Dear Editor,

We would like to express our sincere gratitude to the three reviewers for their valuable comments and constructive suggestions. Their feedback has been instrumental in improving both the scientific quality and the presentation of the manuscript. We have carefully addressed all comments and revised the manuscript accordingly. A detailed, point-by-point response to each comment is provided below.

In the following text, the reviewers' comments are presented in black, whereas the authors' responses are shown in blue.

Kind regards,

Reply to Reviewer #1

This study evaluates the performance of Community Land Model version 5 (CLM5) in simulating snow cover during winter over the Tibetan Plateau (TP) and presents a revised snow cover fraction (SCF) parameterization scheme implemented in the model. This is a very interesting and innovative investigation. The results show that the revised scheme appears to reduce SCF biases and alleviates the cold bias over the TP. Generally, the topic is interesting, as it addresses uncertainties in land surface model simulations of snow processes in alpine cold regions. The findings may therefore provide useful insights for further development and improvement of land surface models. I recommend a minor revision. My comments and concerning that need be clarified are as follows.

Reply: We would like to thank the reviewer for the insightful comments and suggestions that are helpful for improving the quality of the manuscript. We have carefully revised the manuscript accordingly. The detailed point-by-point responses are below.

1. This study focuses on TP snow cover during winter rather than other seasons, the reason behind it should be explained.

Reply: Thank you for your comment. The reason is that the biases in snow cover fraction (SCF) simulated by CLM5 are largest during winter (December–January–February) compared with the other seasons (as shown in Figure R1). We have added an explanation for the focus on this season in the revised manuscript (lines 305-307).

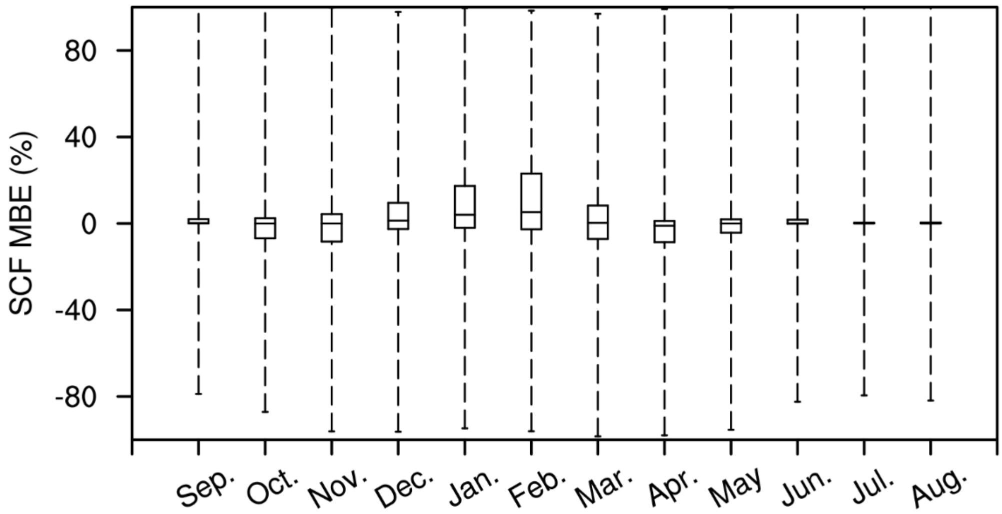

Figure R1. Evolution of the monthly mean bias error (MBE) in CLM5-simulated snow cover fraction over the Tibetan Plateau (TP).

2. The revised scheme parameterizing k_{accum} and revising N_{melt} are based on the consideration of withered grass stems (WGS) and terrain characteristics. While, the proposed formulation appears largely empirical, the physical mechanisms linking these factors (WGS and terrain)

to the spatial distribution of snow cover seem not be sufficiently revealed. The authors should provide a clearer theoretical justification, explain the choice of functional form.

Reply: Thanks for your professional comment. Although the parametrizations of k_{accum} and N_{melt} are empirically developed based on statistical method, their theoretical basis and the choice of functional forms can be physically explained.

Over the Tibetan Plateau (TP), snow cover distribution and snowmelt processes are strongly influenced by complex terrain and short vegetation (i.e., withered grass stems). The effects of terrain are twofold: shallow snow over relatively flat terrain tends to melt faster because fresh shallow snow generally has a relatively low albedo, whereas terrain shading in areas with large topographic relief promotes snow persistence and slows snowmelt. Therefore, both topographic relief (σ_{topo}) and withered grass stems (WGS; represented by the stem area index, SAI) are key factors controlling snow probability distribution (k_{accum}) and snowmelt processes.

