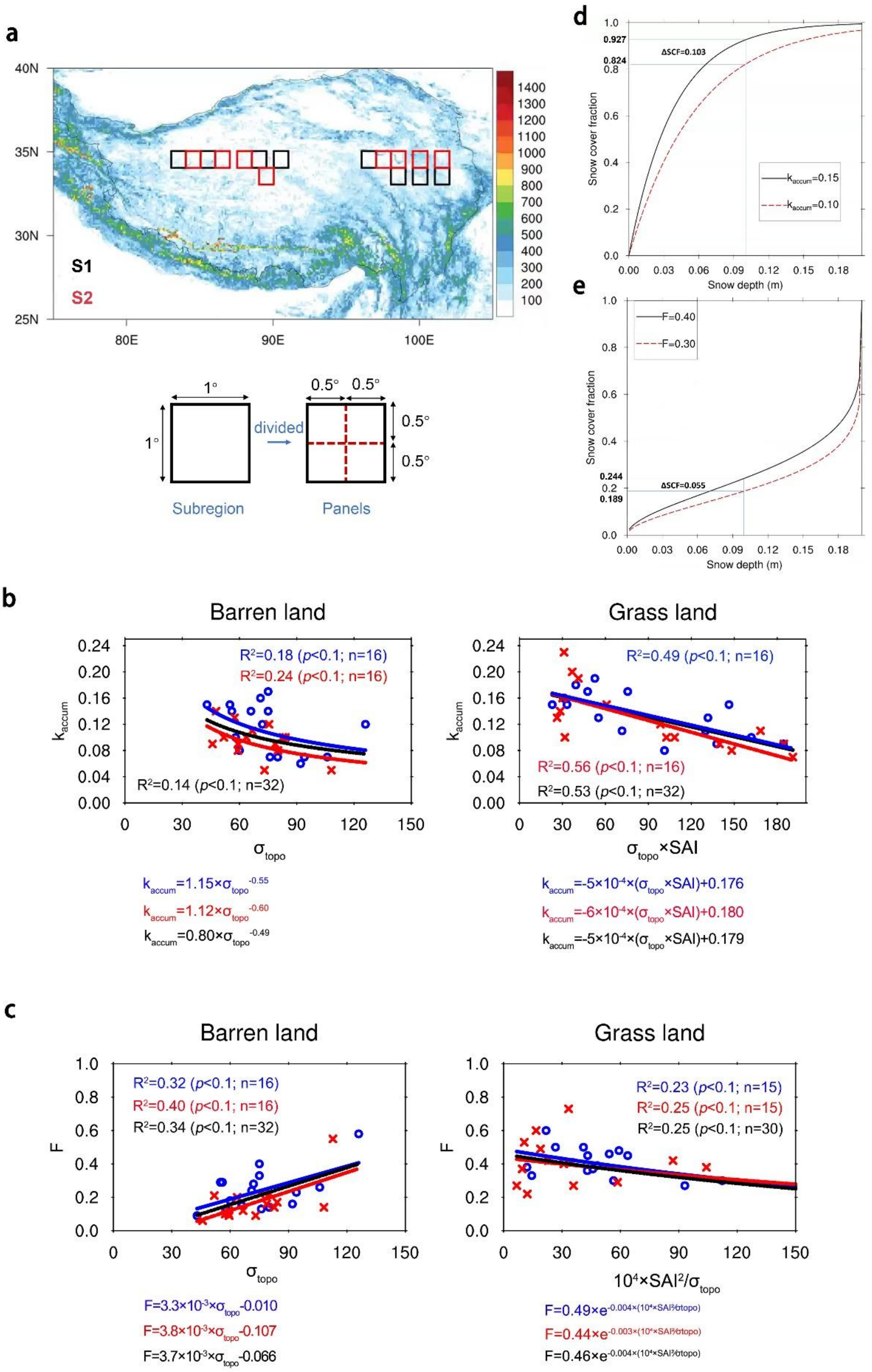


Figure R3. Parameterization of the probability distribution factor (k_{accum}) and the revised factor (F). (**a**) Selected subregions, where the black and red boxes denote the original subregions (group 1) and the newly subregions (group 2) , respectively; each subregion is further divided into four panels. (**b**) Relationship between the optimal value of k_{accum} and σ_{topo}, SAI over barren land and grassland. (**c**) Relationship between F and σ_{topo}, SAI over barren land and grassland. (**d**) Accumulation curves of snow cover fraction (SCF) with increasing snow depth during snowfall under different k_{accum} values. (**e**) Depletion curves of SCF under different F values. The blue and red lines represent the fitting results for the samples from group 1 and group 2, respectively, while the black lines represent the fitting results for the combined samples from both groups.

To demonstrate the robustness of the results, as shown in Figure R3a, we selected additional subregions (group 2) for further analysis and comparison with the original subregions (group 1). The fitted functional forms of the equations for k_{accum} and F derived from the new subregions are generally consistent with those obtained from the original subregions (Figure R3b-c). Although the coefficients in the fitted equations exhibit slight differences, which may lead to variations in k_{accum} and F, the resulting uncertainties in SCF remain within 10% (Figure R3d-e). In revised manuscript, we have added uncertainty analysis.

