Assessing the simulated soil thermal regime from Noah-MP LSM v1.1 for near-surface permafrost modeling on the Qinghai-Tibet Plateau

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Abstract. Land surface models (LSMs) are effective tools for near-surface permafrost modeling. Extensive and rigorous model inter-comparison is of great importance before application due to the uncertainties in current LSMs. This study designed an ensemble of 6912 experiments to evaluate the Noah land surface model with multi-parameterization (Noah-MP) for soil temperature (ST) simulation, and investigate the sensitivity of parameterization schemes at a typical permafrost site on the Qinghai-Tibet Plateau. The results showed that Noah-MP generally underestimates ST, especially that during the cold season. In addition, the simulation uncertainty is greater in the cold season (October-April) and for the deep soil layers. ST is most sensitive to surface layer drag coefficient (SFC) while largely influenced by runoff and groundwater (RUN). By contrast, the influence of canopy stomatal resistance (CRS) and soil moisture factor for stomatal resistance (BTR) on ST is negligible. With limited impacts on ST simulation, vegetation model (VEG), canopy gap for radiation transfer (RAD) and snow/soil temperature time scheme (STC) are more influential on shallow ST, while super-cooled liquid water (FRZ), frozen soil permeability (INF) and lower boundary of soil temperature (TBOT) have greater impacts on deep ST. Furthermore, an optimal configuration of Noah-MP for permafrost modeling were extracted based on the connectivity between schemes, and they are: table leaf area index with calculated vegetation fraction, Jarvis scheme for CRS, Noah scheme for BTR, BATS model for RUN, Chen97 for SFC, zero canopy gap for RAD, variant freezing-point depression for FRZ, hydraulic parameters defined by soil moisture for INF, ST at 8 m for TBOT, and semi-implicit method for STC. The analysis of the model structural uncertainties and characteristics of each scheme would be constructive to a better understanding of the land surface processes on the QTP and further model improvements towards near-surface permafrost modeling using the LSMs.
1 Introduction

The Qinghai-Tibet Plateau (QTP) hosts the world’s largest high-altitude permafrost covering a contemporary area of $1.06 \times 10^6$ km$^2$ (Zou et al., 2017). Under the background of climate warming and intensifying human activities, permafrost on the QTP has been widely suffering thermal degradation (Ran et al., 2018), resulting in reduction of permafrost extent, disappearing of permafrost patches and thickening of active layer (Chen et al., 2020). Moreover, such degradation could cause alterations in hydrological cycles (Zhao et al., 2019; Woo, 2012), changes on ecosystem (Fountain et al., 2012; Yi et al., 2011) and damages to infrastructures (Hjort et al., 2018). Therefore, it is very important to monitor and simulate the state of permafrost to adapt to the degradation.

Soil temperature (ST) is an intuitive indicator to evaluate the thermal state of permafrost. A number of monitoring sites have been established on the QTP (Cao et al., 2019). However, it is inadequate to construct the thermal state of permafrost by considering the spatial variability of the ground thermal regime and an uneven distribution of these observations. In contrast, numerical models are competent alternatives. In recent years, land surface models (LSMs), which describe the exchanges of heat, water, and momentum between the land and atmosphere (Maheu et al., 2018), have received significant improvements in the representation of permafrost and frozen ground processes (Koven et al., 2013; Nicolsky et al., 2007; Melton et al., 2019). LSMs are capable of simulating the transient change of permafrost by describing subsurface hydrothermal processes (e.g. soil temperature and moisture) with soil heat conduction (-diffusion) and water movement equations (Daniel et al., 2008). Moreover, they can be integrated with the numerical weather prediction system like WRF (Weather Research and Forecasting), making them as effective tools for comprehensive interactions between climate and permafrost (Nicolsky et al., 2007).

Some LSMs have been applied to modeling permafrost in the QTP. Guo and Wang (2013) investigated near-surface permafrost and seasonally frozen ground states as well as their changes using the Community Land Model, version 4 (CLM4). Hu et al. (2015)
applied the coupled heat and mass transfer model to identify the hydrothermal characteristics of the permafrost active layer in the Qinghai-Tibet Plateau. Using an augmented Noah LSM, Wu et al. (2018) modeled the extent of permafrost, active layer thickness, mean annual ground temperature, depth of zero annual amplitude and ground ice content on the QTP in 2010s. Despite those achievements based on different models, LSMs are in many aspects insufficient for permafrost modeling. For one thing, large uncertainties still exist in the state-of-the-art LSMs when simulating the soil hydrothermal regime on the QTP (Chen et al., 2019). For instance, 19 LSMs in CMIP5 overestimate snow depth over the QTP (Wei and Dong, 2015), which could result in the variations of the soil thermal regime in the aspects of magnitude and vector (cooling or warming) (Zhang, 2005). Moreover, most of the existing LSMs are not originally developed for permafrost modeling. Many of their soil processes are designed for shallow soil layers (Westermann et al., 2016), but permafrost may occur in the deep soil. And the soil column is often considered homogeneous, which can not represent the stratified soil common on the QTP (Yang et al., 2005). Given the numerous LSMs and possible deficiencies, it is necessary to assess the parameterization schemes for permafrost modeling on the QTP, which is helpful to identify the influential sub-processes, enhance our understanding of model behavior, and guide the improvement of model physics (Zhang et al., 2016).