Over barren land, σ_{topo} is the dominant factor controlling both snow accumulation and snowmelt (as schematically shown in Figure 7 of the revised manuscript). The k_{accum} is represented by a power function of σ_{topo}. When σ_{topo} is small, snowfall is distributed more uniformly, leading to higher SCF. As σ_{topo} increases, snow preferentially accumulates in topographic depressions, thereby reducing SCF. However, this suppressing effect weakens under highly complex terrain because snow over the TP is generally shallow, limiting variations in snow distribution. Over grassland, both σ_{topo} and SAI jointly suppress snow distribution; therefore, k_{accum} is parameterized using a linear relationship that incorporates their combined effects.

The current scheme assumes that larger σ_{topo} values correspond to faster snowmelt, while overlooking the shading effect of complex terrain and the influence of WGS. To address these limitations, a revised factor (F) is introduced in the optimized scheme to comprehensively account for these effects, thereby improving the representation of snow depletion. Under relatively flat terrain, smaller F values provide stronger corrections to the overestimation of SCF. In contrast, under complex terrain, terrain shading partially offsets the enhanced melting on sunlit slopes, causing F to approach 1 and thereby weakening the correction effect. Consequently, over barren land, F increases with σ_{topo} and is represented by a linear function of σ_{topo}. Over grassland, withered grass stems enhance snowmelt and dominate the snow depletion process (Figure 7b). As SAI increases, F decreases, indicating a stronger correction effect. To further account for the combined nonlinear influences of σ_{topo} and SAI, F is parameterized using an exponential function based on a combined factor (SAI^2/σ_{topo}).

3. Results show a large reduction in SCF bias (up to ~88%) after optimizing the parameterization. But, it is unclear whether these improvements are spatially uniform across the TP. To identify the advantages and limitations of the revised scheme, it's suggested to add analysis showing regions where the revised scheme performs particularly well and other regions where biases remain significant.

Reply: Thanks for your comment and suggestion. Indeed, the improvements introduced by the optimized scheme are spatially heterogeneous. As shown in Figure 9a-b, d-e, the optimized scheme significantly reduces the positive biases of SCF over the northwestern TP, the Kunlun Mountains, the Bayan Har Mountains, and the Siguniang

Mountains, while slightly reducing the negative SCF biases over the southeastern TP. However, it has little effect over the southwestern TP (i.e., the Himalaya Mountains). We have added further analysis and discussion in the revised manuscript (lines 330-336).

4. The authors are encouraged to provide a detailed analysis of the energy budget, analyze shortwave and longwave radiation fluxes, sensible and latent heat fluxes, potential changes in snow–albedo feedback, which would help clarify the physical consequences of the revised parameterization scheme.

Reply: Thanks. We have added evaluations of surface shortwave and longwave radiation, as well as surface sensible and latent heat fluxes, in the revised manuscript (lines 410-416, Figure 13).

5. This study does not indicate whether the revised scheme was tested in multi-year or long-term simulations. It is necessary to evaluate that the revised scheme remains stable over longer periods. Specifically, whether interannual variability of snow cover over TP is captured.

Reply: Thanks for your comment. We conducted multi-year and long-term simulations and analyzed the averaged biases of CLM5. In the revised manuscript, we have added evaluations of the optimized scheme in reproducing the interannual variability of SCF during period 2002-2011 (lines 372-380, Figure 10).

Reply to Reviewer #2

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.

Reply: 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.

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 (lines 119-120).

2. Please add the resolution/size of sub regions in Figure 2, A, B, C, D and A1, A2......, otherwise 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 (lines174-179, Figure 2b).

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 (line 187).

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 (lines 145-148).

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).

