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Key Points:

- The overestimated snow cover fraction (SCF) is one of the factors leading to the cold biases in temperature simulations on the Tibetan Plateau
- An improved SCF scheme is adopted in the RegCM4.7 model to enhance the skill in simulating SCF on the Tibetan Plateau
- The improved SCF simulations clearly reduce the cold biases in the soil and surface air temperature simulations on the Tibetan Plateau

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The Cold Biases in the Soil and Surface Air Temperature Simulations of RegCM4.7 Model Over the Tibetan Plateau in Cold Seasons Reduced by Adopting an Improved Snow Cover Fraction Scheme

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Abstract In cold seasons, global and regional climate models exhibit consistent cold biases in the soil and surface air temperature simulations on the Tibetan Plateau (TP), while the overestimated snow cover fraction (SCF) is treated as one of crucial factors leading to the cold biases. To partially solve this issue, this study adopts an improved SCF scheme that adequately consider the impact of sub-grid terrain relief on snow cover into the Regional Climate Model version 4.7 (RegCM4.7) coupled with the CLM4.5 land surface model to enhance the model skill. Results show that adopting the improved SCF scheme in RegCM4.7 model can significantly reduce the SCF overestimation on the TP produced by the original model, leading to obvious improvements in the surface albedo, soil and surface air temperature simulations in cold seasons. Mechanism analysis indicates that the sub-grid terrain relief suppresses the rapid increase of SCF with snowfall and makes the ground more difficult to be fully covered by snow, resulting in the overestimation of SCF obviously reduced and thereafter the surface albedo decreased. It further causes the ground surface to absorb more solar radiation and then more heat released to the overlying atmosphere and deep soils. Thereafter, the cold biases in the soil and surface air temperature simulations on the TP in cold seasons can be clearly reduced. This study highlights that considering the impact of the sub-grid topography relief on snow cover in numerical models is one of the effective ways for reducing the cold biases on the TP.

Plain Language Summary The complex sub-grid terrain highly regulates the snow cover distribution on the TP and thereafter affects the heat and water exchanges at the land-air interface. However, the RegCM4.7 model largely overestimates the SCF on the TP due to the lack of attention to the effects of sub-grid terrain relief on snow cover, leading to overestimation of surface albedo and thereafter evident cold biases in the soil and surface air temperature simulations in cold seasons. In this study, we implement an improved SCF scheme that fully accounts for the effect of sub-grid terrain relief on snow cover distribution in the RegCM4.7 model which clearly reduce the SCF overestimation and further clearly enhance the simulations of soil and surface air temperatures. Overall, considering the impact of sub-grid terrain relief on snow cover in numerical models may be one of efficient strategies to reduce the cold biases in regions with complex topography during cold seasons.

1. Introduction

The CMIP5 global climate models (GCMs) produce consistent cold biases of the surface air temperature, ground temperature, and soil temperature simulations in the Tibetan Plateau (TP), especially in cold seasons (Chen et al., 2017; Chen & Frauenfeld, 2014; Duan et al., 2013; Guo et al., 2013; Slater & Lawrence, 2013; Sun et al., 2015). And the cold biases remain unresolved in the CMIP6 models (Xing et al., 2023; Yang et al., 2021; Zhu & Yang, 2020). The regional climate models (RCMs) present almost the similar cold biases to the GCMs (Liang et al., 2008; Rahimi et al., 2024; Xu & Yang, 2012). This poses a great challenge to project the real future climate (Liu et al., 2020; Wu et al., 2015; Wu & Gao, 2020).

Previous studies reveal that the cold biases are determined by the radiation transfer schemes related to the land-air energy exchange (Hu et al., 2023; Lee et al., 2019; Yue et al., 2021). The cold biases of ground temperature

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simulations produced by the WRF model can be clearly reduced by switching off the snow albedo parameterization and updating the surface condition with the MODIS observed surface albedo data (Meng et al., 2018) or by modifying the fresh snow albedo scheme and SCF scheme (Zhou et al., 2023). Lalande et al. (2023) reduced the cold biases of ground temperature simulations in a global climate model by optimizing the SCF scheme. It is no doubt that the SCF scheme plays important roles in leading to the cold biases through the albedo effect (Jiang et al., 2020; Miao, Guo, Hu, et al., 2024; Miao, Guo, Li, et al., 2024).

The TP stores nearly half the amount of the snow water equivalent in China (Bormann et al., 2018; Ji & Kang, 2013; Shen et al., 2015; Zhang et al., 2004), and the snow cover on the TP in cold seasons is widely recognized as one of the premonitory signals for the prediction of summer precipitation in East China (Liu et al., 2004; Qian et al., 2003; Wang et al., 2018; Xiao & Duan, 2016; Xu & Li, 2010; Yim et al., 2010; Zhang et al., 2004). The snow cover over the TP regulates the land-air heat and water exchanges (Vasiliev et al., 2020; Vecellio et al., 2019; Yang & Wang, 2019a; You et al., 2020), and it in turn affects the seasonal shift in the thermal discrepancy between land and ocean and ultimately the onset date and intensity of the summer monsoon (Guo & Wang, 2013; Lin et al., 2023; Qian et al., 2003; Zhao & Moore, 2004). Moreover, the anomalous signals from snow cover can be preserved in the frozen soil, enhancing the thermal forcing of the TP on East Asian summer monsoon (Yang & Wang, 2019a, 2019b). Obviously, the credibility of regional climate simulations may be compromised due to the persistent cold biases in soil and surface air temperature simulations over the TP during cold seasons.

In the context of global warming, the snow cover and frozen soil show rapid degradation due to its high vulnerability and sensitivity, resulting in the snow cover and frozen soil areas decreased, the active layer thickness increased and the frozen depth decreased (Biskaborn et al., 2019; Guo & Wang, 2017; Li et al., 2021; Peng et al., 2018). This exacerbates the loss of soil water and the emission of greenhouse gases and consequently threatens the stability of the ecosystem (Jorgenson et al., 2001; Li et al., 2021; Peng et al., 2018; Schuur et al., 2008, 2015; Wang et al., 2023).

Generally, the snow cover on the TP is highly influenced by the sub-grid terrain relief and is stable and thick in the mountain areas and thin and quick melting in the central TP (Deng et al., 2017; Pu et al., 2007; Xu et al., 2017). Therefore, implementing the sub-grid terrain effect into snow cover modeling may improve the snow cover simulation on the TP (Aas et al., 2017; He et al., 2021; Helbig & van Herwijnen, 2017). Miao et al. (2022) implemented a sub-grid terrain factor into the SCF scheme of SSiB3, highlighting the importance of the sub-grid terrain effect on snow cover simulation in the TP. Following that, Lalande et al. (2023) and Zhou et al. (2023) introduced this modified SCF scheme into climate models and clearly reduced the cold biases in ground temperature simulations. However, these studies fail to discuss how the modified SCF scheme affect the soil and surface air temperature simulations, especially the soil temperature simulations. Accordingly, this study will address two questions as follows: (a) Can adopting the SCF scheme considering the sub-grid terrain effect effectively reduce the cold biases in the soil and surface air temperature simulations of the RegCM4.7 model over the TP in cold seasons? (b) What are the underling mechanisms?

2. Data and Methods

2.1. The Data for Model Evaluation

In this study, we use the data for model evaluation as follows:

1. The China Meteorological Administration Land Data Assimilation System (CLDAS) hourly ground and soil temperatures (from the depth of 200 cm to ground surface) and surface air temperature (2 m above the ground surface) from 1 October 2011–30 June 2016 with a horizontal resolution of 0.0625°. This data set merges site observations, satellite retrieval data, and climate simulations using advanced assimilation techniques (Jia et al., 2013).
2. The MODIS daily SCF product over the TP with a horizontal resolution of 500 m from 1 October 2011–31 May 2016. It is based on the MOD10A1 product with the removal of cloud impact (Tang et al., 2013).
3. The 8-day frequency clear-sky short-wave albedo product retrieved from the Global Land Surface Satellite (GLASS) with a horizontal resolution of 0.05° (Liang et al., 2013, 2020). It has a good performance over the TP in cold seasons (Chen et al., 2020) and is converted into monthly surface albedo using a look-up table proposed by Gao et al. (2014) before comparing with the model output.