Noah land surface model with multi-parameterization (Noah-MP) provides a unified framework in which a given physical process can be interpreted using multiple optional parameterization schemes (Niu et al., 2011). Due to the simplicity in selecting alternative schemes within one modeling framework, it has been attracting increasing attention in inter-comparison work among multiple parameterizations at point and watershed scales (Hong et al., 2014; Zheng et al., 2017; Gan et al., 2019; Zheng et al., 2019; Chang et al., 2020; You et al., 2020). For example, Gan et al. (2019) carried an ensemble of 288 simulations from multi-parameterization schemes of six physical processes, assessed the uncertainties of parameterizations in Noah-MP, and further revealed the best-performing schemes for latent heat, sensible heat and terrestrial water
storage simulation over ten watersheds in China. You et al. (2020) assessed the performance of Noah-MP in simulating snow process at eight sites over distinct snow climates and identified the shared and specific sensitive parameterizations at all sites, finding that sensitive parameterizations contribute most of the uncertainties in the multi-parameterization ensemble simulations. Nevertheless, there is little research on the inter-comparison of soil thermal processes toward permafrost modeling. In this study, an ensemble experiment of totally 6912 scheme combinations was conducted at a typical permafrost monitoring site on the QTP. The simulated soil temperature (ST) of Noah-MP model was assessed and the sensitivities of parameterization schemes at different depth were further investigated. Considering the general performance and sensitive schemes of Noah-MP, we further explored the interactions between the most influential schemes and configured an optimal combination based on the connections between schemes. We hope this study can provide a reference for permafrost simulation on the QTP.

This article is structured as follows: Section 2 introduces the study site, atmospheric forcing data, design of ensemble simulation experiments, and sensitivity analysis and optimal selection methods. Section 3 describes the ensemble simulation results of ST, explores the sensitivity and interactions of parameterization schemes, and determines the optimal combination for permafrost modeling. Section 4 discusses the schemes in each physical process and proposes further research topics. Section 5 concludes the main findings of this study.

2 Methods and materials

2.1 Site description and observation datasets

Tanggula observation station (TGL) lies in the continuous permafrost regions of Tanggula Mountain, central QTP (33.07°N, 91.93°E, Alt.: 5,100 m a.s.l; Fig. 1). This site is characterized by the sub-frigid and semiarid climate (Li et al., 2019). According to the observations from 2010–2011, the annual mean air temperature of TGL site was
−4.4 °C. The annual precipitation was 375 mm, and of which 80% is concentrated between May and September. Alpine steppe with low height is the main land surface, whose coverage range is about 40% ~ 50% (Yao et al., 2011). The active layer thickness is about 3.15 m (Hu et al., 2017).

The atmospheric forcing data, including wind speed/direction, air temperature/relative humidity/pressure, downward shortwave/longwave radiation, and precipitation, were used to drive the model. These variables above were measured at a height of 2 m and covered the period from August 10, 2010 to August 10, 2012 (Beijing time) with a temporal resolution of 1 hour. Daily soil temperature from October 1, 2010 to September 30, 2011 (Beijing time) were utilized to validate the simulation results.

![Figure 1](https://doi.org/10.5194/gmd-2020-142)

**Figure 1.** Location and geographic features of study site. (a) Location of observation site and permafrost distribution (Zou et al., 2017). (b) Topography of the Qinghai-Tibet Plateau. (c) Photo of the Tanggula observation station.

### 2.2 Ensemble experiments of Noah-MP

The offline Noah-MP LSM v1.1 was assessed in this study. It consists of 12 physical processes that are interpreted by multiple optional parameterization schemes. These sub-processes include vegetation model (VEG), canopy stomatal resistance
(CRS), soil moisture factor for stomatal resistance (BTR), runoff and groundwater (RUN), surface layer drag coefficient (SFC), super-cooled liquid water (FRZ), frozen soil permeability (INF), canopy gap for radiation transfer (RAD), snow surface albedo (ALB), precipitation partition (SNF), lower boundary of soil temperature (TBOT) and snow/soil temperature time scheme (STC) (Table 1). Details about the processes and optional parameterizations can be found in Yang et al. (2011a).