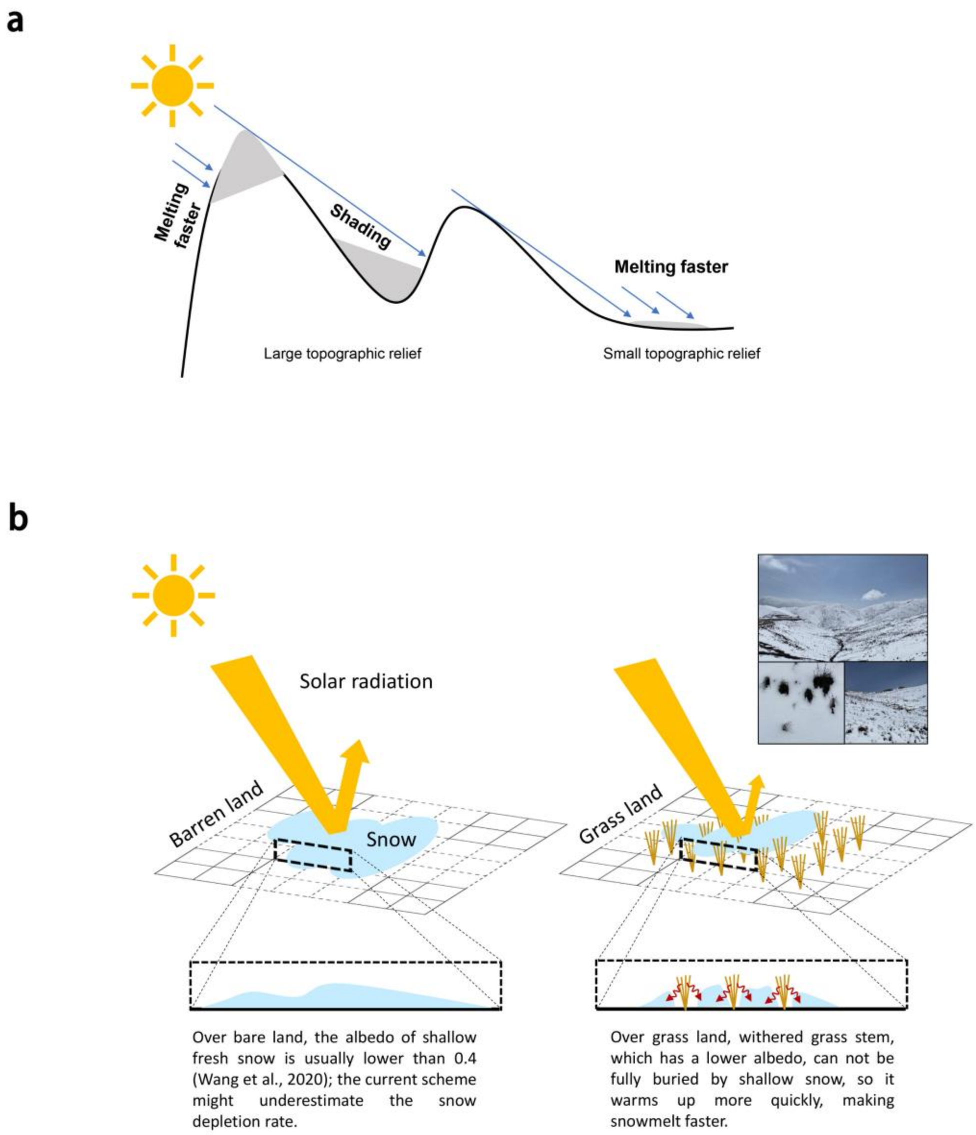

Figure R1. Schematic diagram of (**a**) effects of topographic relief and (**b**) withered grass stems on snow cover.

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} (lines 211-223, 230-236, 261-271, Figure 7).

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 (lines 221-223, 276-277).

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.

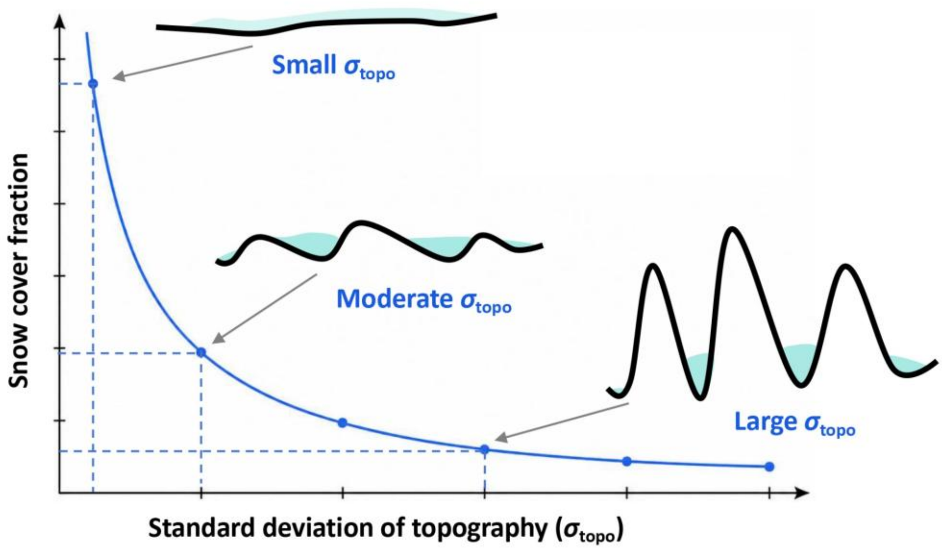

Figure R2. Schematic diagram of the nonlinear variations in snow cover fraction (SCF) under different topographic relief conditions. Topographic relief is represented by the bold black curve, while SCF is illustrated by the light blue shading.