4. The in situ atmospheric forcing data sets including the downward short-wave and long-wave radiations, surface wind speed, temperature, pressure, relative humidity, and precipitation at Maduo site with the temporal resolution of 30 min from 1 January 2014–31 May 2015 (Meng & Lyu, 2022) and Naqu site with the temporal resolution of 1 hr from 1 January 2013–31 May 2014 (Ma et al., 2020). See Figure 2 for the station locations.
5. The boundary data of the TP (Zhang et al., 2021). It defines the extent of the TP with a continuous distribution of elevations above 3,000 m and ensures the integrity of mountains based on high-resolution digital elevation data and remote sensing image.

2.2. Evaluation Metrics

In this study, the root mean square error (RMSE) is used to evaluate the model performance in quantity, and the Taylor score (TS) is employed to reveal its temporal variability. They are formulated as follows:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - y_i)^2} \quad (1)$$

$$TS = \frac{4(1 + R)}{(\sigma + \frac{1}{\sigma})^2 (1 + R_0)} \quad (2)$$

$$R = \frac{\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^N (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^N (y_i - \bar{y})^2}} \quad (3)$$

$$\sigma = \frac{\sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^2}}{\sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \bar{y})^2}} \quad (4)$$

where x_i (y_i) represents the i th simulated (observed) value among N temporal samples, and $\bar{x}$ ($\bar{y}$) denotes the corresponding temporal average. The correlation coefficient, R , quantifies the association between the simulated and observed values. Meanwhile, σ indicates the similarity in temporal variation between simulation results and observed data. $R_0 = 1$ is the achievable maximum correlation. The TS ranges from 0 to 1, and a superior model performance is indicated by a smaller RMSE and a higher TS value (Huang et al., 2019; Luo et al., 2023).

The CLDAS temperatures, MODIS SCF, and GLASS albedo are first interpolated onto the model grids and then compared with the model output data. To ensure a smooth and accurate representation of the validation data on the model grid, the inverse distance weight method (Bartier & Keller, 1996) is employed. Specifically, the interpolated value for each model grid point is calculated by averaging the values from all validation data grid points within a 10 km radius, with weight assigned based on their distances to the model point. This approach facilitates a reliable comparison between the validation data and the simulation results (Huang et al., 2016).

Because the soil freeze-thaw process preserves the hydrothermal anomalies and connects the winter and summer climates over the TP (Lin et al., 2023; Yang & Wang, 2019a, 2019b), according to previous studies (Frauenfeld et al., 2004; Guo & Wang, 2013; Henry, 2008; Peng et al., 2016; Zhang et al., 2014), this study defines the following variables to discuss the soil freeze-thaw process.

1. The frozen onset date is the first day that the daily mean soil temperature is below 0°C for five consecutive days during 1 October to 30 June.
2. The frozen end date is the first day that the daily mean soil temperature changes from negative to positive for five consecutive days during 1 October to 30 June.
3. The frozen duration is the number of days between the frozen end date and the frozen onset date.

3. Model Development and Experimental Design

3.1. Model Description

This study utilizes the Abdus Salam International Center for Theoretical Physics (ICTP) Regional Climate Model version 4.7 (RegCM4.7). It provides a comprehensive set of options for physical packages (Coppola et al., 2021;

Giorgi, 1990), enabling the reproduction of the spatial and temporal distributions of the climatic mean precipitation and air temperature over the TP but with obvious wet and cold biases in cold seasons (Gao et al., 2008; Gao & Giorgi, 2017; Kong et al., 2019). For the land surface component, the CLM4.5 is selected, as it provides advanced snow and soil hydrothermal transport processes (Deng et al., 2020; Lawrence et al., 2012; Wang & Yang, 2018; Xie et al., 2019).

3.2. The Development of SCF Scheme

Dickinson et al. (1993) first proposed a SCF scheme in the BATS land surface model as:

$$f_{sno} = \frac{f_{sn}}{1 + f_{sn}} \quad (5)$$

$$f_{sn} = \frac{0.1 \times SWE}{\rho_s \times Z_{0,g}} \quad (6)$$

where f_{sno} is the grid averaged SCF (unitless), f_{sn} is the coverage of vegetation by snow (unitless), SWE is the snow water equivalent (mm), ρ_s is the snow density ($\text{kg} \cdot \text{m}^{-3}$), and $Z_{0,g}$ is the surface roughness (m) for different vegetation types (set to constants). SWE/ρ_s is the grid averaged snow depth. Following that, the Canadian Climate Center Global Climate Model (Versegny, 1991), the NCAR CCM0A (Marshall et al., 1994) and CCM1.0 (Marshall & Oglesby, 1994), the Météo-France climate model (Douville et al., 1995a), the NCAR LSM1.0 (Bonan, 1996), the SiB (Sellers et al., 1996), and the CCSR/NIES AGCM (Watanabe & Nitta, 1998) parameterized the SCF solely linearly related to the grid-averaged snow depth.

Yang et al. (1997) pointed out that there are two evident stages for the SCF/snow depth relationship based on the observation analysis. During the first stage, the SCF increased sharply with the increased snow depth before it reached a critical depth. Once the snow depth reached the critical depth, the SCF increased slowly as the snow depth increased. Thus, they implemented a hyperbolic tangent function to parameterize the SCF/snow depth relationship as

$$f_{sno} = \tanh\left(\frac{SD}{2.5 \times z_{0,g}}\right) \quad (7)$$

where SD is the snow depth (m). Roesch et al. (2001) revealed that Equation 7 performed well in plain areas. Subsequently, based on the analysis of monthly satellite-retrieved data, Niu and Yang (2007) discovered that there is an evident seasonal variation in the relationship between SCF and snow depth. This variation can be manifested through snow density. They further modified the SCF scheme as

$$f_{sno} = \tanh\left(\frac{SD}{2.5 \times z_{0,g} \times \left(\frac{\rho_s}{\rho_{snew}}\right)^m}\right) \quad (8)$$

where ρ_{snew} is the fresh snow density (100 kg m^{-3}), $m = 1.0$ is a tunable parameter.

However, Swenson and Lawrence (2012) described that the seasonal transition period of the SCF/snow depth relationship may be shorter than a month based on daily observation. Therefore, they parameterized the SCF in snowfall and snowmelt scenarios separately in a closed form for computational efficiency and numerical stability. When the snowfall occurs, it is expressed as

$$f_{sno}^n = 1 - (1 - \tanh(k_a \times q_{sno} \times \Delta t)) \times (1 - f_{sno}^{n-1}) \quad (9)$$

where f_{sno}^n (f_{sno}^{n-1}) is the SCF in current (previous) time step, $k_a = 0.1$ is the accumulation factor, q_{sno} is the rate of snowfall (mm s^{-1}), and Δt is the model time step (seconds). There are two assumptions in Equation 9: (a) the precipitation is randomly distributed in a grid cell, (b) the occurrence of snowfall events in different areas is

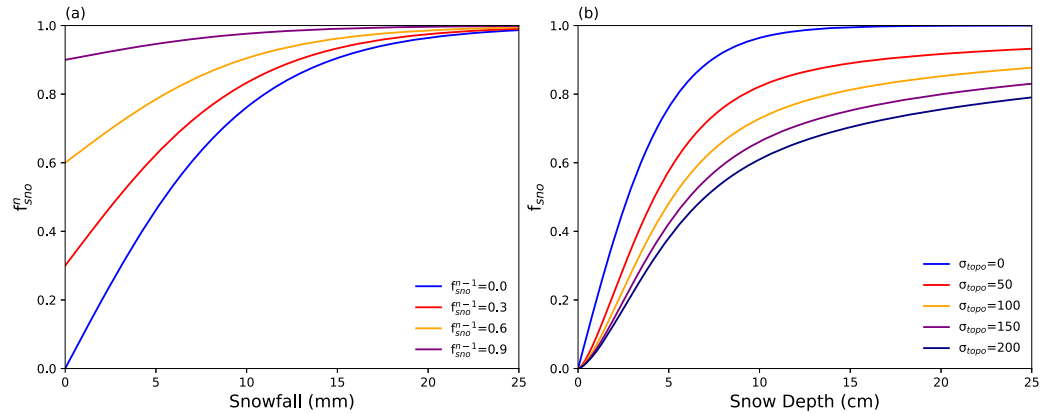


Figure 1. The comparative plots of two SCF schemes formulated by Equations 9a and 12b. The ground roughness $z_{0,g}$ is set to 0.01 m, and the snow density ρ_s is set to $200 \text{ kg}\cdot\text{m}^{-3}$.

spatially independent. Thus, the SCF can be updated after a snowfall event (f_{sno}^n) only by the current SCF (f_{sno}^{n-1}) and the amount of snowfall ($q_{sno} \times \Delta t$).