In this study, the dynamic vegetation option in VEG process was turned off for simplicity. Previous studies has confirmed that Noah-MP seriously overestimate the snow depth on the QTP (Li et al., 2020 (under review); Wang et al., 2020). However, the impact of snow cover on ground temperatures in the permafrost regions of QTP is usually considered weak (Jin et al., 2008; Wu et al., 2018), because the snow cover is thin, short-lived, and patchy-distributed (Che et al., 2019). To avoid the possible bias caused by snow process, the ALB and SNF processes were not considered. As a result, in total 6912 combinations are possible for the left 10 processes and orthogonal experiments were carried out to evaluate their performance in soil thermal dynamics and obtain the optimal combination.

The monthly leaf area index (LAI) was derived from the Advanced Very High-Resolution Radiometer (AVHRR) (https://www.ncdc.noaa.gov/data/, Claverie et al., 2016). The Noah-MP model was modified to consider the vertical heterogeneity in the soil profile by setting the corresponding soil parameters for each layer. The soil hydraulic parameters, including the porosity, saturated hydraulic conductivity, hydraulic potential, the Clapp-Hornberger parameter b, field capacity, wilt point, and saturated soil water diffusivity, were determined using the pedotransfer functions proposed by Hillel (1980), Cosby et al. (1984), and Wetzel and Chang (1987), in which the sand and clay percentages were based on Hu et al., (2017). In addition, the simulation depth was extended to 8.0 m to cover the active layer thickness of the QTP. The soil column was discretized following the default scheme in CLM 5.0 (Lawrence et al., 2018). A 30-year spin-up was conducted in every simulation to reach equilibrium soil states.
Table 1. The physical processes and options of Noah-MP. Options in bold are the optimal selections in this study.

| Physical processes            | Options                                                                 |
|-------------------------------|-------------------------------------------------------------------------|
| Vegetation model (VEG)        | (1) table LAI, prescribed vegetation fraction                           |
|                               | (2) dynamic vegetation                                                 |
|                               | (3) table LAI, calculated vegetation fraction                          |
|                               | (4) table LAI, prescribed max vegetation fraction                      |
| Canopy stomatal resistance (CRS) | (1) Jarvis                                                             |
|                               | (2) Ball-Berry                                                          |
| Soil moisture factor for stomatal resistance (BTR) | (1) Noah                                                               |
|                               | (2) CLM                                                                 |
|                               | (3) SSiB                                                                |
| Runoff and groundwater (RUN)  | (1) SIMGM with groundwater                                             |
|                               | (2) SIMTOP with equilibrium water table                                |
|                               | (3) Noah (free drainage)                                               |
|                               | (4) BATS (free drainage)                                               |
| Surface layer drag coefficient (SFC) | (1) Monin-Obukhov (M-O)                                               |
|                               | (2) Chen97                                                              |
| Super-cooled liquid water (FRZ) | (1) generalized freezing-point depression                              |
|                               | (2) Variant freezing-point depression                                   |
| Frozen soil permeability (INF) | (1) Defined by soil moisture, more permeable                           |
|                               | (2) Defined by liquid water, less permeable                            |
| Canopy gap for radiation transfer (RAD) | (1) Gap=F(3D structure, solar zenith angle)                           |
|                               | (2) Gap=zero                                                            |
|                               | (3) Gap=1-vegetated fraction                                            |
| Snow surface albedo (ALB)     | (1) BATS                                                                |
|                               | (2) CLASS                                                               |
| Precipitation partition (SNF) | (1) Jordan91                                                            |
|                               | (2) BATS: T_{t0} < T_{frz} + 2.2K                                      |
|                               | (3) T_{t0} < T_{frz}                                                   |
| Lower boundary of soil temperature (TBOT) | 1) zero heat flux                               |
|                               | 2) soil temperature at 8m depth                                         |
| Snow/soil temperature time scheme (STC) | (1) semi-implicit                                                |
|                               | (2) full implicit                                                       |

BATS (Biosphere–Atmosphere Transfer Model); CLASS (Canadian Land Surface Scheme); SIMGM (Simple topography-based runoff and Groundwater Model); SIMTOP (Simple Topography-based hydrological model); SSiB (Simplified Simple Biosphere model).

2.3 Methods for sensitivity analysis

The root mean square error (RMSE) and standard deviation (SD) between the
simulations and observations were adopted to evaluate the performance of Noah-MP.

The averages of the RMSEs and SDs of all the soil layers were defined as column RMSE (colRMSE) and column SD (colRMSE), respectively.