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 R1a), 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.

Explanations have been added in the revised manuscript (lines 212-220, 262-271).

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. These subregions were selected because they exhibit relatively large SCF biases, where the standard deviation of topography (σ_{topo}) is generally smaller than 200 m. The panels divided from subregions show diversity in topography and short vegetation condition.

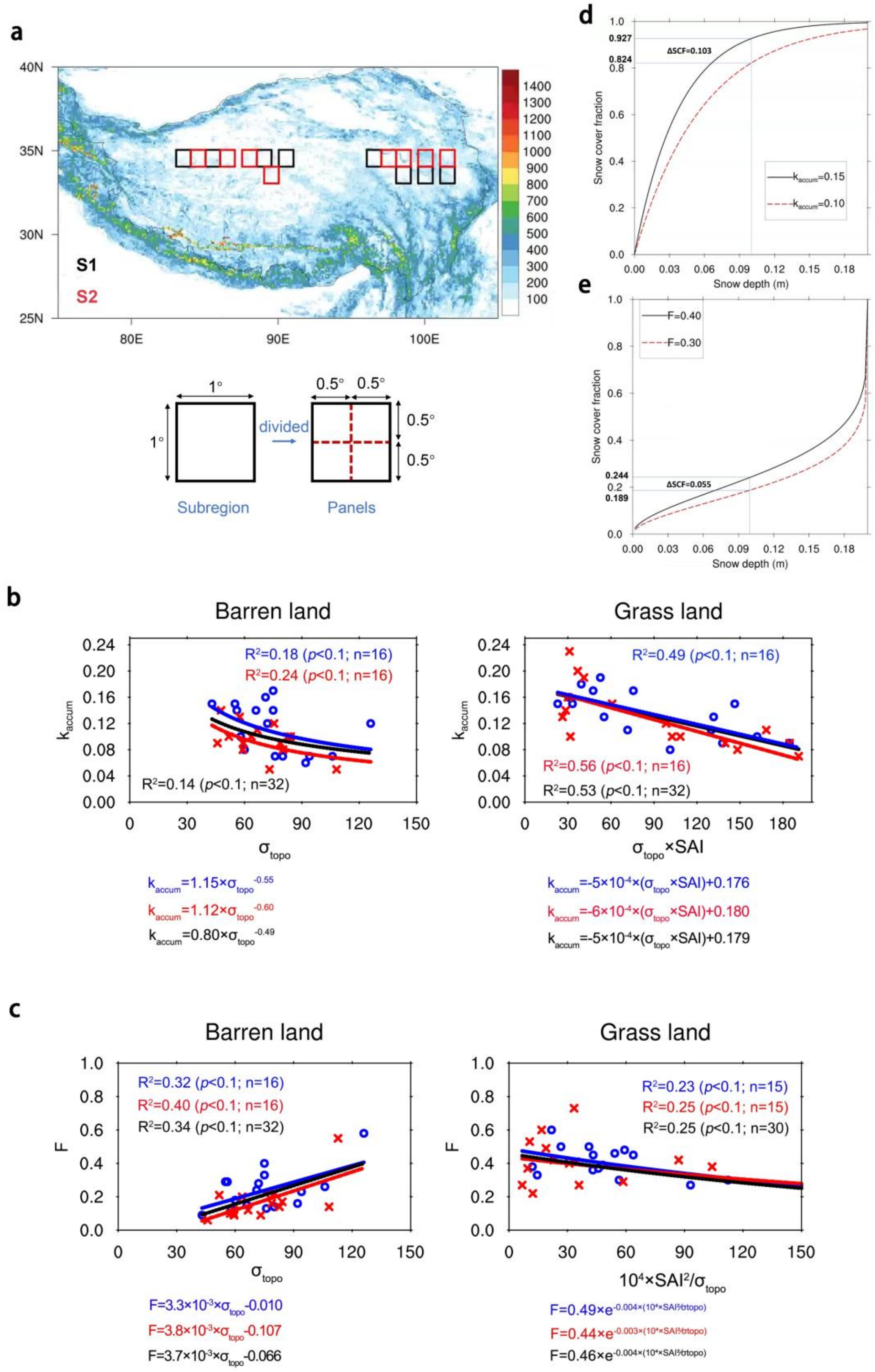

Figure R3. Parameterization of the probability distribution factor (k_{accum}) and the revised factor

(*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 (lines 175-177, 185-186, 211-213, 221-223, 276-277).