Additionally, when the snowmelt occurs, Swenson and Lawrence (2012) related the SCF to the sub-grid terrain as

$$f_{sno} = 1 - \left(\frac{\cos^{-1}(2 \times R_{sno} - 1)}{\pi} \right)^{N_{melt}} \quad (10)$$

where R_{sno} is the proportion of snow water equivalent to the peak snow accumulation, $N_{melt} = \frac{200}{\max(10, \sigma_{topo})}$ is a terrain factor, and σ_{topo} (m) is the standard deviation of the sub-grid terrain elevation within a given grid cell.

Moreover, Douville et al. (1995b) reported that the SCFs in both snowfall and snowmelt scenarios over mountainous areas need to be revised by the sub-grid terrain relief as

$$f_{sno} = \frac{SWE}{SWE + 10} \times \left(\frac{SWE}{SWE + \max(1.0, 0.15 \times \sigma_{topo})} \right)^{0.5} \quad (11)$$

where $\left(\frac{SWE}{SWE + \max(1.0, 0.15 \times \sigma_{topo})} \right)^{0.5}$ is a sub-grid terrain scaling factor. Researches have demonstrated that incorporating the sub-grid terrain scaling factor in Equation 11 into SCF parametrization can mitigate the SCF simulation bias in mountainous areas (Li et al., 2019; Roesch et al., 2001; Yang et al., 1997). Moreover, Miao et al. (2022) enhanced the simulation of SCF on the TP by modifying the SCF scheme proposed by Niu and Yang (2007) with the sub-grid terrain scaling factor in Equation 11, and it is expressed as

$$f_{sno} = \tanh \left(\frac{SD}{2.5 \times z_{0,g} \times \left(\frac{\rho_s}{\rho_{snow}} \right)^m} \right) \times \left(\frac{SWE}{SWE + \max(1.0, 0.15 \times \sigma_{topo})} \right)^{0.5} \quad (12)$$

For simplicity, we call the SCF scheme proposed by Niu and Yang (2007) based on Equation 8 as NY07 scheme and call the SCF scheme proposed by Swenson and Lawrence (2012) based on Equations 9 and 10 as SL12 scheme. And the NY07 scheme modified according to Equation 12 is called as MNY scheme. The NY07 and SL12 schemes are both achieved in original RegCM4.7. The SL12 is the default SCF scheme in RegCM4.7, and the NY07 scheme is an alternative option. The MNY scheme is easy to be implemented into RegCM4.7 because all the variables in Equation 12 are already presented in the original model.

Figure 1 gives a comparison of Equations 9 and 12, with $\rho_s = 200 \text{ kg}\cdot\text{m}^{-3}$ and $z_{0,g} = 0.01 \text{ m}$. From Figure 1a, regardless of the initial SCF produced by Equation 9, a value of 1.0 is achieved with the same snowfall rate. From

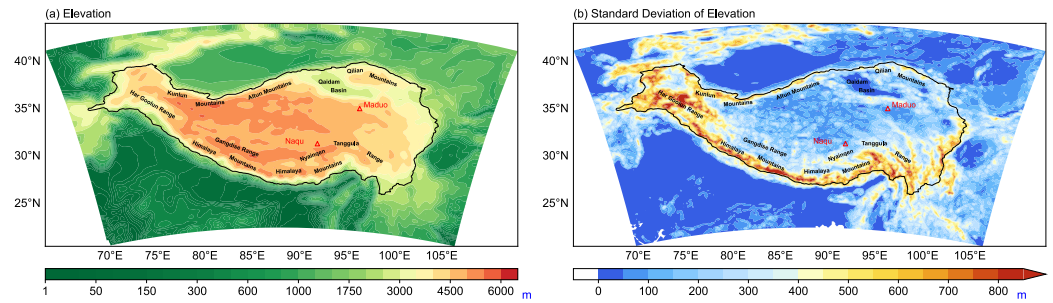


Figure 2. The distributions of the model domain (a) elevation and (b) standard deviation of sub-grid (~ 90 m; Jarvis et al., 2008) terrain elevation (σ_{topo}) within each model grid at the horizontal resolution of 20 km. The black lines outline the Tibetan Plateau (Zhang et al., 2021). The red triangles present the locations of in situ sites.

Figure 1b, the SCF produced by Equation 12 can also achieve a value of 1.0 in plain areas ($\sigma_{topo} = 0$). However, the sub-grid terrain relief inhibits the growth rate of SCF. When the sub-grid terrain relief increases, it becomes more difficult for the ground to be fully covered by snow. This meets the knowledge of snow cover processes in complex terrain areas (Anderson et al., 2014; Feng et al., 2022; He et al., 2021; He & Ohara, 2019). Moreover, Lalande et al. (2023) and Zhou et al. (2023) also proved that Equation 12 is the best scheme for modeling SCF over the TP. Consequently, this study adopts the MNY scheme based on Equation 12 as the improved SCF scheme to simulate the SCF for both snowfall and snowmelt scenarios in RegCM4.7 model.

3.3. Experimental Designs

As shown in Table 1, to quantify how the improved SCF scheme affects the soil and surface air temperature simulations over the TP, this study designs three numerical experiments namely CTL_SL12 conducted by the RegCM4.7 model adopting the default SCF scheme (SL12 scheme), EXP_NY07 conducted by the RegCM4.7 adopting the NY07 SCF scheme, and EXP_MNY conducted by the RegCM4.7 model adopting the improved SCF scheme (MNY scheme).

Both experiments are carried out with the same model configuration in which the parameterization schemes are selected based on previous studies and extensive simulations (Gu et al., 2022, 2023, 2024). In the three experiments, the sole difference in model configuration lies in the adoption of different SCF schemes. The simulation domain centers at 33°N , 88°E , with 200×120 (zonal $\times$ meridian) grids at a 20 km horizontal resolution (Figure 2). Each simulation runs with 18 vertical levels of atmosphere with 50 hPa at the model top. The Global Multi-resolution Terrain Elevation Data (GMTED) with a horizontal resolution of $30''$ (~ 1 km) (Danielson & Gesch, 2011) provides the model sub-grid terrain information. The weekly $1.0^{\circ} \times 1.0^{\circ}$ NOAA Optimum Interpolation Sea Surface Temperature (OISST) (Reynolds et al., 2002) from 2010 to 2016 provides the model oceanic surface condition. The $0.25^{\circ} \times 0.25^{\circ}$ European Space Agency (ESA) Climate Change Initiative (CCI) Essential Climate Variable (ECV) Surface Soil Moisture Combined Product on 31 December 2009 (Dorigo et al., 2021) is used to provide the model initial soil moisture. The 6 hourly ERA-Interim reanalysis data with the horizontal resolution of $1.5^{\circ} \times 1.5^{\circ}$ (Dee et al., 2011) during 1 January 2010–1 July 2016 provide the atmospheric initial and lateral boundary conditions at different vertical levels of RegCM4.7 model. The U.S. Geological Survey (USGS) Global Land Cover Characterization (GLCC) data sets with a horizontal resolution of 1 km (Loveland et al., 2000) offer the model land cover information.

The physical packages employed in this study are the CLM4.5 land surface model (Oleson et al., 2013), the Emanuel cumulus scheme (Emanuel, 1991), the Holtslag planetary boundary layer scheme (Holtslag et al., 1990), the SUBEX large-scale precipitation scheme (Pal et al., 2000), the CCM3 radiation model (Kiehl et al., 1998), and the Zeng ocean flux scheme (Zeng et al., 1998). The lateral boundary condition scheme with a relaxation exponential technique is adopted.