To investigate the influence degrees of each physical process on ST, we firstly calculated the mean RMSE ($\bar{Y}_j^i$) of the $j$th parameterization schemes ($j = 1, 2, \ldots$) in the $i$th process ($i = 1, 2, \ldots$). Then, the maximum difference of $\bar{Y}_j^i$ ($\Delta\bar{RMSE}$) was defined to quantify the sensitivity of the $i$th process ($i = 1, 2, \ldots$):

$$\Delta\bar{RMSE} = \bar{Y}_{\text{max}}^i - \bar{Y}_{\text{min}}^i$$

where $\bar{Y}_{\text{max}}^i$ and $\bar{Y}_{\text{min}}^i$ are the largest and the smallest $\bar{Y}_j^i$ in the $i$th process, respectively. For a given physical process, a high $S_i$ signifies large difference between parameterizations, indicating high sensitiveness of the $i$th process.

The sensitivities of physical processes were determined by quantifying the statistical distinction level of performance between parameterization schemes. The Independent-sample T-test (2-tailed) was adopted to identify whether the distinction level between two schemes is significant, and that between three or more schemes was tested using the Tukey's test. Tukey's test has been widely used for its simple computation and statistical features (Benjamini, 2010). The detailed descriptions about this method can be found in Zhang et al. (2016), Gan et al. (2019), and You et al. (2020).

A process can be considered sensitive when the schemes show significant difference. Moreover, schemes with small mean RMSE were considered favorable for ST simulation. We distinguished the differences of the parameterization schemes at 95% confidence level.

### 2.4 Optimal selection methods

To extract the optimal combinations of parameterization schemes, the connection frequency (CF) between parameterizations was calculated:

1. Sorting the 6912 colRMSEs in an ascending order;
2. Donating the colRMSEs concentrated below the 5th percentile as the "best
combinations" (346 members); 207

(3) Counting the times of a given parameterizations occurring with other parameterizations in the "best combinations";

(4) The CF was then determined by dividing 346.

Obviously, for two given parameterization schemes, a large CF has an advantage in terms of optimal combination.

3 Results

3.1 General performance of the ensemble simulation

We evaluated ST from the 6912 experiments against observations. Figure 2 illustrates the ensemble simulated and observed annual cycle of ST at TGL site. The plots give the uncertainty ranges of the ensemble experiments using five statistical indicators, i.e., the first/third quartile (Q1/Q3), mean, the lower (Q1-1.5(Q3-Q1)) and upper bound (Q3+1.5(Q3-Q1)). The kernel density distribution of the simulated ST is also illustrated. The ensemble experiments basically captured the seasonal variability of ST, whose magnitude decreased with soil depth. In addition, the simulated ST in the cold season (October-April) showed relatively wide uncertainty ranges, particularly at the deep layers. This indicates that the selected schemes perform more differently during the cold season, which is especially so at the deep layers. The simulated ST were generally smaller than the observations with relatively large gap during the cold season. It indicates that the Noah-MP model generally underestimates the ST, especially during the cold season. Moreover, the simulated ST was widely found to be bimodal distribution across the soil column, implying that two schemes dominate the ST simulation in the Noah-MP model.
Figure 2. Monthly soil temperature (ST) at (a) 5 cm, (b) 25 cm, (c) 70 cm, (d) 140 cm, (e) 220 cm, (f) 300 cm at TGL site. Limits of the boxes represent upper and lower quartiles, whiskers extend to 1.5 times the interquartile range (IQR). The green circles in the box are the ensemble mean values. The light orange shading represents the kernel density distribution of simulated ST. The red diamonds are observations and the blue circles are the results of the optimal scheme combination.
3.2 Sensitivity of physical processes

3.2.1 Influence degrees of physical processes

Figure 3. The maximum difference of the mean RMSE ($\Delta \overline{RMSE}$) in each physical process at different soil depths.

Figure 3 compares the influence scores of the 10 physical processes at different soil depths, based on the maximum difference of the mean RMSE over 6912 experiments using the same scheme, for ST at TGL site. The RUN and SFC processes dominated the $\Delta \overline{RMSE}$ at all layers, indicating that they are the most sensitive processes for ST simulation. While the $\Delta \overline{RMSE}$ of the other 8 physical processes were all less than 0.5°C, among which the influence of CRS and BTR processes were negligible. What's more, the VEG, RAD and STC processes were more influential on the shallow STs than the deep STs. Taking the STC process as an example, the $\Delta \overline{RMSE}$ of the 5cm and 25 cm were nearly 0.5°C while that of the 70 cm, 140cm, 220cm and 300cm were no more than 0.3°C. In contrast, the influence of FRZ, INF and TBOT processes were generally greater in deep soils than shallow soils.