11. Line 317-318, when you state that ‘CLM5 still shows cold biases’, it is better to show biases rather than spatial pattern of the CLM5 and observation.

Reply: Thank. The spatial pattern of CLM5 biases in land surface temperature (LST) has been added to the revised manuscript.

12. Line 266-268. It is hard to ‘ identify which process contributes most to the improvement,’ based on current experimental design. Additional experiment (only using optimized SCF during snow accumulation) may required when accurately

investigating the roles of the two optimization (snow accumulation (eq.6) and snow melting (eq.10)). Because snow accumulating and melting could happen each day, and the effects of the two would compensate each other when both are used.

Reply: Thank you for your comment. We have added an additional experiment (MOD3), in which the optimized SCF parameterization scheme is applied only during snowfall, while the original scheme is retained during snowmelt. The related analyses have also been updated in the revised manuscript to identify which process contributes most to the improvement.

13. Table 4, Why using the 8 sub regions for evaluation? If the new method is developed based on these 8 sub regions, the evaluation is not independent.

Reply: Thank you for your comment. The original purpose was to evaluate the optimized scheme over representative regions. In the revised manuscript, we have selected additional representative regions that were not used in the development of the optimized scheme for independent evaluation.

14. Figure 9, I suggest to show the annual cycles. Then the roles of both optimizations can be clearly seen.

Reply: Thank you for your suggestion. The annual cycle of SCF has been shown in Figure 9.

15. Too small and inconsistent font sizes for figures.

Reply: Thanks. These figures have been redrawn to make it clear.

16. I suggest to calculate the error metrics for evaluations and statistical metrics for comparisons.

Reply: Thanks. In addition to the mean bias error (MBE), we have also included the root mean square error (RMSE) for evaluations. Furthermore, for comparison purposes, we added the statistical metric of the spatial correlation coefficient (*R*) in the revised manuscript.

17. Section 4.3, if you want to draw conclusions on surface energy budget, then the energy variables should be evaluated or investigated, including the short wave, long wave and heat fluxes. They are all influenced by SCF. Albedo is only one variable that directly influences the surface short wave budget. Further, the evaluation seems inadequate, authors may consider more comprehensive investigations.

Reply: Thanks for your comment. We have added evaluations of surface shortwave and longwave radiation, as well as surface sensible and latent heat fluxes. In addition, more error metrics have been included in the evaluation.

18. For areas without observations, CMFD forcing is also less reliable. Consequently, the cold biases may be inherited, line 317-318.

Reply: Thanks. We agree with your opinion that biases in the CMFD meteorological forcing dataset may introduce uncertainties, particularly for snowfall, as discussed in Section 5.1. To make the manuscript more rigorous, we have added further discussion on the uncertainties associated with the CMFD forcing dataset in the revised manuscript.

19. Line 318-319, spatial pattern could be quantified by correlation coefficient. When a conclusion is drawn, better to have a quantitative support. Please check the rest of the manuscript.

Reply: Thanks. We have added calculations of the spatial correlation coefficient to quantitatively support the conclusions.

20. The optimizations seems not very effective. The atmosphere forcing restricts the energy input to the land surface, a coupled atmosphere-land simulations may achieve more effective results by enhancing the snowcover-albedo-radiation energy feedbacks. The authors may consider a set of coupled simulations, or at least add some discussions for outlook.

Reply: Thanks for your valuable comment. This study is based on the latest version of the Community Land Model (CLM5), which has been extensively developed and generally performs well over most regions of the TP (Figure 7c) compared with other land surface models, such as Noah-MP (Jiang et al., 2020) and SSiB3 (Miao et al., 2022). Therefore, the improvements introduced by the optimized scheme may be less apparent when evaluated over the entire TP. Nevertheless, CLM5 still shows evident positive SCF biases over the northern TP, particularly in the northwestern TP. In this study, we specifically focus on regions with large SCF biases and optimize the SCF parameterization scheme, which effectively reduces SCF biases.

We agree with your suggestion that coupled atmosphere–land simulations would provide a more comprehensive evaluation of the optimized scheme (Zhou et al., 2023), and this aspect will be explored in future work. In the revised manuscript, we have added further discussion on these issues.

References

Jiang, Y., Chen, F., Gao, Y., He, C., Barlage, M., and Huang, W.: Assessment of uncertainty sources in snow cover simulation in the Tibetan plateau. *Journal of Geophysical Research: Atmospheres*, 125, e2020JD032674. https://doi.org/10.1029/2020JD032674, 2020.

Miao, X., Guo, W., Qiu, B., Lu, S., Zhang, Y., Xue, Y., and Sun, S.: Accounting for topographic effects on snow cover fraction and surface albedo simulations over the Tibetan Plateau in winter. *Journal of Advances in Modeling Earth Systems*, 14, e2022MS003035. https://doi.org/10.1029/2022MS003035, 2022.

Zhou, X., Ding, B., Yang, K., Pan, J., Ma, X., Zhao, L., et al.: Reducing the cold bias of the WRF model over the Tibetan Plateau by implementing a snow coverage-topography relationship and a fresh snow albedo scheme. *Journal of Advances in Modeling Earth Systems*, 15, e2023MS003626. https://doi.org/10.1029/2023ms003626, 2023.