The simulation period for each experiment is from 1 January 2010–1 July 2016 to present the snow cover and soil freeze-thaw processes over the TP on

Table 1
Designs of Experiments by RegCM4.7 and CLM4.5

Cases	SCF scheme
CTL_SL12	SL12 scheme, Equations 9 and 10
EXP_NY07	NY07 scheme, Equation 8
EXP_MNY	MNY scheme, Equation 12

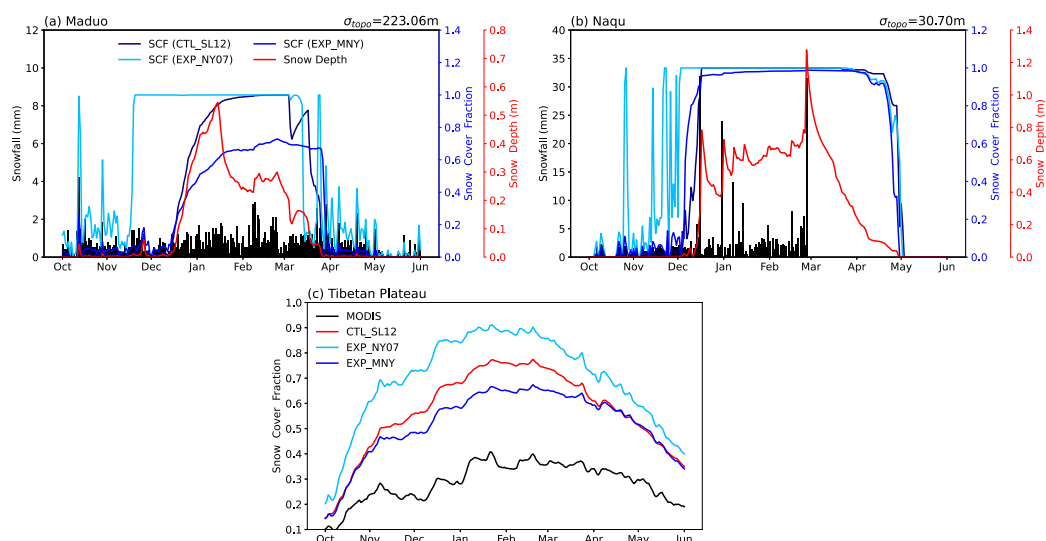


Figure 3. The time series of simulated daily snowfall (black bars in a and b), SCF, and snow depth (red lines in a and b) at Maduo (a, from 1 October 2014–31 May 2015) and Naqu (b, from 1 October 2013–31 May 2014) sites. And the day-to-day variation of observed and simulated multi-year (2011–2016) mean SCF regionally averaged over the Tibetan Plateau during 1 October to 31 May (c).

a climatic scale. The solar radiation module, the adsorption-emission module, the land surface model, and the cumulus module are called with intervals of 10 min, 60 min, 10 min, and 2 min, respectively. The model time step is set to 30 s, and the output frequencies for land surface and atmospheric modules are 24 and 1 hr, respectively. The initial 21 months of the integration are designated as the model spin-up time. The differences in the simulations in the cold seasons (1 October to 31 May) during 2011–2016 between the three experiments are analyzed to reveal how the improved SCF scheme affects the model performance.

Additionally, to reveal how the sub-grid terrain relief influences the SCF simulation over the TP, this study designs three offline experiments at Maduo (from 1 January 2014–31 May 2015) and Naqu (from 1 January 2013–31 May 2014) sites (Figure 2) by adopting the SL12, NY07, and MNY schemes in CLM4.5, respectively. The experiment names consistent with the regional experiments. In the three single-point experiments, the sole difference in model configuration lies in the adoption of different SCF schemes too. The standard deviation of sub-grid terrain elevation is calculated by a $0.1^\circ \times 0.1^\circ$ grid centered on the observation site using the GMTED data. The model time step coincides with the observation interval, and the model output frequency is 24 hr.

It can be seen from Figures 3a and 3b that there are three stages for the SCF variation produced by the SL12 scheme at Maduo and Naqu sites. During the first stage, the SCF increases with the increased snow depth before it reaches 0.4 m. Once the snow depth reaches 0.4 m, the SCF reaches 1.0. Then, the SCF decreases sharply with the decreased snow depth. It is noted that the SCF produced by the NY07 scheme increases evidently when snowfall event occurs during the accumulation and melting periods, and it reaches 1.0 when snow depth is near 0.1 m. It is clear that the MNY scheme suppresses the rapid increase in SCF with snowfall. Moreover, as the sub-grid terrain relief increases, the SCF becomes more difficult to reach 1.0. Consequently, as shown in Figure 3c, compared with the MODIS, the SL12 scheme overall overestimates the SCF over the TP, while adopting the NY07 scheme produces much higher overestimation of SCF over the TP throughout the cold season relative to the SL12 scheme. The MNY scheme considering the effect of sub-grid terrain relief also overestimates the SCF on the TP during the cold seasons relative to the MODIS, largely due to the evident wet bias in precipitation simulation (Gao et al., 2008; Gao & Giorgi, 2017; Kong et al., 2019). However, it effectively reduces the overestimation of SCF over the TP from November to April and performs the best among the 3 schemes. Thus, we adopt the MNY scheme to improve the SCF simulation over the TP.

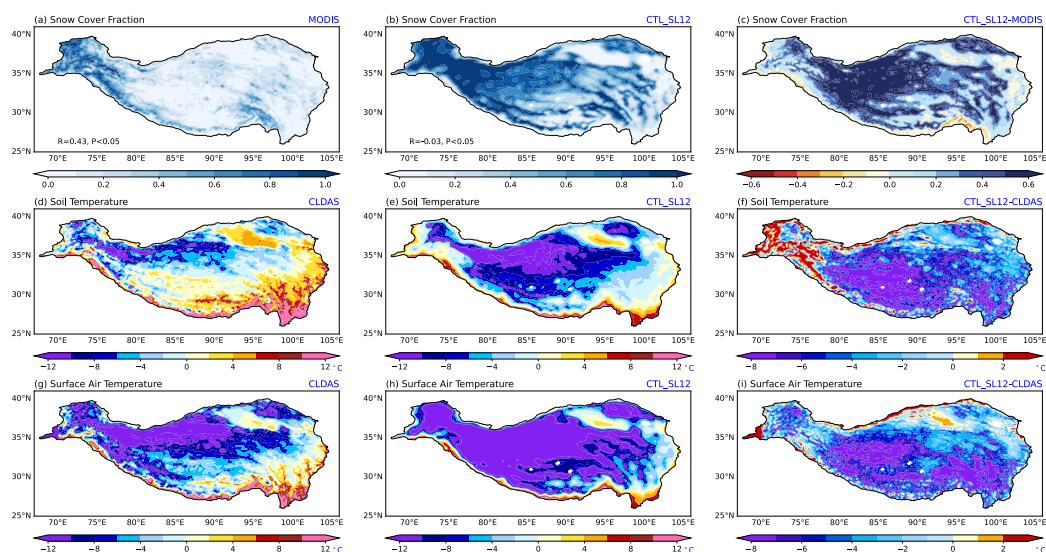


Figure 4. The observed and the CTL_SL12 experiment simulated SCF (a–b), vertically averaged (from 5 to 200 cm) soil temperature (d–e), and surface air temperature (g–h) over the Tibetan Plateau temporally averaged over the cold seasons (1 October to 31 May) of 2011–2016 and their differences (c), (f), and (i). The R in panels (a–b) represents the spatial correlation coefficient between the SCF and the standard deviation of sub-grid terrain elevation (σ_{topo}) at the 95% confidence level.

4. Results

4.1. Evaluation of the Model Performance in Simulating the SCF, Soil, and Surface Air Temperatures in Cold Seasons

As shown in Figure 4a, the spatial distribution of MODIS observed SCF corresponds well to the standard deviation of sub-grid terrain elevation (Figure 2b) with a spatial correlation coefficient of 0.43. Apparently, a large amount of snow cover is concentrated in the Nyaiqen Tanggula Range, the Himalaya Mountains, and the northwestern TP. However, the CTL_SL12 experiment overall overestimates the SCF in the TP with underestimations only in a few areas such as the Qaidam Basin, the Himalaya Mountains, and the south region of the Nyaiqen Tanggula Range (Figure 4c). And the overestimation of SCF is generally more than 0.6 relative to the MODIS. Moreover, it is noted that the CTL_SL12 experiment fails to present the potential relationship between SCF and complexity of sub-grid terrain (Figure 4b), with a spatial correlation coefficient of -0.03 between SCF and standard deviation of sub-grid terrain elevation.

Undoubtedly, the overestimation of SCF results in underestimation of soil temperature due to the high surface albedo, leading to reduction in the absorption of solar radiation at the ground surface. From Figures 4d and 4e, the CTL_SL12 experiment presents a larger area where the averaged soil temperature is below 0°C than the CLDAS. As shown in Figure 4f, compared with the CLDAS, the CTL_SL12 experiment produces cold biases of soil temperature simulations in most TP, despite warm biases in the Har Goolun Range, the Kunlun Mountains, the Altun Mountains, and parts of the Himalaya Mountains. The absolute differences in the soil temperature simulations between the CTL_SL12 experiment and CLDAS are generally larger than 4°C over most TP with much higher value mainly located in the regions bounded by 80°E – 100°E and 28°N – 34°N .