Interactions between two of the most influential physical processes are analyzed in this section. The performance of the simulations with SFC and RUN were rated by rounding the colRMSEs and colSDs (Fig. 4). Given the colRMSE=1.2 for one simulation, then the score of the simulation equals 1 (SCORE=1) for the corresponding combination. It can be seen that SFC(1) in the SFC process and RUN(3) in the RUN
process were the major schemes that contribute to the cold bias of the ensemble simulation, because they dominated the cold bias of the ensemble simulation with relatively low colSD scores (Fig. 4b). Consistent with the bimodal distribution in Fig. 2, most of the simulations with relative low colRMSE and nearly zero colSD were related to SFC(2). It indicates that combinations with SFC(2) result in better performance than SFC(1) by improving the underestimations of ST. Among the schemes in RUN, RUN(1), RUN(2) and RUN(4) had approximately equal chance to produce better and worse performance for ST simulation, implying a dominating role of the SFC process (Fig. 4a). RUN(3) produced much worse performance by aggravating the underestimation of ST. Ultimately, the best results came from the combination of SFC(2) and RUN(4), while the worst results were from the combination of SFC(1) and RUN(3).

![Figure 4. Rating of combinations with SFC and RUN.](https://doi.org/10.5194/gmd-2020-142)

### 3.2.2 Sensitivities of physical processes and general behaviors of parameterizations

To further investigate the sensitivity of each process and the general performance of the parameterizations, the Independent-sample T-test (2-tailed) and Tukey's test were conducted to test whether the difference between parameterizations within a physical process is significant (Fig. 5). In a given sub-process, any two schemes labelled with different letters behave significantly different, and this sub-process therefore can be identified as sensitive. Otherwise, the sub-process is considered insensitive. Moreover, schemes with the letters late in the alphabet have smaller mean RMSEs and outperform
the ones with the letters forward in the alphabet. Using the three schemes in vegetation model process (hereafter VEG(1), VEG(3) and VEG(4)) in Fig. 5 as an example. At the depth of 5cm and 300cm, VEG(1) was labeled with letter "A", while VEG(3) and VEG(4) was labeled with letter "B". For the depth of 25cm, 70cm, 140cm and 220cm, VEG(1), VEG(3) and VEG(4) were labeled with the letter "A", "C" and "B", respectively. As described above, the VEG process was sensitive for ST simulation. Moreover, VEG(3) and VEG(4) had advantages in producing good simulations than VEG(1) at 5cm and 300cm depths, and the performance decreased in the order of VEG(3) > VEG(4) > VEG(1) at other layers. In terms of the whole soil column, VEG(3) outperformed VEG(1) and VEG(4).

Consistent with the result in Fig. 3, all other physical processes showed sensitivities in varying magnitudes except the BTR and CRS process. And the performance difference between schemes of the RUN and SFC were obviously greater than other processes. For the RUN process, the performance orders followed RUN(4) > RUN(1) > RUN(2) > RUN(3) as a whole. Meanwhile, the difference between RUN(1) and RUN(4) was indistinctive at the shallow layers (5 cm, 25 cm and 70 cm) and significant but very small at the deep layers (140 cm, 220 cm and 300 cm). Moreover, the performance orders were SFC(2) > SFC(1) for SFC process, FRZ(2) > FRZ(1) for FRZ process, RAD(3) > RAD(1) > RAD(2) for RAD process, TBOT(1) > TBOT(2) for TBOT process, and STC(2) > STC(1) for STC process. In particular, the FRZ process showed sensitivity at the deep in spite of the shallow soil. Compared with INF(1), INF(2) performed better at the shallow soils while did worse at the deep soils.
Figure 5. Distinction level for RMSE of ST at different layers in the ensemble simulations. Limits of the boxes represent upper and lower quartiles, whiskers extend to the maximum and minimum RMSE. The black stations in the box are the average values. The lines in the box indicate the median value.

3.3 The optimal combination

The CF was calculated to extract the optimal combination of parameterization schemes for ST simulation (Fig. 6). The CF between any two schemes from the same physical process was zero as expected. Consistent with Fig. 5, the CF of RUN(3) with other schemes was zero, implying that using RUN (3) provides an extreme less chance of producing favorable simulations than using RUN(1), RUN(2) or RUN(4). A higher
CF signify greater probability of producing advantageous simulations. For instance, the CF between SFC(2) and VEG(3) was 0.45, about two times than the CFs between SFC(2) and VEG(1)/VEG(4). It indicates that 45% of the 346 best combinations adopted SFC(2) and VEG(3) simultaneously, and the combination of SFC(2) and VEG(3) tend to inducing better ST in comparison of the combination of SFC(2) and VEG(1)/VEG(4).

SFC(2) is firstly determined as one of the schemes that make up the optimal combination, because it was most widely linked to other parameterization schemes with relatively large CFs. Other optimal schemes of each physical process can be determined by choosing the one that has large CF with SFC(2). Obviously, VEG(3), RUN(4), FRZ(2) and INF(1) outperform other schemes in the corresponding physical processes and were selected for optimal combination. The schemes within CRS, BTR, RAD and STC processes scored nearly identical CFs with SFC(2). Due to the insensitivity of CRS and BTR, CRS(1) and BTR(1), which are the default schemes in Noah-MP, were determined as the member schemes of the optimal combination. Combining the selected schemes above with different schemes of RAD and STC processes, there are 6 candidate combinations, among which the one with smallest colRMSE is selected as the optimal combination. Ultimately, the determined schemes for optimal combination is VEG(3), CRS(1), BTR(1), RUN(4), SFC(2), FRZ(2), INF(1), RAD(2), TBOT(2) and STC(1) (Table 1).