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 (Figure 14b).

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 (lines 348-351, 356-361, Figure 9) 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 quantificationally validated the optimized SCF scheme over the entire TP, barren land and grassland, respectively (Table 3), rather than in specific subregions .

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 is now presented in Figure 10 (previously Figure 9). The figure number has been updated due to the addition of new figures in the revised manuscript.

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. As described in Section 2.3, we have expanded the validation metrics in the revised manuscript by including the root-mean-square error (RMSE) and the spatial correlation coefficient (R), in addition to the mean bias error (MBE). The related results and discussions have been revised accordingly.

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 (lines 410-416, Figure 13). In addition, more error metrics (RMSE, R) have been included in the validation.

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. To make the manuscript more rigorous, we have given discussions on the uncertainties associated with the CMFD forcing dataset in Section 5.1 of 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 (lines 421-423, Figure 14).

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 8c) 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 (lines 465-469).

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.

Reply to Reviewer #3

Comments on "Optimization of snow cover fraction parameterization in the Community Land Model: implementation and preliminary validation over Tibetan Plateau" (egusphere-2025-6490)

General comment:

This study shows a systematic overestimation of wintertime snow cover fraction (SCF) over Tibetan Plateau (TP) by the Community Land Model version 5 (CLM5), and proposes an optimized SCF parameterization scheme through incorporating the effects of non-growing-season vegetation (withered grass stems) and topographic characteristics, and modifying the accumulation parameter (kaccum) and the melt parameter (Nmelt). The optimized scheme is evaluated through preliminary simulations over the TP. According to the results presented, the optimized scheme substantially reduces SCF overestimation and improves the simulation of surface albedo and surface temperature. Overall, the manuscript is generally well organized and clearly written. The proposed optimization has the potential to contribute to improvements of snow cover and related surface energy budgets simulations in CLM5. However, several aspects of the methodology and interpretation still require clarification before the manuscript can be considered for publication. I recommend a moderate revision.

Reply: We would like to express our sincere gratitude to the reviewer for the valuable comments and constructive suggestions. These comments have been highly beneficial in improving the quality and presentation of the manuscript. We have carefully revised the manuscript accordingly, and our detailed point-by-point replies are provided below.

Major comments:

1. Physical basis of the optimized parameterization scheme seems unclear. This study proposes modifying kaccum by introducing the influence of non-growing-season vegetation (withered grass stems) and topographic relief. While the idea is plausible, the physical reasoning behind the selected functional form is not sufficiently explained. The authors are encouraged to clarify why these specific factors are expected to control subgrid snow accumulation probability and how the mathematical form of the parameterization was derived.

Reply: Thank you for your comment. In this study, the optimization of the snow cover fraction (SCF) parameterization scheme, which comprehensively considers the effects of topographic relief and withered grass stems, can be well supported by physical mechanisms. Specifically, the underlying surface heterogeneity over the Tibetan Plateau (TP) is primarily characterized by complex topography and short vegetation, with alpine grasslands covering most of the region. In recent decades, the TP has experienced significant greening, accompanied by an increase in non-growing-season short vegetation (i.e., withered grass stems, WGS), which substantially affects the land surface energy budget and snow cover processes. Therefore, topographic relief, represented by the standard deviation of topography (σ_{topo}), and WGS, represented by the stem area index (SAI), are regarded as the key factors controlling snow accumulation and snowmelt processes.

Regarding the mathematical forms, the equations for the probability distribution factor (k_{accum}) and the revised factor (F) in the optimized SCF parameterization scheme were empirically determined from their statistical relationships with topographic relief (σ_{topo}) and SAI , while remaining physically interpretable.

Over barren land, k_{accum} is represented by a power function of σ_{topo}. Under relatively flat terrain (small σ_{topo}), snowfall is distributed more uniformly, resulting in higher SCF. As terrain relief increases, snow preferentially accumulates in topographic depressions, reducing SCF. However, this suppressing effect gradually weakens under highly complex terrain because snow cover over the TP is generally shallow. Over grassland, both σ_{topo} and SAI jointly suppress snow distribution; therefore, k_{accum} is parameterized using a linear equation based on $\sigma_{topo} \times SAI$, which represents their combined effects.