The cold biases in soil temperature simulations lead to underestimation of surface air temperature through the land-air interaction. As shown in Figures 4g–4i, the CTL_SL12 experiment presents cold biases to surface air temperature simulations relative to the CLDAS in most TP with few warm biases in parts of the northern and southern margins of the TP and the Qaidam Basin. The absolute differences of surface air temperature simulations between CTL_SL12 experiment and CLDAS are generally larger than 6°C in most areas south of 35°N over the TP.

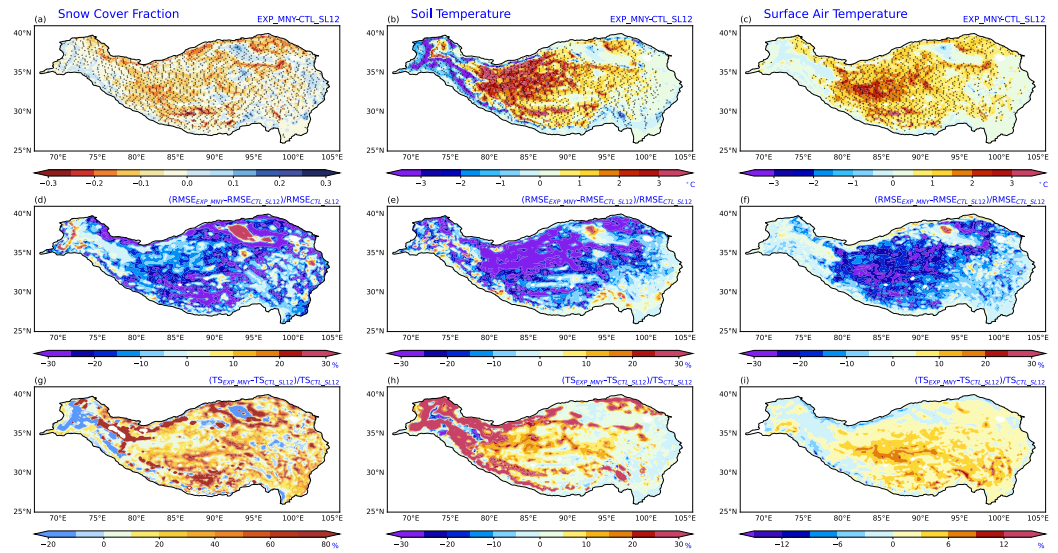


Figure 5. The differences in the simulated SCF (a), vertically averaged (from 5 to 200 cm) soil temperature (b), and surface air temperature (c) over the Tibetan Plateau temporally averaged during the cold seasons (1 October to 31 May) of 2011–2016 between the EXP_MNY and CTL_SL12 experiments. The percentage changes $((\text{EXP_MNY} - \text{CTL_SL12}) / \text{CTL_SL12} * 100)$ of the RMSE and TS for the modeled SCF (d) and (g), vertically averaged soil temperature (e) and (h), and surface air temperature (f) and (i) over the Tibetan Plateau produced by the EXP_MNY experiment relative to the CTL_SL12 experiment. The dots in panels (a)–(c) depict the differences achieving statistical significance at the 95% level.

4.2. Impact of the Improved SCF Scheme on SCF, Soil, and Surface Air Temperature Simulations in Cold Seasons

From Figure 5a, it is clear that the EXP_MNY experiment effectively decreases the overestimated SCF on the TP produced by the CTL_SL12 experiment (Figure 4c). In some mountain areas, such as the Altun, Kunlun, and Qilian Mountains, the southern margin of the Qaidam Basin, and the Gangdise Range (the Qaidam Basin, the Himalaya Mountains, and the eastern margin of the TP), the overestimation (underestimation) of the SCF in the CTL_SL12 experiment can be reduced by 0.20–0.30 (increased by 0.05–0.15) in the EXP_MNY experiment. From Figure 5b, the EXP_MNY experiment significantly reduces the biases of soil temperature simulations in the CTL_SL12 experiment (Figure 4f). The absolute difference in the modeled soil temperature between the EXP_MNY and CTL_SL12 experiments is relatively larger in the western TP, where the difference in the modeled SCF between the CTL_SL12 experiment and MODIS is also relatively larger. Notably, in most regions of the TP, the EXP_MNY experiment yields significantly higher surface air temperature than the CTL_SL12 experiment (Figure 5c), leading to the cold biases of the surface air temperature simulations produced by the CTL_SL12 (Figure 4i) clearly reduced.

From Figures 5d–5i, the EXP_MNY experiment noticeably improves the SCF, soil temperature, and surface air temperature simulations with the RMSE (TS) reduced (increased) relative to the CTL_SL12 experiment. And the EXP_MNY experiment can reduce the RMSE of the SCF, soil temperature, and surface air temperature simulations up to 30% in most areas of the TP, and increase the TS of the SCF, soil temperature, and surface air temperature simulations up to 80%, 30%, and 10% over the TP in comparison with the CTL_SL12 experiment, respectively. Besides, the spatial distribution of percentage changes of RMSE and TS of the modeled SCF, soil temperature, and surface air temperature over the TP correspond well with the differences in the modeled SCF, soil temperature, and surface air temperature between the two experiments.

From Figures 6a and 6b, relative to the CTL_SL12 experiment, the RMSE (TS) of the SCF simulated by the EXP_MNY experiment is reduced by 12.0%–15.6% (increased by 1.4%–18.2%) over the regions with different sub-grid topography reliefs, and the RMSE of the SCF simulated by the EXP_MNY experiment are more clearly reduced over the regions with $100 < \sigma_{\text{topo}} \leq 500$ m in which the simulation biases produced by the CTL_SL12 experiment are more pronounced, while the TS of the SCF simulated by the EXP_MNY experiment over the regions with $\sigma_{\text{topo}} \leq 500$ m are increased by 16.6%–18.2%.

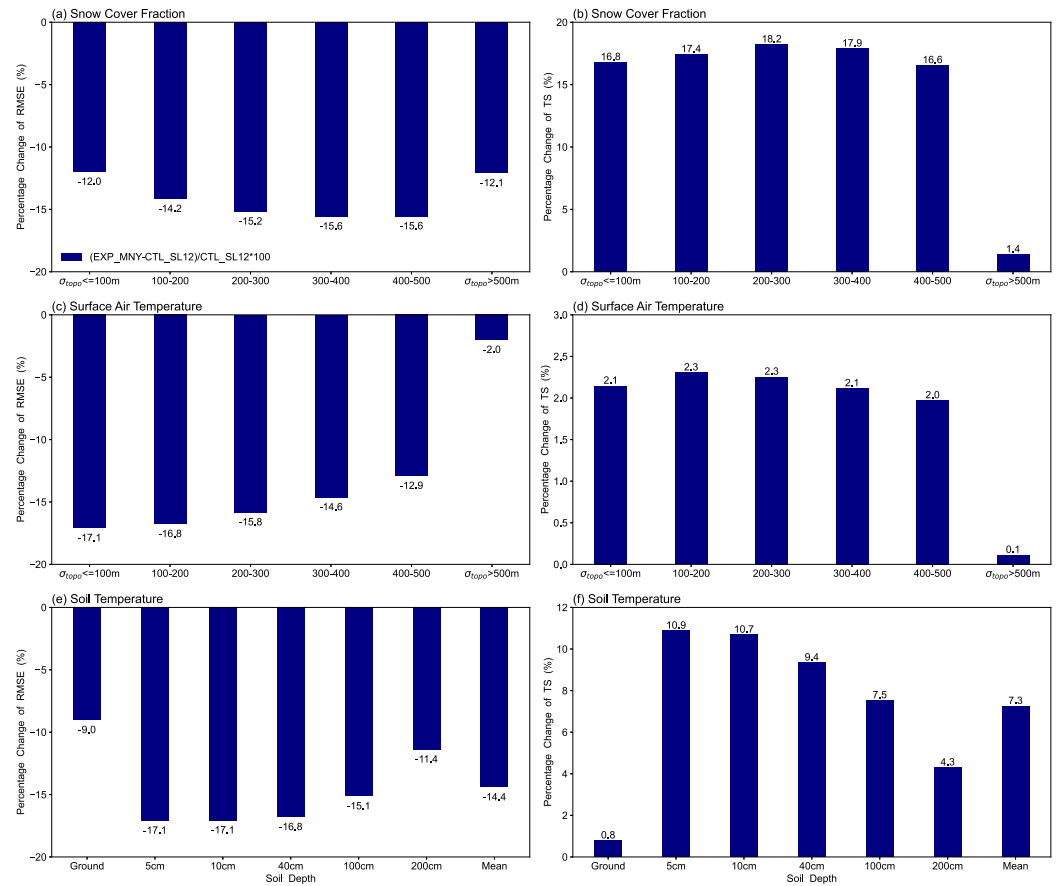


Figure 6. The relative percentage changes ((EXP_MNY-CTL_SL12)/CTL_SL12*100) of the regionally averaged RMSE and TS for the modeled SCF (a–b) and surface air temperature (c–d) in the regions with different sub-grid terrain reliefs (σ_{topo}), and the soil temperature from ground surface to 200 cm (e–f) on the Tibetan Plateau between the EXP_MNY and CTL_SL12 experiments during cold seasons (1 October to 31 May) in 2011–2016.