The simulated results of the optimal scheme combination well captured the variation of ST (Fig. 2). Despite the overestimation of ST at the shallow soil layers from April to July, the optimal combination well produced the ST during the cold season and of the deep layers (Fig. 2).
4 Discussion

4.1 Possible reasons for the cold bias of soil temperature

The cold bias of soil temperature on the QTP are widely reported in many of the state-of-the-art LSMs (Yang et al., 2009; Chen et al., 2019). One of the main reason can be the inability of representing the diurnal variation of roughness length for heat ($Z_{0h}$) on the QTP (Yang et al., 2008; Chen et al., 2010), which is of great importance for a reliable calculation of the sensible and latent heat, and thus for the soil surface/profile temperature calculation (Zeng et al., 2012; Zheng et al., 2012). Noah-MP parameterize $Z_{0h}$ in the two schemes of SFC process (Table 1). In the M-O scheme, $Z_{0h}$ is taken as the same with the roughness length for momentum ($Z_{0m}$, Niu et al., 2011). The Chen97 scheme adopts the Zilitinkevitch approach (Zilitinkevich, 1995). However, both of them couldn't produce the diurnal variation of $Z_{0h}$ (Chen et al., 2010).

Another possible reason is the poor representation of the thermal conductivity ($\lambda$) of frozen soil. Considering that the $\lambda$ of ice is nearly four times higher than liquid
water, \( \lambda \) of frozen soil is generally expected to be greater than that of unfrozen soil. Many parameterization schemes of \( \lambda \), including the Johansen scheme in Noah-MP, follow this pattern (Du et al., 2020). However, contrary phenomenon is widely reported over the QTP (Pan et al., 2016; Hu et al., 2017; Yi et al., 2018; Li et al., 2019), including the TGL site (Li et al., 2019). As a result, a majority of the state-of-the-art LSMs have tended to overestimate the soil thermal conductivity of the QTP (Luo et al., 2009; Chen et al., 2012; Du et al., 2020), which exactly explains the underestimation of soil temperature during cold season and, at times, an overestimation during the warm season (Luo et al., 2009).

4.2 Discussions on the sensitivity of physical processes

4.2.1 Vegetation model (VEG) and canopy gap for radiation transfer (RAD)

As listed in Table 1, VEG process includes three options to calculate the variation of vegetation fraction (FVEG) in this study. VEG(3) calculates the daily FVEG based on the interpolated LAI, while VEG(1) and VEG(4) uses the prescribed monthly and maximum LAI, respectively. Obviously, VEG(3) produces more realistic FVEG over the year, followed by VEG(1) and VEG(4). VEG(4) grossly overestimates the FVEG, especially that during the cold season. Consequently, VEG(3) outperformed VEG(1) and VEG(4). However, VEG(4) is widely used in many studies (Gao et al., 2015; Chen et al., 2016; Li et al., 2018) despite overestimating the FVEG. In this study, VEG(4) performed better than VEG(1).

RAD treats the radiation transfer process within the vegetation, and adopts three methods to calculate the canopy gap. RAD(1) defines canopy gap as a function of the 3D vegetation structure and the solar zenith angle, RAD(2) employs no gap within canopy, and RAD(3) treat the canopy gap from unity minus the FVEG (Niu and Yang, 2004). The RAD(3) scheme penetrates the most solar radiation to the ground, followed by the RAD(1) and RAD(2) schemes. As an alpine grassland, there is a relative low LAI at TGL site, and thus a quite high canopy gap. So, schemes with a larger canopy gap could realistically reflect the environment. Consequently, the performance
decreased in the order of RAD(3) > RAD(1) > RAD(2) for ST simulation.

4.2.2 Canopy stomatal resistance (CRS) and soil moisture factor for stomatal resistance (BTR)

The biophysical process BTR and CRS directly affect the canopy stomatal resistance and thus the plant transpiration (Niu et al., 2011). The transpiration of plants could impact the ST through its cooling effect (Shen et al., 2015) and the water balance of root zone (Chang et al., 2020). However, the annual transpiration of alpine steppe is weak due to the shallow effective root zone and lower stomatal control in this dry environment (Ma et al., 2015). As a result, the BTR process was insensitive at all layers. CRS(1) and CRS(2) had no significant difference at most layers except the last two layers. However, the performance difference between CRS(1) and CRS(2) at the last two layers is very small (Fig. 3 and 5).