The revised factor F is introduced to improve the representation of snow depletion. Over barren land, F increases linearly with σ_{topo}. Small σ_{topo} values correspond to stronger corrections to SCF overestimation, whereas under complex terrain, terrain shading partially offsets enhanced melting on sunlit slopes, causing F to approach 1 and thereby weakening the correction effect. Over grassland, withered grass stems enhance snowmelt and dominate the depletion process, resulting in a negative relationship between F and SAI. To further account for the nonlinear combined effects of σ_{topo} and SAI, F is parameterized using an exponential function based on a combined factor (SAI^2 / σ_{topo}). Impacts of topographic relief and withered grass stems on snowmelt are schematically shown in Figure 7 of the revised manuscript. We also have added a physical explanation of the optimized scheme (lines 211-223, 230-236, 261-271).

2. Universality of the optimized scheme and its applicability beyond the TP should be discussed. Currently, the validation is conducted only over the TP. Given that CLM5 is widely used in globe and it's implied for other models, it is important to discuss the potential applicability of the optimized parameterization in other regions. Whether the parameters are region-specific or globally applicable, possible limitations when applied to different vegetation types also need be discussed.

Reply: Thanks for your comment. Indeed, this study focuses on the TP, where the snow cover biases in CLM5 are most pronounced and climate projections remain highly uncertain. Therefore, we selected the TP as a representative region and optimized the SCF parametrization scheme for environments characterized by shallow snow cover and short vegetation. We believe that the optimized scheme has a certain degree of universality and potential applicability to other regions of the globe, particularly in areas with complex topography, shallow snow cover, and short vegetation (e.g., herbaceous plants, shrubs) whose stems, branches, and withered components cannot be completely buried by snow.

Meanwhile, we acknowledge the limitations of the optimized scheme. 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 to some extent with spatial resolution. Nevertheless, different subregions were selected to test the robustness of the optimized mathematical forms and to evaluate the uncertainties associated with coefficient variations, which are generally less than 10%.

In the revised manuscript, we have added discussions on the universality and potential applicability of the optimized SCF scheme (lines 488-493), possible limitations (lines 465-469, 474-487).

3. More evaluations of the optimized scheme should be added. The evaluation mainly focuses on SCF, surface albedo, and surface temperature. While these variables are relevant indicators of snow processes, the evaluation could be strengthened by including additional snow-related variables, such as snow depth or snow water equivalent (SWE).

Reply: Thank you for your comment. We have added evaluations of surface shortwave and longwave radiation, as well as surface sensible and latent heat fluxes (lines 410-416, Figure 13). In addition, extra analyses of snow-related variables, including snow depth and snow water equivalent, have also been incorporated (lines 384-389, Figure 11).

Minor comments:

1. Line 98: “0.05° × 0.05° dataset” should be “0.05° × 0.05° and 500 m spatial resolution dataset”.

Reply: Thanks. Corrected.

2. It’s suggested to use snow water equivalent instead of snow depth in section 2.4, if the data is available.

Reply: Thank you for your suggestion. In fact, a daily snow water equivalent dataset at 5 km resolution over the Tibetan Plateau (1981–2020) is available from TPDC (https://data.tpdc.ac.cn/zh-hans/data/517e80f6-67b9-4a25-81f7-2d4a78b182c1). However, this dataset is derived from the snow depth dataset. In addition, changes in snow depth can be used as a proxy for snowmelt (Yang et al., 2023), and snow water equivalent is not directly used in the SCF parameterization. Therefore, we retained the use of snow depth in Section 2.4.

3. Figure 1: It's suggested to analyze Fig. 1 in section 3.1 for better understanding the original SCF parameterization scheme, which might be the foundation for the proposed optimization.

Reply: Thanks. Done.

4. Lines 142-143: it's better to add references to support this perspective.

Reply: Thanks. Added.

5. In section 3.4: more detailed information of experimental design should be given, such as integration step, output frequency, component set.

Reply: Thanks. More detailed information on the experimental design has been added to the revised manuscript (lines 292-295).

6. Please carefully proofread the manuscript for minor grammatical issues, and consider simplifying several long or complex sentences to improve.

Reply: Thanks. We have carefully proofread the manuscript and improved the readability of the English writing.