From Figures 6c and 6d, adopting the improved SCF scheme can enhance the surface air temperature simulations with the RMSE (TS) decreased (increased) over the regions in different sub-grid terrain reliefs relative to the CTL_SL12 experiment. Additionally, it is noted that the reductions (increases) of RMSE (TS) of the simulated surface air temperature decrease with the sub-grid terrain relief increasing to some extent. Generally, the RMSE (TS) of the surface air temperature simulated by the EXP_MNY experiment can be reduced by 2.0%–17.1% (increased by 0.1%–2.3%) in the regions with different sub-grid topography reliefs.

As shown in Figures 6e and 6f, the column-mean (from the depth of 200 cm to ground surface) RMSE (TS) of the simulated soil temperature regionally averaged over the TP in the EXP_MNY experiment can be reduced by 14.4% (increased by 7.3%) relative to the CTL_SL12 experiment, respectively. Moreover, greater reductions of RMSE (increases of TS) can be noted at the depths of 5–40 cm.

Overall, relative to the improvements of TS of the soil and surface air temperature simulations, adopting the improved SCF scheme leads to much larger improvements in the RMSE of soil and surface air temperature simulations. Generally, adopting the improved SCF scheme directly reduces the overestimation of SCF and then reduces the biases in the soil temperature (from ground surface to 200 cm) and surface air temperature simulations through complex hydrothermal transfer processes.

4.3. Impact of the Improved SCF Scheme on the Soil Freeze-Thaw Process Simulation

Biases of soil temperature simulations lead to inaccurate simulated soil freeze-thaw processes. Figure 7 gives the observed and simulated soil frozen onset dates, frozen end dates, and frozen duration at depth of 5 cm over the TP and their differences. As shown in Figures 7a–7c, in the areas with lower (higher) soil temperature (Figure 4d), the

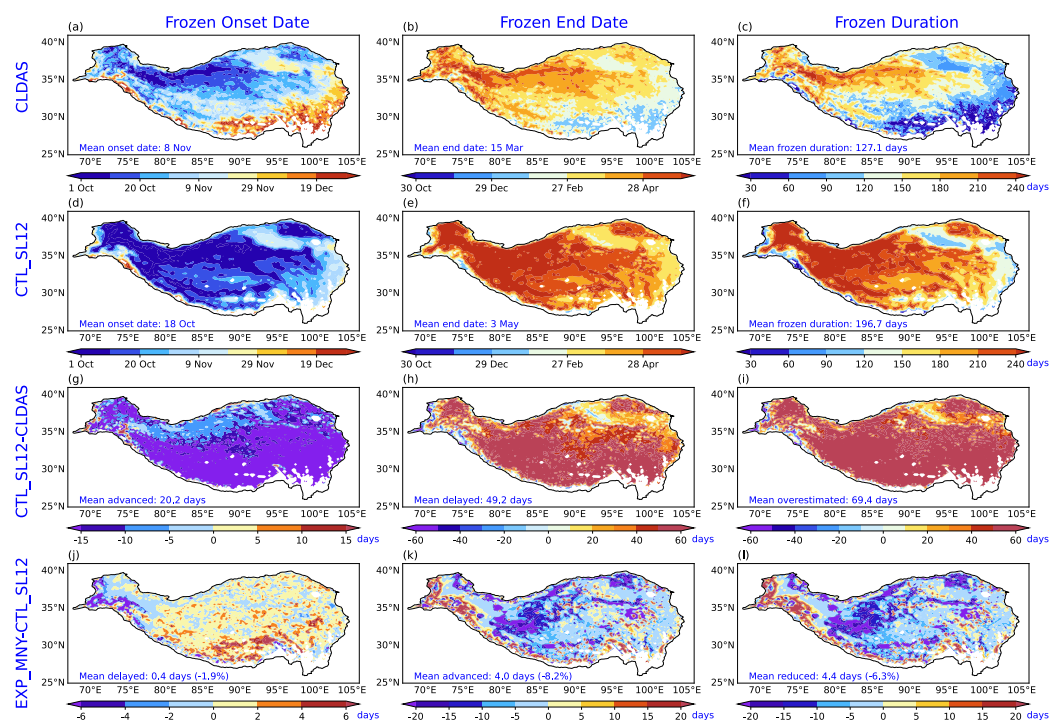


Figure 7. The observed (a–c) and CTL_SL12 experiment simulated (d–f) temporal mean (from 2011 to 2016) soil frozen onset date, frozen end date, and frozen duration at the depth of 5 cm over the Tibetan Plateau, and their differences (g–i), and (j–l) show the differences between the EXP_MNY and CTL_SL12 experiments. The regional average for each panel is given in the lower left corner.

soil shows earlier (later) frozen onset date, later (earlier) frozen end date, and longer (shorter) frozen duration. And there are unfrozen areas at the southeastern and southern margins of the TP where the averaged soil temperatures are over 10°C. On average, the soil at the depth of 5 cm in the TP begins to be frozen on 8 November and ends to be frozen on 15 March with a frozen duration of 127.1 days.

From Figures 7d–7i, the underestimation of soil temperature produced by the CTL_SL12 experiment results in earlier frozen onset date, later frozen end date, and longer frozen duration compared with the observation. It is noted that the CTL_SL12 experiment overestimates the soil temperature in the Har Goolun Range (Figure 4f), but it still produces an earlier (later) frozen onset (end) date and a longer frozen duration in those areas relative to the observation owing to that the averaged soil temperatures are less than 2°C which favors the soil to be frozen. Overall, on average, the soil at the depth of 5 cm in the TP in the CTL_SL12 experiment begins to be frozen on 18 October and ends to be frozen on 3 May with a frozen duration of 196.7 days. From Figures 7g–7i, it is clear that the simulated soil freeze-thaw processes over the TP in the CTL_SL12 experiment show an earlier frozen onset date of 20.2 days, a later frozen end date of 49.2 days, and a longer frozen duration of 69.4 days than the observation.

Although there are still evident biases in the soil freeze-thaw processes in the TP simulated by the EXP_MNY experiment compared with the observation, it can be seen that the increased (reduced) soil temperatures in the EXP_MNY experiment (Figure 5b) delays (advances) the soil frozen onset date (Figure 7j) and advances (delays) the soil frozen end date (Figure 7k), then reduces (increases) the soil frozen duration (Figure 7l) relative to the CTL_SL12 experiment. Generally, adopting the improved SCF scheme delays the soil frozen onset date by 0.4 days, advances the soil frozen end date by 4.0 days, and then reduces the soil frozen duration by 4.4 days on average over the TP, which are more consistent with the observation. And the mean biases in the simulated frozen onset date, frozen end date, and frozen duration regionally averaged across the TP in the EXP_MNY experiment are reduced by 1.9%, 8.2%, and 6.3% relative to the CTL_SL12 experiment, respectively.