4.2.3 Runoff and groundwater (RUN)

For the RUN process, RUN(3) had the worst performance for simulating soil moisture (Fig. S1) and thus for ST (Fig. 5) among the four schemes, likely due to its free drainage assumption for subsurface runoff (Schaeke et al., 1996), which is partly consistent with the study of Zhang et al. (2016) that RUN(3) is the worst-performing scheme for sensible and latent heat simulation in most cases compared with RUN(1) and RUN(2). RUN(4) also adopts the free drainage concept. However, RUN(4) outperformed RUN(3). It can be explained by the fourth power function of wetness at the top 2-m soil in RUN(4), in which the partition of surface runoff and infiltration is regulated by soil moisture (Yang and Dickinson, 1996). RUN(4) was on a par with RUN(1) in the simulation of unfrozen water (Fig. S1). Consequently, there was no or very small difference between RUN(4) and RUN(1) at shallow/deep soils (Fig. 5). For the whole soil column, RUN(4) surpassed RUN(1) and RUN(2), both of which define surface/subsurface runoff as functions of groundwater table depth (Niu et al., 2005; Niu et al., 2007). This is in keeping with the study of Zheng et al. (2017) that soil water storage-based parameterizations outperform the groundwater table-based
parameterizations in simulating the total runoff in a seasonally frozen and high-altitude Tibetan river. Besides, RUN(4) is designed based on the infiltration-excess runoff (Yang and Dickinson, 1996) in spite of the saturation-excess runoff in RUN(1) and RUN(2) (Gan et al., 2019), which is more common in arid and semiarid areas like the permafrost regions of QTP (Pilgrim et al., 1988).

### 4.2.4 Surface layer drag coefficient (SFC)

SFC defines the calculations of the surface exchange coefficient for heat and water vapor (CH), which greatly impact the energy and water balance and thus the temperature of land surface. SFC(1) adopts the Monin-Obukhov similarity theory (MOST) with a general form, while the SFC(2) uses the improved MOST modified by Chen et al. (1997). The most distinct difference between them is that SFC(1) considers the zero-displacement height while SFC(2) parameterizes $Z_{0h}$ and $Z_{0m}$ using different schemes. The difference between SFC(1) and SFC(2) has a great impact on the CH value. Several studies have reported that SFC(2) has a better performance for the simulation of sensible and latent heat on the QTP (Zhang et al., 2016; Gan et al., 2019). The results of Tukey's test in this study showed remarkable distinctions between the two schemes, where SFC(2) was dramatically superior to SFC(1) (Fig. 5). SFC(2) produces lower CH than SFC(1) (Zhang et al., 2014), resulting in less efficient ventilation and greater heating of the land surface (Yang et al., 2011b), and substantial improvement of the cold bias of Noah-MP in this study (Fig. 4).

### 4.2.5 Super-cooled liquid water (FRZ) and frozen soil permeability (INF)

FRZ treats unfrozen water (super-cooled liquid water) in frozen soil using two forms of freezing-point depression equation. FRZ(1) takes a general form (Niu and Yang, 2006), while FRZ(2) exhibits a variant form that considers the increased surface area of icy soil particles (Koren et al., 1999). FRZ(2) generally yields more liquid water in comparison of FRZ(1). In this study, FRZ process did not show sensitivity at the shallow soil layers (5cm and 25cm), but showed an increasing sensitivity at the deep layers (Fig. 3), which can be related to the longer frozen duration of deep soil.

INF(1) uses soil moisture (Niu and Yang, 2006) while INF(2) employs only the
liquid water (Koren et al., 1999) to parameterize soil hydraulic properties. INF(2) generally produces more impermeable frozen soil than INF(1), which is also found in this study (Fig. S2). Due to the more realistic representation of unfrozen water during the cold season (Fig. S2), INF(2) surpassed INF(1) in simulating ST at 5 cm and 25 cm depth, while INF(1) outperformed INF(2) at 70 cm, 140 cm and 220 cm (Fig. 5). This result also indicates that INF(1) and INF(2) could alleviate the overestimation and underestimation of unfrozen water, respectively. INF(2) performed worse than INF(1) at 300 cm depth (Fig. 5) in spite of the better agreement with unfrozen water (Fig. S2), which may be related to the overestimation of soil moisture of INF(2) at the depth of 140 cm.

4.2.6 Lower boundary of soil temperature (TBOT) and snow/soil temperature time scheme (STC)

TBOT process adopts two schemes to describe the soil temperature boundary conditions. TBOT(1) assumes zero heat flux at the bottom of the model, while TBOT(2) adopts the soil temperature at the 8 m depth (Yang et al., 2011a). In general, TBOT(1) is expected to accumulate heat in the deep soil and produce higher ST than TBOT(2). In this study, the two assumptions performed significantly different, especially at the deep soil. Although TBOT(2) is more representative of the realistic condition, TBOT(1) surpassed TBOT(2) in this study. It can be related to the overall underestimation of the model, which can be alleviated by TBOT(1) because of heat accumulation (Fig. S3).