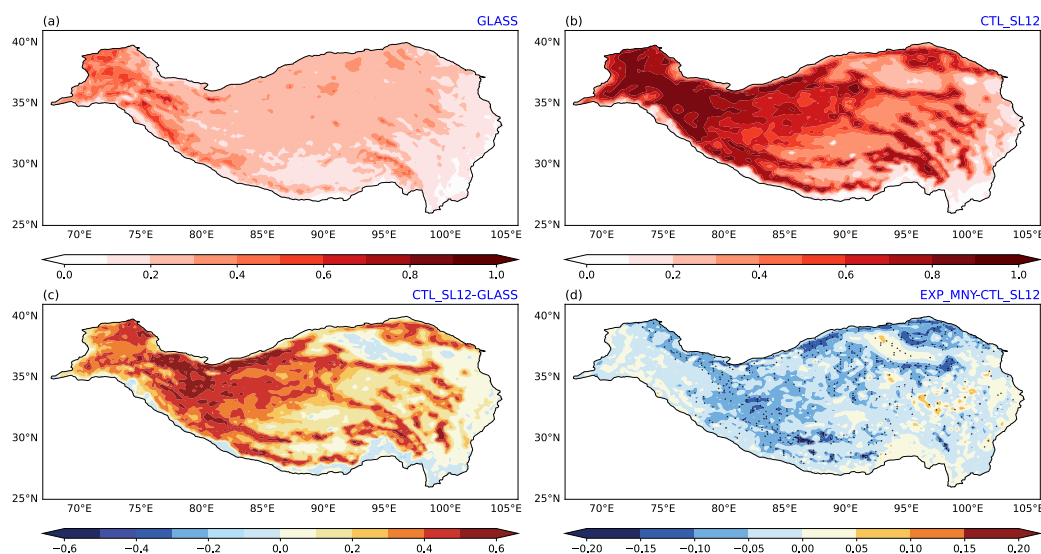


Figure 8. The observed (a) and the CTL_SL12 experiment simulated (b) surface albedo in the Tibetan Plateau averaged over the cold seasons (1 October to 31 May) of 2011–2016 and their differences (c), and (d) shows the differences between the EXP_MNY and CTL_SL12 experiments. The dots in panel (d) depict the differences achieving statistical significance at the 95% level.

4.4. Impact of the Improved SCF Scheme on Surface Heat Balance Simulation in Cold Seasons

Snow cover has a high albedo, and the overestimation of SCF results in overestimation of surface albedo, which further leads to inaccurate surface heat transfer. The observed surface albedo during October–May in most areas over the TP is about 0.2–0.3, and it is near 0.6 in the Nyainqen Tanggula Range, the Himalaya Mountains, and the Har Goolun Range (Figure 8a). The modeled surface albedo simulated by the CTL_SL12 experiment is over 0.6 in most areas of the TP, and near 1.0 in the Nyainqen Tanggula Range, the Himalaya Mountains, the Har Goolun Range, the Qilian Mountains, and south of the Qaidam Basin (Figure 8b). From Figure 8c, compared with the GLASS observation, the CTL_SL12 experiment overestimates the surface albedo by 0.4–0.6 in most parts of the TP. Moreover, the EXP_MNY experiment reduces the overestimation of surface albedo due to the reduced overestimation of SCF relative to the CTL_SL12 experiment, and the reduction of surface albedo is about 0.1–0.2 in the Gangdise Range, the Qilian Mountains, and south of the Qaidam Basin (Figure 8d).

Figure 9 gives the temporal mean differences of the simulated surface heat balance components on the TP between the EXP_MNY and CTL_SL12 experiments. The differences in the simulated surface heat balance components correspond well with the differences in the simulated surface albedo (Figure 8d). The EXP_MNY experiment produces much lower surface albedo relative to the CTL_SL12 experiment, allowing the soil to absorb more short-wave radiation, resulting in a much higher surface net radiation in the TP (Figures 9a and 9b). The increased surface net radiation in the EXP_MNY experiment further increases the modeled ground temperature (Figure 6e), leading to much higher surface net long-wave radiation (Figure 9c), sensible heat flux (Figure 9d), and latent heat flux (Figure 9e). Relative to the CTL_SL12 experiment, the sensible heat fluxes in the Kunlun, Altun, and Himalaya Mountains, and the Nyaiqen Tanggula Range are increased in the EXP_MNY experiment, but the latent heat fluxes are reduced in those regions, this is largely related to the high simulated soil liquid water content (not shown). Consequently, the increased surface net radiation in the EXP_MNY experiment relative to the CTL_SL12 experiment mostly warms the surface air temperature (Figure 5c) through sensible and latent heat fluxes, and a small amount of the increased surface net radiation increases the modeled soil temperature (Figure 5b) through more downward ground heat flux (Figure 9f).

Figure 10a shows the surface net radiation is determined by the net solar and long-wave radiations and then redistributed to sensible, latent, and ground heat fluxes. From Figure 10b, relative to the CTL_SL12 experiment, the EXP_MNY experiment produces more net solar radiation, net long-wave radiation, net radiation, sensible heat flux, latent heat flux, and ground heat flux at surface with a regional average of 4.6, 1.4, 3.2, 1.8, 1.0, and 0.4 $\text{W}\cdot\text{m}^{-2}$, respectively. Overall, adopting the improved SCF scheme results in more surface net radiation which

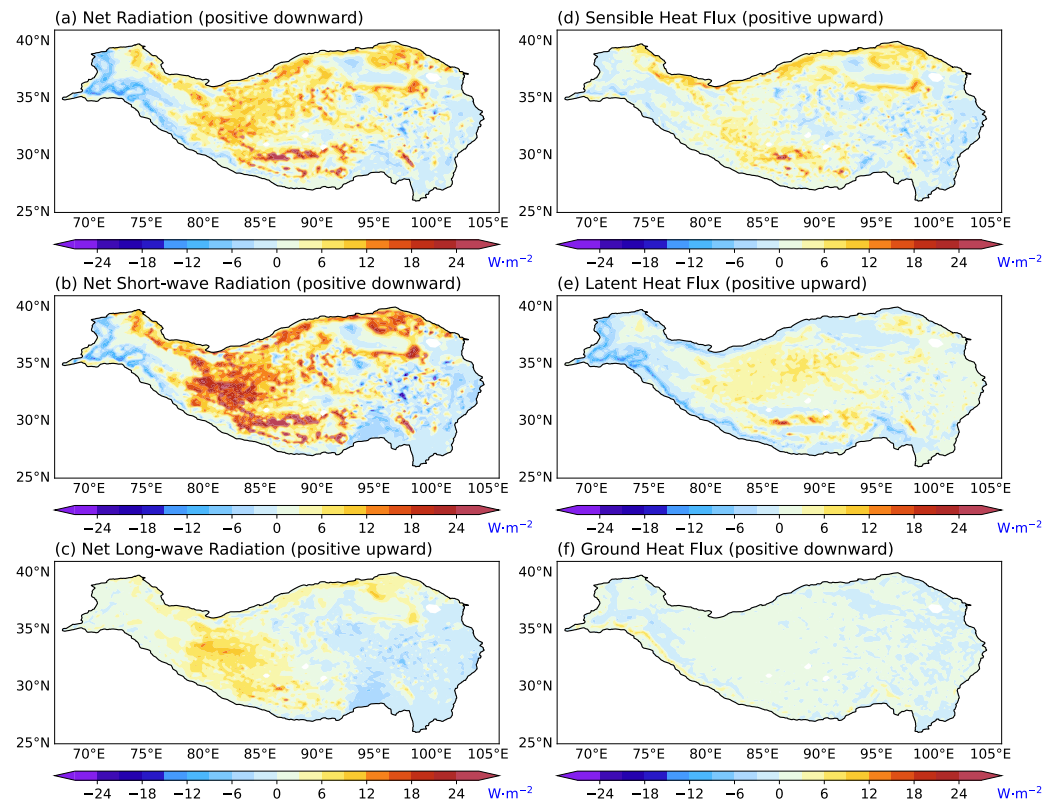


Figure 9. The differences of the simulated surface heat balance components temporally averaged over the cold seasons (1 October to 31 May) of 2011–2016 between the EXP_MNY and CTL_SL12 experiments on the Tibetan Plateau.

is released to the overlying atmosphere and deep soils, and further reduces the cold biases of the soil and surface air temperature simulations in the TP during cold seasons.

5. Conclusion and Discussion

Snow cover over the TP greatly regulates the heat and water exchanges at the land-air interface and the sub-grid terrain relief plays an important role in snow cover distribution over the TP. This study implemented an improved SCF scheme including a more sufficient sub-grid terrain effect into the RegCM4.7 to quantitatively reveal how the SCF modeling affects the soil and surface air temperature simulations over the TP in cold seasons based on numerical experiments. The main findings are summarized as follows:

The RegCM4.7 adopting the original SCF scheme overestimates the SCF over the TP in cold seasons. This overestimation can be evidently reduced by adopting the improved SCF scheme owing to the sub-grid terrain relief suppresses the rapid increase in SCF with snowfall and makes it difficult for the ground to be fully covered by snow. Quantitatively, adopting the improved SCF scheme can lead to the RMSE (TS) of the simulated SCF over the TP reduced by 12.0%–15.6% (increased by 1.4%–18.2%) over the regions with different sub-grid terrain reliefs.

Relative to the CTL_SL12 experiment, the much lower surface albedo produced by the EXP_MNY experiment adopting the improved SCF scheme leads to more surface absorbed solar radiation and thereafter more surface net radiation, which results in more ground heat flux, sensible heat flux, and latent heat flux. Subsequently, the soil temperature at both ground surface and deeper layers in cold seasons becomes warmer, and the surface air temperature also rises. Consequently, the cold biases of the modeled soil and surface air temperatures during cold seasons in the CTL_SL12 experiment are evidently alleviated by the EXP_MNY experiment. The column average of RMSE (TS) of the modeled soil temperature from ground surface to 200 cm on the TP in cold seasons decreased by 14.4% (increased by 7.3%). And the RMSE (TS) of the modeled surface air temperature over the

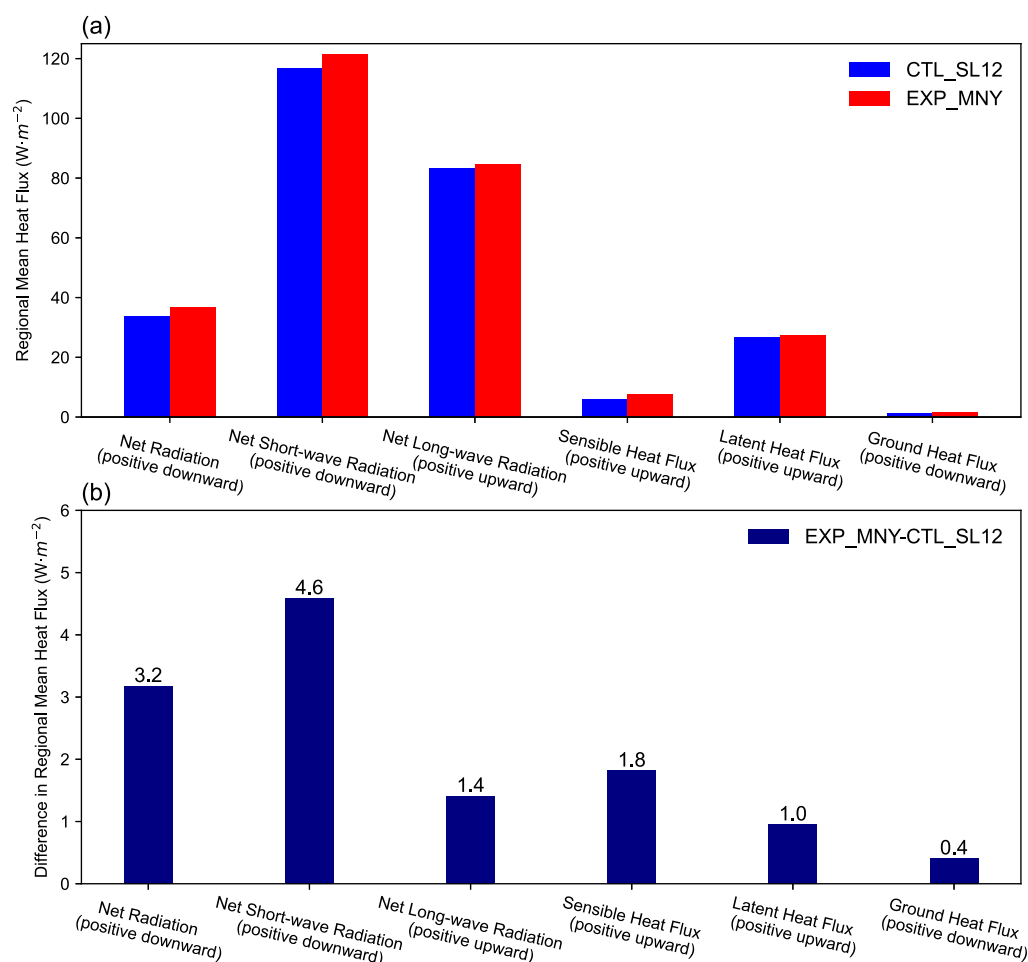


Figure 10. The spatially and temporally averaged surface heat balance components in the CTL_SL12 and EXP_MNY experiments over the Tibetan Plateau during the cold seasons (1 October to 31 May) of 2011–2016 (a) and their differences (b).

regions with different sub-grid terrain reliefs in cold seasons decreased by 2.0%–17.1% (increased by 0.1%–2.3%).

Moreover, adopting the improved SCF scheme delays the soil frozen onset date, advances the soil frozen end date, and then reduces the soil frozen duration, which are more consistent with the observation than the CTL_SL12 experiment, with the mean biases in the simulated frozen onset date, frozen end date, and frozen duration averaged over the TP reduced by 1.9%, 8.2%, and 6.3%, respectively.

This study presents that the implementation of an improved SCF scheme in RegCM4.7 significantly enhances the model performance in simulating SCF and soil and surface air temperatures over the TP in cold seasons. However, several limitations should be acknowledged regarding the evaluation methodology and model performance. First, the evaluation period is constrained to five years (2011–2016) due to limitations in data availability and computational resources. While this duration is sufficient to capture seasonal and interannual variability of snow cover and its impact on surface energy fluxes and thermal conditions, a longer evaluation period would provide more robust assessment of model performance. Second, although the improved SCF scheme enhances temperature simulations, it does not effectively mitigate the persistent wet bias in precipitation simulations. Consequently, the RegCM4.7 continues to exhibit overestimation of SCF and underestimations of soil and surface air temperatures on the TP during cold seasons. These limitations suggest that further improvements in the physical parameterizations are necessary.

The sub-grid terrain reliefs have been validated as an important factor influencing the regional climate simulations (He et al., 2019, 2021; He & Ohara, 2019; Ohara et al., 2008). The sub-grid terrain relief not only blocks incident solar radiation and downward atmospheric long-wave radiation but also reflects the solar radiation and emits long-wave radiation to the surrounding land surface (Gu et al., 2024; Huang et al., 2022; Zhang et al., 2022). Besides, the sub-grid terrain relief can regulate airflow through multi-scale dynamics (Gu et al., 2023; Xu et al., 2021; Zhou et al., 2019). Thus, the sub-grid terrain reliefs affect the surface radiation and energy balance through complex thermal and dynamical effects, and further affects the overlying atmospheric stratification, water vapor transport, and ultimately the phase, intensity, and distribution pattern of local and downstream precipitations (Cai et al., 2023; Gu et al., 2022, 2023, 2024). The standard deviation of sub-grid terrain elevation can effectively claim the inhomogeneity of the spatial distribution of SCF, but it is not sufficient to explain the spatial heterogeneity of snow water equivalent (Anderson et al., 2014; Feng et al., 2022). Therefore, the effects of sub-grid terrain reliefs on regional climate simulations through affecting hydrothermal exchanges at the land-air interface still deserve further exploration.

It is noteworthy that the RegCM4 has been upgraded to RegCM5 (Giorgi et al., 2023), which incorporates significant advances, particularly through the integration of the non-hydrostatic MOLOCH dynamical core. This new version demonstrates enhanced numerical stability and computational efficiency, offering improved performance for climate simulation. Therefore, we recommend the adoption of RegCM5 for future studies.

Data Availability Statement

The data used in this study are as follows: the filed observation data at Maduo (Meng & Lyu, 2022) and Naqu (Ma, 2020) sites; the hourly CLDAS soil and surface air temperatures (Shi et al., 2011); the MODIS daily cloud-free SCF product (Tang et al., 2013); the GLASS albedo products (available at <http://www.glass.umd.edu/>); the boundary data of the TP (Zhang et al., 2021); the 90-m terrain elevation data (Jarvis et al., 2008); the ERA-Interim reanalysis data (ECMWF, 2011); the OISST sea surface temperature data (NOAA, 2002); the surface soil moisture data of ESA CCI ECV (Dorigo et al., 2021); the GMTED terrain height data (Danielson & Gesch, 2011); the USGS GLCC data (available at <https://doi.org/10.5066/F7GB230D>). The code and supporting data of the RegCM4 are publicly available at <https://github.com/ictp-esp/RegCM> and <http://clima-dods.ictp.it/regcm4>. The revised code of RegCM4.7 in this study is available at <https://doi.org/10.5281/zenodo.15005084>.

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