Two time discretization strategies are implemented in the STC process, where STC(1) adopts the semi-implicit scheme while STC(2) uses the full implicit scheme, to solve the thermal diffusion equation in first soil or snow layers (Yang et al., 2011a). STC(1) and STC(2) are not strictly a physical processes but different upper boundary conditions of soil column (You et al., 2019). The differences between STC(1) and STC(2) were significant (Fig. 5). Snow processes are not involved in this study, the impacts of the two options on ST is remarkable (Fig. 5), particularly in the shallow layers (Fig. 3). In addition, STC(2) outperformed STC(1) in the ensemble simulation experiments (Fig. 5), because the higher ST produced by STC(2) (Fig. S4) alleviated
4.3 Perspectives

We identified the systematic cold bias of Noah-MP and discussed the possible sources of error, and analyzed the characteristics and general behavior of each parameterization scheme at a permafrost site on the QTP. This work would be constructive to a better understanding of the land surface processes on the QTP and further model improvements towards near-surface permafrost modeling using the LSMs.

Although the optimal combination demonstrated in this study is only from the selected site, our results provide a practical way to investigate the permafrost state on the QTP. The optimal combination well simulated the ST, especially that of deep layers (Fig. 2). The representation of deep ST is crucial for permafrost modeling, which directly affects the permafrost features such as active layer thickness and temperature at the top of the permafrost. Further investigation with a broad spectrum of climate and environmental conditions is necessary to make a general conclusion.

5 Conclusions

In this study, an ensemble simulation of soil temperature using multi-parameterizations was conducted using the Noah-MP model at the TGL site, aiming to provide a reference for permafrost simulation using LSMs. The model was modified to consider the vertical heterogeneity in the soil and the simulation depth was extended to cover the whole active layer. The ensemble simulation consists of 6912 parameterization experiments, combining ten physical processes (VEG, CRS, BTR, RUN, SFC, FRZ, INF, RAD, TBOT, and STC) each with multiple optional schemes. On this basis, the general performance of Noah-MP was assessed by comparing simulation results with in situ observations, and the sensitivity of soil temperature at different depth of active layer to parameterization schemes was explored. Furthermore,
we proposed a new method to extract the optimal combination of schemes to simulate soil temperature in the permafrost regions of the QTP. The main conclusions are as follows:

(1) Noah-MP model has relatively large uncertainties in the cold season, particularly at the deep layers. Moreover, the model tends to underestimate soil temperature, especially during the cold season. This is largely due to the imperfect model structure with regard to the roughness length for heat and soil thermal conductivity.

(2) Soil temperature is dominated by the surface layer drag coefficient (SFC) while largely influenced by runoff and groundwater (RUN). SFC(2) and RUN(3) could significantly alleviate and aggravate the cold bias of soil temperature, respectively. Other physical processes have little impact on ST simulation, among which VEG, RAD, and STC are more influential on shallow ST, while FRZ, INF and TBOT have greater impacts on deep ST. In addition, CRS and BTR do not significantly affect the simulation results.

(3) The best scheme combination for permafrost simulation are as follows: VEG (table LAI, calculated vegetation fraction), CRS (Jarvis), BTR (Noah), RUN (BATS), SFC (Chen97), RAD (zero canopy gap), FRZ (variant freezing-point depression), INF (hydraulic parameters defined by soil moisture), TBOT (ST at 8 m), STC (semi-implicit).

Code availability. The source code of offline 1D Noah-MP LSM v1.1 is available at https://ral.ucar.edu/solutions/products/noah-multiparameterization-land-surface-model-noah-mp-lsm (last access: 15 May 2020). The modified Noah-MP with the consideration of vertical heterogeneity, extended soil depth, and pedotransfer functions is available upon request to the corresponding author. The data processing code are available at http://dx.doi.org/10.17632/gc7vfgkyng.1.

Data availability. The 1-hourly forcing data and daily soil temperature data at the TGL site are available at http://dx.doi.org/10.17632/gc7vfgkyng.1. Soil texture data can be
obtained at https://doi.org/10.1016/j.catena.2017.04.011 (Hu et al., 2017). The AVHRR LAI data can be downloaded from https://www.ncei.noaa.gov/data/ (Claverie et al., 2016).

Author contributions. TW and XL conceived the idea and designed the model experiments. XL performed the simulations, analyzed the output, and wrote the paper. XW, XZ, GH, RL contributed to the conduction of the simulation and interpretation of the results. YQ provided the observations of atmospheric forcing and soil temperature. CY and JH helped in downloading and processing the AVHRR LAI data. JN and WM provide guidelines for the visualization. Everyone revised and polished the paper.

Competing interests. The authors declare that they have no conflict of interest.

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